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Abstract

In this thesis, I study topics in development economics and finance, focusing on the effects of policies in the digital payments' market and regulation of immigration. The thesis comprises three distinct papers that explore financial behavior, technological adoption, and economic policy impacts in developing contexts.

The first paper examines the impact of substituting bank deposits with digital currency on banks' lending behavior in developing countries. Using an unexpected tax on Mobile Money in Uganda as a natural experiment, the study finds that the tax led to decreased mobile money usage and increased bank deposits and ATM withdrawals. This influx of new deposits allowed banks to increase their lending. However, the nature of new liquidity resulted in shorter loan repayment terms and a shift of credit from high-risk to low-risk borrowers. Consequently, low-risk borrowers received larger loans at lower interest rates.

The second paper investigates the trade-off between competition and financial inclusion due to vertical integration of mobile network and money operators in Africa. By analyzing data on mobile money fees, network coverage, and financial performance, the study finds that platform interoperability policies lowered fees and reduced fee disparities across operators. However, this benefit was offset by a reduction in mobile towers and network coverage, particularly in rural and poor areas, leading to decreased financial inclusion. The study suggests that combining interoperability with rural telecommunications subsidies can reduce fees without compromising coverage.

The third paper explores the effects of restrictive immigration policies on technology adoption in migrant-sending countries. Analyzing the dramatic drop in Italian emigration to the United States following the 1921 Emergency Quota Act, the study uses a difference-in-differences approach to show that reduced emigration hindered technology adoption and capital investment. This is consistent with the theory that increased labor supply decreases firms' incentives to adopt labor-saving technologies. Data indicates that districts more exposed to migration restrictions saw significant increases in population and manufacturing employment due to the "missing migrants" who could not emigrate.

These essays provide insights into the complex dynamics of financial behavior, technology adoption, and policy impacts in developing economies, highlighting the trade-offs and interconnected outcomes that policymakers must consider to foster inclusive and sustainable economic development.

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Back to bank:
digital currency, deposits' substitution and credit*

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Abstract

We study the consequences of substitution between bank deposits and digital currency on banks' lending behavior in developing countrie. Leveraging an unexpected tax on Mobile Money in Uganda and using an exclusive dataset on the universe of mobile money transactions, we show a drop in mobile money usage and an increase in the flow of bank deposits and ATM withdrawals. The high turnover of new deposits helps us uncover unique insights into banks' hedging against liquidity risk: we show a general decrease in loans' repayment terms, and a transfer of rent from high-risk borrowers lacking credit history to low-risk borrowers. Consequently, the latter group experiences relatively higher loans and lower interest rates.

Keywords: Mobile Money, Financial Inclusion, Digital Currency

JEL Codes: G21, E41, O11

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1 Introduction

The dynamic landscape of digital payments is undergoing a transformative phase, with implications reaching far beyond transactional convenience. Within this context, we explore the intricate interactions between digital and traditional payment systems, focusing on the repercussions for bank lending and financial inclusion.

A pivotal catalyst for our investigation is the ongoing debate on the potential introduction of Central Bank Digital Currencies (CBDCs), with raising questions about the ambiguous effects on the credit market (Andolfatto (2021), Agur et al. (2022)). The global interest in CBDCs highlights the need for empirical investigations into their potential repercussions on the banking sector. While theoretical frameworks, as exemplified by Chiu et al. (2023), offer diverse perspectives on the consequences of CBDC introduction, empirical validations remain scarce.

Our research aims to bridge this gap. We exploit an unexpected tax on Mobile Money introduced by the Ugandan government in July 2018 to study how a shock to the cost of digital currencies induces substitution with cash and bank deposits, eventually affecting banks' liquidity and credit provision.

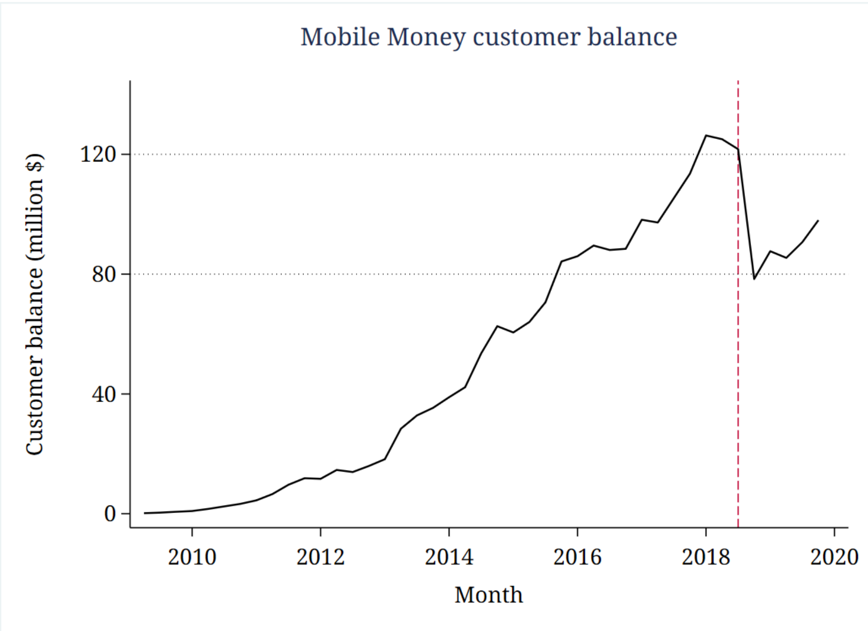
From a policy perspective, we also provide empirical evidence on the unintended consequences of digital currency taxation in developing countries (Okunogbe and Tourek, 2024). Indeed, the palpable tension surrounding Mobile Money taxes across African nations[1] underscores a broader concern about the trade-offs inherent in the adoption of digital currencies. Mobile money has emerged as one of the most widespread digital payment systems (Demirguc-Kunt et al., 2018), and its diffusion resulted in tangible changes in various economic and financial indicators like risk-sharing (Jack and Suri (2011); Blumenstock et al. (2016)), remittances (Riley (2018); Aker et al. (2020)), lending (Suri et al., 2021) and savings (Breza et al., 2022), among others. Despite these significant developments, research on the functioning and regulation of this technology remains limited

[1] In the last few years, taxes on mobile money transactions have increasingly been implemented in various African countries, with Uganda, Zimbabwe, Côte d'Ivoire, Kenya and the Republic of the Congo having implemented this tax prior to the Covid pandemic in 2020, while Tanzania, Cameroon and Ghana have done the same since.

(Brunnermeier et al., 2023).

Positioning Mobile Money in competition with both cash for transactions and bank deposits for money storage, our conceptual framework elucidates its comparative advantages. Factors such as accessibility, cost-effectiveness, and ease of account opening underscore the potential dominance of Mobile Money in specific contexts. The Mobile Money tax introduced by the Ugandan Government in July 2018 affected the convenience of Mobile Money with respect to other systems, resulting in an abrupt drop in its usage. In Figure 1 we show that in the first quarter following the tax users withdrew the equivalent of 40 million US $ from the Mobile Money network. With our analysis, we support evidence that this money was (partly) moved to the banking sector for its storage as deposits, inducing a positive liquidity shock to banks, that influenced their lending behavior.

Figure 1: Mobile Money customer balance



Notes: This figure plots the quarterly customer balance of mobile money, expressed in US $. It represents the value of mobile money detained by users. We show that in the trimester after the implementation of the tax, the value of mobile money detained by users decreased of about 40 million US $.

As outlined in our model in Appendix C - Theoretical Framework, the tax-induced shock triggers a shift in payment systems usage, depending on users' responsiveness to the increased cost of digital currency. To empirically investigate the outlined mechanisms, our research leverages an exclusive dataset on the universe of Mobile Money transactions in Uganda, allowing us to track individual users. We employ a quasi-experimental design, leveraging the temporal variation introduced by the Mobile Money tax and the variation at geographical level coming from the heterogeneous access to Mobile Money alternatives, proxied by the density of ATMs. Difference-in-differences and event-study approaches form the backbone of our empirical methodology.

We exploit the same identification to provide evidence of increased bank deposits and cash usage in districts where access to banks is made easier by the pervasiveness of ATMs. We show that the mobile money tax triggers the adoption of a new bank-related technology, called banking agents, that facilitates the opening of bank accounts and the deposit of cash, and we provide evidence that bank deposits grow through this new technology. These results are in line with previous literature on complementarity of network technologies, such as Crouzet et al. (2019). Indeed, being the presence of Points of Sales (POS) still underdeveloped, and hence being it difficult to pay with credit and debit cards, consumers need to use cash for day-to-day payments. While the new banking technology facilitates the opening of bank accounts and the deposit of money, the presence of ATMs is the facilitator through which people can easily access the money they store into banks. There is hence complementarity between this new banking technology and ATMs. Our results on increased ATMs withdrawals and cash issuance support our hypothesis that mobile money competes with bank deposits for money storage and with physical cash for payments.

Eventually, we leverage the transition from mobile money to bank deposits for money storage and its subsequent positive impact on bank liquidity to examine its effects on the credit market. Our study unveils novel insights into the lending behaviors of banks amidst increased deposit volatility. We observe heightened deposit flows and ATM withdrawals post the tax implementation: our evidence however reveals a significant change only in the stock of demand deposits at the bank level. This suggests the precarious nature of the newfound liquidity, which banks cannot depend on for long-term and secure credit.

The data indicates a widespread reduction in the repayment term of new loans, reflecting the imperative for banks to cope with the continual cash withdrawals. Additionally, there is a discernible shift in rent from high-risk borrowers lacking credit history to low-risk borrowers with established credit records. These findings imply a shift in banks' strategies as they hedge against the risk of liquidity shortages. The anticipated outcomes encompass varied effects on banks, resulting in modified credit provision and potential rent transfers to specific borrower subgroups (Agarwal et al. (2018), Beck et al. (2018)). We exploit the methodology proposed by Khwaja and Mian (2008) within our difference-in-difference setting to isolate the bank lending channel.

Our research project intersects with multiple literature streams, each offering valuable insights into the multifaceted dimensions of digital payments, banking competition, and financial inclusion.

The recent surge in Central Bank Digital Currencies (CBDCs) research, exemplified by Chiu et al. (2023), Andolfatto (2021), and Agur et al. (2022), offers varied perspectives on the potential impact of CBDCs on financial sector competition. Concerns about disintermediation raised by Keister and Sanches (2023) underscore the critical backdrop for our study on real-world consequences (Meaning et al. (2018), Brunnermeier et al. (2019), Brunnermeier and Niepelt (2019), Piazzesi and Schneider (2020), Duffie (2019), Sockin and Xiong (2023)). While the extensive theoretical literature has no clear agreement on the effects of the introduction of CBDCs, we try to provide empirical evidence to fill this gap. The most recent evidence that can be found in the literature is Di Maggio et al. (2024), who reveal that policies which increase transaction costs for current digital payment methods catalyze a substitution effect, bolstering CBDC adoption.

Exploring the evolving FinTech landscape, Buchak et al. (2018) and Erel and Liebersohn (2022) examine technology's role in traditional banking decline and FinTech's response to financial service demand. These insights contextualize the coexistence of digital and traditional payment systems (Beaumont et al. (2022), Ferrari et al. (2010)).

In the literature on the economic effects of instant payment systems, Parlour et al. (2022), Di Maggio and Yao (2021), and Babina et al. (2022) link payment systems to lending decisions and financial inclusion. This stream of literature enriches our understanding of the interconnectedness of digital payments and broader financial services (Higgins

(2020), Bachas et al. (2018), Duarte et al. (2022), Sarkisyan (2023), Balyuk and Williams (2021), Dubey and Purnanandam (2023), Bian et al. (2023), Dupas et al. (2018)).

Drawing parallels with the literature on demonetization, our investigation into the Mobile Money tax-induced shock finds resonance with studies exploring policy changes that induce shifts in currency use. Chodorow-Reich et al. (2020) examine the consequences of demonetization, noting relative reductions in economic activity and shifts towards alternative payment technologies. Similarly, Crouzet et al. (2019) document how a cash contraction spurs the adoption of new payment technologies.

The extensive literature on the effects of Mobile Money provides a foundational understanding of its role in financial inclusion and transactional behavior. Pioneering studies by Jack and Suri (2011), Jack et al. (2013), and Jack and Suri (2014) highlight the transformative impact of Mobile Money on access to formal financial systems. Our research builds on this foundation, acknowledging the dual role of Mobile Money as both a facilitator of financial inclusion and a potential disruptor of traditional banking systems (Suri and Jack (2016), Suri (2017), Suri et al. (2021), Brunnermeier et al. (2023)).

The literature on liquidity, credit supply, and the impact of shocks on financial markets offers a theoretical and empirical foundation for our exploration. Khwaja and Mian (2008), Limodio (2022), and Choudhary and Limodio (2022) delve into the intricacies of liquidity shocks and their effects on credit provision. These insights inform our investigation into how shocks to the cost of digital currency might influence banks' credit supply. Choudhary and Jain (2022) study the distributional impacts of bank credit rationing. We differentiate from this paper showing the effects of volatile liquidity on credit.

Eventually, a rich body of literature explores the relationship between information asymmetries, credit provision, and the implications of data portability in the financial sector. Agarwal et al. (2018), Banerjee et al. (2021), and Beck et al. (2018) provide insights into the benefits of data portability and its role in enhancing credit provision. Our research contributes to this discourse by examining how shifts in payment systems might influence established relationships between banks and borrowers (Berlin and Mester (1999), Sette and Gobbi (2015)).

The rest of the paper is as follows. Section 2 offers details about the institutional aspects of the Ugandan mobile money tax, and provides an insight on a new bank-related technology, banking agents, that allow easier access to banks' services. Section 3 describes the data we use, comprehensive of a unique dataset on individual transactions of the whole Ugandan population of Mobile Money users, a dataset on individual banking agents, a dataset on the Central Bank's issuance of cash at local level, and a dataset on the universe of loans granted by private banks. Section 4 provides evidence on the substitution of Mobile Money with traditional payment and money storage systems. In Section 5 we show the effects of the Mobile Money tax induced positive liquidity shock to banks on the credit market. Section 6 concludes.

2 Institutional framework

In this section we provide insights on the Ugandan mobile money market and the introduction of the tax, which was unexpected by the public. We also give details about banking agents, a new bank-related technology that facilitates cash deposits. Indeed, this technology had a pivotal role in driving the shift from mobile money to bank deposits: while banking agents had never taken over before the introduction of the tax, the increased cost of mobile money spurred their adoption.

2.1 Mobile Money Tax

Mobile money services were first introduced in Uganda by MTN in 2009 and, since then, the sector has seen significant growth. During the first year of operation, the number of registered accounts grew to 770,000 and the total value of transactions amounted to approximately UGX 133 billion (US$ 36 million) over the year.

After MTN, other mobile network operators (MNOs) soon introduced similar services. Within a decade, the number of registered, active accounts had surpassed 16 million and the total annual value of transactions had grown to UGX 73 trillion (US$ 20 billion). [2]

[2] Source: Bank of Uganda, 2021

This growth is due, in part, to the accessibility of mobile money, enabled through a national network of roughly 212,500 registered mobile money agents who are markedly more prevalent than more traditional financial service providers, such as commercial banks.[3]

As the sector, and its turnover, has grown, governments are increasingly viewing mobile money as a convenient tax handle. This is especially true for governments facing pressures, both domestic and external, to increase domestic revenue mobilisation and reduce the reliance on aid and borrowing to fund public services. The resulting tax measures are often controversial and have drawn sharp criticism from those who fear that they will undermine the growth of nascent digital finance sectors and the development gains that (digital) financial inclusion is claimed to enable.[4]

Uganda presents an interesting case study of this trend. On 1 July 2018, the government introduced an especially contentious new tax of 1%[5] on the value of all mobile money transactions, aimed at mobilising more revenue from the telecommunications and financial sectors (Lees and Akol, 2021).

The mobile money tax legislation was initially drafted such that every stage of a mobile money transfer was taxed – depositing, sending, receiving, and withdrawing the money. These were identified as separate, and thus individually taxable, transactions. In effect, one transfer between two users might have been taxed up to four times.

Uganda currently has the foundations of a strong, well-structured system for policy development, providing for an orderly progression from an idea for change to the implementation of a final tax measure (Wales and Lees, 2020). Tax policy development in Uganda follows a series of distinct phases, closely linked to the annual budget cycle However, unanticipated expenditure requirements, and the rejection of several revenue-raising tax proposals, created pressure to find new sources of revenue late in the budget cycle. This led to surpass the standard steps required by the Ugandan legislation for law promulgation. These resulted in the introduction of a Mobile Money tax strongly advised

[3]Surveys have indicated that whereas 54% of the population had a mobile money point-of-service within one kilometer of their home, just 16% per cent of the population had a point-of-service for a traditional bank (Bank of Uganda 2017).

[4]See link

[5]After widespread public outcry and significant challenges in implementation, the tax rate was adjusted to 0.5 % and restricted to withdrawals in November 2018.

by Ugandan President Yoweri Museveni[6]. The faster than usual process for the approval of this tax led to a lack of widespread citizen engagement and the tax proposal seemed largely absent from the general public discourse at the time. Indeed, the tax was unexpected by citizens, and as an indication of this, Figure B.1 shows Google search interest from Uganda in the terms "tax" and "mobile money" throughout 2018. Search interest for "tax" and "mobile money" peak in the week starting 1 July 2018.

The introduction of the mobile money tax triggered immediate public outcry, with concerns about double taxation, financial inclusion, job losses, and the impact on the poor. Civil society, journalists, students, and activists organized protests, gaining international media attention.[7] In response, the President requested Parliament to amend the tax on July 12. Cabinet limited the tax to withdrawals, halving the rate. Despite delays, the Finance Committee supported the amendment for budgetary reasons. The Amendment Bill was implemented on November 17 As shown in Figure 1, the tax had a huge impact on the usage of mobile money.

2.2 Agent Banking

In July 2017 (one year before the mobile money tax), Bank of Uganda passed a new regulation aimed at establishing a new tool through which commercial banks can operate: Agent Banking[8]. Agent banking is a banking model that involves the use of third-party agents, such as retail shops, to provide banking and financial services on behalf of traditional banks. This approach is particularly relevant in regions with limited access to physical bank branches, as it enables financial institutions to expand their reach and offer their services to underserved or remote areas. In Uganda, agent banking has gained momentum in recent years as a means to enhance financial inclusion and improve access to banking services, especially in rural and underserved areas. Agent banking services typically include cash deposits, cash withdrawals, balance inquiries, fund transfers, utility

[6]The President wrote on his blog that the informal sector is "never taxed" and a tax on mobile money would ensure a "modest contribution"

[7]A public opinion survey of nearly 3,000 people conducted in the second week of July found that 98% of respondents did not support or were strongly opposed to the mobile money tax (?).

[8]The Financial Institutions (Agent Banking) Regulations, 2017

bill payments, and sometimes even account opening. The key feature of Agent Banking is that it does not require the opening of a bank account in order to perform operations such as depositing, withdrawing or transferring money. When depositing money, for example, the banking agent releases a receipt to the customer, who will use it to withdraw the money later on. While this tool has been long used by banks, in 2017 it was formalized through the creation of an inter-banks agency. The Agent Banking Company (ABC) was established in 2017 by Uganda Banker's Association (UBA) the umbrella organization for commercial banks in Uganda and Eclectics a pan-African technology company. Similar to the Mobile Money model, Agent Banking empowers commercial banks to appoint agents to provide banking services such as deposits, withdrawals and more on their behalf. Agents can be the local shopkeeper, kiosk owners, supermarket attendant or anyone in your community who has been authorized by your bank. The financial services currently offered through the ABC platform include cash deposits, cash withdrawals, bill payments and money transfers. The platform enables commercial banks to enhance customer experience, reduce the cost to serve and increase coverage while avoiding duplication of investment and effort. As at the end of 2021, there were 22 commercial banks with 20,108 agents enrolled on the platform. Between 2017 and 2021, agents on the platform cumulatively processed over 12 million transactions worth $ 4.3 billion.

In the analysis, we show the spur of banking agency after the introduction of the Mobile Money tax. We claim that this shock to the cost of digital currency triggers the adoption of this new banking-related technology that drives the registered increase in the flow of bank deposits.

3 Data

This section describes the datasets employed in the analysis.

1. Mobile Money transaction data. We have access to the universe of mobile money transactions from one of the two major companies in Uganda. MTN and Airtel share the mobile money market equally, have similar coverage and set extremely similar prices

on mobile money transactions. We expect no major differences in individual level usage between the two comapnies, indeed it is estimated that at least 30% of the Ugandan population with access to a a mobile phone has a SIM subscription with both operators.[9] For the only year 2018, we have access to more than 50 million transactions, divided by person-to-person transfers (P2P), cash-in (deposits) and cash-out (withdrawals). We are able to access both the sender, the receiver or the mobile money agent identifier, hence allowing us to reconstruct the whole network of mobile money transactions. We have access to the type of transaction, to its value in Ugandan Shillings (UGX), to the fees applied on the transactions, as well as on the time and day it was performed.

2. Mobile Money user location. Out of the 5.5 million mobile money users active before the introduction of the tax, we are able to identify the district of residence for a random sample of about 1.5 million users. This allows us to present evidence of heterogeneity in mobile money usage elasticity between different district, depending on local characteristics.

3. Issuance of physical cash. The Central Bank of Uganda has also provided daily data on the issuance of cash by local private banks' branches for the years 2017-2022. Bank of Uganda has 10 offices spread throughout the Ugandan territory. Each of these offices provide cash on a daily basis to the major branch of private banks present in that area. We hence have a bank-location panel of cash issued. We use these data as a proxy of cash demand at the local level. Indeed, the only reason why banks issue physical cash is to meet the demand of depositors withdrawing money.

4. Credit registry loan-level data. Our study employs detailed data on the commercial and household lending activities of banks. Uganda has a fully functional and comprehensive credit register that is maintained by the private credit bureau Compuscan Uganda CRB Ltd. under the supervision of the Bank of Uganda. The credit register collects data on all new originated loans based on monthly reports from all commercial banks, microfinance deposit-taking institutions, and other credit institutions. We have access to the full dataset covering the period 2017-2023. For each granted loan we are able to identify

[9]National IT Survey Uganda (NITA), 2018. See link.

both borrower-specific and loan-specific variables. We observe: i) the nature of the borrower, wether individual or business; ii) the type of loan (secured or unsecured); iii) the credit risk of the borrower); iv) the purpose of the loan (business, mortgage, school loan, house restructuring, land purchase); v) for credit to individuals, we are able to identify the income of the borrower and her professional activity; for businesses, we are able to identify the sector of activity; vi) for all borrowers we identify the district of residency; vii) the day on which the loan was granted; viii) the rate of repayment as stated on the day of the granting; ix) the term/maturity of the loan.

5. Bank-level data on deposits. The Bank of Uganda provides monthly data on private institutions deposits. We are able to identify different types of deposits (bank owned, demand, saving, time and cash deposits).

6. Agent Banking Company individual agent's data. The Bank of Uganda has provided the details of deposits and withdrawals for each banking agent. We aggregate data at the district level. Data are available since April 2018.

7. Ugandan National Panel Survey. We employ household-level panel microdata from the Uganda Bureau of Statistics. These data provides information of a wide range of topics on households' income, savings, entrepreneurial activity, mobile money usage.

8. Geographical data on urban development and nighttime light intensity. We exploit the dataset introduced by Cattaneo et al. (2021) to create a district's measure of urban development.

9. Individual Bank's ATMs and branches location. We obtained data for the location of all ATMs and branches of each bank. We exploit these data to create a district-level proxy of access to mobile money substitutes, namely bank deposits and cash. We will use this measure in our identification strategy presented in Section 4

4 Results on Mobile Money, bank deposits and cash

We develop our analysis adopting two empirical approaches. For our main results, we first develop an event study design meant to test for pre-trends and to investigate the dynamics of the treatment effect. Second, we implement a difference-in-differences specification using two-way fixed effects regressions. Our main assumption is that individuals substitute mobile money with other means of payment and money storage (namely cash and deposits) depending on the conveniency or the easiness of access to them. We rationalize these results through a simplified model of currency choice in Appendix C - Theoretical Framework. For our identification strategy, we employ a quasi-experimental design, leveraging the temporal variation introduced by the Mobile Money tax and the variation at geographical level coming from the heterogeneous access to Mobile Money alternatives, proxied by the density of ATMs.

We provide evidences at the user's, district's and bank's level.

In the first subsection we show that mobile money usage dropped for individuals residing in districts where access to banks is made easier by a higher density of ATMs. We provide evidence both using adminstrative level data on the universe of Mobile Money transactions and the panel survey data from the Ugandan National Panel Survey.

In the second subsection, we show that the take up of a new technology (agent banking) that facilitates bank deposits is significatively starker in those districts with higher density of ATMs. We also show that banks' with a higher market share of ATMs are the ones witnessing the highest surge in banking agents. Hence the higher adoption of this new technology is not only district-specific, but also bank-specific.

In the third subsection we show the effects of the tax on bank deposits. We first show that deposits made through the new banking technology, banking agents, increase relatively more in districts with higher ATM density. We then show that bank deposits increase relatively more for banks with higher ATM market share. We differentiate between different types of deposits: indeed, we show significant and positive effects only for demand deposits and for the amount of cash detained by banks.

In fact, in the last subsection we eventually show that the request for cash becomes higher in districts with more access to ATMs and that those financial institutions who detain a higher share of the ATMs market register a higher increase in customers' cash withdrawals.

This is in line with our narrative. These pieces of evidence suggest that mobile money is substituted by banks' deposits for money storage and by cash for transactions. The fact that the we register an increase only in demand deposits and cash deposits is due to the fact that the new liquidity is highly volatile, as customers use bank deposits only for safe storage of money, but withdraw it constantly in order to use it for payments. Banks are hence facing the constant request for cash from customers. After showing these results, in the last section we will show how this new liquidity impacts the provision of credit by banks.

4.1 Mobile Money

Our assumption is that mobile money users are differentially affected by the introduction of the tax depending on the possibility of access to other means of payments. We exploit the density of ATMs in a given district as measure of access to mobile money alternatives.

At the intensive margin, i.e. conditional on keeping using Mobile Money, the drop in the growth of value transacted is of more than 10% for individuals in those high-ATM-density districts.

The difference-in-differences design we exploit is the following:

$$Y_{idt} = \alpha_i + \alpha_t + \beta \text{Post Tax}_t \times \mathbf{I}\left[\text{High ATM density}\right]_d + \epsilon_{idt} \tag{1}$$

where we define individual i in district d in the pre or post policy period defined by t. The dummy $\mathbf{I}\left[\text{High ATM density}\right]_d$ indicates whether the individual resides in a district in the upper quartile of the ATM density distribution. We assign to each user the ATM density (calculated as number of ATMs over the districts area) of the district where she resides. We define $\mathbf{I}\left[\text{High ATM density}\right]_d$ as a dummy indicating whether the users i in district d is in the highest 25 percentile of the users' distribution of ATM density. We use the subscript d as there are no users in the same district assigned to a different value of the dummy variable. We interact it with a post tax dummy. We include individual α_i and time α_t FEs.

We collapse data over four months before and after the introduction of the tax (respectively February, March, April and May, and August, September, October, November). We do not include June and July due to the serious limitations of the observations in those months, as several glitches made it impossible to the mobile money company to collect the data. However, even including the available data from those two months, the results remain qualitatively and quantitatively similar. We are hence using two observations for each user: at time 0 (before the tax) and at time 1 (after the tax). This allows us to ease the interpretation of results.

We instead use the following event study approach for testing for pretrends:

$$Y_{idt} = \alpha_i + \alpha_t + \sum_{\tau=1,\tau\neq 5}^{T} \beta_\tau \text{Month}_\tau \times \mathbf{I}\left[\text{High ATM density}\right]_d + \epsilon_{idt} \tag{2}$$

where we use May as the baseline category and again exclude June and July from the analysis due to data limitations. In this case, we use observations at the monthly level. We control for individual α_i and time (month) α_t fixed effects.

4.1.1 User-level data

We here presents results of the same specification of Eq. 2, using as outcome variable the individual's average daily amount of a given type of transaction, the number of times and the share of days in which that type of transaction was performed in a given month. We express all outcomes in log. We however restrict the sample to those users that perform a given type of transaction both in the pre-tax and the post-tax period. The β coefficient estimates the differential effect on users in high ATM density districts that keep using mobile money after the tax. Long story short, zeros are hence excluded. Table 1 present the results on the log average daily value of transactions. We hence interpret the coefficients as percentage change.

Table 1 shows that, conditional on keeping performing a transaction, high-ATM-density users reduce the average amount transacted daily by between 4% and 12%. These results are further confirmed in Appendix A - Additional Tables, Tables A.1 and A.2, where we present results for the daily average number of transactions and for the share of days in which a type of transaction is performed. High-ATM-density users decrease

Table 1: Intensive margin: performed transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Post tax dummy	-0.103***	-0.117***	-0.040***	-0.060***
$\times$ High ATM density$_d$	(0.017)	(0.014)	(0.008)	(0.005)
User FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Users	285044	450730	1171380	1382856
Adj. R sq.	0.438	0.349	0.407	0.448

Notes: In this table, we use the specification presented in Eq. 1 and we show how mobile money users in high ATM density districts respond to the introduction of the mobile money tax at the intensive margin, relatively to users in low ATM density districts. High-ATM-density users transact between 4% and 12% less with respect to low-ATM-density users, after the tax. We estimate the effect on the sample of users that performed transactions of a given type before and after the tax. Column (1) show the effects on the amount of mobile money sent, column (2) on the amount received, column (3) on the amount deposited, column (4) on the amount withdrawn. For columns (1)-(4) outcome variables are the log of the average daily amount. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

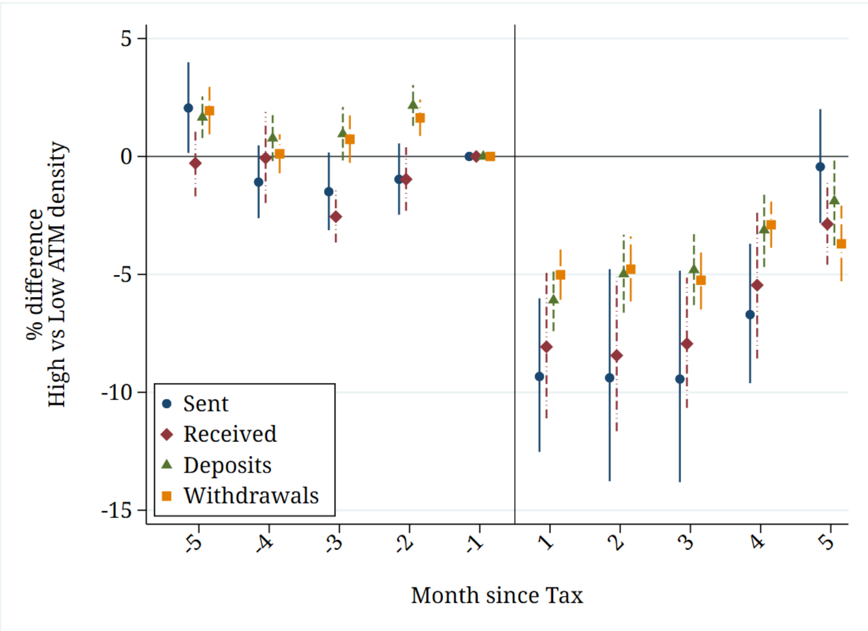
significatively their usage at all levels.

We complement the analysis on the intensive margin adopting a difference-in-differences and an event study approach using monthly level data at the individual level. So, in this case, t will identify a month. In Appendix A - Additional Tables, Tables A.3, A.4 and A.5 we respectively show the results for the average daily value of transactions in a month, the log average daily number of transactions in a month, and the share of days in which a transaction is performed in a month. In practice, we are exploiting Eq. 1 without collapsing observations over two periods pre and post policy.

Below, in Figure 2 we show results for the event study on the log average daily value transacted in a month.

These two last specifications come with no ease interpretation. Hence, it is worthwhile to spend a few words describing the structure of the dataset and the meaning of the estimated coefficients. Also in this case we are estimating the intensive margin, this means that we observe no value (missing) for when no transaction is made by the user. Users can however potentially transact every month. The first issue hence derives by the fact that users might be different in the timing of their transactions (i.e. user i might transact in April and August, while user j might transact in May, September and November). Including individual fixed effects hence controls for patterns of transactions: we are hence estimating the effect within individuals that make transactions in the same months. Months fixed effects instead clear out month specific differences. For the difference-in-differences, the β represents the average effect of the tax on otherwise similar high-ATM-density users with respect to low-ATM-density users. The β_τ's in the event study, instead, represent the average difference in the outcome of otherwise similar high-ATM-density users with respect to low-ATM-density users within a given month, with respect to the reference month, which is May. Figure B.2 also shows results for the average number of transactions and the share of days. In both figures, we already express the y-axis in percentage change.

Figure 2: Differential effect of the tax on users in high ATM density districts



Notes: This figure plots the coefficients β of the event study described in Eq. 2. We use as outcome variable the log of average daily value of mobile money transactions in a month at the individual level. We differentiate between type of transactions. We already express the y axis in terms of % change. We use May as the baseline month. Data for June and July are excluded due to issues with data collection. Standard errors are clustered at the individual level, and the figure reports 95% confidence interval.

4.1.2 Survey data

To further confirm our previous results, we analyzed data from the Ugandan National Panel Survey (UNPS). The UNPS is carried out by the Ugandan Bureau of Statistics over a twelve-month period (a "wave") on a nationally representative sample of individuals/households, for the purpose of accommodating the seasonality associated with the composition of and expenditures on consumption. The UNPS set out to track and interview more than 5'000 individuals.

We employ data from the 2018/2019 wave, focusing on the outcomes related to mobile money usage. We adopt the identification proposed by Bassi and Rasul (2017), where the identification comes from the timing of the interview, before or after the tax. Controlling for individuals' characteristics, district and time FEs. To notice, as the authors propose, we cluster standard error at the week level. This clustering reflects that identification in our research design is based on time variation.

We provide further evidence of the drop of mobile money usage in districts with high ATM density after the introduction of the tax, and exploit the following:

$$Y_{idt} = \alpha_d + \alpha_t + \beta \mathbf{I} \left[\text{High ATM density}\right]_d + \gamma \mathbf{X}_i + \epsilon_{idt} \tag{3}$$

where the outcome is referred to individual i in district d at time t. We control for the individual's characteristics, and include district and time FEs. Since during one wave individuals cannot be tracked (as they answer questions on mobile money just once), our source of variation comes from the timing of their interview, before or after the introduction of the tax. In Table 2 we report the results of the linear probability model described in Eq. 3, where outcome variables are dichotomous as they indicate whether the individual used a given mobile money service or not in the last week. For all measures, we find that individuals in high ATM density areas are up to 9% less likely to use mobile money.

4.2 Banking agents: Adoption of a new banking technology

The introduction of the tax lowered the conveniency of Mobile Money with respect to other technologies that facilitate the exchange of money. Corroborating the findings of Crouzet et al. (2019), consistent with the predictions of a technology adoption model with complementarities, we show that the adoption of Banking Agents increased persistently

Table 2: Mobile Money usage - Survey data

	Send	Transfer cash	Withdraw	Pay utilities	Pay school
	(1)	(2)	(3)	(4)	(5)
Tax dummy$_t$ $\times$ $\mathbf{I}$ [High ATM density] $_h$	-0.061*	-0.019*	-0.093***	-0.036**	-0.019*
	(0.034)	(0.010)	(0.030)	(0.015)	(0.010)
District FE	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes
Obs.	5044	5047	5060	5043	5044
Adj. R sq.	0.224	0.117	0.246	0.160	0.046
Mean Dep. Var.	0.336	0.021	0.320	0.030	0.010

Notes: This table reports the coefficients of Eq. 3. The outcome variables are dummy variables taking value 1 if the individual used a given mobile money service in the past week. We control for individual's characteristics such as gender, age and marital status. Time and district FEs are included. Standard errors are clustered at the week level, as suggested by Bassi and Rasul (2017). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

as a response to the contraction registered by mobile money after the tax. As explained, banking agents are a technology that allows the execution of bank-related activities, such as deposits, in the fashion of branchless banking. The adoption of this technology is highly demand driven: indeed, it is not the bank who decides where to open a new banking agents. Like mobile money agents, it is merchants or individuals themselves who decide whether to start offering this service. While they bear the fixed costs needed to start such activity, they earn a fee on each transaction they perform.

In this subsection, we present evidence that the spread of banking agents spurred after the introduction of the mobile money tax. This is particularly true in districts with high ATM density and for banks with a high ATM market share. These results are justified by the complementary that arises between banking agents and ATMs. Indeed, banking agents have more incentive to start their activity where the users are already acquainted to the banking system or where there is a pervasive access to ATMs, that facilitate the withdrawal of deposited cash. Moreover, banking agents also have an incentive to provide the service for banks which are more pervasive: being the fixed costs of becoming a banking agent the same for any bank (consisting it in learning how to use the technology, which is shared between all banks), agents surely want to serve the highest possible number of customers. Similarly, we will also show that the number of banking agents grow relatively more for those banks who have a higher market share of ATMs.

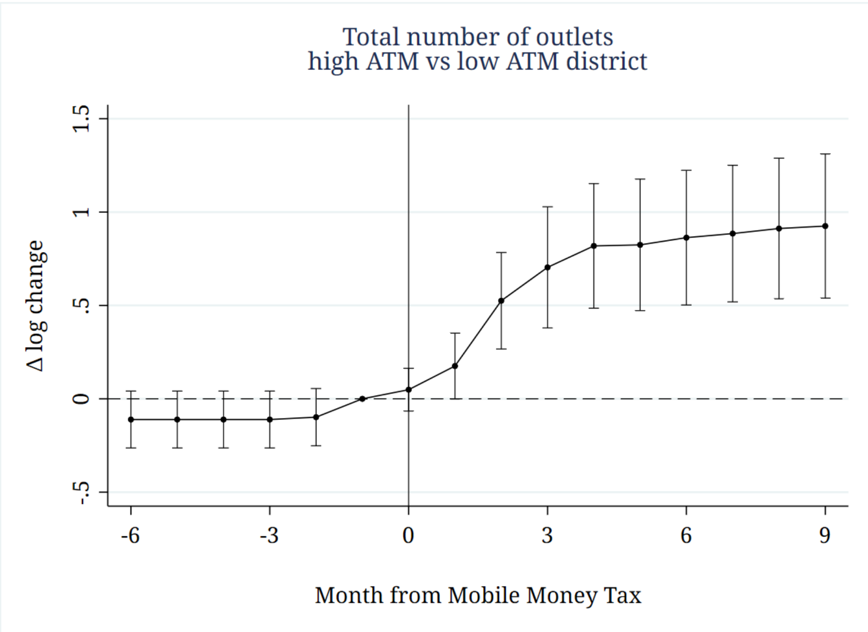
4.2.1 District level

We first propose an event study to show the differential increase between high and low ATM-density districts in the number of new banking agents. In Figure 4 we show the results of the following:

$$Y_{dt} = \alpha_d + \alpha_t + \sum_{\tau=-6,\tau\neq-1}^{10} \beta_\tau \text{Month}_\tau \times \mathbf{I}\left[\text{High ATM density}\right]_d + \epsilon_{dt} \quad (4)$$

where $\mathbf{I}\left[\text{High ATM density}\right]_d$ indicates districts in the top quartile of the ATM density distribution. We include district, α_d, and time, α_t, FEs.

Figure 3: Banking agents: high- vs low-ATM density districts



Notes: In this figure we plot the coefficients of Eq. 4, where we use as outcome variable the log number of banking agents at the district level. The plotted coefficient represents the differential between high- and low-ATM density district, with respect to the reference period. We use as reference the month before the introduction of the mobile money tax. Standard errors are clustered at the district level and we report 95% confidence intervals.

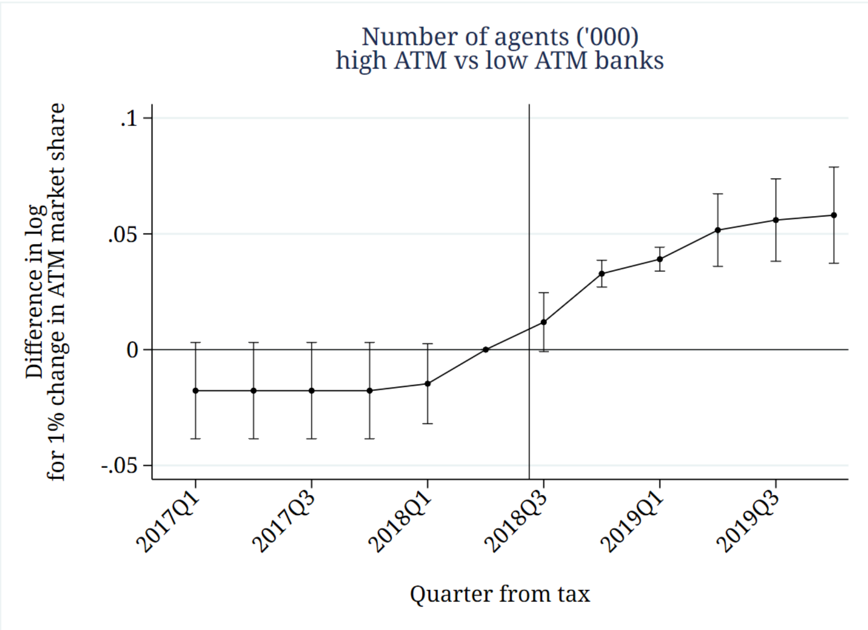
4.2.2 Bank level

Similarly, we show an increase in the number of banking agents at the bank level. We exploit quarterly data on the number of banking agents that decide to provide the service for a given bank. We exploit the following:

$$Y_{bt} = \alpha_b + \alpha_t + \sum_{\tau=-6,\tau\neq-1}^{10} \beta_\tau \text{Quarter}_\tau \times \mathbf{I}\left[\text{High ATM market share}\right]_d + \epsilon_{dt} \qquad (5)$$

where $\mathbf{I}\left[\text{High ATM market share}\right]_d$ indicates banks in the top quartile of the ATM market share distribution. We include bank, α_b, and time, α_t, FEs.

Figure 4: Banking agents: high- vs low-ATM market share banks



Notes: In this figure we plot the coefficients of Eq. 5, where we use as outcome variable the log number of banking agents at the bank level. The plotted coefficient represents the differential between high- and low-ATM market share banks, with respect to the reference period. We use as reference the quarter before the introduction of the mobile money tax. Standard errors are clustered at the bank level and we report 95% confidence intervals.

4.3 Bank deposits

In this subsection, we present evidence at the district level on the deposits made through banking agents. As outcome we will use the inflow of new money deposited through banking agents. We will then present evidence on the increase of deposits using as outcome the stock of deposits from the banks' balance sheets. In this case, we will differentiate between different types of deposits. Indeed, we will show that the stock of deposits will increase only for demand deposits and cash withheld by banks: these are deposits that banks keep to face the demand for money by customers.

4.3.1 Inflow of deposits through Banking Agents

We first show evidence that the new banking technology, banking agents, was the mean through which bank deposits increased. We show that districts with a higher ATM density register a relatively higher increase in the inflow of money deposited through banking agents.

In Table 3 we present results from the following difference-in-differences:

$$Y_{dt} = \alpha_d + \alpha_t + \beta \text{Post Tax}_t \times \mathbf{1}\left[\text{High ATM density}\right]_d + \epsilon_{dt} \tag{6}$$

where the observations are at the district d, month m in year y level. The outcome Y is either the volume and value of new deposits to banking agents. We use three different specification outcome variable in order to overcome the issue related to the presence of zeros as described in Chen and Roth (2023): as suggested in the paper, we express the outcome variable in level, log, or as a dummy indicating values above and below the median.

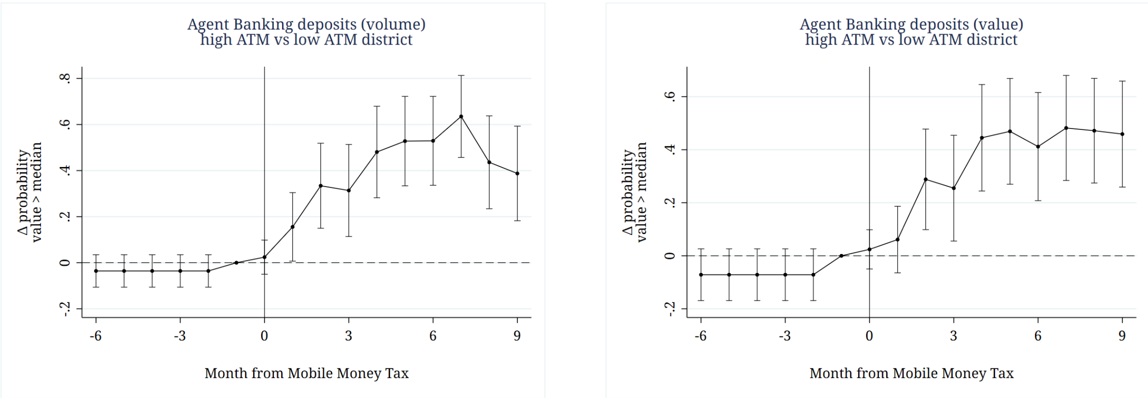
Table 3: Banking agents deposits

	Volume			Value		
	Δ Level ('000) (1)	Δ Log (2)	Δ Pr > median (3)	Δ Level ('000) (4)	Δ Log (5)	Δ Pr > median (6)
Tax dummy$_t$ × High ATM density$_c$	0.323**	2.164***	0.390***	0.098*	6.748***	0.395***
	(0.142)	(0.369)	(0.064)	(0.050)	(1.271)	(0.066)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1495	1495	1495	1495	1495	1495
Adj. R sq.	0.484	0.683	0.528	0.500	0.664	0.539
Mean Dep. Var.	0.076	1.098	0.146	0.023	4.863	0.157

Notes: This table reports the coefficients of Eq. 6. The outcome variables are the number and the value of deposits made by customers to Banking Agents. They are expressed in level, log, or as a dummy indicating whether the value is below or above the median as proposed in Chen and Roth (2023). Time and district FEs are included. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

We then exploit the event study specification defined in Eq. 5 to ensure the absence of pretrends. We use as outcome variable the probability that the the value or volume of deposits in a given district is above the median of the distribution of deposits (outcomes in columns 3 and 6 of Table 3), as suggested by Chen and Roth (2023).

Figure 5: Differential effect of the tax on the inflow of deposits at district level



Notes: This figure reports the coefficients of Eq. 4. The outcome variable is the probability that the volume (left) and value (right) of deposits to banking agents in a given district is above the median of the distribution. The unit of observation is the district. The reference period is the month before the introduction of the tax. We include district and time FEs. Standard errors are clustered at the district level. We include indicate significance at the 95% confidence interval.

4.3.2 Stock of deposits at bank level

We further confirm the results in the previous subsection, by showing the effects on the stock of deposits at the bank level using the bank's balance sheets.

We estimate an equation as the following:

$$Y_{bt} = \alpha_b + \alpha_t + \beta \text{Post Tax}_t \times \mathbf{1}\left[\text{High ATM market share}\right]_b + \epsilon_{bt} \tag{7}$$

where we use as outcome variable the (log) value of the stock of deposits at the bank level. We use monthly data on deposits. We differentiate between savings, time, bank owned, demand and cash deposits. We register a positive and significant increase of more than 10% on demand and cash deposits. This is in line with our hypothesis that the new inflow of liquidity into banks cannot be used for payments, but need to be withdrawn every time by users. Banks, on the other side, need to keep the cash in order to face the continuous demand of cash. In the next subsection, we show that banks in the upper quartile of the distribution of ATM market share also register a significant increase in the value of ATM withdrawals. Table 4 shows the results of Eq. 7.

Table 4: Bank deposits

	Bank owned deposits	Time deposits	Savings deposits	Demand deposits	Cash stored
	(1)	(2)	(3)	(4)	(5)
Post Tax × **I**[ATM Market share]	-0.039	-0.109	0.104	0.131***	0.191**
	(0.199)	(0.155)	(0.068)	(0.044)	(0.071)
Bank FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	831	831	831	831	831
Adj. R sq.	0.442	0.949	0.997	0.992	0.984
Mean Dep. Var.	1.848	31.439	30.504	60.233	5.874

Notes: This table reports the coefficients of Eq. 6. The outcome variable is the (log) value of the stock of deposits at the bank-monthly level. Time and district FEs are included. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

4.4 ATM Withdrawals and Cash

In this last subsection, we show evidence of the increased usage of cash. We provide two levels of analysis, at the district and at the bank level. We first show that the request for cash at the district level increases relatively more in districts with high ATM density after the tax. Then, we also provide evidence that banks in the top quartile of the ATM market share distribution witness a significant increase in cash withdrawn through ATMs. Again, this corroborates our thesis that users use cash for payments, and hence constantly withdraw the cash deposited in banks through ATMs.

4.4.1 Withdrawal of cash at district level

We present evidence that district with high ATM density present an increased demand for physical cash. These results further corroborates the hypothesis that mobile money is substituted by bank deposits and cash after the introduction of the tax: banks are used for money storage through banking agents, ATMs register an increase in withdrawals, and physical cash is now used for transaction.

We use data from total issuance of physical cash. While data on cash withdrawals at the individual branch do not exist, we exploit data at the bank-district level. We use data from 26 banks in 10 different districts. We define the bank-district pairs as branches. We use monthly data spanning from 2017 to 2022.

We exploit the following difference-in-differences specification, where we include the interactions between the post tax dummy and a dummy identifying those districts in the highest quartile of the ATM density distribution. This means that all branches within the same district will be assigned the same ATM density. We exploit the following difference-in-differences:

$$\mathrm{Y}_{bdmy} = \alpha_{bd} + \alpha_{my} + \beta \text{Post Tax}_{my} \times \mathbf{I}\left[\text{High ATM density}\right]_d + \epsilon_{bdmy} \tag{8}$$

where the outcome variable is the log value of notes issued by bank b in district d. Our preferred specification contains district-month FE that account for seasonality and bank-district FE that allow comparison of the same branch.

Table 5: Cash issuance

	Log cash withdrawn	
	(1)	(2)
Post Tax$_t$ × High ATM density $_d$	0.304***	0.231***
	(0.061)	(0.055)
Branch FE	Yes	Yes
Time FE	Yes	Yes
District × Month FE		Yes
Obs.	2622	2622
Adj. R sq.	0.543	0.542
Mean Dep. Var.	21.745	21.745

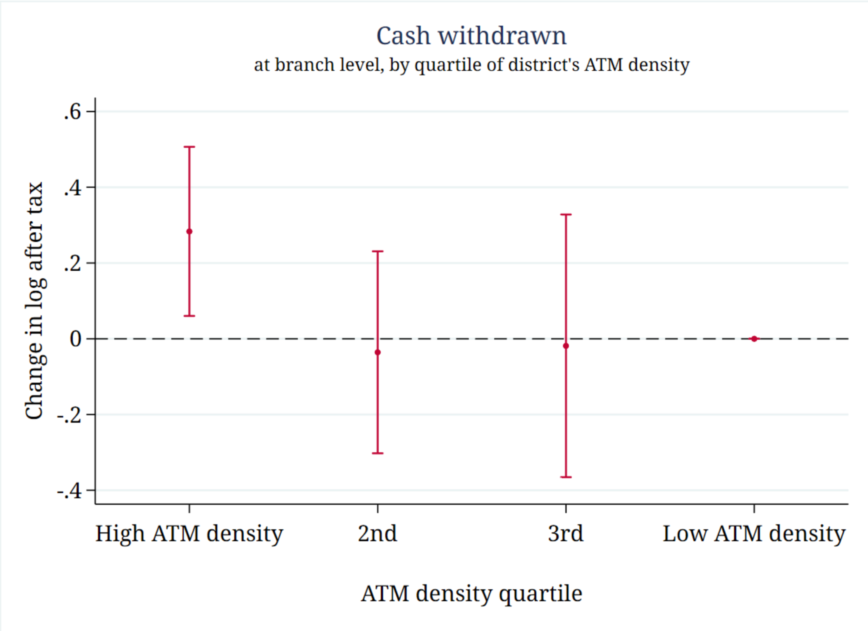
Notes: This table reports the coefficients of Eq. 8. The outcome variable is the log value of cash issued by the Central Bank to private banks. The unit of observation is the private bank-district pair, that we define as branch. We control for branch and time FEs in column (1), and add branch-month FEs in column (2) to account for seasonality. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Figure 6 shows the difference in the log of cash issued at the bank-district level. We plot the coefficients of an equation of the type:

$$Y_{bdqy} = \alpha_{bd} + \alpha_{qy} + \sum_{i=1}^{4} \beta_i \mathbf{I}_i \left[\text{ATM density quartile}\right]_d \times \text{Post Tax}_{qy} + \epsilon_{bdqy} \tag{9}$$

The coefficients represent the change in log cash withdrawn after the policy at the branch level after, with respect to the group of branches in the districts in the lowest quartile of ATM density distribution.

Figure 6: Differential effect of the tax on cash issued in urban branches



Notes: This figure reports the coefficients of Eq. 9. The outcome variable is the log value of cash issued by the Central Bank to private banks. The unit of observation is the private bank-district pair, that we define as branch. We include branch FE and quarter FE. Standard errors are clustered at the district level. We include 95% confidence interval.

4.4.2 ATM withdrawals at bank level

Eventually, we provide evidence of the increased ATM withdrawals for those banks in the higher quartile of the ATM market share distribution. We use quarterly data at the bank level on the value of ATM withdrawals.

We estimate the following:

$$Y_{bqy} = \alpha_b + \alpha_{qy} + \beta \text{Post Tax}_{qy} \times \mathbf{I}\left[\text{ATM market share}\right]_b + \epsilon_{bqy} \tag{10}$$

where the unit of observation is bank b in quarter q in year y. The coefficient β express the differential change in the outcome after the tax for banks in the highest quartile of the ATM market share. The independent variable ATM market share$_b$ is defined at the bank level in the pre-policy period. It is interacted with a post-policy dummy. Bank and time FEs are included, hence all individual terms are absorbed. We report the results in Table 6, and also include the results when using as independent variable the ATMs market share of the bank.

Table 6: ATM withdrawals and number of agents

	ATM withdrawals	
	Log	Log
	(1)	(2)
Post Tax × **I**[ATM Market share]	0.029**	
	(0.012)	
Post Tax × Market share of urban ATMs		0.003***
		(0.000)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Obs.	263	263
Adj. R sq.	0.984	0.992
Mean Dep. Var.	0.025	0.025

Notes: This table reports the coefficients of Eq. 10. The outcome variables are the value of ATM withdrawals (in billion UGX) and the number of banking agents. The unit of observation is the private bank at quarterly level. We control for bank and time FEs. Standard errors are clustered at the bank level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Eventually, we also provide event study evidence exploiting the following:

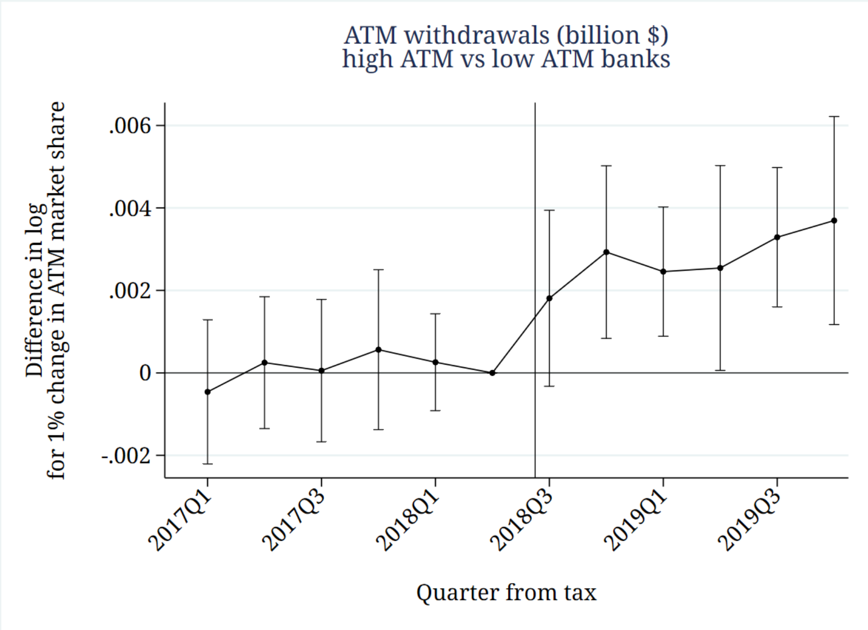
$$Y_{bt} = \alpha_b + \alpha_{qy} + \sum_{\tau=-6,\tau\neq-1}^{6} \beta_\tau \text{Quarter}_\tau \times \text{ATM Market share}_b + \epsilon_{bqy} \tag{11}$$

We show the results in Figure 7. We interpret the coefficient as the differential change in the log outcome for 1% higher ATM market share, with respect to the quarter before the introduction of the mobile money tax. In Figure B.3 we propose the same event study, where we use as independent variable the dummy $\mathbf{I}\left[\text{ATM market share}\right]_b$ as in Eq. 10.

5 Credit and transfer of rent

The imposition of the mobile money tax has engendered a multifaceted economic transformation. The discernible outcome of the tax has been a substantial reduction in the usage of mobile money services, precipitating a noteworthy exodus of funds from the mobile money system. Users, reacting strategically to the tax burden, have exhibited

Figure 7: Bank's ATM market share & ATM withdrawals



Notes: In this figure we plot the coefficients of Eq. 11, where we use as outcome variable the log value of ATM withdrawals at the bank level. The plotted coefficient represents the differential change in the outcome for 1% higher ATM market share, with respect to the reference period. We use as reference the quarter before the introduction of the mobile money tax. Standard errors are clustered at the bank level and we report 95% confidence intervals.

a pronounced reduction of the usage of mobile money, likely in favor of other means of payment, such as cash, and means of money storage, such as bank deposits.

The consequence of this shift has been twofold: a surge in traditional banking activities and heightened liquidity within the banking sector. As shown in Section 4.2, the surge in banking agents has emerged as a profitable alternative to mobile money services. This has led to a discernible increase in both the number of banking agents and volume/value of deposits to banking agents.

However, the newfound liquidity within the banking system is likely to be exceptionally volatile. Individuals, while utilizing banking agents for secure fund storage, overwhelmingly favor cash for transactions, a behavior validated by a concurrent rise in ATM withdrawals. This liquidity volatility has prompted banks to adopt risk management strategies in their lending practices.

Our results show that banks have selectively increased lending to established customers with a demonstrated low risk of default. Conversely, lending to new customers, particularly those perceived as high risk, has contracted. To mitigate the potential risk of defaults, banks have raised interest rates for high-risk borrowers and shortened repayment terms. This cautious lending approach aligns with theoretical frameworks outlined in Berger and Bouwman (2015), illustrating how banks adapt their lending behavior in response to external shocks.

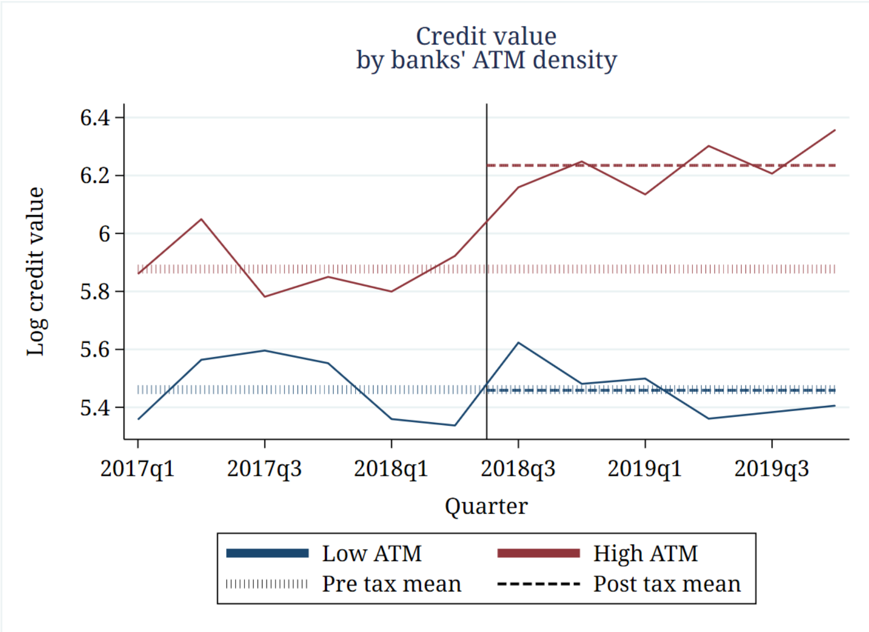
This intricate interplay between taxation, user behavior, and banking dynamics highlights the nuanced challenges within the financial ecosystem. Furthermore, the ongoing public discourse surrounding the mobile money tax introduces an element of uncertainty. The prevailing uncertainty in tax policy may influence user behavior (Gulen and Ion, 2016) and potentially lead to a reversion to mobile money. This complex landscape underscores the need for adaptive financial policies that can navigate the evolving dynamics of user preferences and regulatory frameworks.

In this section, we exploit data from the Uganda credit registry to study the behavior of banks in lending. We first show that in the first year and a half following the mobile money tax, lending from banks who were more exposed to liquidity shock increases by the equivalent of US $ 100 million. We identify these banks as the ones with the highest ATM market share. We identify as high-ATM those banks in the top quartile of the ATM market share distribution. As shown in previous results in Section 5, banks with the highest share of ATMs are also the ones experience the highest increase in banking agents, and hence in banking agents' deposits. Figure 8 plots the log of the credit granted by banks with high and low ATM market share, in the six quarters before and after the introduction of the mobile money tax. We see an increase in the total level of lending in the quarters following the tax for banks with high ATM share.

We propose an analysis adopting the methods proposed by Khwaja and Mian (2008) for estimating the bank-lending channel. Our data have the following structure: for each bank, district and quarter we manage to identify those loans provided to customers with or without credit history and who are defined are low or high risk.[10] The credit registry is comprehensive, and banks share customers' information. Hence, we manage to identify

[10]Banks define five levels of customer's risk: Substandard, Watch, Doubtful, Loss, Normal. We define as low risk those customers identified as "Normal".

Figure 8: Differential effect of the tax on cash issued in urban branches



Notes: This figure reports the coefficients of Eq. 9. The outcome variable is the log value of cash issued by the Central Bank to private banks. The unit of observation is the private bank-district pair, that we define as branch. We include branch FE and quarter FE. Standard errors are clustered at the district level. We include 95% confidence interval.

those customers who had previous credit relations with any bank. We hence study the distributional effect of the tax on credit by banks using the following regression:

$$Y_{bdt} = \alpha_b + \alpha_{dt} + \text{Post Tax}_t \times \mathbf{I}\left[\text{ATM market share}\right]_b + \epsilon_{bdt} \tag{12}$$

where Y_{bdt} is the outcome variable defined at bank b in district d at time t. The independent variable is the interaction between a post-policy dummy and an indicator variable taking value 1 for those banks in the upper quartile of the distribution of ATMs market share. We include bank and district-time FEs.

The regression is run for different groups of borrowers separately. In Table 7 we report the results for the log amount of loans provided by banks

We then provide evidence for the interest rate in Table 8 and the term of repayment in Table 9. In this case, the estimation weights for the number of loans of that given type provided by bank b.

We interpret these results as a transfer of rent from high-risk customer with no credit

Table 7: Log amount lent

	w/ Credit history		w/o Credit History	
	Low risk (1)	High risk (2)	Low risk (3)	High risk (4)
Tax dummy$_{qy}$ $\times$ $\mathbf{I}$ [ATM share]$_b$	0.152**	-0.027	-0.023	-0.043***
	(0.063)	(0.037)	(0.026)	(0.013)
Bank FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
N. of banks	26	22	26	21
Adj. R sq.	0.372	0.329	0.357	0.141
Mean Dep. Var.	0.251	0.059	0.189	0.034

Notes: This table reports the coefficients of Eq. 12. The outcome variable is the log amount lent by private banks. Observations are defined at the bank, district, time level. We include bank and district-time FEs. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 8: Interest rate on loans

	w/ Credit history		w/o Credit History	
	Low risk (1)	High risk (2)	Low risk (3)	High risk (4)
Tax dummy$_{qy}$ $\times$ $\mathbf{I}$ [ATM share]$_b$	0.681	5.130**	-2.966	3.588***
	(4.063)	(1.905)	(2.004)	(0.699)
Bank FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
N. of banks	26	22	26	21
Adj. R sq.	0.892	0.725	0.831	0.750
Mean Dep. Var. High ATM	22.690	26.240	23.460	26.964

Notes: This table reports the coefficients of Eq. 12. The outcome variable is the interest rate applied on loans provided by private banks. Observations are defined at the bank, district, time level. We include bank and district-time FEs. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

history to low-risk ones with credit history. Indeed, we show that banks more affected by the positive liquidity shock increase their lending to low risk customers with credit history by 15%, while decreasing lending to high risk customer with no credit history by 4%. High risk customers register an increase in the interest rate by more than 3 percentage points. Eventually, repayment terms decrease for all customers, indicating the need for the bank to deal with possible abrupt shortages of liquidity due to the possible shortages of liquidity that might derive by the nature of new deposits: as these are considered mainly a way to safely store money between transactions performed by individuals.

Table 9: Log term of repayment

	w/ Credit history		w/o Credit History	
	Low risk (1)	High risk (2)	Low risk (3)	High risk (4)
Tax dummy$_{qy}$ $\times$ $\mathbf{I}$ [ATM share]$_b$	-2.240***	-0.875***	-2.223***	-0.803**
	(0.654)	(0.543)	(0.638)	(0.327)
Bank FE	Yes	Yes	Yes	Yes
District-Time FE	Yes	Yes	Yes	Yes
N. of banks	26	22	26	21
Adj. R sq.	0.923	0.719	0.907	0.691
Mean Dep. Var.	5.966	5.874	6.138	6.179

Notes: This table reports the coefficients of Eq. 12. The outcome variable is the log term of repayment of loans provided by private banks. Observations are defined at the bank, district, time level. We include bank and district-time FEs. Standard errors are clustered at the district level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

6 Conclusions

Our research delves into the dynamic landscape of digital payments, exploring the intricate interactions between digital and traditional payment systems and shedding light on their implications for bank lending and financial inclusion. The examination is contextualized within the ongoing debate on Central Bank Digital Currencies (CBDCs), emphasizing the necessity for empirical investigations into their potential repercussions on the banking sector.

Exploiting a quasi-experimental design and leveraging a comprehensive dataset encompassing the universe of Mobile Money transactions in Uganda, we study how competition between payment systems affects the credit market. In particular, our study investigates the consequences of an unexpected Mobile Money tax. We show that the increased cost of Mobile Money triggers the adoption of a new bank-related technology that facilitates deposits and that banks' deposits substitute Mobile Money for cash storage: we document that in those districts where the access to the banking system is made easier by the pervasiveness of ATMs, the flow of deposits and withdrawals increases after the introduction of the tax.

We leverage the transition from mobile money to bank deposits and its subsequent positive impact on bank liquidity to examine its effects on the credit market. Our study unveils novel insights into the lending behaviors of banks amidst increased deposit volatility. In line with the heightened deposit inflows and ATM withdrawals post the tax implementation, our evidence reveals a significant change in demand deposits and cash deposits at the bank level, but no effect on other types of deposits such as savings and time deposits. This suggests the precarious nature of the newfound liquidity, which banks cannot depend on for long-term and secure credit.

The data indicates a widespread reduction in the repayment term of new loans, reflecting the imperative for banks to cope with the continual cash withdrawals. Additionally, there is a discernible shift in rent from high-risk borrowers lacking credit history to low-risk borrowers with established credit records. These findings imply a shift in banks' strategies as they hedge against the risk of liquidity shortages. This mechanism is particularly relevant for financial inclusion, as reduced credit provision and higher interest rates to customers with no credit history might hinder local development of more fragile areas.

We contribute empirically to the debate on digital payments, banking competition, and financial inclusion. This research intersects with the literature on CBDCs, providing insights into how the introduction of digital payment systems may influence competition in the financial sector. Additionally, it aligns with literature exploring the impact of FinTech on traditional finance, emphasizing the expansion of financial services in response to evolving demands. Our empirical findings not only contribute to the ongoing dialogue surrounding the adoption of digital currencies but also unveil a novel mechanism that elucidates how volatile liquidity within banks can lead to discernible shifts in credit provision, impacting different customer segments.

Last but not least, we provide empirical evidence of a widely discussed topic developing countries, Mobile Money taxation, and contribute to the extremely scarce literature studying the effects of Mobile Money regulation. We highlight the possible negative implications of increased digital currency cost in developing countries, leading to both a drop in the usage of such system and to a drop in bank lending to more fragile households.

In conclusion, our empirical investigation offers nuanced insights into the complex interplay between digital and traditional payment systems, presenting implications for the credit market and financial inclusion. As the financial ecosystem continues to evolve, our research contributes valuable perspectives to the ongoing discussions surrounding the adoption of digital currencies and their impact on the broader financial services landscape.

Appendix

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A Appendix A - Additional Tables

A.1 Mobile Money

A.1.1 Intensive margin: individual level

Table A.1: Intensive margin: average daily number of transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$ × High ATM density$_d$	-0.086***	-0.092***	-0.015***	-0.048***
	(0.005)	(0.004)	(0.003)	(0.002)
User FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of users	142522	225365	585690	691428
Obs.	285044	450730	1171380	1382856
Adj. R sq.	0.429	0.318	0.408	0.447

Notes: In this table, we use the specification presented in Eq. 1 and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. Urban users perform between 2% and 6% less daily transactions with respect to rural users, after the tax. We estimate the effect on the sample of users that performed transactions of a given type before and after the tax. Column (1) show the effects on the number of transactions sent to another user, column (2) on the number of transactions received, column (3) on the number of deposits, column (4) on the number of withdrawals. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.2: Intensive margin: share of days for transaction

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$ × High ATM density$_d$	-0.010***	-0.006***	-0.005***	-0.006***
	(0.000)	(0.000)	(0.000)	(0.000)
User FE	Yes	Yes	Yes	Yes
N. of users	156967	237653	601693	707320
Time FE	Yes	Yes	Yes	Yes
Obs.	313934	475306	1203386	1414640
Adj. R sq.	0.552	0.402	0.476	0.538

Notes: In this table, we use the specification presented in Eq. 1 and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. Urban users transact about 0.5% less days with respect to rural users, after the tax. We estimate the effect on the sample of users that performed transactions of a given type before and after the tax. Column (1) show the effects on the share of days in which the user sent mobile money, column (2) on the share of days in which the user received mobile money, column (3) on the share of days in which the user deposited mobile money, column (4) on the share of days in which the user withdrew mobile money. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.3: (Log) average daily value of transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$ × High ATM density$_d$	-0.034***	-0.037***	-0.034***	-0.037***
	(0.006)	(0.005)	(0.003)	(0.003)
User FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of users	434262	663043	1145494	1192352
Obs.	1667485	2398051	5797682	6327527
Adj. R sq.	0.494	0.408	0.452	0.446

Notes: In this table, we use the specification presented in Eq. 1 and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. In this case, we are using individual-month level data, and we are exclusively employing observed transactions, i.e. we are excluding zeros and hence estimating the intensive margin. Are outcome variable, we are using the log of the average daily value transacted in a month at the individual level. Urban users transact about 3.5% less with respect to rural users, after the tax. Column (1) show the effects on the value of transactions sent to another user, column (2) on the value of transactions received, column (3) on the value of deposits, column (4) on the value of withdrawals. Outcome variables are the log of the average daily amount. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.4: (Log) average daily number of transactions

	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$ × High ATM density$_d$	-0.039***	-0.027***	-0.024***	-0.028***
	(0.003)	(0.002)	(0.002)	(0.001)
User FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of users	434262	663043	1145494	1192352
Obs.	1667485	2398051	5797682	6327527
Adj. R sq.	0.449	0.308	0.491	0.397

Notes: In this table, we use the specification presented in Eq. 1 and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. In this case, we are using individual-month level data, and we are exclusively employing observed transactions, i.e. we are excluding zeros and hence estimating the intensive margin. Are outcome variable, we are using the log of the average daily number of transactions in a month at the individual level. Urban users transact about 3.5% less with respect to rural users, after the tax. Column (1) show the effects on the number of transactions sent to another user, column (2) on the number of transactions received, column (3) on the number of deposits, column (4) on the number of withdrawals. Outcome variables are the log of the average daily amount. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.5: Share of days in a month in which transaction type is made

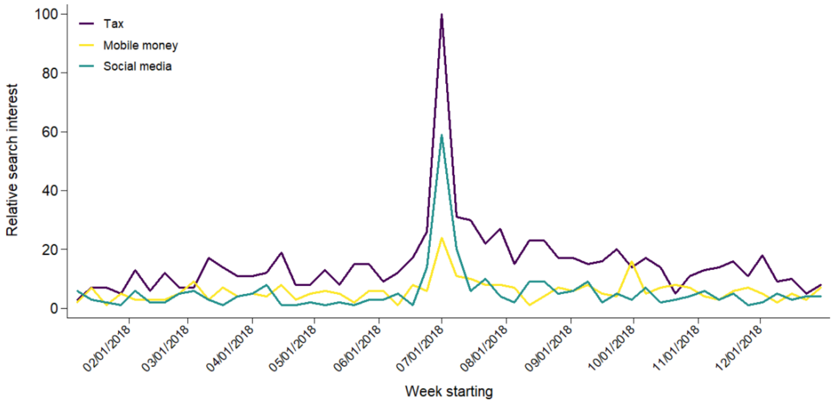
	Sent	Received	Deposits	Withdrawals
	(1)	(2)	(3)	(4)
Tax dummy$_t$ × High ATM density$_d$	-0.007***	-0.003***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
User FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
N. of users	434262	663043	1145494	1192352
Obs.	1667485	2398051	5797682	6327527
Adj. R sq.	0.498	0.377	0.520	0.474

Notes: In this table, we use the specification presented in Eq. 1 and we show how urban mobile money users respond to the introduction of the mobile money tax at the intensive margin, relatively to rural users. In this case, we are using individual-month level data, and we are exclusively employing observed transactions, i.e. we are excluding zeros and hence estimating the intensive margin. Are outcome variable, we are using the share of days in a month in which the individual perfomed a given type of transaction. Urban users transact about 3.5% less with respect to rural users, after the tax. Column (1) show the effects on the share of days in which the user sent mobile money, column (2) on the share of days in which the user received mobile money, column (3) on the share of days in which the user deposited mobile money, column (4) on the share of days in which the user withdrew mobile money. Outcome variables are the log of the average daily amount. Standard errors are clustered at the individual level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A Appendix B - Additional Figures

B.1 Mobile Money and Tax

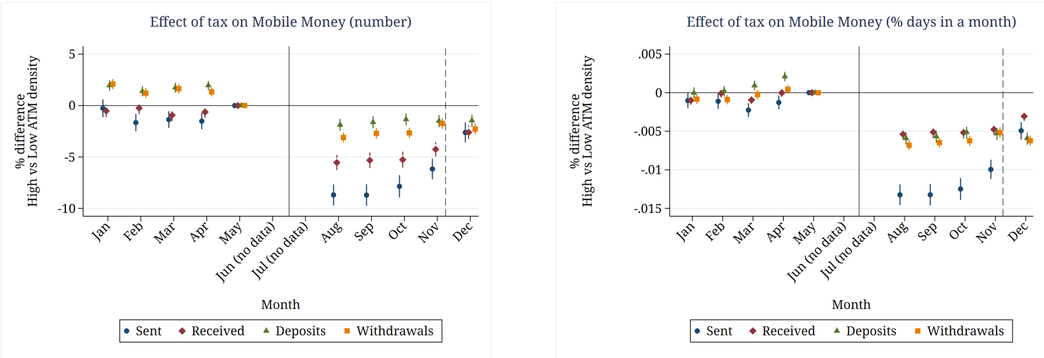
Figure B.1: Google Trend for Mobile Money Tax



Notes: Google Trends gives the relative popularity of a search query for a defined location and time period. The data is indexed to 100, where 100 indicates the maximum search interest across the terms, time period, and geographical area. We assume that search indicators provide representative information about the behaviours of the literate and internet-enabled segment of the population (who may be more likely to be mobile money users). There is relatively limited interest in these terms before July, even in May when the Mobile Money tax proposals were discussed in Parliament.

B.2 Mobile Money

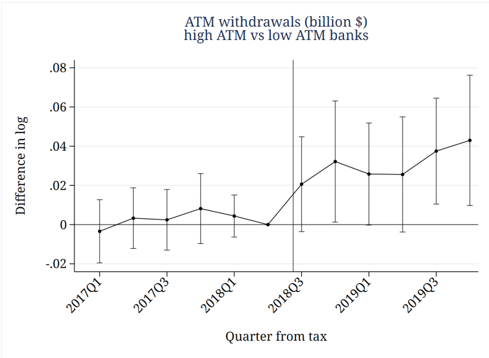
Figure B.2: Differential effect of the tax on users in high ATM density districts



Notes: This figure plots the coefficients β of the event study described in Eq. 2. We use as outcome variable the log of the average number of mobile money transactions in a month at the individual level (left panel) and the share of days in which a given type of transaction is performed by the individual (right panel). We differentiate between type of transactions. In the left panel, we already express the y axis in terms of % change. We use May as the baseline month. Data for June and July are excluded due to issues with data collection. Standard errors are clustered at the individual level, and the figure reports 95% confidence interval.

B.3 Banking agents

Figure B.3: Bank's ATM market share & ATM withdrawals



Notes: In this figure we plot the coefficients of Eq. 11, where we use as outcome variable the log value of ATM withdrawals. In this case, we use as independent variable a dummy indicating whether the bank is in the highest quartile of the ATM market share distribution. The plotted coefficient represents the differential change in the outcome for banks with high relatively to banks with low ATM market share, with respect to the reference period. We use as reference the quarter before the introduction of the mobile money tax. Standard errors are clustered at the bank level and we report 95% confidence intervals.

A Appendix C - Theoretical Framework for currency substitution

We propose a finite-horizon model where we include mobile money, cash and bank deposits as means of payment and money storage in order to rationalize the empirical analysis. We differentiate between two types of household: rural and urban ones. Urban household can use all three types of payments/money storage, while rural households have no access to bank deposits (lacking, in their case, access to the banking system). This setting mirrors our assumptions in the empirical model.

To keep the model simple, we assume that there are only two means of payment and money storage, cash B and mobile money M. Households can decide whether to pay for their consumption using cash or mobile money. Households can also decide how to store their money, in cash on mobile money. We assume that neither money storage system pays interest (as it actually happens in Ugandan economy). We assume that money stored in cash is subject to a known depreciation rate. This reflects the access to safe cash storage systems, such as banks and ATMs. The more pervasive ATMs are, the less cash is subject to theft (for example, a high density of ATMs allows you not to carry cash around). For simplicity, we assume it to be fixed.

We base our model on Sarkisyan (2023), however allowing households to buy any good with both type of currencies, cash and mobile money. We solve the partial equilibrium for the household only, providing a hint for guiding our empirical results.

C.1 The Model

Households defined on the continuum $[0, 1]$ are denoted by i. Households decide on their consumtpion C_t, the quantity of mobile money M_t and of cash B_t to hold. They maximize their utility function

$$U_0^i = \sum_{t=0}^{T} \log C_t^i \tag{C.1}$$

and they are subject to two constraint. An intertemporal budget constraint:

$$C_t^i + M_{t+1}^i + B_{t+1}^i \leq Y_t^i + M_t^i + B_t^i \delta \tag{C.2}$$

where δ is a certain depreciation rate that household know to face when deciding to keep money as cash, and it is such $\delta \in [0, 1)$. This reflects the fact that cash is easily subject to theft. A higher δ implies a safer cash storage: we can think of it as the easy access to ATMs or banks, that allow households not to carry cash around and withdraw it near the point where the make the purchase. The model is qualitatively the same if we introduce bank deposits as mean of storage of cash. The implicit assumption in this simplified model is that households always store cash in banks, but they are subject to theft is banks are not widespread. We do not include any interest rate paid on cash or mobile money, as this would not change the model implications.

The second constraint is written in the fashion of a liquidity-in-advance constraint in the fashion of Lucas Jr (1982), Lucas Jr and Stokey (1985) and Svensson (1985). We however allow households to be able to purchase any consumption good with both cash or mobile money. While households pay no additional cost in using cash for consumption, they might incur in an additional cost u_t^i when using mobile money. This reflects changing fees applied to mobile money, and we include it as an i.i.d. shock with mean $\bar{u}$ and support $[0, u^{upper})$.

$$C_t^i \leq B_t^i + u_t^i M_t^i \tag{C.3}$$

This model hence reflects the decision of households as follows: (i) the shock u_i^t is realized and household decide their consumption; (ii) households choose how to store their money for the next period, whether in cash B_{t+1}^i or in mobile money M_{t+1}^i.

If the support of of u_t^i is large enough, households will keep precautionary savings in cash, in order not to have to face extreme negative shocks to their consumption.

C.2 Solving the model

In order to solve the model, we first write down the Lagrangian as:

$$\begin{aligned}\mathcal{L}\left(C_t, M_{t+1}, B_{t+1}, \lambda_t, \mu_t\right) = \sum_{t=0}^{T} \beta^t \Big[& \log C_t^i + \\ & \lambda_t \left(Y_t^i + M_t^i + B_t^i \delta - C_t^i - M_{t+1}^i - B_{t+1}^i\right) + \\ & \mu_t \left(M_t^i u_t^i + B_t^i - C_t^i\right) \Big]\end{aligned} \tag{C.4}$$

and we obtain the following F.O.C.:

$$C_t : \qquad \frac{1}{C_t} - \lambda_t - \mu_t = 0 \tag{C.5}$$

$$M_{t+1} : \qquad -\beta\lambda_{t-1} + \beta\lambda_t + \beta\mu_t \mathbf{E}_{t-1} u_t^i = 0 \tag{C.6}$$

$$B_{t+1} : \qquad -\beta\lambda_{t-1} + \beta\lambda_t \delta + \beta\mu_t = 0 \tag{C.7}$$

We proceed by combining Eq. C.6 and Eq. C.7, obtaining:

$$\lambda_t \left(1 - \delta\right) = \mu_t \left(1 - \mathbf{E}_{t-1} u_t^i\right) \tag{C.8}$$

From this equation conclude that, since $\mathbf{E}_{t-1} u_t^i \neq 1$, then $\lambda_t \neq 0$. This implies that the constraint of Eq. C.2 binds. Similarly, also the constraint in Eq. C.3 binds: if it were not so, we would have that $\mu_t = 0$, implying that $\delta = 1$. This would reduce our model to have no conveniency in mobile money, as cash would be completely safe.

Since the constraints bind, we can equate consumption C_t from both Eq. C.2 and C.3, to obtain:

$$I_t^i = M_t^i (1 + u_t^i) + B_t^i (1 - \delta) \tag{C.9}$$

where $I_t^i = Y_t^i - M_{t+1}^i - B_{t+1}^i$. Starting from this equation, we can rewrite B_t and M_t as:

$$B_t^i = \frac{I_t^i - M_t^i(u_t^i - 1)}{1-\delta} \tag{C.10}$$

$$M_t^i = \frac{I_t^i - B_t^i(1-\delta)}{u_t^i - 1} \tag{C.11}$$

In order to obtain the consumtpion expressed as function of M_t or B_t we combine one of the two binding constraints (Eq. C.2 or Eq. C.3) respectively with the second F.O.C. in Eq. C.10 and with the third F.O.C. in Eq C.11, to obtain:

$$C_t^i = \frac{M_t^i(1 - \delta u_t^i) + I_t^i}{1-\delta} \tag{C.12}$$

$$C_t^i = \frac{B_t^i(\delta u_t - 1) + u_t^i I_t^i}{u_t^i - 1} \tag{C.13}$$

C.3 Equilibrium

From now on we drop the superscript i to ease notation.

C.3.1 Obtaining μ_t as function of M_t and λ_{t-1}

What we need to do now is the following: we need to combine the consumption expressed in term of M_t in Eq. C.12 with the first F.O.C. in Eq. C.5 and then with the F.O.C. obtained deriving by B_{t+1} in Eq. C.7.

By combining Eq. C.12 with Eq. C.5 we first obtain:

$$\lambda_t = \frac{1-\delta}{M_t(1-\delta u_t) + I_t} - \mu_t \tag{C.14}$$

Then combining Eq. C.14 with Eq. C.7 we get:

$$\mu_t = \left[\beta\delta \frac{1-\delta}{M_t(1-\delta u_t) + I_t} - \lambda_{t-1}\right] \cdot \beta\,(\delta - 1) \tag{C.15}$$

Similarly, we proceed for obtaining the same expressed in terms of B_t. We combine the consumption expressed in term of B_t in Eq. C.13 with the first F.O.C. in Eq. C.5

and then with the F.O.C. obtained deriving by M_{t+1} in Eq. C.6.

C.3.2 Obtaining μ_t as function of B_t and λ_{t-1}

By combining Eq. C.13 with Eq. C.5 we first obtain:

$$\lambda_t = \frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} - \mu_t \tag{C.16}$$

Then combining Eq. C.16 with Eq. C.6 we get:

$$-\lambda_{t-1} + \beta \left[\frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} - \mu_t \right] + \beta \mu_t \mathbf{E}_{t-1} u_t = 0 \tag{C.17}$$

Notice that we need to get rid of the expectation term $\mu_t \mathbf{E}_{t-1} u_t$. We can do this by combining Eq. C.17 with Eq. C.8, and substituting $\mu_t \mathbf{E}_{t-1} u_t$ with $\lambda_t(1-\delta)$, obtaining:

$$-\lambda_{t-1} + \beta \left[\frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} \right] = \beta \lambda_t (1 - \delta) \tag{C.18}$$

Now we need to subtitute λ_t again with Eq. C.16, finally obtaining:

$$\mu_t = \left[\beta \delta \frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} - \lambda_{t-1} \right] \cdot \beta \left(\delta - 1 \right) \tag{C.19}$$

C.3.3 Equilibrium

Now that we obtained μ_t expressed in terms of λ_{t-1} and rispectively in terms of M_t in Eq. C.15 and in terms of B_t n Eq. C.19, we can equate these two equations to obtain:

$$\frac{1 - \delta}{M_t(1 - \delta u_t) + I_t} = \frac{u_t - 1}{B_t(\delta u_t - 1) + u_t I_t} \tag{C.20}$$

and simplifying further this equation we obtain:

$$M_t(1 - u_t) = B_t(1 - \delta) + I_t \tag{C.21}$$

Let us suppose to be in the simplest case in which $Y_t == 0$ for $t! = 0$. At $T - 1$ the households will choose to allocate no money neither to cash B_T or mobile money M_T.

We can extremely simplify the model to a two-period model, at time 0 and 1. Indeed households will have to choose only C_0, M_1, B_1 and C_1, since $B_2 = 0$ and $M_2 = 0$. If we assume $Y_1 = 0$, we get:

$$\frac{B_t}{M_t} = \frac{1-u_t}{1-\delta} \tag{C.22}$$

Let us suppose a shock to u_t, the ratio between cash B_t and M_t would change by:

$$\partial_u \frac{B_t}{M_t} = -\frac{1}{1-\delta}$$

it is clear that a higher conveniency of storing cash δ leads to a higher elasticity of substitution between cash and mobile money.

Mobile Money, Interoperability, and Financial Inclusion¶¶

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Abstract

This paper investigates the tradeoff between competition and financial inclusion resulting from the vertical integration between mobile network and money operators. Joining newly assembled data on mobile money fees through the WayBack machine, with sources on network coverage and financials, we examine the staggering across African operators and countries of platform interoperability – a policy that promotes transactions and competition across mobile money operators. Our results show that interoperability benefits users by lowering mobile money fees and their dispersion across operators. However, these positive effects are offset by a decrease in mobile towers and network coverage, especially in rural and poor districts, which, in turn, leads to a lower financial inclusion. We note that combining interoperability with subsidies for rural telecommunications delivers lower fees without hurting coverage.

Keywords: Mobile Money, Interoperability, Financial inclusion

JEL Codes: E42, L14, O10

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1 Introduction

Mobile money has emerged as one of the most widespread digital payment systems (Demirguc-Kunt et al., 2018). Its diffusion resulted in tangible changes in various economic and financial indicators like risk-sharing (Jack and Suri (2011); Blumenstock et al. (2016)), remittances (Riley (2018); Aker et al. (2020)), lending (Suri et al., 2021) and savings (Breza et al., 2022), among others. Despite these significant developments, research on the functioning and regulation of the corresponding financial institution, the mobile money company, remains limited.

This paper investigates the role of competition on the behaviour of mobile money companies and its corresponding effects on financial inclusion. Specifically, we examine the effects of a competition-promoting policy, platform interoperability, which facilitates transactions between users of different mobile money operators. By mitigating the barriers to exchange payments, this regulatory intervention can impact the profit margins of mobile money operators and influence their pricing, network, and infrastructure investment.

Our paper proposes conceptually and explores empirically a novel tradeoff between competition and financial inclusion in the context of mobile money. It is crucial first to introduce the typical structure of this market, which comprises two main players: mobile network companies that offer phone and internet services; and mobile money companies that focus on payment exchanges. Typically, these two actors are vertically integrated as discussed by Bourreau and Valletti (2015), which creates a limited competitive environment (Williamson (1979); Grossman and Hart (1986); Hart et al. (1990)) and results in higher fees charged to mobile money users. At the same time, this lack of competition may also provide incentives for mobile network companies to extend their reach to underserved locations, enhancing financial inclusion. Consequently, low levels of competition may increase the size of the mobile network, which may be labelled as the extensive margin of financial inclusion. Nonetheless, this scenario may harm the poorest users within covered areas due to high transaction fees, which weakens the intensive margin of inclusion.

To guide our empirical analysis, we build a compact theoretical framework inspired by the work of Laffont et al. (1997) and Bianchi et al. (2022). These papers examine respectively the role of competition in the telecommunication market and the mechanics of interoperability in mobile money. Our contribution lies in introducing the margin of infrastructure via tower installation. We show that interoperability breaks the possibility for platforms to exercise monopoly power by inducing competition on fees. At the same time, this reduction in the profit margin of the mobile company leads to a decline in tower installation and network provision. One central aspect of this paper is the role of mobile network towers. We model this via the tower infrastructure that moves with economic incentives and is not necessarily fixed and unresponsive to the underlying economic characteristics. This assumption, which we validate empirically, is inspired by the market structure of mobile towers in Africa, which we describe in detail in Section 2.3. In short, mobile towers in Africa present high variable costs given that most are disconnected from electricity and powered through expensive power-generating commodities, such as diesel fuel. This cost structure implies that companies respond by reducing their tower network in response to a negative shock to mobile revenue, since towers in this setting are not a sunk cost.

The empirical challenge is to identify a source of quasi-experimental variation, which increases the competition between mobile money companies and affects the extent of the money-phone integration. To do this, we exploit a unique natural experiment taking place in Africa: the staggered introduction of interoperability across operators and countries that has been taking place between 2010 and 2020. In this context, interoperability is a policy that induces mobile money companies to permit and facilitate the exchange of payments with mobile money users that operate on a different platform. The introduction of interoperability does not appear to be related to specific conditions of the mobile money industry. It is instead a reform initiated by the central bank, which expands the country infrastructure of payment systems involving banks, merchants and correspondingly mobile operators. This fact is documented in the paper appendix and validated by the presence of balanced economic characteristics in our country sample and parallel trends in the pre-period across our empirical specifications.

We combine this source of variation with numerous novel datasets. Our innovative contribution in terms of data is to construct a panel dataset on mobile money fees per company, which covers 129 operators across 42 countries in Africa from 2010 onward. Building this data was particularly challenging, since this information is not publicly available and retrospective surveys asking users for fees tend to be inaccurate. To address these gaps, we used the "Wayback Machine": an online archive that routinely scans most websites and takes screenshots of their pages. We digitized this information and created the panel, which reveals some original descriptive findings on the functioning of this market.

Mobile money fees in Africa are high and penalize small transactions, which are generally used more extensively by poorer people (Yao et al., 2022). The average cost of sending a transfer to another user on the same mobile money company accounts for an average of 4% of the total, if the user has a different company this fee levitates at 10%. As presented in the paper, small payments are particularly hit by high fees, which exceed 30% of the transferred amount for amounts placed in the smallest brackets. Beyond their level, fees are also highly dispersed across operators, with small payments exhibiting the most intense variation.[11]

To join a measure of prices with quantities and network, we partnered with the GSM Association (GSMA), the leading organisation grouping mobile telecommunications operators to access various datasets on mobile network companies. First, we employ data on the second-generation cellular network technology (also referred to as 2G) used for mobile money transactions across the entire African continent through rasters of 250×250 meters, containing information on the presence of mobile signal and number of companies operating. This information is then aggregated at the district level for all countries in Africa, using maps from the Database of Global Administrative Areas (GADM). Second, we received access to a source of operator-specific information on financials as well as other statistics (towers, market penetration, price for other services). In addition, we use the

[11] In evaluating fees, we refer to the nominal cost of a transaction, which in this setting transcends from misconducts of financial intermediaries, who may overcharge specific demographics beyond the nominal expenses as noted by Annan (2022).

World Bank Global Findex Survey and IMF Financial Access Survey to shed additional light on the effects of interoperability on financial inclusion.

Our results validate the existence of a tradeoff between financial inclusion and competition. In terms of prices, an event study setting shows that the fees of companies operating in different countries lie on parallel trends prior to the introduction of interoperability and sharply fall thereafter. A difference-in-difference specification quantifies the decline in fees after interoperability to be at 0.3 percentage points for on-network transactions, which are transactions between users on the same network (20% of the mean) and at 1.3 percentage points cross-network transactions, which are transactions between users across the different networks (35% of the mean). This decline is almost entirely due to small payments that become substantially cheaper, with fees falling by 20% for on-network transactions and more than 45% for cross-network ones. At the same time, we show that the dispersion of mobile money fees drops by more than 50% with the introduction of interoperability, with small payments presenting the strongest decline.

We exploit the granularity of our data and the ability to measure the network coverage for each operator across multiple districts to study the impact of interoperability at the operator-district level. We document that interoperability induces an overall decline in coverage and probability that a district is covered by a company. These results are confirmed by a different dataset on operators and their yearly financials. Companies operating in countries where interoperability was implemented experienced a decline of 18% in share of population covered, 22% in market penetration, 29% in revenue and 12% in the number of towers. The profits of mobile network companies seem to be negatively affected as well, though the estimates are imprecise.

In addition to this evidence at the operator-district level, we also present results regarding network availability within districts to understand the overall effects of this policy. We find that the arrival of interoperability lowers various measures of network coverage. In all cases, we present event study specifications showing the existence of parallel trends before the treatment and use a difference-in-difference specification to quantify the average effects. We find that districts in countries that introduce interoperability experience a 5% drop in the share of the district covered by mobile network coverage (almost 8% of the mean), a 3.4% decline in the probability of presenting any coverage (4% of the mean) and a 19% lower number of mobile network companies operating in the geographic unit. Furthermore, districts that may present high ex-ante costs of tower installation and therefore be marginal for mobile companies (rural, poorer) before the policy are the ones presenting the strongest hit. In fact, the relative decline in their telecommunication access is severe both in terms of coverage and the number of operators. These findings highlight that the lack of competition and untargeted regulation can shape the geographic access to goods and services, both financial and non-financial, and promote within-country inequality (Alesina et al., 2016).

To investigate the effect of interoperability on financial inclusion, we take advantage of the Global Findex dataset and find that individuals in countries introducing interoperability see a reduction in the likelihood of sending and receiving remittances, and in the likelihood of saving for their own business activity. At the same time, the IMF FAS dataset reveals that as interoperability is launched, countries experience a reduction in the aggregate number of mobile money transactions, agents and users. We show that these effects are driven by those countries with a stronger pre-existent mobile money network: these results can be seen as the consequences of a reduction in mobile network coverage both at the extensive margin (i.e. in terms of geographical outreach) and the intensive margin (i.e. in terms of signal quality) following the introduction of interoperability. We further validate our results using also data from the DHS surveys.

In terms of policy implications, our study focuses on a source of market imperfection behind the competition-inclusion tradeoff: the prevalence of uniform pricing across different locations. As discussed by (DellaVigna and Gentzkow, 2019), it is common for businesses to apply uniform or nearly-uniform prices across various locations, regardless of the local demographic characteristics and competitive landscape. While such pricing scheme may be good since it potentially alleviates economic differences between groups coexisting in the same country (Alesina et al., 2016), it also presents some significant side effects. In fact, if mobile companies were able to discriminate their fees based on the local cost of providing connection services, increased competition would reduce mark-ups without affecting service provision. Although such mechanisms of price discrimination do not exist in telecommunications, neither in Africa nor elsewhere, we draw a close analogy from a policy that creates de facto heterogeneous fees: the presence of subsidies to promote rural telecommunications. These policies result in price discrimination between urban and rural locations once the subsidy is combined with the fee. To investigate this further, we collected data on policies aimed at promoting access to telecommunication services in remote areas and note a crucial heterogeneity of our key findings to these policies. Our empirical results validate that the combination of interoperability and these subsidies presents a promising opportunity to lower fees for users while maintaining the scale of the mobile network.

We conclude our paper with a set of the robustness tests of our results through different approaches. First, we use the methods for dynamic treatment effects in event studies with heterogeneous treatment effects proposed by Sun and Abraham (2021) and the framework for difference-in-differences designs with staggered treatment adoption and heterogeneous causal effects proposed by Borusyak et al. (2021). Second, we replicate our main results weighting for the district's population, and also using alternative clustering methods for the standard errors. In addition to this, we explore several other tests: for example, we verify that the introduction of interoperability does not affect operations of Mergers and Acquisitions between mobile network operators, we provide several heterogeneity analysis using different measures of local urban development, and we test the robustness of our results to the inclusion of time-varying country-specific characteristics.

The main contribution of this paper is to provide evidence that a higher level of competition between mobile money providers has mixed effects on consumers and infrastructure investment. This intuition applies more broadly to telecommunications and tower installation technology, and to digital payment systems and the underlying server infrastructure. Our work is in line with studies that highlight the mixed effects of competition on consumers and infrastructure, for example Ferrari et al. (2010) show that banks underinvest in their ATM network in Belgium due to the prohibition to charge additional fees on users of other banks, which resembles the concept of interoperability that we study in this paper. Genakos et al. (2018) study the tradeoff between market power and efficiency in the OECD telecommunication industry, showing that a higher market concentration is associated with both higher mobile telecommunication fees and investment. Through a study of the Rwandan network, Björkegren (2022) relates the role of competition to the intrinsic networked nature of mobile networks to study welfare and investment, finding that the free interconnection of systems can lower the incentives to invest. Brunnermeier et al. (2022) show that enforcing interoperability in the digital money market reduces ledger controllers' rents, but also lowers credit extension in the economy. Related to this literature, there are two important review articles: Bourreau and Valletti (2015) offer a comprehensive analaysis of the economic features of mobile payment systems in developing countries, while Bianchi et al. (2022) connect various streams of academic literature to shed light on how the degree of interoperability in mobile payments affects market outcomes and welfare. This paper advances this literature by combining granular and innovative data on the mobile market with an empirical design exploiting a plausible source of variation.

At the same time, our paper is related to the growing literature on mobile money. Jack and Suri (2011), Jack et al. (2013) and Jack and Suri (2014) have pioneered this stream of research, by using survey data to understand the role of mobile money in attenuating the effect of negative income shocks by fostering risk sharing. Blumenstock et al. (2016) also studies the response to shocks (in the context of an earthquake in Rwanda) using administrative data on mobile phone records, airtime purchases, and transfers of airtime. Suri and Jack (2016) show that increased access to mobile money has increased long-term consumption in Kenya and reduced the number of households in extreme poverty. Riley (2018) underlines how developing countries have gained increased access to remittances through the introduction of mobile money services. Suri et al. (2021) study how a new digital loans system operating over the rails of mobile money helps households in facing negative income shocks. Breza et al. (2022) finds that a financial technology that allows individuals to automatically receive their wage on their mobile money account leads to higher savings and stronger resilience. Our paper brings a perspective focusing on the supply of mobile money, exploring their functioning and corresponding regulation. This paper is also related to the literature studying how access to mobile networks can foster economic development.[12]

The rest of the paper is as follows. Section 2 presents a theoretical framework of competition in the mobile money sector, offers details about the institutional aspects of mobile money interoperability, and provides an insight on how the telecommunication infrastructure works in Africa. It describes the data we use, comprehensive of a newly self-collected dataset on mobile money fees across African operators, and offers insights on the the identification strategy that exploits the staggering of interoperability across African countries. Section 3 investigates the effects of interoperability at different levels. It first provides evidence on operators' fees, financials and network coverage. It then presents aggregate results at geographical level, by also showing the implications for financial inclusion. Eventually, it provides several heterogeneity analyses and a set of robustness checks. Section 4 concludes.

2 Theoretical framework, Data and Identification

The aim of this section is twofold. We first present a theoretical framework relating mobile money interoperability, competition between operators and financial inclusion. We then introduce the institutional changes experienced in the mobile money industry across African operators and countries, by also providing an insight on the relation between phone cell towers and network coverage. In the remaining part of the section, we describe the data we use, comprehensive of a newly collected dataset on mobile money fees across African operators. We eventually offer insights on the identification strategy, that exploits

[12] Among the prominent contributions in this literature is the work of Jensen (2007), which shows how mobile network and towers can improve market allocation efficiency and lead to uniform prices in the fishing industry in India. Aker and Mbiti (2010) explore the main channels through which mobile phones can affect economic outcomes and appraise current evidence of its potential to improve economic development. Blumenstock et al. (2020) present experimental evidence on the economic impacts of mobile phone access: the introduction of mobile phones had large and significant impacts on household income and expenditure, particularly for wage workers. Riley (2022) shows that providing microfinance loan in a private mobile money account positively impacts the businesses of female microfinance borrowers.

the staggering of interoperability across African countries.

2.1 Theoretical Framework

2.1.1 Economic Environment

This theoretical framework is built on the work of Bianchi et al. (2022) and Laffont et al. (1997), it is a simplification meant to guide our empirical analysis and provide a compact and original setting to think about the role of competition in the mobile money sector.

The market for mobile customers is composed by a continuum of locations on a unit line, and each point is populated by a household engaging in a set of mobile money transactions. The mobile company decides how many towers to open, $m \in [0, 1]$, which is costly, but allows it to reach a new locus and to interact with agents. If $m = 1$, then all locations are reached, whereas with $m = 0$, no towers are operating. When a tower is installed, the mobile company interacts with a client and decides on a fee f for transactions. This model presents the following two stages: (1) the mobile company invests in financial inclusion, deciding on the number of towers, m; (2) the company decides on its fee f given the user demand for mobile services. The game can be solved by backward induction.

2.1.2 Setting

2.1.2.1 Consumer Utility

The utility function of users reached by a mobile tower can be described by $U = \tau + \beta m - f$, in which τ expresses a taste parameter, β is a parameter capturing the network externality of the overall number of connected households and f is the fee to make mobile money transfers.

In principle, users can also keep the same mobile network services, while choosing an alternative provider only for the mobile money service. The utility function in this case can be described by $U = \tau + \beta m - f_{other}$ as users in this case need to pay a fee to the other company, f_{other}, to continue to use their mobile network and use the mobile money service from the new company.

2.1.2.2 Mobile Company Profits

The profit function of the mobile money company in a location conditional on this being reached by a tower m is given by $\pi(m) = f - c$ in which the profit margin of the company is given by the difference between its fee, f, minus the marginal cost of the communication, c, for those on network.

2.1.2.3 Mobile Tower Installation

In the first period, the mobile company decides how many mobile towers m to install, given the profit margin in each location π, the fee f and some convex cost of tower installation $c(m)$. Its convexity is due to the fact that further towers are worse connected to the electricity grid and present higher costs of energy supply and maintenance, as documented in Section 2.3.

This financial inclusion problem can be written as $\max_{m \geq 0} \Pi = \pi(m) - \eta \frac{m^2}{2}$. Note that in this setting, we introduce a new parameter η: this is a tower-installation technology parameter affecting both the average and marginal cost of branch opening.

2.1.3 Solution

In this subsection, we solve this problem for two cases: 1) the case without interoperability, in which the mobile company is a monopolist; 2) the case with interoperability, in which the mobile company faces competition.

2.1.3.1 No Interoperability

This setting can be interpreted as one in which there is no alternative mobile money platform available. This market structure gives the mobile company the possibility to extract all rents from consumers by setting their utility function to zero, making their participation constraint binding, which defines f^M as the monopoly fee: $f^M_{on} = \tau + \beta m$. In this case the company appropriates not only the utility from using the service, expressed by τ, but also the network externalities reported by βm. As a result, the tower-installation problem simplifies to $\max_{m \geq 0}(\tau + \beta m)m - \eta \frac{m^2}{2}$ leading to the following solution for the decisions of the mobile company $m^M = \frac{\tau}{\eta - 2\beta}$ and $f^M = \tau \frac{\eta - \beta}{\eta - 2\beta}$ this relies on the assumption that the costs of tower installation exceeds the network externalities in the utility, $\eta > 2\beta$, otherwise the problem simplifies to a full installation of towers in all cases and undefined fees.

2.1.3.2 Interoperability

We model interoperability as a policy allowing individuals to operate an alternative mobile money service, without switching the mobile network service. In our setting, this is modelled as a competing company, which offers transactions at a fee $f_{other} = \theta$.

This changes the competitive nature of the market, since the former monopolist can no longer extract all rents from this market and will have to compete on prices. Suppose that individuals pay an individual switching cost κ in moving exclusively their mobile money services from the former monopolist to the new company (i.e. cost of infrastructure, account opening). Then the fee of the former monopolist emerges from solving the following incentive compatibility constraint: $\tau + \beta m - f \geq \tau + \beta m - \theta - \kappa$ stating that the utility of the user remaining on the network of the former monopolist is higher or equal to the utility of an individual switching network and paying a fee θ and a switching cost κ. Under the plausible assumptions that this fee exceeds the marginal cost of operating in an area, $\theta + \kappa > c$, and that competition benefits consumers, $\theta + \kappa < \tau$, then this change in the competitive structure leads to a decline in fees and in availability of mobile network, since the optimal f and m are now: $m^C = \frac{\theta + \kappa}{\eta} \ \ and \ \ f^C = \theta + \kappa$. Therefore the arrival of interoperability leads to lower fees since $\theta + \kappa < \tau$ and $\frac{\eta - \beta}{\eta - 2\beta} > 1$ but also to lower mobile tower installation for the same reason. The proposition below summarizes these results and presents an additional heterogeneity.

Proposition

In the presence of a mobile company that decides on fees and tower installation, the introduction of interoperability leads to lower mobile money fees and a reduction in tower installation and signal. One central heterogeneity emerge from this setting: locations with higher costs of tower installation experience a stronger decline in towers and coverage. In Appendix C - Theoretical Framework we provide the derivation of this proposition.

2.2 A new dataset on mobile money fees

The literature on mobile money lacks information on the fee structure of operators. A comprehensive dataset on mobile money operators' tariffs does not exist,[13] and hence for the purpose of this paper we are the first to introduce such a dataset, comprehensive of most mobile money service providers operating in Africa. We collected monthly data on each operator's fees, spanning the year 2010-2021, calculated as a share of the paid amount. The main source of our data is the website of each Mobile Money provider, as the tariff plans are usually available not only to the agent offices but also online. However, operators rarely keep their past fees structure publicly available on their website: to overcome this issue, we rely on the Wayback Machine, which is a tool that enables the recovery of web pages that are no longer available. For instance, as shown in Figure B.1 of Appendix B - Additional Figures, if we want to find all the previous "versions" of the Telma (the first operator launched in Madagascar) webpage, we can type the URL of today's webpage in the search bar and choose the year/month we are interested in.

In most cases, the web pages are available and the tariff plans published, so it is possible to browse the archived website and find the information needed. However, finding the rates for each year is not easy: different problems can hamper our search, such as images or documents not visible/downloadable, absence of screens for entire years, issues in loading pages, fees not present on the web pages, etc. For this reason, we rely on additional sources to fill in the gaps. Secondary sources are 1) providers' pages in different

[13]See the article on IPA's two-year pilot by Blackmon and Pizatella-Haswell (2022): www.poverty-action.org/blog/tracking-real-cost-mobile-transactions-ipas-new-two-year-pilot.

social networks like Facebook, Twitter, or Linkedin, where photos of tariff plans are often published, 2) articles concerning Mobile Money fees published in newspapers online or blogs. In Data Appendix D - Fees & Interoperability, we provide a detailed description of how data on Mobile Money fees are built. Figure B.2 in Appendix B - Additional Figures shows the complexity of the structure of mobile money tariff plans, which are not constant across transaction values. We build two main datasets, containing the mobile money fees charged by each operator over time. We differentiate between fees charged to transfer money to subscribers to the same operator ("on-network") and fees charged to send money to subscribers of other operators ("cross-network"). The first output is a panel data set that includes the operator name, country, year, and the yearly fees' median value for on-network and cross-network ransactions. The second data set is more detailed, because it includes tariffs for all transaction ranges ("brackets") defined by companies' tariff plans. To this aim, we take the most disaggregated fee structure in the country and adjust all operators' rates (in that country) accordingly, as explained in Data Appendix D - Fees & Interoperability. Figure 1 shows how fees change across brackets: we plot the mean yearly fees for a mobile money transfer between two users belonging to the same company, i.e. on-network transaction. This is plotted for each operator and is different depending on the amount of the mobile money transaction. In particular we document that higher fees are applied to lower transactions: Figure 1 shows that the first and second bracket of lowest-value payments experience the highest fee, on average 30% and 10% respectively, with such fees declining progressively and regressively as the underlying value of the transaction increases. In Figure 7 and Table A.37 we show how the introduction of interoperability decreases the dispersion of transaction fees across and within brackets. The top left and right panels of Figure 7 show the distribution of operators' on net fees, across brackets, before and after interoperability, respectively. From the two figures it comes out that after interoperability the dispersion of fees in the lowest transaction brackets decreases. This is confirmed by Table A.37, where we regress the standard deviation of fees across interoperable and non-interoperable operators in a given year and a given bracket, on a dummy taking value 1 for interoperable operators.

We show that the standard deviation of on net fees is lower for interoperable operators. In Table A.37 we also confirm that the dispersion of fees is higher for lower transaction brackets. These results hint at the convergence of prices across markets and can be rationalized throught the law of one price.

2.3 Mobile network coverage and infrastructures

Mobile money services are vertically integrated with the network operator providing the service. This means that the mobile money service can be used exclusively where a given mobile network operator's connection covers the area (Bourreau and Valletti, 2015). Therefore, it is important to understand the infrastructure enabling the network coverage, and in particular the economics behind the installation and maintenance of towers. It is key to clarify that mobile network towers are not necessarily a sunk and long-term investment, as they present sizeable operating costs.

The towers used for the commercial transmission of mobile signals are typically powered through an electrical connection: they are "on-grid", as they receive power from the electrical grid as an input and release signal as an output. However, there are instances in which it is impossible to operate on-grid towers, because the grid may be unreliable or the tower may be in a remote location. In this case, the technology for transmitting the mobile signal is through an "off-grid" system: The electricity supply is provided through the installation of a diesel-powered generator, which is used as the main or backup source of electricity.

As a result, mobile operators in Africa face challenges to power their mobile networks, because of unavailable or unreliable power supply and consequential heavy reliance on expensive diesel power generators. Major infrastructural and operational challenges make it extremely costly for mobile network provider to expand their coverage or to keep it active in marginal areas. The most common costs faced by mobile operators as pointed out by Kumar (2014) are due to: limited or no road access infrastructure which increase Operation and Maintenance (O&M) costs of sites, higher cost of security and monitoring systems to protect assets and infrastructure to prevent diesel theft, equipment theft and vandalism of site equipment, lack of local skilled technical resources that causes a further increase in the costs of operations. These infrastructural impediments translate in the lack of economic incentives for mobile network operators to provide their services in remote areas.

The limited reach of grid infrastructure and inadequate power generation capacities has greatly affected the availability and quality of electricity supply to mobile network sites, and therefore impacted the configuration and geographic spread of mobile networks in Africa. The majority of telecom tower sites in Africa are deployed in either off-grid areas or problematic grid areas with unreliable power supply (Ahmad et al., 2015). This observation is in line with the fact that the growth in mobile networks has tremendously outpaced the local expansion of grid infrastructure across countries in Africa. As a result, the majority of the tower sites are deployed in off-grid areas. The necessity for diesel generators, and increasingly battery backups, is not limited to off-grid towers in Africa, but includes also a large share of on-grid towers. This is due to the fact that energy provision planning was traditionally ignored by the network expansion teams during the aggressive network roll-out (Kumar, 2014). The limited reach of grid infrastructure and its snail-paced expansion further widened the demand-supply gap and have adversely affected the availability (with more frequent/longer power cuts) as well as quality of power supply.

In this respect, energy costs constitute a major chunk of network operational expenditure (OPEX) for mobile operators in Africa. As reported by Kumar (2014), for a typical tower site in Africa, the share of energy costs is as high as 40% of the overall network OPEX, and the power consumption from diesel is about a factor 10-20% higher than the power requirements of the cell base stations.

2.4 Data

We employ several different and novel sources of data. We do not only provide new self-collected datasets on mobile money fees and mobile money institutions, but also a new dataset on individual network operators' coverage, as well as their financial and non-financial information. The main databases employed in this research are listed as follows:

1. Mobile Money fees. As explained in Section 2.2, we introduce a new panel dataset on mobile money fees for all mobile money operators providing their service across African countries. We collected yearly data for 129 mobile money operators, operating in 42 African countries, in a time span of 12 years, from 2010 to 2021. To make the panel reliable and usable, we spell the mobile money tariffs as percentage of the total transaction, and then define the median transaction across brackets to make fees comparable across operators, countries and years. We provide a comprehensive dataset including fees for all types of transactions and for all transaction brackets harmonized at the country level.

2. Mobile network operator coverage. We use a new dataset on mobile network coverage by operator over the years 2010-2021. This is a novel use of data collected by Harper Collins and the Global System for Mobile Communications (GSMA) for research purposes. The collection of this dataset works as follows: every year GSMA collects coverage data from each mobile network operator worldwide. We are hence able to see the development of individual operators' coverage over the last decade. Data are detailed for different kind of connections (1G, 2G, 3G, 4G and, now, 5G) and are provided at a raster level of approximately 250 squared meters. This means that we observe for the entire African continent the presence of mobile network signal for each raster by each operator and over time. For our empirical analysis, we aggregate this data for each operator at the smallest administrative unit in each country, as defined by the Database of Global Administrative Areas (GADM).[14] We use data on 2G coverage only, as this is the mobile technology that enables the usage of mobile money.

3. GSMA Intelligence Mobile Network Data. This is the most comprehensive source of mobile industry insights, forecasts and research, available. GSMA collects data on every mobile network operator (MNO) in every country worldwide. They provide yearly data on several financial, usage and performance indicators of MNOs. We exploit data of 253 mobile network operators, operating in 57 African countries over a period of 22 years

[14]The Database of Global Administrative Areas is a comprehensive database of country administrative units, published with the objective of standardizing and uniforming information across countries and time periods.

spanning from 2000 to 2021. [15] In the analysis, outliers above the 99th percentile and below the 1st percentile are excluded.

4. Interoperability data. As later explained in Section 2.5, we also construct and provide a novel dataset on the introduction of mobile money interoperability across African countries. We register each policy change regarding interoperability, i.e. the possibility to exchange mobile money between different mobile money operators introduced in each African country. We are also able to identify whether mobile money interoperability was initiated by the local Government, or whether interoperability was introduced by the operators themselves, without the presence of a clear institutional framework.

5. Global Findex World Bank data. We exploit the Global Findex dataset provided by the World Bank, based on nationally representative surveys and containing updated indicators on access to and use of formal and informal financial services and digital payments. We exploit this dataset to investigate the effects of the introduction of interoperability on financial inclusion. Data are taken from about 150'000 surveyed adults, in 48 African countries, for the years in which the survey was conducted (2011, 2014, 2017, 2021).

6. IMF Financial Access Survey. To further study the effect of interoperability on financial inclusion, we exploit country level data on measures of finacial access in Africa provided by the IMF. The IMF FAS contains yearly data on access to and use of financial services, including mobile money. Our dataset covers 57 countries spanning more than 10 years. In order to avoid our results being driven by outlier, the observations above the 99th percentile and below the 1st percentile are excluded.

7. Geographical data on urban development and nighttime light intensity. We exploit the dataset introduced by Cattaneo et al. (2021) to create a district's measure of urban development. In this dataset, raster pixel are assigned a value ranging from 1 to 30, where 1 identify most urban areas and 30 most rural areas. The district's measure of urban development is hence constructed as the average of the pixel values in the district's itself.

[15] While this dataset does not contain information on contribution of mobile money services to the network operators' financials, in Data Appendix E - Mobile Network Operators Balance Sheets we provide, as an example, balance sheets (financial statements and revenue breakdowns) from selected MNOs also reporting revenues and costs of their mobile money service. In this restricted sample, the revenue from mobile money services lies between 7.7% for the overall Airtel group to 38.3% for Safaricom both in 2021.

We then divide our districts into rural and urban following the classification proposed by Cattaneo et al. (2021). We also exploit the data on nighttime light intensity provided by the National Centers for Environmental Information. They provide pixels with value ranging from 0 (no light) to 63 (maximum light intensity), all over the globe. We construct a district's measure of light intensity by averaging nighttime light intensity across all pixels contained in the district.

Table 1 reports summary statistics for the main variables used in our analysis. Panel A presents two variables with a subscript it, which labels a variable that varies by mobile money operator i during year t: *Fees on network* describes the average yearly fee applied to transaction between users of the same operator over the transaction value; *Fees cross network*, instead, represent the relative cost of the transaction when this is done between users of different mobile money networks. Panel B present summary statistics for performance and usage indicators of mobile network providers taken from the GSMA Intelligence dataset. Variables are expressed in log and vary by mobile network operator i over year t. Panel C and Panel D summarize the coverage variable at operator-district level and at district level, respectively. Variables in Panel C vary by operator i in district d over year t, while variable in Panel D vary by district d over year t. These two panels also report summary statistics for *Interoperability*, an indicator of the presence of interoperability in the mobile money market. In Panel C an operator-specific measure of interoperability is reported (which takes value 1 when the operator effectively became interoperable), while Panel D reports a country-specific measure of interoperability (which takes value 1 when the national legislation starts requiring mobile money operators to be interoperable). Panel E reports the summary statistics for the World Bank Global Findex Survey: we report three variables that we use as a proxy of financial inclusion and resilience. Variables vary by individual j in country c in year t. Panel F reports summary statistics for the IMF Financial Access Survey, that contains country-level data on mobile money usage. In Panel F, variables are reported in log, and vary by country c in year t.

2.5 Identification: the staggering of Interoperability

In line with Naji (2020), we define Interoperability as the possibility given by Mobile Money Operators to transfer money between two accounts in different mobile money schemes. While mobile money was born as a stand-alone service, in which transfers were allowed only within the same network, in the following years, it experienced an integration process that brought the connection of operators between themselves and other payment services. While we are aware that different types of interoperability exist depending on the level of integration of systems, as explained in Data Appendix D - Fees & Interoperability we focus on the case of wallet-to-wallet interoperability, i.e. the possibility to transfer mobile money between users of different operators. Indeed, as we document, institutional regulations about interoperability and bilateral agreements between mobile money providers in African countries always request this level of integration between mobile money systems. In recent years, various development organizations, industry bodies, and regulators have embarked on enabling mobile money interoperability between digital financial services providers in different markets across the globe.[16] We exploit the staggered deployment of mobile money interoperability across African countries as main source for our identification scheme.

In the legal system of African countries, in fact, mobile money is generally settled together with other payment instruments. This means that mobile money interoperability is defined and enacted within the regulatory framework of financial operators. However, discrepancies between the regulatory framework and the actual adoption of interoperability by mobile money operators might arise. This is due to several causes, that differ across countries. Indeed, we might observe both countries where interoperability is introduced by the regulator but not yet adopted by operators, and countries where operators allow interoperable transactions even in the absence of a institutional regulation. The first case might arise when the new regulatory framework concerning the introduction of interoperability is not clear and does not specify the details through which this policy

[16]In September 2014 the mobile financial services industry in Tanzania signed its first agreement on interoperability, making Tanzania one of the first countries in the world with an industry-agreed interoperable market for mobile financial services (Naji, 2020).

should be enacted.[17] The second case might instead arise when operators themselves see potential benefits from the introduction of interoperability or when they want to precede a regulation that, soon or later, will be enacted by the regulator.[18] We are able to identify both cases. By collecting information coming from national law bulletin and from operators' websites, we are able to differentiate whether in a given country the regime of interoperability is introduced by the law or if it is the operator itself that makes its system interoperable. In some cases, in fact, bilateral agreements between mobile money providers precede the formal introduction of interoperability by the local political institution. In Data Appendix D - Fees & Interoperability we provide details about the introduction of mobile money interoperability for each African country in which such policy was enacted.

Figure 2 presents the staggering of interoperability until 2021. Up to date, 20 African countries and 58 mobile money operators have introduced mobile money interoperability. Our empirical strategy revolves around three different empirical specifications, which all rely on the economic characteristics of countries adopting and not-adopting interoperability to be balanced both at baseline and over time, as shown respectively in Tables A.1 and A.2 in Appendix A - Additional Tables.

3 Empirical Model and Results

We develop our analysis adopting three main empirical approaches. First, we develop an event study design meant to test for pre-trends and to investigate the dynamics of the treatment effect. Second, we implement a staggered difference-in-difference specification using two-way fixed effects regressions. The staggered difference-in-difference provides compact estimates of the average treatment effect under the assumptions of no pretrends.

[17] For example, the Bank of Botswana in 2019 published the "Electronic Payment Services Regulations", where it was stated that "the resources shall be a system which is interoperate with other payment system within Botswana": this regulation requires payment systems to be interoperable, but no technical standards for interoperability are prescribed, hence leaving to the operators too much discretion about how and when to enact interoperability.

[18] This is the case of Airtel Money and Safaricom's MPESA in Kenya, which in January 2018 undertook a pilot phase, enabling the seamless transfer of funds between mobile accounts on different networks. In April 2018, in a press release, the Central Bank of Kenya welcomed the implementation of interoperability of mobile financial services, stressing its benefits and importance to Kenya's mobile money market.

Third, we test the heterogeneities described by our proposition by studying the effect of interoperability in rural and poor districts. This allows us to draw specific policy implications and bring more clarity in the debate about the effects of mobile money interoperability (Bourreau and Valletti, 2015).

Following the structure of the paper, this section is divided into four subsections. In the first, we study the effect of interoperability introduced at the operator level. We first show how an interoperable system fosters competition between mobile money operators. We show that mobile money operators lower their tariffs, reduce their coverage, and register a decrease in revenues and investments. We conclude this subsection with an instrumental variable approach. The second subsection provides aggregate results on the effect of interoperability at the district and at the country level, and shows the negative effects of interoperability on financial inclusion. In the third subsection we provide heterogeneity analysis, which confirm previous results on financial inclusion. In the last subsection, we present several robustness checks.

3.1 Evidence at the operator level

3.1.1 Fees

We exploit the staggering of interoperability by African operators to study its effect on the fee structure of mobile money services. Our main variables of interest are: *On Net Fees*$_{it}$, the median fee over transaction values for transactions between users of the same operator, *Cross Net Fees*$_{it}$, the median fee over transaction values for transaction between users of different operators.

The first exercise that we propose is an event study as defined in the following equation:

$$Y_{ict} = \alpha_i + \beta_t + \sum_{k=-5}^{5} \gamma_k I\left\{K_{ict} = k\right\} + \varepsilon_{ict} \tag{1}$$

where Y_{ict} represents the dependent variable for operator i in country c in year t; α_i and β_t are operator and year fixed effects. The observation window is 2010–2021, while we restrict the event window to be the interval $[-5; +5]$ from the year of the adoption of interoperability by operator i. K_{ict} is the relative year from the adoption of interoperability by operator i in country c. We set the year before the adoption of interoperability as the baseline category, as is standard in the literature. Standard errors are clustered at the operator level. Figure 3 reports the results of Equation 1, in particular those of coefficients γ_j for $j = -5, .., 5$. The left panel refers to on net fees, i.e. fees of transactions between users of the same operator, and shows no pre-trends; this means that before the introduction of interoperability, the point estimates are close to zero, and none of them are statistically significant. The coefficients become negative and statistically significant when interoperability is introduced. In particular, we observe an immediate jump, where the on-net fees register a decrease of 0.5%, followed by a similar decrease in the following years. The right panel refers to cross net fees, i.e. those paid when transacting mobile money to a different operator. Similar to before, no pre-trends can be detected and the coefficients are negative and decreasing starting from year 0, and they are statistically different from zero from period 1. The decrease over years is starker in this case: coefficients show a decrease in cross-net fees of more than 1% after 1 year from the introduction of interoperability, and this drop remains stable over the following years. Overall, we interpret these results as a negative effect of the introduction of interoperability on tariffs imposed by mobile money providers.

The second exercise we propose is a staggered difference-in-differences specification as specified below:

$$Y_{ict} = \alpha_i + \beta_y + \gamma Interoperability_{ict} + \varepsilon_{ict} \tag{2}$$

where, again, Y_{ict} represents the dependent variable, for operator i in country c in year t; α_i and β_t are operator and and year fixed effects; and $Interoperability_{ict}$ is a dummy variable that equals one after the operator adopts interoperability. Table 2 reports the estimates from the staggered difference-in-difference specification as defined in equation 2. This two-way fixed effects regression provides a compact measure of the average causal effect of interoperability on our two mobile money tariffs outcomes. It imposes no pre-trends and assumes constant treatment effects. The results from Table 2 confirm those from the event studies. Introduction of mobile money interoperability is associated with a significant decrease in mobile money tariffs, both on net and cross net. The estimates are also large in magnitude: introducing interoperability decreases on net tariffs by 20% and cross net by 35%, with respect to the mean value before the policy change. We propose the same analysis of Table 2, but now differentiating between different transaction brackets.

As explained in Section 2.2, mobile money operators apply different tariffs for different transaction values. In particular, these tariffs happen to be regressive, in the sense that fees are relatively higher for lower transactions. We harmonize transaction brackets at country level, for all operators. We define the first bracket as the lowest transaction bracket in a given country. Consequently, the second bracket will be the second lowest bracket, and so on. Table A.3 present results for pairs of transaction brackets. We group transaction brackets in seven pairs and obtain estimates of the following equation:

$$Y_{bjict} = \alpha_i + \beta_t + \gamma_b + \sum_{j=1}^{7} \delta_j Interoperability_{ict} \times \mathbf{1}_j + \varepsilon_{ict} \tag{3}$$

where α_i is the operator's specific fixed effects, β_t the year fixed effect, γ_b if bracket b fixed effects. Brackets are paired in seven groups, denoted by j: $\mathbf{1}_j$ indicate whether bracket b belongs to group j. We interact the groups' indicator variables with the Interoperability$_{ict}$ dummy. Our coefficients δ_j will hence show the effect of operator-level interoperability on brackets belonging to group j. In Table A.3 and Figure 4 we report the coefficients of Equation 3. We show that our results are driven by the lowest two transaction brackets, that decrease of about 20%, which corresponds to a drop of more than 60% with respect to the pre-policy average. This corroborates our hypothesis that interoperability fosters competition between mobile money operators. In so doing, they try to attract more people in their network by decreasing the tariffs for the lowest transaction values. This is line with many policy reports, that mention that low-value transactions constitute the bulk of mobile money operations (Yao et al., 2022).

3.1.2 Coverage

In this section, we provide an analysis of how operator coverage in districts evolves over time and its response to interoperability. This means, that we consider as unit of analysis the operator-district pair. Using the GADM database, we focus on the district as our geographic unit of observation. In most cases, districts are designed as second-level administrative units and in rare cases as third-level or above. We harmonize this administrative definition across countries to study a consistent set of comparable geographic units. This section shows the main results of our analysis, providing evidence of how Mobile Network Operators change their coverage after the introduction of mobile money interoperability. This analysis is of particular interest because it also allows us to provide an insight on the heterogeneous effect of interoperability depending on the dominance of a given operator in the local market. Indeed, the same operator might decide to behave differently in different areas, depending on its coverage in the areas before the policy change. We exploit an event study and a difference-in-differences approach. The event study will take the following form:

$$Y_{idct} = \alpha_{id} + \beta_t + \sum_{k=-5}^{5} \gamma_k I\left\{K_{ict} = k\right\} + \varepsilon_{idct} \tag{4}$$

The staggered difference-in-differences will instead be of the following type:

$$Y_{idct} = \alpha_{id} + \beta_t + \gamma \text{Interoperability}_{ict} + \varepsilon_{idct} \tag{5}$$

In both cases the variable Y_{idct} refers to the outcome of operator i in district d in country c at time t. We include operator-district fixed effects α_{id}, and year fixed effects β_t. The outcome variables are: the operator's coverage in a given district, i.e. the share of coverage relative to the district's area, in percentage; and the probability of signal of the operator in the district, which is a dummy that takes value 1 if the operator has signal in the district.

Table 3 provides insights on the behavior of operators at the local level when interoperability is introduced. Both column (1) and column (2) suggest a general decrease in the total coverage of an operator at the district level and its lower probability of keeping signal. In particular, individual operator's coverage decreases by almost 4 percentage points after the introduction of interoperability, while the probability of signal decreases by almost 5 percentage points. To further investigate our mechanism, in Table A.4 in Appendix A - Additional Tables we show that the drop in total coverage is driven by dominant operators.

Figure 4 reports the results of the event study, which is in line with our difference-in-differences approach. It shows the presence of parallel trends, and the significant effects of the introduction of interoperability for both variables.

3.1.3 Operator's performance

In this section, we verify whether the registered drop in coverage of mobile network operators goes parallel with a reduction in operator's market penetration and investment in infrastructure, and whether this has an impact on its financial performances. We exploit the staggered introduction of interoperability to also study the effects on mobile network operators' performance. To this aim, we use the same specification as the one described in Equation 5. Our estimates show how interoperability affects performances, investments and usage of the operator, and explore the response of operators to prices of different services they provide, such as calls, texts and internet.

Table 4[19] confirms that the total coverage of mobile network operators linked to mobile money services drop after the introduction of interoperability: this, of course, has a repercussion on the operator's market penetration as well. The increased competition to which mobile money interoperability leads increases the marginal cost of covering the "last mile", and hence operators disinvest in infrastructure. Column (1) shows results for the percentage of population covered: we register a decrease of 18% in the country's population covered by the mobile network. Column (4) shows that after the introduction of interoperability, the number of towers decreases by 12%. This is in line with what we have highlighted in Section 2.3 about the high cost of maintaining infrastructure that

[19] In Table 4 outcome variables are expressed in log.

allows coverage in more remote areas. Similarly, revenues decrease by 30%.

In Table A.5 we test whether increased competition in mobile money affect also prices for other services provided by mobile network operators. We find no significant effect on prices for calls, messages or internet data. For the three categories of prices coefficients are close to 0 and not significant. In Table A.6 we instead show that interoperability has no effect on the probability of mobile network operators to take part in a M&A operation. We do this to ensure that interoperability does not affect the structure of the mobile network market.

3.1.4 Instrumental Variable approach

We develop an instrumental variable approach, where we instrument our operator-specific measure of interoperability, with the country-specific one. Table A.7 presents the first stage estimates. Tables A.8, A.9 and A.10 reproduce the results from Tables 2, 3 and 4, by adopting the instrumental variable and this IV appears to be relevant and strong, with the first stage F statistic higher than 20, depending on the sample size of each regression. At the same time, we note that these results are very close in terms of sign, magnitude and statistical precision. The main reason for which these different estimations yield similar results is to be found in the high correlation between operator-level and country-level mobile money interoperability. In fact, while some companies appear to voluntarily introduce interoperability, sometimes anticipating the official country-wide introduction led by policy-makers, most companies appear to follow the introduction of this policy. In addition to this, the use of the IV allows us to preempt possible concerns related to the determinants of company-level interoperability adoption, by showing that the most relevant proxy, namely the country-level policy, appears to drive the vast majority of our underlying variation.

3.2 Evidence at the District and Country level

3.2.1 Coverage at the District level

This section studies the effect on interoperability on mobile network coverage at the local level. We extend the results presented in Section 3.1.2 by providing aggregate evidence at the district level. Here, we focus on coverage at sub-national units, hence aggregating individual operator level data at the smallest geographical unit as defined by the maps provided by GADM, as explained in Section 2.4. The dataset used for the analysis in this section is hence composed by 47'480 administrative units, over a period of 12 years spanning 2010-2021, for a total of about 570'000 observation. We exploit a more aggregate version of Eq. 1 and Eq. 2, where the unit of analysis is now given by the district d. In particular, we estimate the following event study design:

$$Y_{dct} = \alpha_d + \beta_t + \sum_{k=-5}^{5} \gamma_k I\left\{K_{ct} = k\right\} + \varepsilon_{dct} \tag{6}$$

and the following two-way fixed effects model:

$$Y_{dct} = \alpha_d + \beta_t + \gamma \text{Interoperability}_{ct} + \varepsilon_{dct} \tag{7}$$

where the dependent variable is defined Y_{dct} and refers to a district d in country c in year t. It represents the following variables: *Total Coverage*$_{dct}$, which is the percentage of district's area covered by any mobile network operator (i.e., 0 means that no mobile network operator has signal in the district, while 100 means that the district is completely covered by mobile connection); *Probability of signal in district*$_{dct}$ is instead a dummy variable taking value 1 whether at least one operator in active in the district, while it takes value 0 when there is no operator covering that given district; *Number of MNOs*$_{dct}$ is the log of the number of operators active in the district. Figure 6 reports the event study specified in Eq. 6, and Table 5 reports the results of Eq. 7. The left panel of Figure 6 shows parallel trends in the pre-period and then the negative effect of the introduction of interoperability on mobile network coverage, expressed as percentage of the district's area. After one year, we register a decrease of 5 percentage points in coverage. This decrease grows in the following year, up to 10 percentage points. Similarly, the right panel shows a decrease in the number of operators in the district, after the introduction of interoperability. The number of mobile network operators decreases by more than 20% after one year from the introduction of interoperability, and this decrease is even higher in the following years. In the lower central panel, we show that the probability of signal in the district decreases by more than 3 percentage points in the three years following the introduction of interoperability.

3.2.2 Financial Inclusion

The debate around mobile money interoperability has increasingly focused on the effects on financial inclusion (Bourreau and Valletti, 2015). Because mobile money is seen as a tool that enhances financial inclusion and gives access to digital financial services to the poorest and those ones living in the most remote areas of developing countries (Suri and Jack, 2016), any policy change on this payment system needs to take into account the potential implications on individuals that are unbanked and financially-underserved.

To investigate the implication of interoperability for financial inclusion, we present results both from survey data and from country-level data. We use the World Bank Global Findex dataset on the following empirical model:

$$Y_{ict} = \alpha_c + \beta_t + \gamma \text{Interoperability}_{ct} + \varepsilon_{ict} \tag{8}$$

where Y_{ict} refers to answers to the survey questions of individual i living in country c, α_c and β_t are respectively country c and year t fixed effects.

We present results from the World Bank Global Findex in the first three columns of Table 6. In Panel A we show that interoperability negatively affects several measures of financial inclusion, and that access and usage of mobile money transactions for different purposes (e.g. sending and receiving remittances) decreases. After the introduction of interoperability, individuals are 7% less likely to send remittances with mobile phones, 6% less likely to receive remittances with mobile phones, 2% less likely to save for their business and 6% less likely to have access to funds in case of an emergency.

While estimates are not precise, we further investigate the underlying mechanism showing that countries with a stronger pre-existent mobile money network are significatively more affected by the introduction of interoperability. In Panel B of Table 6 we replicate the results of Eq. 8 by adding an interaction term between interoperability and a measure of the strength of the mobile money network before the introduction of the policy:

$$\begin{aligned} Y_{ict} = \alpha_c + \beta_t + &\gamma \text{Interoperability}_{ct} \\ &+ \delta \text{Interoperability}_{ct} \times \text{Mobile Money Network}_c + \varepsilon_{ict} \end{aligned} \tag{9}$$

where Mobile Money Network_c is the standardized number of all survey respondents with a mobile money account in country c before the introduction of interoperability. We show that our results are hence amplified by network effects, in line with the work of Björkegren and Karaca (2022). These results can be seen as the consequences of a reduction in mobile network coverage both at the extensive margin (i.e. in terms of geographical outreach) and the intensive margin (i.e. in terms of signal quality) following the introduction of interoperability. Indeed, for one standard deviation increase in the number of mobile money users, we register a significant decrease of 20% for sending domestic remittances through mobile phones, a decrease of 18% for receiving domestic remittances through mobile phones, a decrease of 10% for saving for own business activity and of 8% for having access to emergency funds.

In the last three columns of Table 6, we provide similar results for data aggregated at country level in the IMF FAS dataset. In Panel A, we first document a decrease in the number of users and outlets (mobile money agents), as well as in the number of transactions. Panel B shows further evidence that the pre-esisting strength of the mobile money network drives our results. Again, we provide a heterogeneity analysis by interacting the dummy for interoperability with a standardized measure of the number of registered mobile money accounts in the country before the introduction of interoperability. Also in this case, the coefficients of the interaction show that the negative effects of interoperability on all the measures of financial inclusion are amplified by network effects. A 10% increase in the number of mobile money accounts with respect to the pre-policy mean, leads to a significant reduction of 3.5% in the number of mobile money agents, a reduction of 2.5% in the number of mobile money accounts, and a significant decrease of 5% in the number of mobile money transactions, after the introduction of interoperability.

To further validate our results, in Table A.32 of Appendix A - Additional Tables, we use the DHS data and report the effect of interoperability on the the probability of having made a transaction using mobile money in the last month. Interoperability has a negative impact on this probability, especially in rural areas. In Section 3.3.1 and 3.3.2 we eventually provide further heterogeneous analysis confirming the differential effect that interoperability has on rural and urban areas, by exploiting our granular data on network coverage and different measures of local urban development.

3.3 Additional Heterogeneities

This section provides additional heterogeneity analyses aimed at further investigating the mechanism leading our results. We confirm the differential effect that interoperability has on urban and rural areas, by showing that less developed districts are more affected by the introduction of interoperability. We also provide evidence that the negative effect of interoperability is attenuated in countries with a stronger network of Mobile Money agents.

3.3.1 Rural

In Columns (1), (2) and (3) of Table 7 we differentiate between rural and urban areas, to study the differential effect of interoperability depending on local development, and test our proposition, which predicts that the negative effects of interoperability are stronger in area with higher costs of tower installation. We identify rural districts by following the approach proposed by Cattaneo et al. (2021): see Section 2.4 for further details. We create a dummy variable, Rural Area$_d$, which takes value 1 for rural districts and 0 otherwise.

We hence use the following specification:

$$\begin{aligned} Y_{dct} = \alpha_d + \beta_t + &\gamma \text{Interoperability}_{ct} + \\ &\rho \text{Interoperability}_{ct} \times \mathbf{1}\text{Rural Area}_d + \varepsilon_{dct} \end{aligned} \tag{10}$$

where interoperability is now interacted with Rural Area$_d$. As outcome variables, we still use the mobile network coverage as percentage of the district's area, the probability of signal in the district and the number of mobile network operators active in the district. In this specification, since we are using district-time varying variation, we change the clustering at district level. Table 7 shows that less developed rural districts are negatively affected by the introduction of interoperability, which leads to a decrease of 2.4 percentage points in the network coverage, in a 0.5 percentage points decrease in the probability of signal in the district, and in a 5.1% decrease in the number of operators active in the district, more than urban districts.

3.3.2 Night Lights

Similarly, we exploit Nighttime Lights data to provide a measure of the district's urban development. We exploit the following model:

$$\begin{aligned} Y_{dct} = \alpha_d + \beta_t + &\gamma \text{Interoperability}_{ct} + \\ &\rho \text{Interoperability}_{ct} \times \mathbf{1}\text{Night Lights}_{dc} + \varepsilon_{dct} \end{aligned} \tag{11}$$

where as independent variable we use the dummy for interoperability and its interaction with Night Light Above Median$_{dc}$, which is a dummy taking value 1 for those district whose Night Light activities is above the median of night light activity of all districts. We define the variable on the subsample of illuminated districts; i.e., we exclude from the analysis all those districts that have no nightlight activity at all. To construct our measures of night light activity, we use the data provided by the National Centers for Environmental Information. Columns (4), (5) and (6) of Table 7 displays the results. As for Table 7, we cluster standard errors at the district level, because we are using district-time varying variation. The negative effect of interoperability is attenuated in those districts that register nighttime lights above the median. Again, these results confirm the ones already shown comparing rural and urban districts.

3.3.3 Mobile Money Agents' network

We here show the differential effect of interoperability on network coverage, depending on the strength of the Mobile Money Agents' network. In Table A.11 we first show that the introduction of interoperability has a negative effect on the number of Mobile Money agents. We show that interoperability negatively affects different measure of the Mobile Money agents' networks: we show the effect on the log number of agents, on the log number of agents per 1'000 squared kilometers, and the log number of agents per 100'000 adults. As in Section 3.2.2, we also provide an heterogeneity analysis looking at the differential effect of interoperability depending on the strength of the Mobile Money users' network in the pre-policy period.

In Table A.12 we show that districts in countries with a stronger network of Mobile Money agents are less affected by the introduction of interoperability. In Table A.12 we interact the dummy for interoperability with a dummy taking value 1 if the number of Mobile Money agents in country c in the pre-policy period is above the median value. We show that districts in countries with a higher number of Mobile Money agents register a significant lower reduction in their network coverage by 13% with respect to districts in countries with a lower number of agents.

3.4 Policy implications

Our study proposes a policy that complements our research and is based on a theoretical intuition regarding a crucial source of market imperfection contributing to the competition-inclusion tradeoff at the heart of this paper: the prevalence of uniform pricing across different locations. As discussed by (DellaVigna and Gentzkow, 2019), it is common for businesses to apply uniform or nearly-uniform prices across various locations, regardless of the local demographic characteristics and competitive landscape. This aspect assumes particular significance in our context, as if mobile companies were able to discriminate their fees based on the local cost of providing connection services, increased competition would lead to reduced mark-ups without affecting service provision. Although such mechanisms of price discrimination do not exist in African telecommunications, we draw a close analogy from countries that implement subsidies for mobile operators to facilitate rural telecommunications. Consequently, this results in de facto price discrimination between urban and rural locations once the subsidy is combined with the fee. To investigate this further, we collected data on policies aimed at promoting access to telecommunication services in remote areas and show a crucial heterogeneity of our key findings to these policies. Our empirical results validate that the combination of interoperability and these subsidies presents a promising opportunity to lower fees for users while maintaining the scale of the mobile network. In Table A.36 we propose the following:

$$
\begin{aligned}
Y_{dct} = \alpha_d + \beta_t + & \gamma \text{Interoperability}_{ct} + \\
& \theta \text{Subsidy}_{ct} + \\
& \rho \text{Interoperability}_{ct} \times \text{Subsidy}_{ct} + \varepsilon_{dct}
\end{aligned} \tag{12}
$$

where $Subsidy_{ct}$ is a time-varying dummy variables that takes value 1 after country c provides subsidies for rural telecommunications. In Table A.36 we show the differential effect that interoperability has on total network coverage for rural and urban districts, conditional on subsidies for the development of rural telecommunications. In Columns (1) and (2) of Table A.36 we run the above regression on the subsamples of rural and urban districts, respectively. We classify districts following the metholody proposed by Cattaneo et al. (2021). In Column (3) and (4), instead, we differentiate between districts whose level of nighttime light intensity is below or above median, respectively. For all subsamples we show that the general effect of interoperability is negative. However, Columns (1) and (3) show that the effect is attenuated for those less developed districts in countries providing subsidies for rural telecommunications: indeed, for the subsamples of rural districts or districts with nighttime light intensity below median, the interaction term between $Interoperability_{ct}$ and $Subsidy_{ct}$ is positive and significant. These attenuated effects is not registered in urban and more developed districts.

3.5 Robustness Checks

In this section, we include additional checks to test the robustness of our results. In Appendix A - Additional Tables we show that our key results are robust to a variety of alternative specifications: 1) we first replicate our main results using the latest methods for dynamic treatment effects in event studies with heterogeneous treatment effects proposed by Sun and Abraham (2021); 2) we then apply the framework for difference-in-differences designs with staggered treatment adoption and heterogeneous causal effects proposed by Borusyak et al. (2021); 3) we propose alternative clustering methods of standard errors; 4) we weight our main regression specifications with a measure of district's population 5) we test the robustness of our results to the inclusion of time-varying country-specific characteristics. These robustness checks complement the ones already presented in previous sections. As explained in Section 3.1.3, we construct a novel dataset on network operators' M&A activities, and show that the introduction of interoperability has no effect on the probability of mobile network operators in taking part in mergers and acquisitions. In 3.1.4 we replicated our analyses at the operator level adopting an instrumental variable approach. In Section 3.3 we provided several heterogeneity analyses, showing also that our estimates are robust to different measures of local urban development.

3.5.1 New methods in difference-in-differences and event study design: Sun and Abraham (2021) and Borusyak et al. (2021)

We replicate our main results of Tables 2, 3, 4 and 5 using the methods proposed by Sun and Abraham (2021) and Borusyak et al. (2021). Estimates do not differ from the ones previously obtained, nor in their sign, nor in their magnitude, neither in their significance.

Figures B.3 and B.4 replicate the event studies for On Net and Cross Net fees and for the different measures of coverage at the operator-district level.

In Table A.13, A.14, A.15 and A.16 we replicate our main results using the method proposed by Sun and Abraham (2021). Our coefficient of interest is the average treatment effect, which is obtained by averaging the estimation weighted estimators for the first four years after the introduction of interoperability.

Table A.17, A.18, A.19 and A.20, and Figures B.3, B.4 and B.5 respectively present the treatment effect estimation and the pre-trend testing in event studies obtained from the difference-in-differences designs with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). This method is particularly adapt to our setting, as it is designed to estimate the effects of a binary treatment with staggered rollout allowing for arbitrary heterogeneity and dynamics of causal effects. The benchmark case of this method considers each unit i getting treated as of period t and remaining treated forever: indeed, when interoperability is deployed, it is never retracted in our case.

3.5.2 Alternative clustering and population weight

We here include three additional robustness checks on our main results at the operator and at the district level. First, in Tables A.21, A.22 and A.23 we replicate the results of Tables 2, 3 and 4 by clustering standard errors at the country-level. As we were suggesting in Section 3.1.4, operator-level introduction of interoperability might be the response to a changing local market or institutional framework at the country level. The staggering of interoperability between operators in the same country might hence be correlated with country specific characteristics. We do this to clean out all possible country-time specific variations from our estimates.

Second, in Tables A.24, A.25, A.26 and A.27 we replicate the results of Tables 2, 3, 4 and 5 computing standard errors using the wild cluster bootstrap methodology. Estimates remain significantly different from zero.

Last, in Tables A.28 and A.29, we replicate the results of Tables 3 and 5 using weighted least squares, where we weight for the district's population count. We retrieve data from Warszawski et al. (2017) to construct our measures of population at the district level.

Warszawski et al. (2017) provide data at raster level. We hence aggregate raster level data at the district level: population count is the log of people living in the district. Weights for population allow us to verify that operators cut coverage in general, even once the population is taken into account. The smaller magnitudes of the reduction in coverage are aligned with the fact that areas with a lower population see larger declines than areas with a higher one. This is consistent with a standard model in which operators cut more extensively marginal markets, as our findings on rural and poorer districts show.

3.5.3 Additional tests

We provide two different tests aimed at understanding whether the introduction of interoperability changes the propensity and convenience of mobile users to own multiple SIMs, and at understanding whether countries where users hold multiple SIMs are differentially affected by the introduction of interoperability. To tackle the first point, in Table A.30 we present results from a regression where the independent variable is a dummy taking value 1 when interoperability is enacted at the country level, and where the dependent variable is the number of mobile phone subscriptions, both as the number of SIM cards over 100 inhabitants and in absolute terms. No effect of interoperability on the number of SIMs is detected. To tackle the second point, we instead leverage granular data at the operator-district pair. Table A.31 in Appendix A - Additional Tables reports an OLS regression where interoperability is interacted with a country specific measure of mobile phone subscriptions (i.e. number of SIM cards over 100 inhabitants). Estimates show that there is no differential effect of interoperability depending on the number of mobile phone subscriptions. Indeed, coefficients of the interaction term are extremely small and non significant.

Eventually, to test the robustness of our results to the macroeconomic environment, in Tables A.33, A.34 and A.35 we replicate the analysis of Tables 2, 3 and 5 by including time-varying country-specific controls such as real GDP and GDP growth.

4 Conclusions

This paper investigates the effects of competition on the behavior of mobile money companies and its corresponding effects on financial inclusion. The study focuses on competition induced by a specific policy framework: the introduction of platform interoperability, a regulatory intervention that facilitates transactions between users of different mobile money operators. The objective is to relate this change in competition to the profit margins of mobile money operators and their investment in pricing, network, and infrastructure.

Our study finds that there is a trade-off between competition and financial inclusion in the context of mobile money. The vertical integration between mobile network and mobile money companies results in higher fees charged to mobile money users, which lowers consumer welfare and financial inclusion on the intensive margin. At the same time, this lack of competition also provides incentives for mobile network companies to extend their reach to underserved locations, enhancing financial inclusion on the extensive margin.

To test this hypothesis, we construct a novel panel which collects information on more than 120 mobile operators across all African countries from 2010 onward. This is done by using the “Wayback Machine”, which is a digital repository that systematically scans a vast number of websites and captures screenshots of their pages. By digitizing this information, we have constructed a panel that presents novel descriptive insights into the operation of this market. This information has been further combined with extensive documentation on companies network coverage across all districts of Africa and financial and non-financial documentation. This empirical exercise requires the identification of a source of quasi-experimental variation that generates higher competition between mobile money companies. For this reason, we leverage a natural experiment that has unfolded in Africa over the period spanning from 2010 to 2020: the staggered deployment of platform interoperability.

In line with the main hypothesis, our findings show that the introduction of this policy lowers fees on mobile money transactions and this particularly large for small-value payments. At the same time, interoperability also has negative effects on network availability, as districts in countries that introduce interoperability experience a drop in their coverage, which is particularly severe for rural districts.

Overall, the study highlights the need for policymakers to strike a balance between competition and financial inclusion in the mobile money market. The findings suggest that competition-promoting policies such as platform interoperability can have a positive effect on inducing lower fees but also have negative effects on network availability. Additionally, the study provides valuable insights into the functioning and regulation of mobile money companies, an area that remains largely unexplored in the literature. By proposing and exploring this novel trade-off, our study contributes to a better understanding of the implications of digital payment systems for financial inclusion.

Tables

Table 1: Summary statistics

	Observations	Mean	Std. Dev.	Min	Max
Panel A: Mobile Money Fees					
Fees on netwotk$_{it}$	617	.04	.1	0	1.25
Fees cross network$_{it}$	418	.1	.14	0	.98
Panel B: GSMA Intelligence Mobile Network data					
Total cellular connection$_{it}$	2335	13.75	2.36	4.06	18.18
3G connections$_{it}$	1810	12.7	2.25	3.3	17.79
Total cellular network coverage; by population$_{it}$	210	4.31	.32	2.71	4.61
Total revenue; cellular$_{it}$	3007	17.43	2.07	7.69	22.1
Recurring revenue; cellular$_{it}$	3015	17.53	2.08	7.72	22.53
Non-Recurring revenue; cellular$_{it}$	2950	14.46	2.3	4.29	21.1
Total Capex$_{it}$	683	17.36	1.67	9.07	20.71
Panel C: Network coverage at operator-district level					
Total coverage$_{idt}$	1113012	75.1	33.98	0	100
Probability of signal in district$_{idt}$	1113012	.96	.19	0	1
Interoperability$_{it}$	1113012	.1	.3	0	1
Panel D: Network coverage at district level					
Total coverage$_{dt}$	569760	71.21	38.26	0	100
Probability of signal in district$_{dt}$	569760	.88	.33	0	1
Number of MNOs$_{dt}$	569760	1.88	1.19	0	5
Interoperability$_{ct}$	569760	.14	.35	0	1
Panel E: WB Global Findex Survey					
Recived domestic remittances w mobile phone$_{jct}$	25681	.41	.49	0	1
Sent domestic remittances w mobile phone$_{jct}$	21444	.44	.5	0	1
Saved for own business activity$_{jct}$	77478	.2	.4	0	1
Panel F: IMF Financial Access Survey					
Number of mobile money transactions$_{ct}$	267	16.48	3.51	0	21.98
Outstanding balances on active mobile money accounts, Domestic Cur$_{ct}$	157	20.23	4.09	9.15	29.26
Number of registered mobile money agent outlets$_{ct}$	271	8.89	2.42	1.1	13.4
Number of registered mobile money accounts$_{ct}$	293	14.18	2.36	6.79	18.01

Notes: This table reports the summary statistics for the main datasets used in the analysis. The columns respectively report the variable's name, the number of observations (Observations), its mean value (Mean), its standard deviation (Std. Dev.), its minimum (Min) and maximum (Max) value. All datasets are observed at the yearly frequency. We report six different panels. Panel A summarizes the dataset we constructed containing information on the fees structure of Mobile Money Operators. Fees are reported as transaction value share. Panel B reports the summary statistics of the main variables (in log) in the GSMA Intelligence dataset. Panel C and D report summary for mobile network operators' coverage and interoperability. Panel E and Panel F reports survey based individual- and country-level data on financial inclusion, respectively. In Panel F, variables are reported in log.

Table 2: Fees and interoperability

	Fees	
	On Net	Cross Net
	(1)	(2)
$Interoperability_{ict}$	-0.002**	-0.013***
	(0.001)	(0.004)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Obs.	613	411
Adj. R sq.	0.783	0.701
Mean Dep. Var.	0.009	0.035

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are On Net, which is the operator's fees for mobile money transactions to subscribers of the same operator (1); and Cross Net, which is the operator's fees for mobile money transactions to subscriber of different operators (2). Both dependent variables are expressed as percentage of transaction value. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 3: Network Coverage and Interoperability - Operator-District Level

	Total coverage	Probability of signal in district
	(1)	(2)
$Interoperability_{ict}$	-4.811**	-0.036*
	(2.149)	(0.021)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1113012	1113012
Adj. R sq.	0.808	0.276
Mean Dep. Var.	75.153	0.957

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability, i.e. if operator i is interoperable. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 4: Mobile Operators and Interoperability

	Total network coverage	Market penetration mobile connections	Total Revenue	Towers	EBIT	EBITDA
	(1)	(2)	(3)	(4)	(5)	(6)
Interoperability$_{ict}$	-0.186***	-0.224**	-0.293**	-0.123*	-0.097	-0.062
	(0.033)	(0.112)	(0.134)	(0.063)	(0.336)	(0.224)
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	125	1842	1684	280	366	565
Adj. R sq.	0.789	0.884	0.866	0.974	0.811	0.861
Mean Dep. Var.	4.354	2.213	17.909	7.061	16.164	16.279

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's share of population covered in country c (1); the operator's market penetration of mobile connection in country c (2); the operator's total revenue (3); the number of towers used by the operator for its coverage (4); the operator's earnings before interest and taxes (EBIT) and the operator's earnings before interest, taxes, depreciation and amortization (EBITDA) in column (5) and (6), respectively. Dependent variables are expressed in log. These are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 5: Network Coverage and Interoperability - District Level

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
Interoperability$_{ct}$	-5.024**	-0.034*	-0.186**
	(2.147)	(0.020)	(0.077)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	569760	569760	569760
Adj. R sq.	0.903	0.873	0.912
Mean Dep. Var.	69.606	0.860	1.762

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t. District and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the total mobile network coverage, expressed as percentage of the district d area (1); the probability of mobile network signal in the district, i.e. a dummy taking value 1 whether at least one Mobile Network Operator (MNO) is active in the district (2); the number of Mobile Network Operators active in the district (3). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean in the pre-policy period is reported in the last row of the table. In column (3) we report the mean of the number of Mobile Network Operators active in the district, not expressed in log. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table 6: Financial inclusion: WB Global Findex & IMF Financial Access

	WB Global Findex				IMF Financial Access		
	Saved for own business	Access emergency fund	Sent remittances w mobile phone	Received remittances w mobile phone	MM Agents	MM Accounts	MM Transactions
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Interoperability							
$\text{Interoperability}_{ct}$	-0.018	-0.060*	-0.069	-0.062	-0.242	-0.380	-0.740**
	(0.044)	(0.032)	(0.078)	(0.080)	(0.255)	(0.333)	(0.342)
Panel B: Network effects							
$\text{Interoperability}_{ct}$	-0.098**	-0.083**	-0.195***	-0.182***	-0.123	-0.409	-0.437
	(0.047)	(0.032)	(0.046)	(0.049)	(0.257)	(0.316)	(0.358)
$\text{Interoperability}_{ct} \times$	-0.117**	0.000	-0.231**	-0.207*	-0.439***	-0.322	-0.657***
$\text{Mobile Money Network}_{ct_0}$	(0.023)	(0.046)	(0.051)	(0.198)	(0.136)	(0.285)	(0.183)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	77258	90309	21380	25613	283	247	286
Adj. R sq.	0.078	0.149	0.365	0.358	0.894	0.902	0.898
Mean Dep. var	0.189	0.467	0.442	0.401	8.799	12.998	16.314

Notes: This table presents ordinary least squares (OLS) estimates on two different datasets. In Columns (1), (2) and (3) we use data from the World Bank Global Findex Survey, where the unit of observation is individual respondent's i in year t. In Columns (4), (5) and (6) we use data from the IMF Financial Access Survey, where the unit of observation is country c in year t. Country and year fixed effects are present in all columns and standard errors are clustered at the country level. For the WB Global Findex Survey observations span all available years between 2010 and 2021. Controls for individual respondent's specific characteristics are included. The dependent variables are dummy variables taking value 1 if in the last month the respondent has saved for own business (1); has had easy access to funds in case of any emergency (2); has sent domestic remittances through mobile money (3); has received domestic remittances through mobile money (4). For the IMF Financial Access Survey (FAS) the observations span the years 2010-2021. The dependent variables, expressed in log, are the total number of registered Mobile Money agents in country c in year t (5); the total number of Mobile Money accounts in country c in year t (6); the total number of Mobile Money transactions in country c in year t (7). In Panel A, the outcome variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if interoperability is active in country c. In Panel B, we add the interaction between $Interoperability_{ct}$ and $\text{Mobile Money Network}_{ct_0}$, a measure of the size of the mobile money network in country c before the introduction of interoperability. We construct the measure using data from the same dataset of the outcome variable. For the WB Global Findex, we standardize the total number of survey respondents who own a mobile money account in country c, before the introduction of interoperability. For the IMF FAS we standardize the average number of registered mobile money accounts in country c before the introduction of interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. Column (4), (5) and (6) report the mean in millions. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

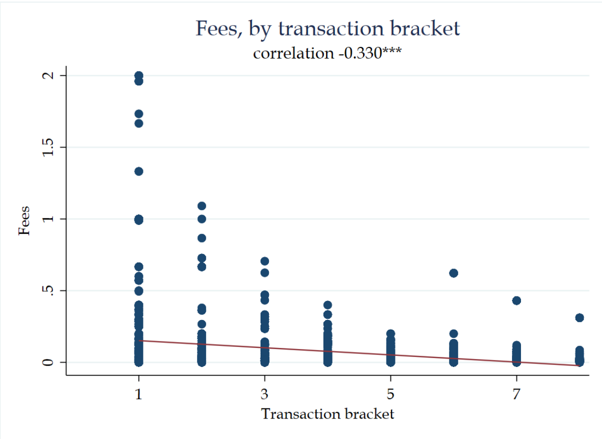
Table 7: Network Coverage, Rural area, Nightlights and Interoperability - District Level

	Rural area			Nightlight intensity		
	Total coverage	Probability of signal in district	Number of MNOs	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)	(4)	(5)	(6)
Interoperability$_{ct}$	-4.058***	-0.032***	-0.166***	-1.803***	-0.006***	-0.046***
	(0.080)	(0.000)	(0.002)	(0.187)	(0.000)	(0.002)
Interoperability$_{ct}$ × Rural area$_d$	-2.393***	-0.005***	-0.051***			
	(0.231)	(0.000)	(0.002)			
Interoperability$_{ct}$ × Night Light above median$_d$				0.480**	0.001***	0.029***
				(0.198)	(0.000)	(0.002)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of Districts	47480	47480	47480	15768	15768	15768
Obs.	569760	569760	569760	189216	189216	189216
Adj. R sq.	0.903	0.873	0.912	0.946	0.961	0.970
Mean Dep. Var.	69.606	0.860	1.762	85.325	0.934	2.360

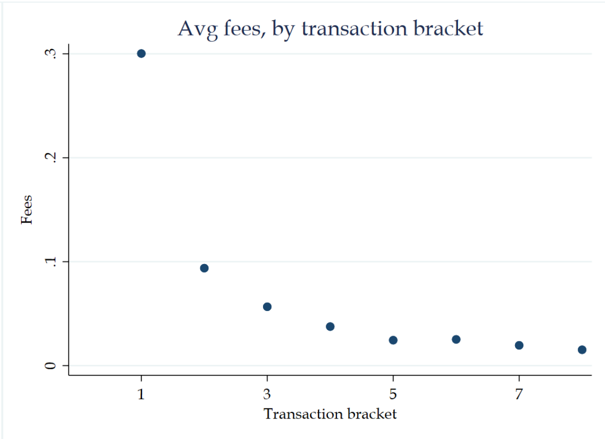
Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t, as specified in Eq. 10. In all columns we include district and year fixed effects and standard errors are clustered at the district level. The dependent variable is the mobile network coverage as percentage of the district's area, the probability of signal in the district and the number of mobile network operators active in the districts. The dependent variable is regressed over two variables. The first is $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The second is a measure of local development. For columns (1), (2) and (3) we include the interaction between $Interoperability_{ct}$ and Rural area$_d$, a dummy taking value 1 if the district is classified as rural using geographical characteristics as proposed by Cattaneo et al. (2021). In Columns (4), (5) and (6) we include the interaction between $Interoperability_{ct}$ and Night Light$_d$, a continuous variables that represents the standardized nighttime light intensity of the district, according to the data on Nighttime lights provided by the National Centers for Environmental Information, kept fixed at the year 2012, i.e. before that interoperability was introduced in any country. Rural area$_d$ and Night Light Intensity$_d$ are district-specific constants. The dependent variable's mean in the pre-policy period is reported in the last row of the table. In column (3) we report the mean of the number of Mobile Network Operators active in the district, not expressed in log. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Figures

Figure 1: Fees and brackets



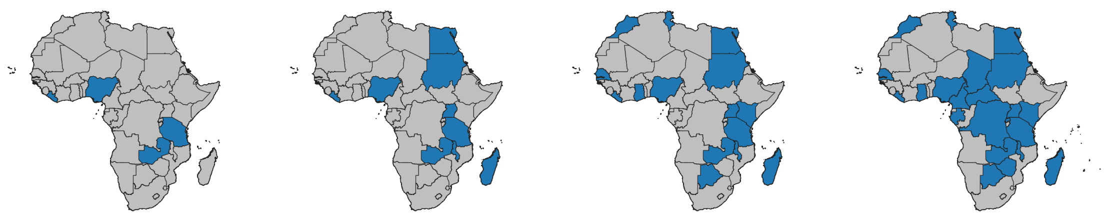
(a) Fees, by transaction bracket



(b) Fees, by transaction bracket

Notes: This figure plot the yearly fees for sending a mobile money transfer between two agents belonging to the same operator, i.e. on-network transaction. Fees are expressed as percentage of transaction values. In Panel (a) each dot within a bracket corresponds to an operator-year observation. Brackets represent cross-country harmonized transaction value ranges as explained in Section 2.2. Panel (b) shows the average fees across all operators and all years, for each bracket.

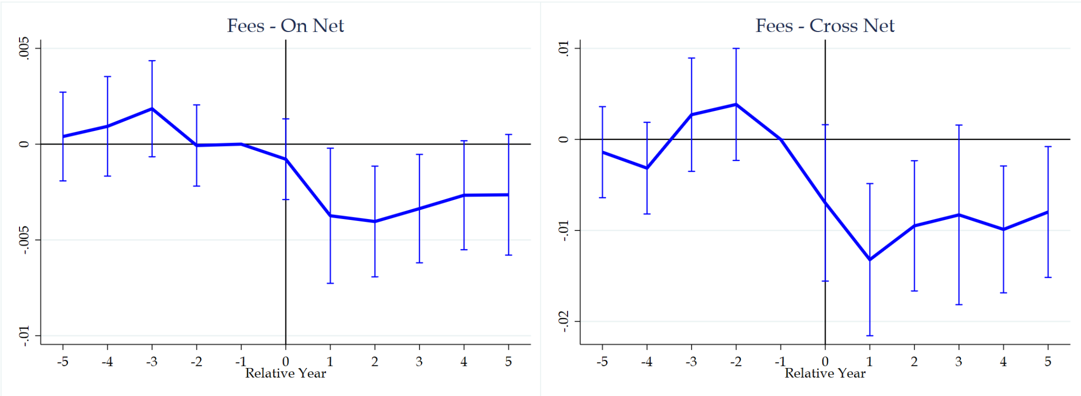
Figure 2: Deployment of Interoperability



(a) Year 2015 (b) Year 2017 (c) Year 2019 (d) Year 2021

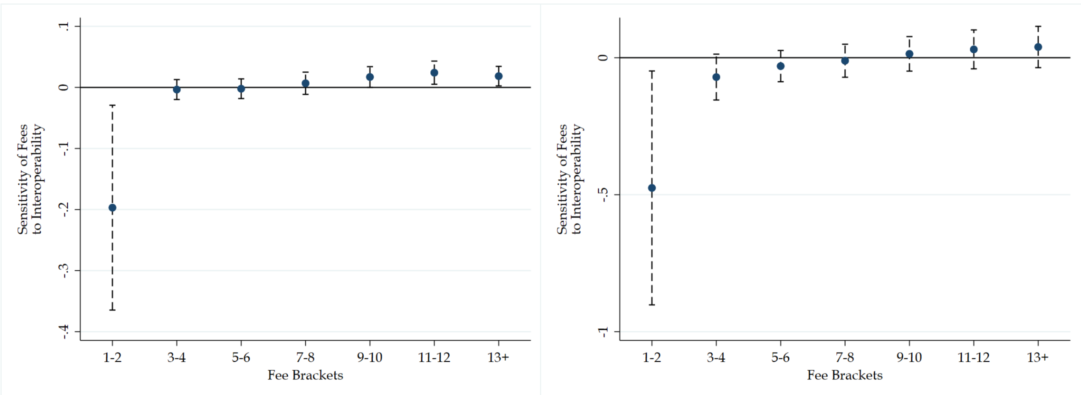
Notes: These maps show the staggered introduction of interoperability across African countries. Interoperability is currently active in 20 African countries and 58 mobile money operators. The maps present four reference years, 2015 (a), 2017 (b), 2019 (c) and 2021 (d), in which countries colored in blue are those ones in which interoperability is active. Interoperability is never retracted.

Figure 3: Fees and interoperability



Notes: This figure reports the coefficients of the event study specification described in Equation 1. Both left and right panels display the value of the coefficients, γ_k, which describe differential evolution of the fees applied by mobile money operators operating under interoperability relative to operators operating in the absence of interoperability. In the left panel we present results for fees applied to transactions between subscribers of the same operator, i.e. on-network transactions. The right panel presents results for fees applied to transaction between subscribers of different operators, i.e. cross-network transactions. The year marking the introduction of interoperability is year 0 on the x-axis and exhibits a vertical black line. The reference year is the year -1. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the operator level, and the empirical specification includes year and operator fixed effects.

Figure 4: Fees and interoperability

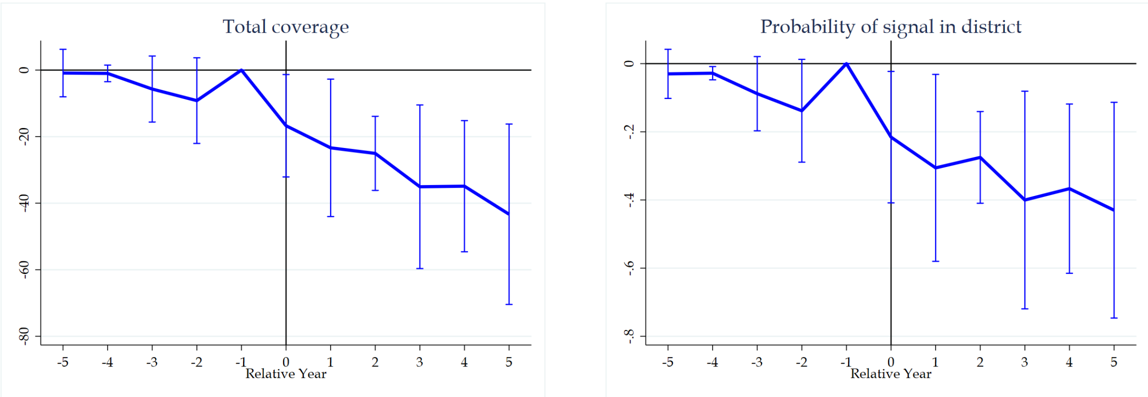


(a) On Net Fees

(b) Cross Net Fees

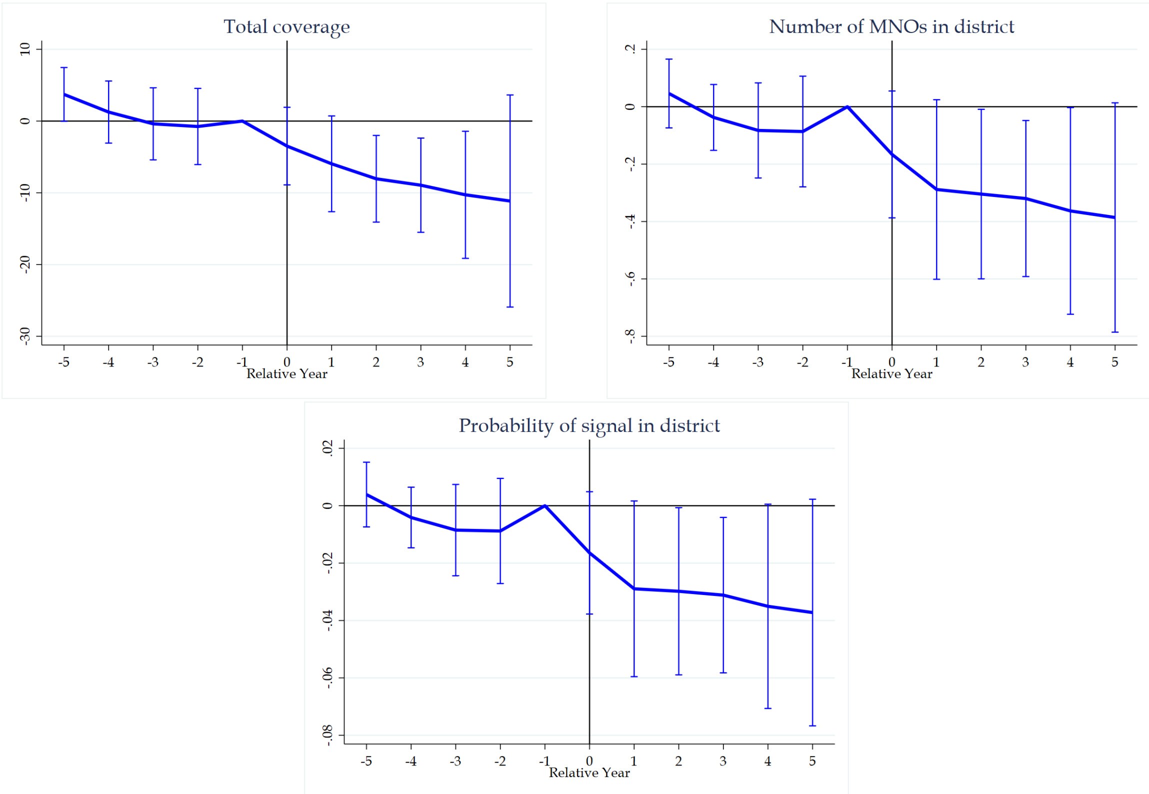
Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is fee bracket b of operator i in country c in year y. We report the δ_j coefficients of Equation 3, which are displayed in Table A.3. Bracket, operator and year fixed effects are included in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's fees for mobile money transactions to subscribers of the same operator, in the left panel; the operator's fees for mobile money transactions to subscriber of different operators, in the right panel. Both dependent variables are expressed as share of transaction value. We pair brackets in seven groups, and show the differential effect that the introduction of interoperability at the operator level has on different transaction brackets, where brackets represent cross-country harmonized transaction value ranges as explained in Section 2.2. Dependent variables are regressed over the interaction between $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability, and an indicator variable $\mathbf{1}_j$, indicating to which pair bracket b belongs. The table hence reports the estimates of coefficients δ_j of Equation 3. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the operator level.

Figure 5: Event Study - Operator-District analysis



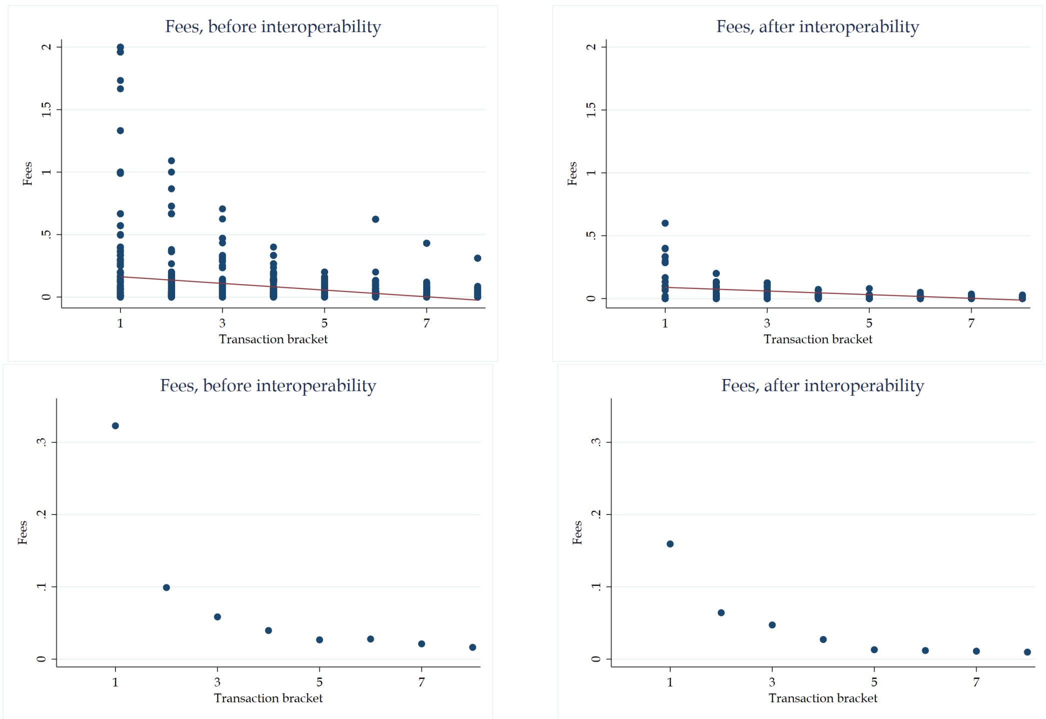
Notes. This figure reports the coefficients of the event study specification described in Equation 4. The three panels display the value of the coefficients, γ_k, which describe differential evolution of the outcome variables for the pairs operator-district for which interoperability is active relative to operator-districts with no interoperability. In the left panel we present results for operator's i network coverage in district d, i.e. the percentage of district's d area covered by mobile network operator i. The right panel presents results for the probability that the operator i is active in district d. The year marking the introduction of interoperability is year 0 on the x-axis and exhibits a vertical black line. The reference year is the year -1. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the operator level, and the empirical specification includes year and operator-district fixed effects.

Figure 6: Event Study - District level



Notes: This figure reports the coefficients of the event study specification described in Equation 6. Both left, right and central panels display the value of the coefficients, γ_k, which describe differential evolution of the outcome variables for district where interoperability is active relative to districts with no interoperability. In the left panel we present results for district's mobile network coverage, i.e. the percentage of district's area covered by mobile network operators. The right panel presents results for the number of mobile network operators active in the district. The central panel presents results for the probability of mobile network signal in the district. The year marking the introduction of interoperability is year 0 on the x-axis and exhibits a vertical black line. The reference year is the year -1. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the country level, and the empirical specification includes year and district fixed effects.

Figure 7: Fees dispersion by transaction bracket



Notes: This figure plot the yearly fees for sending a mobile money transfer between two agents belonging to the same operator, i.e. on-network transaction. Fees are expressed as percentage of transaction values. In the top panel on the left each dot within a bracket corresponds to an operator-year observation, for only those operators which are not interoperable yet. The top right panel, instead, shows interoperable operators. Brackets represent cross-country harmonized transaction value ranges as explained in Section 2.2. The left and right panels on the bottom display the average fees across all operators and all years, for each bracket, for non interoperable and interoperable operators respectively. These figures show that the dispersion of fees across brackets diminishes after the introduction of interoperability.

Appendix
Mobile Money, Interoperability, and Financial Inclusion

A Appendix A - Additional Tables

A.1 Balance Tables

Table A.1: Balance Table - Selection into interoperability

	Non Interoperable			Interoperable			Difference
	Mean	St. Dev.	N	Mean	St. Dev.	N	
Real GDP (Log Mn)	8.07	4.53	565	9.49	2.10	219	1.364
GDP growth (%)	1.62	18.06	532	-1.03	21.40	201	-3.133
Export of Goods and Services (Log Mn)	6.77	5.07	431	8.95	1.30	105	2.222*
Import of Goods and Services (Log Mn)	7.23	5.04	413	9.19	1.30	105	2.027
Government Consumption Exp (Log Mn)	6.25	5.03	412	8.38	1.44	101	2.209
Gross Fixed Capital Formation (Log Mn)	6.76	4.93	407	8.55	1.02	89	1.778
Households Expenditure (Log Mn)	8.66	2.35	353	9.82	1.60	105	1.165
Unemployment rate (%)	11.12	8.52	192	8.20	5.21	97	-3.772
Domestic Claims (Log Mn)	7.42	2.23	600	8.14	1.88	240	0.929
Net Foreign Assets (Log Mn)	7.19	2.07	631	7.40	1.76	255	0.309
Broad Money Liabilities (Log Mn)	2.49	0.22	632	2.54	0.19	258	0.073

Notes: This table is the balance table for interoperability. We compare African countries that never introduced interoperability (Non Interoperable), with African countries that eventually introduced interoperability (Interoperable). For Interoperable countries we use data only on the years before the introduction of interoperability. Our data span from 2000 to 2021. The table shows averages for baseline (Mean), their standard deviation (St. Dev.) and the number of observations (N). The Difference column is the coefficient of an OLS regression of a dummy taking value 1 for those countries that eventually introduced mobile money interoperability (and 0 otherwise) on the reported variable, with clustered standard errors at the country level. Regressions include year fixed effects. Country fixed effects are not included as the interoperability dummy, as here defined, is constant at the country level. This table shows that there is no selection into introducing interoperability at the country level, as country specific characteristics do not differ between countries in the two groups. The variables we take into consideration are, in order, Real GDP, the GDP growth, the value of Exports of goods and Services, the value of Import of goods and services, the value of Government Consumption Expenditure, the Gross fixed Capital Formation, the Household Expenditures, the Unemployment rate, the Domestic claims, the Net Foreign Assets and the Broad Money Liabilities. All variables are expressed as the logarithm of the US $ value in Millions. GDP growth and Unemployment rate are expressed as percentage. The Difference column is the coefficient of an ordinary least squares (OLS) regression of the interoperability dummy as above defined on the variable, with year fixed effects and standard errors clustered at the country level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.2: Balance Table - Interoperability in time series

	Non Interoperable			Interoperable			Difference
	Mean	St. Dev.	N	Mean	St. Dev.	N	
Real GDP (Log Mn)	8.47	4.05	784	9.98	1.95	73	-0.186
GDP growth (%)	0.89	19.05	733	-2.68	17.46	73	1.114
Export of Goods and Services (Log Mn)	7.20	4.66	536	9.51	1.29	42	0.048
Import of Goods and Services (Log Mn)	7.62	4.61	518	9.52	1.04	42	-0.191
Government Consumption Exp (Log Mn)	6.67	4.63	513	8.72	1.26	42	-0.243
Gross Fixed Capital Formation (Log Mn)	7.08	4.54	496	9.44	1.20	38	0.120
Households Expenditure (Log Mn)	8.93	2.26	458	10.56	1.44	42	-0.119
Unemployment rate (%)	10.14	7.69	289	7.18	5.21	28	1.516
Domestic Claims (Log Mn)	7.63	2.16	840	9.53	1.86	66	0.027
Net Foreign Assets (Log Mn)	7.25	1.99	886	8.05	1.77	70	-0.120
Broad Money Liabilities (Log Mn)	2.50	0.21	890	2.68	0.15	67	0.024

Notes: This table shows the difference in country specific characteristics between interoperable and non-interoperable countries. We compare African countries that never introduced interoperability or that have not introduced interoperability yet (Non Interoperable), with African countries that have introduced interoperability (Interoperable). Our data span from 2000 to 2021. The table shows averages for baseline (Mean), their standard deviation (St. Dev.) and the number of observations (N). The Difference column is the coefficient of an OLS regression of a dummy taking value 1 when interoperability is enacted at the country level (and 0 otherwise) on the reported variable, with clustered standard errors at the country level. Regressions include year and country fixed effects. The interoperability dummy varies across time, as it takes value 1 only when the country introduces interoperability. This table shows that country-specific characteristics do not differ between countries in the two groups. The variables we take into consideration are, in order, Real GDP, the GDP growth, the value of Exports of goods and Services, the value of Import of goods and services, the value of Government Consumption Expenditure, the Gross fixed Capital Formation, the Household Expenditures, the Unemployment rate, the Domestic claims, the Net Foreign Assets and the Broad Money Liabilities. All variables are expressed as the logarithm of the US $ value in Millions. GDP growth and Unemployment rate are expressed as percentage. The Difference column is the coefficient of an ordinary least squares (OLS) regression of the interoperability dummy as above defined on the variable, with country and year fixed effects and standard errors clustered at the country level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.2 Fees by bracket

Table A.3: Fees by bracket and Interoperability

	On net	Cross net
	(1)	(2)
Bracket 1-2	-0.197**	-0.475**
	(0.085)	(0.215)
Bracket 3-4	-0.004	-0.071*
	(0.008)	(0.042)
Bracket 5-6	-0.002	-0.031
	(0.008)	(0.029)
Bracket 7-8	0.007	-0.011
	(0.009)	(0.030)
Bracket 9-10	0.017**	0.014
	(0.009)	(0.032)
Bracket 11-12	0.024**	0.030
	(0.010)	(0.036)
Bracket 13+	0.018**	0.039
	(0.008)	(0.038)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Bracket FE	Yes	Yes
Obs.	11442	7546
Adj. R sq.	0.085	0.265
MDV Bracket 1-2	0.310	0.827
MDV Bracket 3-4	0.049	0.211
MDV Bracket 5-6	0.027	0.091
MDV Bracket 7-8	0.019	0.052
MDV Bracket 9-10	0.012	0.040
MDV Bracket 11-12	0.009	0.033
MDV Bracket 13+	0.006	0.022

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is fee bracket b of operator i in country c in year t. We report the δ_j coefficients of Equation 3. Bracket, operator and year fixed effects are included in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's fees for mobile money transactions to subscribers of the same operator, in Column (1); the operator's fees for mobile money transactions to subscriber of different operators, in Column (2). Both dependent variables are expressed as share of transaction value. We pair brackets in seven groups, and show the differential effect that the introduction of interoperability at the operator level has on different transaction brackets, where brackets represent cross-country harmonized transaction value ranges as explained in Section 2.2. Dependent variables are regressed over the interaction between $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability, and an indicator variable $\mathbf{1}_j$, indicating to which pair bracket b belongs. The table hence reports the estimates of coefficients δ_j of Equation 3. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.3 Dominant operators and competition

To further investigate our mechanism, we provide a heterogenous effect analysis and study whether the effects of interoperability differs depending on the dominance of the operator in the local market. We exploit the following:

$$\begin{aligned} Y_{idct} = \alpha_{id} + \beta_t + &\gamma \text{Interoperability}_{ict} + \\ &\rho \text{Interoperability}_{ict} \times \mathbf{1}\left[> \text{Dominant}\right]_{idct_0} + \varepsilon_{idct} \end{aligned} \tag{13}$$

where $\mathbf{1}\left[> \text{Dominant}\right]_{idct_0}$ indicates whether the operator covered more than 30% of the district's area in which it was operating the year before the introduction of interoperability. Table A.4 shows that results on total coverage, column (1), are driven by dominant operators. Those are the ones that drive the drop in total coverage. Indeed, dominant operators reduce their coverage by 10% more than non dominant operators, after the introduction of interoperability.

Table A.4: Network Coverage, Dominant Operators and Interoperability - Operator-District Level

	Total coverage	Probability of signal in district
	(1)	(2)
$\text{Interoperability}_{ict_0}$	4.021	-0.049**
	(4.525)	(0.023)
$\text{Interoperability}_{ict_0} \times \text{Dominant}_{jdct_0}$	-10.206**	0.015
	(4.851)	(0.013)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1113012	1113012
Adj. R sq.	0.809	0.276
Mean Dep. Var.	75.153	0.957

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over two variables. The first is $Interoperability_{ict}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability, i.e. if operator i is interoperable. The second is the interaction between $Interoperability_{ict}$ and Dominant_{idt_0}, a dummy taking value 1 if the operator i was covering more than 30% of the district d's area before the arrival of interoperability at t_0. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.4 Evidence of Mobile Network tariffs and M&A operations

Table A.5: Mobile Network Fees and Interoperability

	Voice Price per minute	Data Price per GB	Messages Price per SMS
	(1)	(2)	(3)
Interoperability$_{ict}$	-0.002	0.003	0.001
	(0.007)	(0.002)	(0.003)
Operator FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	392	52	121
Adj. R sq.	0.681	0.767	0.736
Mean Dep. Var.	0.055	0.003	0.015

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's price per minute of call (1); the operator's price per megabyte of Internet usage (2); the operator's cost of text messages (3). Dependent variables are expressed in dollars. These are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.6: M&As in the mobile network market and Interoperability

	Mergers and Acquisitions	
	(1)	(2)
$\text{Interoperability}_{ict}$	-0.018	
	(0.017)	
$\text{Interoperability}_{ct}$		-0.010
		(0.007)
Unit FE	Operator	Operator
Year FE	Yes	Yes
Obs.	3408	3408
Adj. R sq.	0.023	0.022
Mean Dep. Var.	0.008	0.009

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the mobile network operator i in year y. In all columns we include operator and year fixed effects and standard errors are clustered at the operator level. The dependent variable is a dummy taking value 1 when a mobile network operator is involved in an M&A operation. The dependent variable is regressed over two different measures of interoperability. Column (1) uses as independent variable an operator-specific dummy, that takes value 1 when the operator provides an interoperable mobile money service. Column (2), that presents the estimates for $Interoperability_{ct}$, uses a country-specific dummy that takes value 1 when interoperability is enacted by the national regulatory framework. The table suggests no relation between interoperability and the probability of mobile network operators to take part in a M&A operation. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.5 Robustness check: Instrumental Variable approach

Table A.7: First stage - IV

	First stage
	(1)
Interoperability_*ct*	0.330***
	(0.102)
Operator FE	Yes
Year FE	Yes
Obs.	2340
Adj. R sq.	0.435
F-stat	10.405
Mean Dep. Var.	0.034

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the operator i in year t. Operator and year fixed effects are included and standard errors are clustered at the country level. The dependent variable is a dummy variable taking value 1 if the mobile network operator i is interoperable. The dependent variables is regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the country c where operator i is present is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.8: Fees and interoperability - IV

	IV		Reduced form	
	On Net (1)	Cross Net (2)	On Net (3)	Cross Net (4)
Interoperability$_{ict}$	-0.002	-0.018*		
	(0.002)	(0.010)		
Interoperability$_{ct}$			-0.001	-0.010*
			(0.001)	(0.005)
Operator FE	Yes	Yes	Yes	Yes
Yeas FE	Yes	Yes	Yes	Yes
Obs.	589	395	589	395
F-stat	31.837	22.324		
Mean Dep. Var.	0.008	0.035	0.008	0.035

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are On Net, which is the operator's fees for mobile money transactions to subscribers of the same operator (1, 3); and Cross Net, which is the operator's fees for mobile money transactions to subscriber of different operators (2, 4). Both dependent variables are expressed as percentage of transaction value. In Column (1) ans (2) we present the results of the Instrumental Variable approach, where the independent variable $Interoperability_{ict}$, a dummy taking value 1 if operator i is interoperable, is instrumented by $Interoperability_{ct}$, a dummy variable taking value 1 if interoperability is active in country c. In Column (3) and (4) we present the results of the reduced form, where the dependent variables are regressed over $Interoperability_{ct}$. The dependent variable's mean in the pre-policy period is reported in the last row of the table. Column (1) and (2) report the F statistic of the First Stage. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.9: Network Coverage and Interoperability - Operator-District Level - IV

	IV		Reduced form	
	Total coverage	Probability of signal in district	Total coverage	Probability of signal in district
	(1)	(2)	(3)	(4)
Interoperability$_{ict}$	-10.046**	-0.108*		
	(4.552)	(0.063)		
Interoperability$_{ct}$			-5.353**	-0.058*
			(2.311)	(0.032)
Operator-District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	1113012	1113012	1113012	1113012
F-stat	206.803	206.803		
Mean Dep. Var.	74.937	0.953	74.937	0.953

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). In Column (1) ans (2) we present the results of the Instrumental Variable approach, where the independent variable $Interoperability_{ict}$, a dummy taking value 1 if operator i is interoperable, is instrumented by $Interoperability_{ct}$, a dummy variable taking value 1 if interoperability is active in country c. In Column (3) and (4) we present the results of the reduced form, where the dependent variables are regressed over $Interoperability_{ct}$. The dependent variable's mean in the pre-policy period is reported in the last row of the table. Column (1) and (2) report the F statistic of the First Stage. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.10: Mobile Operators and Interoperability - IV

	Total network coverage	Market penetration mobile connections	Total Revenue	Towers	EBIT	EBITDA
	(1)	(2)	(3)	(4)	(5)	(6)
Interoperability$_{ict}$	-0.186***	-0.333*	-0.168	-0.218*	0.466	0.143
	(0.034)	(0.178)	(0.211)	(0.127)	(0.566)	(0.396)
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	125	1842	1684	280	366	565
Adj. R sq.	-0.118	-0.007	-0.006	-0.064	-0.094	-0.048
F-stat		52.193	36.097	38.512	49.851	53.312
Mean Dep. Var.	4.296	1.523	17.451	6.819	15.992	16.019

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the operator's share of population covered in country c (1); the operator's market penetration of mobile connection in country c (2); the operator's total revenue (3); the number of towers used by the operator for its coverage (4); the operator's earnings before interest and taxes (EBIT) and the operator's earnings before interest, taxes, depreciation and amortization (EBITDA) in column (5) and (6), respectively. Dependent variables are expressed in log. We present the results of the Instrumental Variable approach, where the independent variable $Interoperability_{ict}$, a dummy taking value 1 if operator i is interoperable, is instrumented by $Interoperability_{ct}$, a dummy variable taking value 1 if interoperability is active in country c. The dependent variable's mean in the pre-policy period is reported in the last row of the table. All columns report the F statistic of the First Stage. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.11: Number of MM agents

	MM Agents Total		MM Agents over 1k sq. km		MM Agents over 100k adults	
	(1)	(2)	(3)	(4)	(5)	(6)
Interoperability$_{ct}$	-1.025	-0.845	-0.705	-0.550	-0.830	-0.662
	(0.681)	(0.646)	(0.436)	(0.418)	(0.494)	(0.475)
Interoperability$_{ct}$ × Std Num of MM accounts$_{c}$		-0.447**		-0.401***		-0.429***
		(0.198)		(0.128)		(0.147)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	270	261	270	261	270	261
Adj. R sq.	0.793	0.800	0.869	0.879	0.752	0.765
Mean Dep. Var.	3.1e+04	3.1e+04	228.662	228.662	308.201	308.201

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is country c in year t. Country and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the number of registered Mobile Money agents, in columns (1) and (2); the number of registered Mobile Money agents per 1'000 squared kilometers, in columns (3) and (4); the number of registered Mobile Money agents per 100k adults, in columns (5) and (6). Dependent variables are expressed in log. Dependent variables are regressed over two variables. The first is $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The second is the interaction between $Interoperability_{ct}$ and Mobile Money Network$_{ct_0}$, a measure of the size of the mobile money network in country c before the introduction of interoperability: We construct the measure by standardizing the average number of mobile money accounts in country c before the introduction of interoperability. The dependent variable's mean in the pre-policy period is reported, in absolute value, in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.12: Network Coverage, Interoperability and MM Agents Network

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
Interoperability$_{ct}$	-16.021**	-0.020*	-0.214*
	(6.364)	(0.011)	(0.108)
Interoperability$_{ct}$ $\times$ N. Agents above median$_{ct_0}$	13.628**	0.011	0.125
	(6.445)	(0.009)	(0.091)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	395400	395400	395400
Adj. R sq.	0.897	0.897	0.931
Mean Dep. Var.	76.095	0.922	2.114

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t. In all columns we include district and year fixed effects and standard errors are clustered at the country level. The dependent variable is the mobile network coverage as percentage of the district's area, the probability of signal in the district and the number of mobile network operators active in the districts. The dependent variable is regressed over two variables. The first is $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The second is the interaction between $Interoperability_{ct}$ and N. Agents above median$_c t_0$, a dummy taking value 1 if the log of the mean number of Mobile Money agents in country c before the introduction of interoperability is above the median value. N. Agents above median$_c t_0$ is a country-specific constant. The dependent variable's mean in the pre-policy period is reported in the last row of the table. In column (3) we report the mean of the number of Mobile Network Operators active in the district, not expressed in log. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.6 Robustness check: Sun & Abraham

Table A.13: Fees and Interoperability

	Fees	
	On Net (1)	Cross Net (2)
ATE	-0.002**	-0.007**
	(0.001)	(0.003)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Obs.	613	411
Mean Dep. Var.	.009	.035

Notes: This table presents estimates obtained from the method proposed by Sun and Abraham (2021). The coefficient of interest is the average treatment effect, which is obtained by averaging the estimation weighted estimators for the first four years after the introduction of interoperability. The unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's fees for mobile money transactions to subscribers of the same operator (1); the operator's fees for mobile money transactions to subscriber of different operators (2). Both dependent variables are expressed as share of transaction value. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.14: Operator-district level geographical analysis

	Total coverage	Probability of signal in district
	(1)	(2)
ATE	-11.893***	-0.105**
	(4.177)	(0.053)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1113012	1113012
Mean Dep. Var.	75.10	.96

Notes: This table presents estimates obtained from the method proposed by Sun and Abraham (2021). The coefficient of interest is the average treatment effect, which is obtained by averaging the estimation weighted estimators for the first four years after the introduction of interoperability. The unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.15: GSMA Intelligence yearly outcomes

	Total network coverage	Market penetration mobile connections	Total Revenue	Towers	EBIT	EBITDA
	(1)	(2)	(3)	(4)	(5)	(6)
ATE	-0.230***	-0.251*	-0.316*	-0.115**	-0.020	-0.060
	(0.087)	(0.148)	(0.171)	(0.058)	(0.425)	(0.275)
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	125	1842	1684	280	366	565
Mean Dep. Var.	4.354	2.213	17.909	7.061	16.164	16.279

Notes: This table presents estimates obtained from the method proposed by Sun and Abraham (2021). The coefficient of interest is the average treatment effect, which is obtained by averaging the estimation weighted estimators for the first four years after the introduction of interoperability. The unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's share of population covered in country c (1); the operator's market penetration of mobile connection in country c (2); the operator's total revenue (3); the number of towers used by the operator for its coverage (4); the operator's earnings before interest and taxes (EBIT) and the operator's earnings before interest, taxes, depreciation and amortization (EBITDA) in column (5) and (6), respectively. Dependent variables are expressed in log. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.16: Sub-national unit geographical analysis

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
ATE	-9.211***	-0.074*	-0.418**
	(2.645)	(0.041)	(0.174)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	569760	569760	569760
Mean Dep. Var.	69.606	.86	1.762

Notes: This table presents estimates obtained from the method proposed by Sun and Abraham (2021). The coefficient of interest is the average treatment effect, which is obtained by averaging the estimation weighted estimators for the first four years after the introduction of interoperability. The unit of observation is district d in year t. District and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the total mobile network coverage, expressed as percentage of the district d area (1); the probability of mobile network signal in the district, i.e. a dummy taking value 1 whether at least one Mobile Network Operator (MNO) is active in the district (2); the number of Mobile Network Operators active in the district (3). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.7 Robustness check: Borusyak, Jaravel & Spiess

Table A.17: Fees and interoperability

	Fees	
	On Net (1)	Cross Net (2)
ATE	-0.002**	-0.014***
	(0.001)	(0.004)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Obs.	599	382
Mean Dep. Var.	0.010	0.037

Notes: This table presents the treatment effect estimation obtained from the difference-in-differences designs with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's fees for mobile money transactions to subscribers of the same operator (1); the operator's fees for mobile money transactions to subscriber of different operators (2). Both dependent variables are expressed as share of transaction value. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.18: Operator-district level geographical analysis

	Total coverage	Probability of signal in district
	(1)	(2)
ATE	-5.688**	-0.042
	(2.602)	(0.031)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1113012	1113012
Mean Dep. Var.	67.439	0.856

Notes: This table presents the treatment effect estimation obtained from the difference-in-differences designs with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.19: GSMA Intelligence yearly outcomes

	Total network coverage	Market penetration mobile connections	Total Revenue	Towers	EBIT	EBITDA
	(1)	(2)	(3)	(4)	(5)	(6)
ATE	-0.196***	-0.227**	-0.307**	-0.128**	-0.060	-0.057
	(0.021)	(0.111)	(0.128)	(0.064)	(0.374)	(0.220)
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	137	1842	1684	282	369	570
Mean Dep. Var.	4.307	1.523	17.451	6.776	15.964	16.010

Notes: This table presents the treatment effect estimation obtained from the difference-in-differences designs with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the operator's share of population covered in country c (1); the operator's market penetration of mobile connection in country c (2); the operator's total revenue (3); the number of towers used by the operator for its coverage (4); the operator's earnings before interest and taxes (EBIT) and the operator's earnings before interest, taxes, depreciation and amortization (EBITDA) in column (5) and (6), respectively. Dependent variables are expressed in log. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.20: Sub-national unit geographical analysis

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
ATE	-5.755***	-0.041*	-0.230**
	(1.530)	(0.022)	(0.095)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	569760	569760	569760
Mean Dep. Var.	69.606	0.860	1.762

Notes: This table presents the treatment effect estimation obtained from the difference-in-differences designs with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The unit of observation is district d in year t. District and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the total mobile network coverage, expressed as percentage of the district d area (1); the probability of mobile network signal in the district, i.e. a dummy taking value 1 whether at least one Mobile Network Operator (MNO) is active in the district (2); the number of Mobile Network Operators active in the district (3). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.8 Additional robustness: Country Clustering

Table A.21: Fees and Interoperability

	Fees	
	On Net (1)	Cross Net (2)
Interoperability$_{ict}$	-0.002**	-0.013***
	(0.001)	(0.004)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Obs.	613	411
Ad. R sq.	0.783	0.701
Mean Dep. Var.	0.010	0.037

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are On Net, which is the operator's fees for mobile money transactions to subscribers of the same operator (1); and Cross Net, which is the operator's fees for mobile money transactions to subscriber of different operators (2). Both dependent variables are expressed as percentage of transaction value. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.22: Operator-district level geographical analysis

	Total coverage	Probability of signal in district
	(1)	(2)
Interoperability$_{ict_0}$	-4.811**	-0.036
	(2.215)	(0.022)
Operatora-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1113012	1113012
Adj. R sq.	0.808	0.276
Mean Dep. Var.	67.439	0.856

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.23: GSMA Intelligence yearly outcomes

	Total network coverage	Market penetration mobile connections	Total Revenue	Towers	EBIT	EBITDA
	(1)	(2)	(3)	(4)	(5)	(6)
Interoperability$_{ict}$	-0.186***	-0.224*	-0.293**	-0.123**	-0.097	-0.062
	(0.034)	(0.119)	(0.136)	(0.060)	(0.333)	(0.221)
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	125	1842	1684	280	366	565
Adj. R sq.	0.789	0.884	0.866	0.974	0.811	0.861
Mean Dep. Var.	4.296	1.523	17.451	6.819	15.992	16.019

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the operator's share of population covered in country c (1); the operator's market penetration of mobile connection in country c (2); the operator's total revenue (3); the number of towers used by the operator for its coverage (4); the operator's earnings before interest and taxes (EBIT) and the operator's earnings before interest, taxes, depreciation and amortization (EBITDA) in column (5) and (6), respectively. Dependent variables are expressed in log. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.9 Additional robustness: Wild Cluster Bootstrap

Table A.24: Fees and interoperability

	Fees	
	On Net (1)	Cross Net (2)
Interoperability$_{ict}$	-0.002***	-0.013***
	(0.001)	(0.004)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Obs.	613	411
Adj. R sq.	0.783	0.701
Mean Dep. Var.	0.010	0.037

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns. Standard errors are computed through the wild cluster bootstrap method and clustered at the operator level. The dependent variables are On Net, which is the operator's fees for mobile money transactions to subscribers of the same operator (1); and Cross Net, which is the operator's fees for mobile money transactions to subscriber of different operators (2). Both dependent variables are expressed as percentage of transaction value. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.25: Network Coverage and Interoperability - Operator-District Level

	Total coverage	Probability of signal in district
	(1)	(2)
Interoperability$_{ict_0}$	-4.811**	-0.036
	(2.063)	(0.026)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1113012	1113012
Adj. R sq.	0.808	0.276
Mean Dep. Var.	67.439	0.856

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns. Standard errors are computed through the wild cluster bootstrap method and clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability, i.e. if operator i is interoperable. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.26: GSMA Intelligence yearly outcomes

	Total network coverage	Market penetration mobile connections	Total Revenue	Towers	EBIT	EBITDA
	(1)	(2)	(3)	(4)	(5)	(6)
Interoperability$_{ict}$	-0.186**	-0.224*	-0.293**	-0.123**	-0.097	-0.062
	(0.082)	(0.119)	(0.127)	(0.057)	(0.312)	(0.242)
Operator FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	125	1842	1684	280	366	565
Adj. R sq.	0.789	0.884	0.866	0.974	0.811	0.861
Mean Dep. Var.	4.296	1.523	17.451	6.819	15.992	16.019

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns. Standard errors are computed through the wild cluster bootstrap method and clustered at the operator level. The dependent variables are the operator's share of population covered in country c (1); the operator's market penetration of mobile connection in country c (2); the operator's total revenue (3); the number of towers used by the operator for its coverage (4); the operator's earnings before interest and taxes (EBIT) and the operator's earnings before interest, taxes, depreciation and amortization (EBITDA) in column (5) and (6), respectively. Dependent variables are expressed in log. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.27: Network Coverage and Interoperability - District Level

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
$\text{Interoperability}_{ct}$	-5.024*	-0.034	-0.186**
	(2.765)	(0.024)	(0.084)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	569760	569760	569760
Adj. R sq.	0.903	0.873	0.912
Mean Dep. Var.	69.606	0.860	1.762

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t. District and year fixed effects are present in all columns. Standard errors are computed through the wild cluster bootstrap method and clustered at the country level. The dependent variables are the total mobile network coverage, expressed as percentage of the district d area (1); the probability of mobile network signal in the district, i.e. a dummy taking value 1 whether at least one Mobile Network Operator (MNO) is active in the district (2); the number of Mobile Network Operators active in the district (3). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean in the pre-policy period is reported in the last row of the table. In column (3) we report the mean of the number of Mobile Network Operators active in the district, not expressed in log. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.10 Additional robustness: Weighting for district's population

Table A.28: Network Coverage and Interoperability - Operator-District Level

	Total coverage	Probability of signal in district
	(1)	(2)
Interoperability$_{ict_0}$	-4.882**	-0.035**
	(2.022)	(0.017)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1112880	1112880
Adj. R sq.	0.826	0.250
Mean Dep. Var.	67.441	0.856

Notes: This table presents weighted ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns and standard errors are clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability, i.e. if operator i is interoperable. The dependent variable's mean in the pre-policy period is reported in the last row of the table. Estimations are weighted for the district's population. Data on population are retrieved from Warszawski et al. (2017). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.29: Network Coverage and Interoperability - District Level

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
Interoperability$_{ct}$	-4.838**	-0.030	-0.165**
	(2.220)	(0.019)	(0.077)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	569664	569664	569664
Adj. R sq.	0.913	0.893	0.926
Mean Dep. Var.	69.613	0.860	1.762

Notes: This table presents weighted ordinary least squares (OLS) estimates, where the unit of observation is district d in year t. District and year fixed effects are present in all columns and standard errors are clustered at the country level. The dependent variables are the total mobile network coverage, expressed as percentage of the district d area (1); the probability of mobile network signal in the district, i.e. a dummy taking value 1 whether at least one Mobile Network Operator (MNO) is active in the district (2); the number of Mobile Network Operators active in the district (3). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The dependent variable's mean in the pre-policy period is reported in the last row of the table. In column (3) we report the mean of the number of Mobile Network Operators active in the district, not expressed in log. Estimations are weighted for the district's population. Data on population are retrieved from Warszawski et al. (2017). ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.11 Additional tests

Table A.30: Mobile subscriptions and Interoperability

	Mobile subscriptions (SIMs)		Fixed telephone subscriptions	
	100 inhabitants (1)	Total (Log) (2)	100 inhabitants (3)	Total (Log) (4)
Interoperability$_{ct}$	-2.210	-0.043	-0.324	0.024
	(3.746)	(0.059)	(0.309)	(0.219)
Unit FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
St. Err.	Clustered	Clustered	Clustered	Clustered
N. of operator-district	55	55	55	55
Observations	640	640	629	629
R2	0.894	0.983	0.968	0.867
F-stat	0.348	0.550	1.096	0.013
Mean Dep. Var.	79.617	15.600	3.754	10.750

Notes: This table shows ordinary least squares (OLS) estimates, where the unit of observation is country c in year t. We regress outcome variables over interoperability, a dummy taking value 1 after interoperability is introduced in country c. Regressions include year and country fixed effects, and standard errors are clustered at the country level. Outcome variables include: the number of registered mobile users (i.e. the number of SIM cards) per 100 inhabitants (1); the log of the number of total mobile phone subscriptions (2); the number of registered fixed phone users per 100 inhabitants (3); the log of the number of total fixed phone subscriptions (4). Data on phone subscriptions are taken from the World Bank Data Portal. This table shows that there is no relation between the number of mobile phone subscribers (i.e. number of SIM cards) and interoperability at the country level. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.31: Network Coverage, Mobile Subscriptions and Interoperability - District Level

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
Interoperability$_{ct}$	-8.415	-0.030	-0.149
	(6.248)	(0.021)	(0.102)
Interoperability$_{ct}$ $\times$ SIMs (100 inhab)$_c$	0.057	-0.000	-0.001
	(0.077)	(0.000)	(0.001)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	569712	569712	569712
Adj. R sq.	0.903	0.872	0.912
Mean Dep. Var.	69.613	0.860	1.762

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t, as specified in Eq. 10. In all columns we include district and year fixed effects and standard errors are clustered at the district level. The dependent variable is the mobile network coverage as percentage of the district's area, the probability of signal in the district and the number of mobile network operators active in the districts. The dependent variable is regressed over two variables. The first is $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The second is the interaction between $Interoperability_{ct}$ and SIMs_c, a continuous variable for the number of mobile phone subscriptions over 100 inhabitants in country c prior to the introduction of interoperability. SIMs_c is a country-specific constant. Coefficients are extremely small, suggesting almost no differential effects of interoperability on countries, depending on their number of mobile phone subscriptions. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.32: DHS

	Transactions with mobile phone	
	(1)	(2)
Interoperability$_{ct}$	-0.203***	-0.200***
	(0.021)	(0.022)
Rural$_{ict}$		-0.242***
		(0.029)
Interoperability$_{ct}$ × Rural$_{ict}$		0.034
		(0.029)
Country FE	Yes	Yes
Year FE	Yes	Yes
Obs.	105478	105478
Adj. R sq.	0.135	0.185
Mean Dep. Var.	0.480	0.480

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is individual respondent's i in year t. Country and year fixed effects are present in all columns and standard errors are clustered at the country level. Data are taken from the Demographic and Health Survey (DHS). Observations span the years 2008-2021. The impossibility to trace respondents through years impedes the usage of individual respondent's fixed effects. In order to partially overcome this issue we control for individual respondent's specific characteristics, such as gender, education and income. The dependent variable is a dummy variable taking value 1 if the last month the respondent has done any transaction through mobile phone. In Column (1), this is regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the individual i is subject to mobile money interoperability, i.e. if interoperability is active in country c. In Column (2), we include the interaction with the variable Rural$_{ict}$, which is a dummy indicating whether the respondent lives in a rural area. The dependent variable's mean and standard deviation are reported as the last two rows of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A.12 Additional robustness: Controlling for time-varying country-specific characteristics

Table A.33: Fees and interoperability

	Fees	
	On Net (1)	Cross Net (2)
Interoperability$_{ict}$	-0.002*	-0.012**
	(0.001)	(0.005)
Operator FE	Yes	Yes
Year FE	Yes	Yes
Obs.	491	330
Adj. R sq.	0.742	0.678
Mean Dep. Var.	0.010	0.038

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is operator i in year t. Operator and year fixed effects are present in all columns. Standard errors are clustered at the operator level. The dependent variables are On Net, which is the operator's fees for mobile money transactions to subscribers of the same operator (1); and Cross Net, which is the operator's fees for mobile money transactions to subscriber of different operators (2). Both dependent variables are expressed as percentage of transaction value. These are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the operator i is subject to mobile money interoperability. In this regression we add time-varying country-specific characteristic taken from the IMF. Namely we use real GDP and GDP growth. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.34: Network Coverage and Interoperability - Operator-District Level

	Total coverage	Probability of signal in district
	(1)	(2)
Interoperability$_{ict}$	-5.833**	-0.051
	(2.716)	(0.032)
Operator-District FE	Yes	Yes
Year FE	Yes	Yes
Obs.	1057315	1057315
Adj. R sq.	0.808	0.305
Mean Dep. Var.	75.488	0.956

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the pair operator i district d, in year t. Operator-district and year fixed effects are present in all columns. Standard errors are clustered at the operator level. The dependent variables are the individual mobile network operator i coverage in district d, expressed as percentage of the district d area (1); the probability that the mobile network operator is active in the district, i.e. a dummy taking value 1 whether the operator i has signal in the district d (2). Dependent variables are regressed over $Interoperability_{ict}$, a dummy variable taking value 1 if the pair operator-district id is subject to mobile money interoperability, i.e. if operator i is interoperable. In this regression we add time-varying country-specific characteristic taken from the IMF. Namely we use real GDP and GDP growth. The dependent variable's mean in the pre-policy period is reported in the last row of the table. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.35: Network Coverage and Interoperability - District Level

	Total coverage	Probability of signal in district	Number of MNOs
	(1)	(2)	(3)
Interoperability$_{ct}$	-5.224**	-0.031**	-0.185***
	(2.089)	(0.014)	(0.047)
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Obs.	531261	531261	531261
Adj. R sq.	0.899	0.857	0.903
Mean Dep. Var.	70.926	0.870	1.783

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t. District and year fixed effects are present in all columns. Standard errors are clustered at the country level. The dependent variables are the total mobile network coverage, expressed as percentage of the district d area (1); the probability of mobile network signal in the district, i.e. a dummy taking value 1 whether at least one Mobile Network Operator (MNO) is active in the district (2); the number of Mobile Network Operators active in the district (3). Dependent variables are regressed over $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. In this regression we add time-varying country-specific characteristic taken from the IMF. Namely we use real GDP and GDP growth. The dependent variable's mean in the pre-policy period is reported in the last row of the table. In column (3) we report the mean of the number of Mobile Network Operators active in the district, not expressed in log. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.36: Network Coverage, Interoperability and Rural subsidies

	Local development		Night Light intensity	
	Rural (1)	Urban (2)	Below median (3)	Above median (4)
Interoperability$_{ct}$	-7.613***	-2.453***	-5.433***	-0.485***
	(0.417)	(0.193)	(0.624)	(0.145)
Subsidy$_{ct}$	-1.079***	-4.088***	-1.684***	-0.930***
	(0.324)	(0.123)	(0.201)	(0.052)
Interoperability$_{ct}$ $\times$ Subsidy$_{ct}$	5.527***	-3.205***	4.107***	-0.559***
	(0.452)	(0.201)	(0.626)	(0.152)
District FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	183660	386100	94608	94608
Adj. R sq.	0.927	0.888	0.949	0.917
Mean Dep. Var.	61.147	73.380	75.490	94.427

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is district d in year t. District and year fixed effects are present in all columns. Standard errors are clustered at the district level. The dependent variable is the total mobile network coverage, expressed as percentage of the district d area. The dependent variable is regressed over three variables. The first is $Interoperability_{ct}$, a dummy variable taking value 1 if the district d is subject to mobile money interoperability, i.e. if interoperability is active in country c. The second is $Subsidy_{ct}$, which is a time varying dummy taking value 1 from the year in which country c has received subsidies to promote telecommunications in rural areas. The third variable is an interaction between $Interoperability_{ct}$ and $Subsidy_{ct}$. The dependent variable's mean in the pre-policy period is reported in the last row of the table. We report four different regressions. In Column (1) we report the estimates on the subsample of districts that are classified as rural adopting the metholody of Cattaneo et al. (2021); similarly, Column (2) provides the analysis on the subsampe of districts classified as urban. Columns (3) and (4), instead, provide estimates of the subsample of districts whose nighttime light activitiy is respectively below and above median. The coefficient of the interaction in Columns (1) and (3) shows how the negative effect of interoperability is attenuated in more rural and developed districts in those countries who provided subsidies to telecommunications. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

Table A.37: Fee dispersion, Transaction brackets and Interoperability

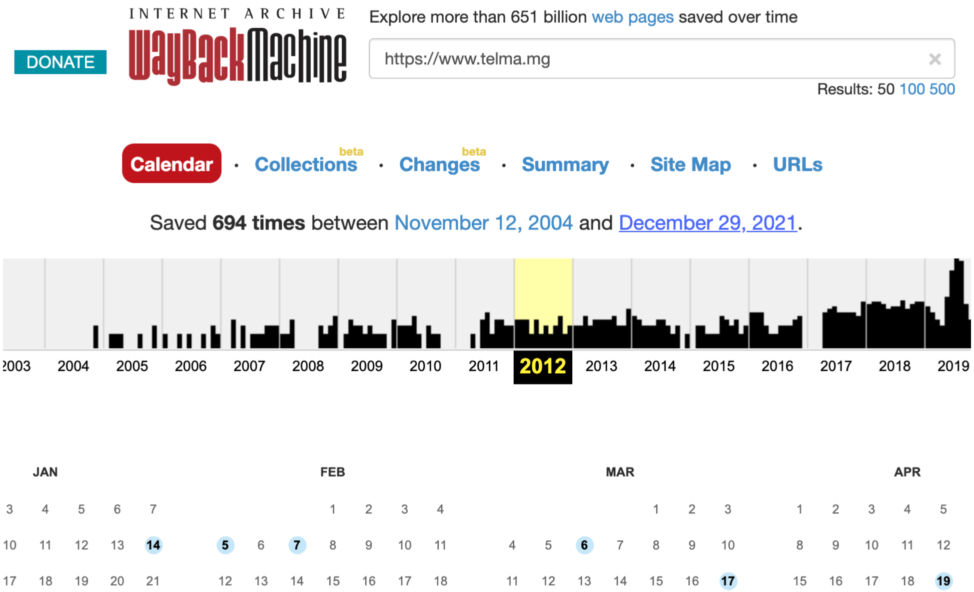
	(1)	(2)	(3)
$\text{Interoperability}_{bt}$	-0.057***	-0.215***	-0.203***
	(0.011)	(0.045)	(0.036)
Bracket_{b}		-0.055***	
		(0.008)	
$\text{Interoperability}_{bt} \times \text{Bracket}_{b}$		0.034***	0.032***
		(0.009)	(0.007)
Year FE	Yes	Yes	Yes
Bracket FE	Yes	No	Yes
Obs.	150	150	150
Adj. R sq.	0.723	0.520	0.772
Mean Dep. Var.	0.107	0.107	0.107

Notes: This table presents ordinary least squares (OLS) estimates, where the unit of observation is the transaction bracket b in year t. The outcome variable is the standard deviation of fees for a given transaction bracket b over a given year t, across respectively interoperable and non interoperable countries. Our first independent variable is $Interoperability_{bt}$, which is a dummy taking value 1 if the outcome variable is constructed over the sample of interoperable countries, 0 otherwise. $Bracket_b$ is the rank of the transaction bracket. We include year and transaction bracket fixed effects. Standard errors are robust. ***, ** and * indicate significance at the 1%, 5% and 10% level, respectively.

A Appendix B - Additional Figures

B.1 Fees dataset construction

Figure B.1: Wayback Machine



Notes: This figure shows a screenshot of the online tool we epxloited in order to retrieve webpages that are no longer available and that contained information regarding mobile money operators' tariff plans, as explained in Section 2.2. In this example, we are retrieving the webpage of Telma Madagascar in 2012.

Figure B.2: Tariff plans for different companies in the same country.

Rising		Transfer	
Minimum	Maximum	To Orange Money subscribers	To other operators and financial institutions *
200	1,000	50	25
1,001	5,000	50	120
5,001	10,000	100	250
10,001	25,000	200	400
25,001	50,000	400	880
50,001	100,000	800	1,300
100,001	250,000	1,500	3,000
250,001	500,000	1,500	4,500
500,001	1,000,000	2,500	6,900
1,000,001	2,000,000	3,000	11,500
2,000,001	3,000,000	3,000	14,000
3,000,001	4,000,000	3,000	17,600
4,000,001	5,000,000	3,000	18,600
5000001	6000000	3,000	21,000
6000001	7000000	3,000	24,000
7000001	8000000	3,000	28,000
8000001	9000000	3,000	32,000
9000001	10000000	3,000	37,000

(a) Orange Madagascar

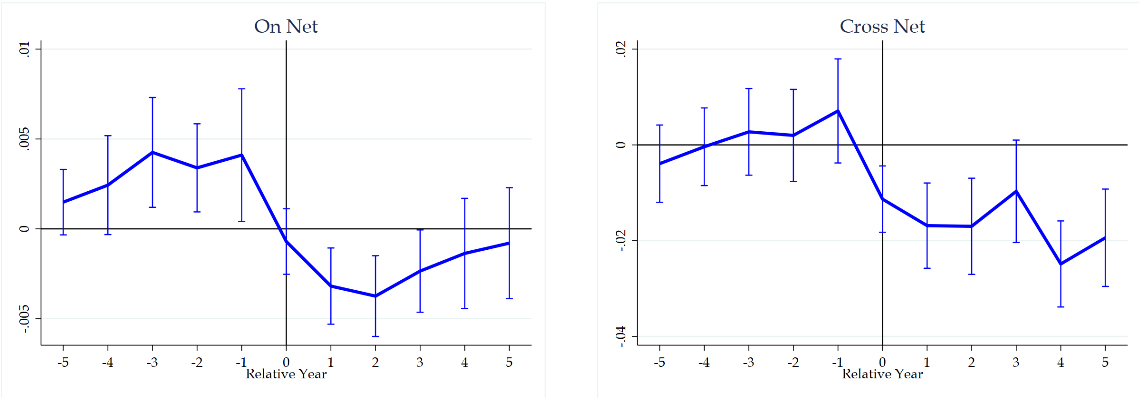
Rising		Money transfer fees	
Minimum	Maximum	To Airtel Money subscribers	To other operators
300	1 000	50	300
1 001	5 000	50	700
5 001	10 000	100	800
10 001	20 000	200	1 200
20 001	25 000	300	1 400
25 001	30 000	300	2 800
30 001	40 000	400	2 800
40 001	50 000	600	2 800
50 001	60 000	600	3 600
60 001	80 000	800	3 600
80 001	100 000	800	3 600
100 001	150 000	1 500	7 600
150 001	250 000	1 500	7 600
250 001	500 000	1 500	10 000
500 001	1 000 000	2 500	13 600
1 000 001	2 000 000	3 000	23 000
2 000 001	3 000 000	3 000	30 000
3 000 001	4 000 000	3 000	38 000
4 000 001	5 000 000	3 000	44 000

(b) Airtel Madagascar

Notes: This figure compares the tariff plans of two mobile money operators in the same country, Orange Madagascare (a) and Airtel Madagascar (b). These tariff plans are relative to the year 2012. As pointed out in Section 2.2, we can notice that the transaction ranges specified by the two operators differ, and, in particular, Airtel's tariff plan is more disaggregated.

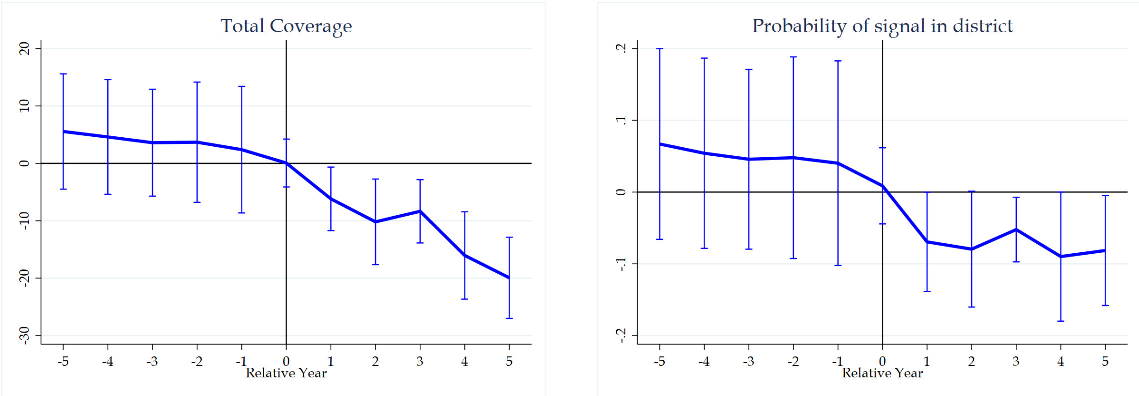
B.2 Robustness check: Borusyak, Jaravel & Spiess

Figure B.3: Event Study Robustness Borjusak



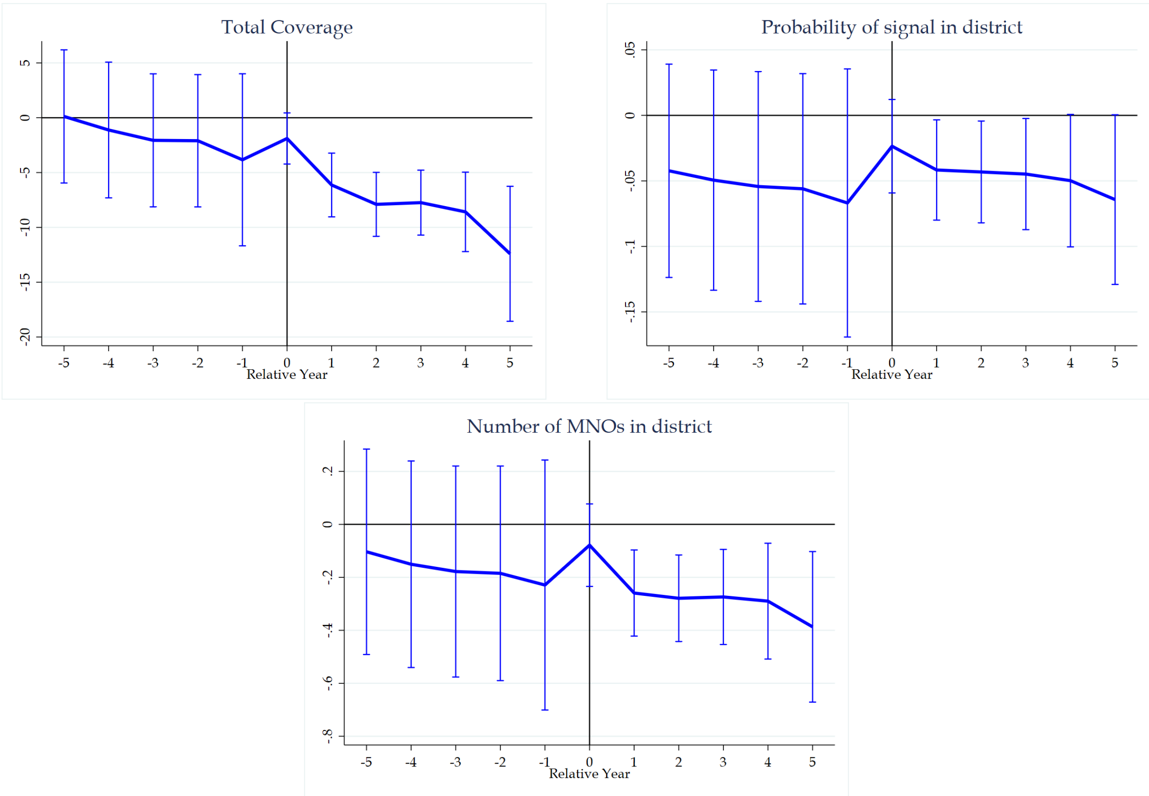
Notes: This figure reports the coefficients of the event study design with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The two panels display the value of the coefficients which describe differential evolution of the outcome variables for the unit of observation for which interoperability is active relative to units with no interoperability. In the left panel we present results for operator's i On Net fees, i.e. fees applied to mobile money transactions between users of the same network. The right panel present results for operator's i Cross Net fees, i.e. fees applied to mobile money transactions between users of different networks. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the operator level, and the empirical specification includes year fixed effects.

Figure B.4: Event Study Robustness Borjusak et al. - Operator-District



Notes: This figure reports the coefficients of the event study design with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The two panels display the value of the coefficients which describe differential evolution of the outcome variables for the unit of observation for which interoperability is active relative to units with no interoperability. In the left panel we present results for operator's i network coverage in district d, i.e. the percentage of district's d area covered by mobile network operator i. The right panel present results for the probability of signal of the operator in the district. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the operator level, and the empirical specification includes year fixed effects.

Figure B.5: Event Study Robustness Borjusak et al. - District



Notes: This figure reports the coefficients of the event study design with staggered adoption of treatment, using the imputation approach of Borusyak et al. (2021). The two panels display the value of the coefficients which describe differential evolution of the outcome variables for the unit of observation for which interoperability is active relative to units with no interoperability. In the left panel we present results for district's mobile network coverage, i.e. the percentage of district's area covered by mobile network operators. The right panel present results for the number of mobile network operators active in the district. The central panel presents results for the probability of mobile network signal in the district. The year marking the introduction of interoperability is year 0 on the x-axis and exhibits a vertical black line. The reference year is the year -1. The bars around each observation represent the 95% confidence interval. Standard errors are clustered at the country level, and the empirical specification includes year and district fixed effects.

A Appendix C - Theoretical Framework

We can define the change in mobile tower installation induced by the arrival of interoperability as follows

$$\Delta m = \frac{\theta + \kappa}{\eta} - \frac{\tau}{\eta - 2\beta} = (\eta - 2\beta)(\theta + \kappa - \tau) + 2\beta\tau$$

by taking the difference in the equilibrium number of towers between the post-policy amount, $\frac{\theta+\kappa}{\eta}$, and the pre-policy variable, $\frac{\tau}{\eta-2\beta}$. Our analysis of the heterogeneous effects of the policy is developed as a comparative static over this expression.

Proposition: locations with higher cost of tower installation before interoperability, see a more extensive decline in signal.

$$\frac{\partial \Delta m}{\partial \eta} = -\frac{\theta + \kappa}{\eta^2} + \frac{\tau}{(\eta - 2\beta)^2} < 0$$

This result is always true if tower installation costs are especially high and exceed a threshold $\eta > \widetilde{\eta}$, with $\widetilde{\eta} = 2\beta \left[1 - \left(\frac{\tau}{\theta+\kappa}\right)^{\frac{1}{2}}\right]^{-1}$.

A Data Appendix D - Fees & Interoperability

D.1 Fees

We here detail the procedure we followed for the construction of our dataset containing information of fees of Mobile Money operators.

We build two main datasets, containing the mobile money fees charged by each operator over time. We differentiate between fees charged to transfer money to subscribers to the same operator ("on-network") and fees charged to send money to subscribers of other operators ("cross-network")[20]. The first output is a panel data set that includes the operator name, country, year, and the yearly fees' average value for on-network and cross-network transactions. The second data set is more detailed, because it includes tariffs for all transaction ranges defined by companies' tariff plans. To this aim, we take the most disaggregated fee structure in the country and adjust all operators' rates (in that country) accordingly, as explained in the next paragraph.

It is important to highlight that the structure of mobile money tariffs is complex. Different tariffs are in fact applied for sending mobile money on-network or cross-network, and within operation types different tariffs are applied for different amounts of money exchanged. In Panel (a) of Figure 1, for example, we plot the average yearly fees for sending a mobile money transfer between two agents belonging to the same company, i.e. on-network transaction. This is plotted for each operator and is different depending on the amount of the mobile money transaction. Because fees are different by amount transacted and correspondingly by currency, in order to create a simpler measure which makes fees comparable, we create a "bracket" for all companies operating in the same country: bracket 1 reports the fees for transactions of the lowest amount, bracket 2 for the second lowest and so on.

For example, let us consider the case of Madagascar. In Madagascar, Orange Madagascar and Airtel Madagascar are two active operators, among others, offering the Mobile Money services. Orange's Mobile Money tariff plans differ from those of Airtel. Figure B.2 in the Appendix B - Additional Figures compares the 2022 tariff plans for these companies. We first notice that the minimum and maximum amounts that can be transferred differ between the two companies: while Orange's subscribers (Panel (a)) can transfer a minimum of 200 and a maximum of 10 million Malagasy ariary (the currency of Madagascar), Airtel's subscribers (Panel (b)) can transfer between 300 and 5 million ariary. Second, it has to be noticed that Airtel's and Orange's amount ranges differ: in particular, Airtel's tariff plans are more disaggregated. For example, while Orange sets the same

[20] We also collected fees for other types of operations (such as those for withdrawal of cash from mobile money accounts by operator's subscribers and by non-subscribers, for deposit, for payments to merchants, and for transfer of money from the Mobile Money account to the bank account, and viceversa), but the data happen to be partially lacking.

tariff for all on-network transactions between 10'000 and 25'000 ariary (hence specifying one tariff for this range), Airtel applies different fees for on-network transactions between 10'000 and 20'000 ariary, and between 20'000 and 25'000 ariary. In order to make tariff plans of different companies within the same country and across different years comparable, we define new country-specific brackets by adopting the shortest common ranges across all companies within the country in all years. For example, we will disaggregate Orange's tariffs for transactions between 10'000 and 25'000 ariary into the new ranges 10'000-20'0000 and 20'000-25'000, so that they match Airtel's tariff ranges: Orange will hence now display two different ranges, to which the same tariff is applied. Obviosuly, transaction ranges will span from the minimum value to the maximum values that can be found across all companies. The country-specific bracket 1, in this example, will range from 200 and 300 ariary: for this range, Airtel does not provide the possibility to exchange money and will be hence shown as missing, while Orange will display the tariff that is applied for its range 200-1000 ariary. Similarly, for brackets ranging between values greater than 5 million ariary, Airtel will be displayed as missing.

In order to make tariffs comparable across countries, we express them as percentage of the transaction values. While in many cases tariff plans are already defined in percentage by mobile money operators, in other cases, as the one we take as example, they are defined as a fixed sum for the transaction whole bracket. In those cases, we express the fee as percentage of the mean value of the bracket. In Panel (b) of Figure 1, we notice not only a higher dispersion of tariffs in the lowest brackets, but also how rates decrease for higher brackets. This fee structure hence burdens on those users who make smaller transactions.

D.2 Interoperability

A core concept of our analysis is mobile money interoperability. In line with the GSMA (2020) report, we define account-to-account (A2A) Interoperability as the possibility given by Mobile Money Providers (MMPs) for customers to transfer money between two accounts in different mobile money schemes. While mobile money was born as a stand-alone service, in which transfers were allowed only within the same network, in the latest years, it experienced an integration process that brought the connection of MMPs between themselves. By studying the development of the Mobile Money market in each African country, we aim to identify where the regulatory environment provides requirements or recommendations for interoperability. It is not a trivial effort as the regulatory frameworks vary widely between African countries, and the role of authorities in obliging the adoption of interoperability is sometimes uncertain. For each country, we report a brief overview of the introduction of interoperability from a regulatory perspective. In Table D.1 we summarize key information regarding the introduction of interoperability and its initiator for the African countries in which mobile money interoperability is active.

Table D.1 clearly shows the growing involvement of institutional regulators in interoperability matters. In Naji (2020) and Mhella (2020) we can find different definitions of interoperability, depending on the level at which the integration of systems is developed. In particular, we can distinguish between (a) wallet-to-wallet interoperability: i.e. the possibility to exchange mobile money between accounts of different operators; (b) agent interoperability: which consists in the removal of exclusivity of agents, i.e. the possibility for agents to serve more than one operator; (c) wallet-to-bank (or other financial services) interoperability: i.e. the possibility to exchange money between a mobile money account and a bank account or other financial technologies. In our paper, we consider the case of wallet-to-wallet interoperability, which allows account-to-account transfers between users of different mobile money operators. As it can be seen below from country specific regulations, the introduction of mobile money interoperability in African countries has always entailed wallet-to-wallet interoperability.

Table D.1: Interoperability proponents in Africa

Reason for interoperability	Country	Year effective
Central Bank regulation	Botswana	2019
	Cameroon (BEAC)	2020
	Chad (BEAC)	2020
	Central African Republic (BEAC)	2020
	Egypt	2016
	Equatorial Guinea (BEAC)	2020
	Gabon (BEAC)	2020
	Ghana	2018
	Liberia	2014
	Malawi	2017
	Morocco	2018
	Nigeria	2013
	Rwanda	2021
	Republic of Congo (BEAC)	2020
	Sudan	2016
	Tanzania	2015
	Uganda	2018
	Zimbabwa	2020
Agreement between providers	Kenya (Airtel, Safaricom, Telkom)	2018
	Madagascar (Airtel, mVola, Orange)	2016

Notes: This table reports information about the proponent of interoperability in the African countries were interoperability is currently active. While the majority of countries introduce interoperability following an institutional regulation issued by the national Central Bank, there are cases in which agreements between mobile money operators preceded the regulator. Cameroon, Central African Republic, Equatorial Guinea, Gabon and the Republic of Congo are part of The Economic and Monetary Community of Central Africa (CEMAC), an organization of states of Central Africa that share a common currency: In their case, interoperability was proposed by the Bank of Central African States (Banque des États de l'Afrique Centrale, BEAC).

D.2.1 Botswana

The relevant regulatory framework in Botswana, which applies to mobile money providers, is the Electronic Payment Service Regulations, issued in January, 2019, by Bank of Botswana (the Central Bank of Botswana). According to the GSMA report "Mobile Money Regulatory Index 2021", the Mobile Network Operators (MNOs) in Botswana can offer mobile money and to provide this service they must apply for a license directly from Bank of Botswana and comply with the Electronic Payment Services Regulations (2019). As regards Interoperability, Part III, Art. 16 (2) (c) of the regulation reads: [...] *The resources shall be a system which is interoperate with other payment system within Botswana.* This regulation hence requires payment systems to be interoperable.

D.2.2 Cameroon

Being Cameroon a member of the Economic ad Monetary Community of Central Africa (CEMAC), its mobile money market is regulated by The Bank of Central African States (BEAC). In 2012, the Groupement Interbancaire Monétique d'Afrique Centrale (GIMAC) was created by the CEMAC with the purpose of promoting interbank electronic banking, regulation, supervision and the provision of processing services. Since 2018, GIMAC has been in charge of implementing full mobile money interoperability in accordance with instruction 001/GR/2018 from the Governor of BEAC.[21] In April 2020, after a pilot phase, an integrated electronic payment service, known as GIMACPAY, was introduced in all six countries of the Economic and Monetary Community of Central Africa. [22] Among other services, this platform allows people to transfer money between mobile money accounts of different operators, therefore, guarantees mobile money interoperability within the region. Since we found no evidence for any CEMAC countries of the introduction of domestic interoperability and since this regional interoperability also implies interoperability within each country (the possibility to transfer money between different MNOs in the same country), we consider April 2020 as the date of the launch of Interoperability for all countries in the region.

D.2.3 Central African Republic

Although the Central African Republic is a member of the CEMAC, we do not consider the presence of Interoperability since just one mobile operator (Orange) is providing mobile money services.

D.2.4 Egypt

According to the 2013 Regulations Governing Provision of Payment Orders through Mobile Phones issued by the Central Bank of Egypt (CBE), only banks operating under the supervision of the CBE may, subject to CBE's approval, issue electronic money units. Accordingly, to offer mobile money services, the MNOs must contract with the banks as only banks can be responsible for customer accounts.[23] In a bank-led model, a bank is the service provider. The role of the MNO is peripheral, limited to providing either the communications infrastructure, agency services or both Consistently with GSMA (2021), we consider applicable to mobile money services the "Regulations for the Provision of Mobile Payment Services (2016)", issued by the Central Bank of Egypt in November 2016. These regulations determine the activation of interoperability between different payment schemes. Specifically, they require all banks providing mobile payment services with the

[21] See link

[22] Cameroon, Republic of Congo, Chad, Central African Republic, Equatorial Guinea, and Gabon

[23] See link

CBE authorization to guarantee the interoperability service within six months.[24]

In addition, in June 2017, the Central Bank of Egypt, in collaboration with the the Ministry of Finance and the Egyptian Banks Company (EBC), introduced the mobile Interoperability scheme Ta7weel .[25] Through this platform, users of different mobile payment schemes are able to transact with each other directly. We set as Interoperability introduction the date of the issuance of the "Regulations for the Provision of Mobile Payment Services (2016)", i.e., November 2016, since they explicitly require providers of mobile banking services (and therefore mobile money) to become interoperable.

D.2.5 Ghana

The commitment to achieve payment systems Interoperability began in 2007 when the Ghana Interbank Payment and Settlement Systems Limited (GhIPSS) was established by Bank of Ghana (the Central Bank of Ghana). This wholly-owned subsidiary of the Bank of Ghana is responsible for implementing and managing interoperable payment system infrastructures for banks and non-bank financial institutions in Ghana.[26] According to GSMA (2020), Bank of Ghana's 2008 and 2015 Branchless Banking Guidelines mandated a "many-to-many" model whereby MNOs were required to interconnect with a minimum of three banks to issue electronic money, as well as share agents. In 2015, more progressive guidelines were introduced replacing those of 2008. Ghana has reached full interoperability in May 2018 through the Interbank Payment and Settlement Systems (GhIPSS). Indeed, the existing payment switch Gh-Link was upgraded to give access also to Mobile Money Operators (MMOs). The connection to this platform enabled the link of different payment systems, such as mobile money accounts, bank accounts, and e-zwitch cards. Therefore, mobile money users can seamlessly transfer money wallet-to-wallet across networks. Although payment aggregator Nsano has enabled interoperability between MNOs since 2016,[27] we take the launch of hub-based mobile money interoperability by GhIPSS as the starting date.

D.2.6 Kenya

In January 2018, the three mobile money providers networks, Airtel, Safaricom, and Telkom, reached an agreement regarding the implementation of interoperability. On the 22nd of the same month, Safaricom's M-Pesa and Airtel Money undertook a pilot phase, enabling the seamless transfer of funds between mobile accounts on different networks. In a press release, the Central Bank of Kenya welcomed the implementation of interoperability of mobile financial services on the 10th of April 2018, stressing its benefits and

[24] See link
[25] See link
[26] See link
[27] See link

importance to Kenya's mobile money market: accordingly, we set April 2018 as the date of the introduction of interoperability.

D.2.7 Liberia

In May 2014, the Central Bank of Liberia (CBL) issued the Mobile Money Regulations, requiring all authorized institutions to provide interoperable systems. In this regards, Part III, Art. 17 reads: *All Authorized Institutions should endeavor to render systems interoperable with systems provided by other Authorized Institutions, in such a way that transactions between Authorized Institutions are executed to allow a realtime customer experience for customers of both Institutions, as the services mature [...]*

D.2.8 Madagascar

Intending to reduce cash in the Madagascar economy, in 2014 the Mobile Money Providers (MMPs) engaged GSMA, a project facilitator, to advance sector-wide discussions on account-to-account (A2A) interoperability.[28] According to GSMA in September 2016 Airtel Money, mVola, and Orange Money signed a deal to launch interoperable mobile money services across the entire country; this made Madagascar the second market in Africa, after Tanzania, to allow seamless transactions on all MMPs.[29] Similarly to Tanzania, the implementation of Interoperability in Madagascar was market-led, with the presence of a facilitator (GSMA) that helped the providers to finalize bilateral agreements and connections. Although there was no mandate from the judicial authorities, we set September 2016 as Interoperability, as it is the date of the formal launch.

D.2.9 Malawi

In September 2017, the Reserve Bank of Malawi (RBM) passed the Payment System Act, mandating interoperability of Payment Systems through the connection to a National Switch. Specifically, Part IV, Art. (6) (1) states: *Any authorized or licensed payment service provider offering payment services on auto-teller machines, point of sale devices, mobile payment systems, internet based payments and all other related payment channels as approved by the Bank, shall connect its infrastructure that supports interoperability to the National Switch.*

D.2.10 Morocco

In November 2018, The Morocco's Central Bank Al-Maghrib and the National Telecommunications Regulatory Agency (ANRT) launched *m-wallet*, a new means of payment by mobile phone, in collaboration with banks, payment institutions, telecom operators

[28] See link
[29] See link

and Hightech Payment Systems (HPS) Switch. The "Décision Réglementaire Relative au Paiement Mobile Domestique"[30] issued by the Central Bank of Morocco includes the rules and specifies the technical standards for interoperability. Article 5 reads: *The payment services offered by m-wallet are interoperable and instantaneous.* This tool entails not only interoperability between mobile money operators but also across all payment systems.

D.2.11 Nigeria

With the aim of ensuring the interoperability of all authorized schemes, in December 2012 the Central Bank of Nigeria required the Mobile Money Operators to connect to the National Central Switch (NCS).[31] In particular, the "Timeline for Interoperability and Interconnectivity" released by the Central Bank of Nigeria reads: *In furtherance of the CBN's efforts at ensuring effective and robust mobile payments system, all MMOs are hereby directed to fully connect to the National Central Switch (NCS) on or before February 28, 2013, to ensure interoperability and interconnectivity of their schemes.*

D.2.12 Rwanda

As early as 2012, the National Bank of Rwanda (BNR) issued Regulation N°06/2012 governing Payment Service Providers concerning interoperability. Specifically, Article 21 requires that *Financial institutions and Mobile Network Operators shall be interconnected to offer services to virtually all banked and unbanked customers in order to achieve interoperability and to substantially increase the financial services outreach to the unbanked communities.* In addition, Article 26 outlined the timeframe for this clause implementation: it provided that the connection would take place within one year of the effect of the regulation.[32] However, according to the "Interoperability Policy" issued in June 2014, the Bank of Rwanda recognizes the complexity of achieving interoperability given the differences among the several payment streams, schemes, and systems: *The implementation of this regulation has lagged while the complexity and diversity of the Rwandan payment market have grown. BNR recognizes that the question of how to promote interoperability in payment systems is a complex one that may be considered in the general case but must rather be defined and addressed in respect of particular payment types. BNR has therefore decided to review its policy approach towards interoperability so that it can achieve the objectives set out in this policy.* In response to this recognition, the policy document was aimed at setting the general guidelines for promoting greater interoperability over the five year period from 2014 to 2019. In October 2015, Airtel and Tigo launched a six-month bilateral pilot project for interoperability, an initiative strongly supported by the National

[30] See link
[31] See link
[32] See link

Bank of Rwanda. In December 2017, Airtel signed an agreement with Millicom to acquire Tigo Rwanda, creating a duopoly in the mobile money market. The two market leaders MTN and Airtel did not reach interoperability until 2021. Indeed, the New Times (Rwanda's leading daily) [33] reports that in June 2021, a draft law governing payment systems proposed a new provision that allows the Central Bank to impose interoperability and that the government was in negotiations with RSwitch to provide the interoperability system, operational in a short time. In December 2021, the national e-payment switch of Rwanda, RSwitch, was upgraded to connect all payment schemes, including MNOs.

D.2.13 Sudan

According to GSMA (2021) the Central Bank of Sudan is the only entity allowed to issue money in Sudan. Banks, by purchasing e-money directly from the Central Bank, play the role of Financial Service Providers (FSP), while the MNOs play most the customer facing functions. As far as it concerns interoperability, GSMA report reads: *The mobile payment system in Sudan is centralised thereby imposing on technical requirements for all financial system operators are required to inter-link their platforms to be interoperable.* Moreover, the 2017 Alliance for Financial Inclusion (AFI) report "National retail payment systems to support financial inclusion" claims that the Central Bank of Sudan implemented the National Switch in 2006 that provides interoperable, robust national payments infrastructure, to provide payment services for all cardholders through ATMs and POS terminals, across the nation; as well through Short Messaging Service (SMS). Among the terminals integrated with this National Switch, Mobile payments are included. Following these sources, we consider the regulation requiring all the payment systems to be interoperable. As a result, since their launch year in 2016, the mobile money platforms have been meeting the interoperability requirements.

D.2.14 Tanzania

Tanzania has been the first country to reach full mobile money Interoperability in Africa. Discussion on account-to-account innteroperability started as early as 2013, mandated by the Bank of Tazania, after the intergration between the MMPs and the banking sector (GSMA, 2016). The interconnection between the four MMPs, Tigo, Airtel, Zantel, and Vodacom, took place the following years through bilateral/multilateral agreements. First, Airtel and Tigo signed a deal on interoperability in September 2014. Then in December 2014, Tigo connected with Zantel, and, in February 2016, Vodacom announced the joining of the interoperability agreement. In terms of legislation, the National Payment Systems (NPS) Act 2015 and the Bank of Tanzania Act 2006 assign to Bank of Tanzania the responsibility to regulate and supervise the payment systems services and products

[33] See link

offered by both banks and non-bank institutions in Tanzania.[34] As far as it concerns interoperability, the National Payment Systems (NPS) Act, passed in May 2015, reads "*A payment system that may be eligible to be licenced by the Bank shall have any of the following objects: [...] facilitation of interoperability of payment systems and services between payment systems providers and consumers.*" In addition to the interoperability standard, the legislation mandates non-discriminatory pricing for cross-net and on-net person-to-person (P2P) transactions (GSMA, 2020). As interoperability has been market-driven and achieved gradually, we set as introduction of interoperability the date on which the National Payment Systems (NPS) law was passed.

D.2.15 Uganda

In 2013 the Bank of Uganda issued some guidelines[35] to mobile money service providers, recommending to "*utilize systems capable of becoming interoperable with other payment systems in the country and internationally in order to facilitate full interoperability*". In September 2017, this recommendation became more pressing as the Bank of Uganda issued the National Payment System (NPS) Policy Framework[36], which required all mobile money providers to achieve interoperability within a few months, without providing technical standards. The two market leaders, MTN and Airtel, initially used the Pegasus aggregator and then connected bilaterally in 2019. They still make use of Pegasus for interconnection with smaller MMPs (GSMA, 2020).

D.2.16 Zimbabwe

The Statutory Instrument 80 of 2020 (Banking Money Transmission, Mobile Banking and Mobile Money Interoperability) Regulations released by the Reserve Bank of Zimbabwe, in section 4 " Additional requirements for provision of money transmission and mobile banking services" reads: "*It shall be mandatory for every money transmission provider and mobile banking provider shall be connected to a national payment switch, as shall be directed by written notice by the Reserve Bank from time to time that enables interoperability of payments systems and services.*" In a press statement of June 2020, The Reserve Bank of Zimbabwe announced the designation of Zimswitch as a national payment switch with immediate effect. Therefore, as required by section 4 of the Regulations above, all money transmission providers and mobile money providers had to complete the necessary installation or deployment, or commissioning of infrastructure and connection protocols, credentials, and documentation to connect to Zimswitch, by no later than 15 August 2020.

[34] See link
[35] See link
[36] See link

A Data Appendix E - Mobile Network Operators Balance Sheets

In this appendix we report the financial statement and revenue breakdown for the Fiscal Years 2020-2021 and 2021-2022 for the main mobile network operators (MNOs) in Africa offering mobile money services.

Table E.1: Summary of financial revenues of MNOs

Mobile Network Operator (MNO)	**Mobile Money Company**	**Countries**	**Financial Services Revenues 2020-2021 (as % of Total Revenues)**	**Financial Services Revenues 2021-2022 (as % of Total Revenues)**
Vodacom	M-Pesa	Democratic Republic of Congo, Tanzania Mozambique, Lesotho	34.2%	37.7%
Safaricom	M-Pesa	Kenya	33%	38.3%
MTN	MTN MoMo	Sudan, South Sudan, Rwanda, Cameroon, Eswatini, Guinea Bissau, Uganda, Ivory Coast, Liberia, Nigeria, Benin	10.6%	10%
Airtel	Airtel Money	Madagascar, Nigeria, Rwanda, Uganda, Kenya Chad, Congo, Democratic Republic of Congo, Gabon, Malawi, Niger, Seychelles, Uganda, Tanzania, Zambia	7.7%	9%

Notes: This table summarizes information about the financial revenues of major mobile network operators in Africa. The last two columns of the table report the financial service revenues as percentage of total revenues. We also report the countries in which MNOs operate and the name of the mobile money service they provide.

In Table E.1 we summarize the information about the revenues of financial services offered by these MNOs.

Airtel Money, the mobile money service provided by Airtel in Chad, Congo, Democratic Republic of Congo, Gabon, Kenya, Madagascar, Malawi, Niger, Nigeria, Rwanda, Seychelles, Uganda, Tanzania, Zambia, accounted for 9% of total revenues of Airtel in the Fiscal Years 2022.

MTN MoMo, in 2022, accounted for 10% of total revenues in the countries where MTN operates (Sudan, South Sudan, Rwanda, Cameroon, Côte d'Ivoire, Liberia, Eswatini, Guinea Bissau, Uganda, Nigeria, Benin).

Vodacom in the Democratic Republic of Congo, Lesotho, Mozambique and Tanzania, and Safaricom in Kenya, instead, registered revenues for about 38% from their mobile money service M-Pesa. Vodacom and Safaricom have the same mobile money service because Vodacom is the major owner of Safaricom's stocks, holding the 35% of its shares.

Below, we attach the financial statements and revenue breakdowns of these mobile network operators.[37]

[37] We also information for Orange, which, in Africa, operates in following countries: Botswana, Burkina

Figure E.1: Airtel's Financial Statements - Fiscal Year 2020-2021

Consolidated statement of comprehensive income

(All amounts are in US$ millions unless stated otherwise)

	Notes	For the year ended 31 March 2021	31 March 2020
Income			
Revenue	6	**3,908**	3,422
Other income		**11**	17
		3,919	3,439
Expenses			
Network operating expenses		**694**	628
Access charges		**376**	376
Licence fee/spectrum usage charges		**198**	189
Employee benefits expense	7	**275**	234
Sales and marketing expenses		**187**	148
Impairment loss/(reversal) on financial assets		**7**	(2)
Other operating expenses		**382**	333
Depreciation and amortisation	9	**681**	632
		2,800	2,538
Operating profit		**1,119**	901
Finance costs	10	**432**	440
Finance income	10	**(9)**	(67)
Non-operating income	11	**–**	(70)
Share of profit of associate		**(1)**	(0)
Profit before tax		**697**	598
Income tax expense	12	**282**	190
Profit for the year		**415**	408
Profit before tax (as presented above)		**697**	598
Less: Exceptional items (net)	11	**(14)**	(65)
Underlying profit before tax		**683**	533
Profit after tax (as presented above)		**415**	408
Less: Exceptional items (net)	11	**(50)**	(112)
Underlying profit after tax		**365**	296
Other comprehensive income (OCI)			
Items to be reclassified subsequently to profit or loss:			
Net losses due to foreign currency translation differences		**(138)**	(219)
Net (loss)/gain on net investments hedge		**(11)**	5
Net loss on cash flow hedge		**–**	(2)
		(149)	(216)
Items not to be reclassified subsequently to profit or loss:			
Re-measurement (loss)/gain on defined benefit plans		**(0)**	1
Tax credit/(expense) on above		**0**	(0)
		(0)	1
Other comprehensive loss for the year		**(149)**	(215)
Total comprehensive income for the year		**266**	193
Profit for the year attributable to:		**415**	408
Owners of the company		**339**	370
Non-controlling interests		**76**	38
Other comprehensive loss for the year attributable to:		**(149)**	(215)
Owners of the company		**(140)**	(224)
Non-controlling interests		**(9)**	9
Total comprehensive income for the year attributable to:		**266**	193
Owners of the company		**199**	146
Non-controlling interests		**67**	47
Earnings per share			
Basic	13	**9.0c**	10.3c
Diluted	13	**9.0c**	10.3c

Notes: Year ended 31 March 2021

Faso, Cameroon, Central African Repuclic, Guinea Bissau, Ivory Coast, Liberia, Morocco, DRC, Senegal, Sierra Leone, Madagascar, Tunisia, Egypt. However, the Financial Statement of Orange is consolidated for all the countries where the company operates, including European ones, and as a consequence there is not a clear entry for Mobile Money Revenues.

Figure E.2: Airtel's Revenue Breakdown - Fiscal Year 2020-2021

6. Revenue continued

Investment elimination upon consolidation and resulting goodwill impacts are reflected in the 'eliminations/adjustment' column.

Summary of the segmental information and disaggregation of revenue for the year ended and as of 31 March 2021 is as follows:

	Nigeria	East Africa	Francophone Africa	Unallocated	Eliminations	Total
Revenue from external customers						
Voice revenue	896	649	558	0	–	2,103
Data revenue	549	354	254	–	–	1,157
Mobile money revenue[1]	0	227	74	–	–	301
Other revenue[2]	104	147	96	–	–	347
	1,549	1,377	982	0	–	3,908
Inter-segment revenue	3	4	3	–	(10)	–
Total revenue	1,552	1,381	985	0	(10)	3,908
Segment results: Underlying EBITDA	839	631	364	(30)	(12)	1,792
Less:						
Depreciation and amortisation	236	221	207	2	15	681
Finance costs						432
Finance income						(9)
Share of profit of associate						(1)
Charitable donation	1	2	1	2	–	6
Exceptional items pertaining to operating profit	–	–	(14)	–	–	(14)
Profit before tax						697
Other segment items						
Capital expenditure	275	249	88	2	–	614
As of 31 March 2021						
Segment assets	1,889	2,042	1,791	25,622	(21,352)	9,992
Segment liabilities	1,192	2,989	2,715	16,895	(17,152)	6,639
Investment in associate (included in segment assets above)	–	–	4	–	–	4

1 Intra-segment elimination of $100m adjusted with mobile money revenue. It includes $64m pertaining to East Africa and balance $36m pertaining to Francophone Africa

2 This includes messaging, value added services, enterprise, site sharing and handset sale revenue

Notes: Year ended 31 March 2021

Figure E.3: Airtel's Financial Statements - Fiscal Year 2021-2022

Consolidated statement of comprehensive income

(All amounts are in US$ millions unless stated otherwise)

	Notes	For the year ended 31 March 2022	31 March 2021
Income			
Revenue	6	4,714	3,908
Other income		10	11
		4,724	3,919
Expenses			
Network operating expenses		817	694
Access charges		407	376
Licence fee and spectrum usage charges		244	198
Employee benefits expense	7	297	275
Sales and marketing expenses		224	187
Impairment loss on financial assets		5	7
Other operating expenses		451	382
Depreciation and amortisation	9	744	681
		3,189	2,800
Operating profit		1,535	1,119
Finance costs	10	441	432
Finance income	10	(19)	(9)
Other non-operating income	11	(111)	–
Share of profit from associate		(0)	(1)
Profit before tax		1,224	697
Income tax expense	12	469	282
Profit for the year		755	415
Profit before tax (as presented above)		1,224	697
Less: exceptional items (net)	11	(60)	(14)
Underlying profit before tax		1,164	683
Profit after tax (as presented above)		755	415
Less: exceptional items (net)	11	(62)	(50)
Underlying profit after tax		693	365
Other comprehensive income (OCI)			
Items to be reclassified subsequently to profit or loss:			
Loss due to foreign currency translation differences		(4)	(147)
Tax (expense)/credit on above		(3)	9
Share of OCI of associate		1	0
Net loss on net investments hedge		(8)	(11)
		(14)	(149)
Items not to be reclassified subsequently to profit or loss:			
Remeasurement loss on defined benefit plans		(0)	(0)
Tax credit on above		0	0
		(0)	(0)
Other comprehensive loss for the year		(14)	(149)
Total comprehensive income for the year		741	266
Profit for the year attributable to:		755	415
Owners of the Company		631	339
Non-controlling interests		124	76
Other comprehensive loss for the year attributable to:		(14)	(149)
Owners of the Company		(12)	(140)
Non-controlling interests		(2)	(9)
Total comprehensive income for the year attributable to:		741	266
Owners of the Company		619	199
Non-controlling interests		122	67
Earnings per share			
Basic	13	16.8 cents	9.0 cents
Diluted	13	16.8 cents	9.0 cents

Notes: Year ended 31 March 2022

Figure E.4: Airtel's Revenue Breakdown - Fiscal Year 2021-2022

Summary of the segmental information and disaggregation of revenue for the year ended and as of 31 March 2022 is as follows:

	Nigeria	East Africa	Francophone Africa	Unallocated	Eliminations	Total
Revenue from external customers						
Voice revenue	984	782	592	–	–	2,358
Data revenue	734	457	334	–	–	1,525
Mobile money revenue[1]	0	326	98	–	–	424
Other revenue[2]	157	146	104	–	–	407
	1,875	1,711	1,128	–	–	4,714
Inter-segment revenue	3	6	3	–	(12)	–
Total revenue	1,878	1,717	1,131	–	(12)	4,714
Segment results: underlying EBITDA	1,037	848	464	(38)	(0)	2,311
Less:						
Depreciation and amortisation	268	240	203	33	0	744
Finance costs						441
Finance income						(19)
Other non-operating income (net)						(111)
Share of profit of associate						(0)
Exceptional items pertaining to operating profit	–	32	–	–	–	32
Profit before tax						1,224
Other segment items						
Capital expenditure	251	271	125	9	–	656
As of 31 March 2022						
Segment assets	2,254	2,394	1,720	27,422	(23,426)	10,364
Segment liabilities	1,437	2,869	2,495	14,491	(14,577)	6,715
Investment in associate (included in segment assets above)	–	–	6	–	–	6

1 Intra-segment elimination of $129m adjusted with mobile money revenue. It includes $85m pertaining to East Africa and a balance of $44m pertaining to Francophone Africa

2 It includes messaging, value added services, enterprise, site sharing and handset sale revenue

Notes: Year ended 31 March 2022

Figure E.5: MTN's Financial Statements - Fiscal Year 2020-2021

Group income statement

for the year ended 31 December 2021

	Note	2021 Rm	2020 Rm
Revenue	2.1, 2.2	**181 646**	179 361
Other income	9.4.2.4, 9.4.2.5	**677**	99
Direct network and technology operating costs		**(27 649)**	(28 208)
Costs of handsets and other accessories		**(10 584)**	(11 093)
Interconnect and roaming costs		**(9 622)**	(10 992)
Staff costs	2.3	**(11 716)**	(12 741)
Selling, distribution and marketing expenses		**(22 452)**	(21 158)
Government and regulatory costs		**(6 895)**	(6 823)
Impairment and write-down of trade receivables and contract assets	2.3	**(1 116)**	(2 169)
Other operating expenses		**(12 570)**	(9 584)
Depreciation of property, plant and equipment	5.1	**(21 181)**	(22 704)
Depreciation of right-of-use assets	6.5.3	**(7 216)**	(7 204)
Amortisation of intangible assets	5.2	**(6 243)**	(5 743)
Impairment of goodwill and investment in joint ventures	5.2, 9.2	**(583)**	(1 065)
Gain on disposal of investment in associates	9.4.1; 9.4.2.1	**1 212**	6 129
Loss on deconsolidation of subsidiary	9.4.2.3	**(4 720)**	–
Impairment loss on remeasurement of non-current assets held for sale	9.4.2.1; 9.4.2.3	**(53)**	(1 510)
Finance income	2.4	**1 198**	1 493
Finance costs	2.4	**(15 646)**	(19 726)
Net monetary gain		**275**	1 582
Share of results of associates and joint ventures after tax	9.2	**2 054**	1 142
Profit before tax		**28 816**	29 086
Income tax expense	3.1	**(11 822)**	(9 439)
Profit after tax		**16 994**	19 647
Attributable to:			
Equity holders of the Company		**13 750**	17 022
Non-controlling interests		**3 244**	2 625
		16 994	19 647
Basic earnings per share (cents)	2.5	**763**	946
Diluted earnings per share (cents)	2.5	**744**	936

Notes: Year ended 31 March 2021

Figure E.6: MTN's Revenue Breakdown - Fiscal Year 2020-2021

2 **RESULTS OF OPERATIONS** (continued)

2.1 **Operating segments** (continued)

These exclusions have remained unchanged from the prior year, apart from the fair value gain on acquisition of subsidiary, loss on deconsolidation of subsidiary, gain on exit in Yemen, gain on disposal of subsidiary and impairment loss on Yemen property, plant and equipment and intangible assets. Impairment losses on property, plant and equipment and intangible assets are generally included in the CODM EBITDA as they are operational in nature. As the impairment of Yemen's property, plant and equipment and intangible assets arises from the MENA exit strategy, it is not considered reflective of Yemen's performance for the period.

Irancell proportionate results are included in the segment analysis as reviewed by the CODM and excluded from reported proportionate results for revenue, CODM EBITDA and capital expenditure (capex) due to equity accounting for joint ventures. The results of Irancell in the segments analysis exclude the impact of hyperinflation accounting.

Revenue 2021	Network services Rm	Mobile devices Rm	Inter-connect and roaming Rm	Digital and fintech Rm	Other Rm	Revenue from contracts with customers Rm	Interest revenue Rm	Total revenue Rm
South Africa	31 030	9 271	4 070	2 429	1 521	48 321	395	48 716
Nigeria	50 241	107	5 594	3 216	892	60 050	–	60 050
SEA	11 830	211	759	3 598	557	16 955	–	16 955
Uganda	5 728	84	378	2 199	160	8 549	–	8 549
Zambia	1 606	77	108	596	42	2 429	–	2 429
Other SEA	4 496	50	273	803	355	5 977	–	5 977
WECA	34 371	223	2 499	9 750	1 162	48 005	–	48 005
Ghana	13 046	56	642	5 151	292	19 187	–	19 187
Côte d'Ivoire	6 022	47	879	1 456	499	8 903	–	8 903
Cameroon	5 475	38	385	1 262	84	7 244	–	7 244
Other WECA	9 828	82	593	1 881	287	12 671	–	12 671
MENA	5 209	13	1 055	200	73	6 550	–	6 550
Sudan	1 619	6	548	43	10	2 226	–	2 226
Afghanistan	1 670	7	341	57	17	2 092	–	2 092
Other MENA[1]	1 920	–	166	100	46	2 232	–	2 232
Major joint venture – Irancell[2]	5 831	128	289	324	138	6 710	15	6 725
Head office companies[3]	1 515	–	5 076	188	12 183	18 962	134	19 096
Eliminations	(438)	(1)	(5 303)	(206)	(11 635)	(17 583)	(130)	(17 713)
Hyperinflation impact	(229)	1	226	(5)	(6)	(13)	–	(13)
Irancell revenue exclusion	(5 831)	(128)	(289)	(324)	(138)	(6 710)	(15)	(6 725)
Consolidated revenue	133 529	9 825	13 976	19 170	4 747	181 247	399	181 646

[1] Syria and Yemen segment analysis has been included until the Group lost control of MTN Syria on 25 February 2021 and the Group exited Yemen on 17 November 2021. Refer to note 9.4.2.3 and note 9.4.2.4.

[2] Irancell proportionate results are included in the segment analysis as reviewed by the CODM. This is, however, excluded from IFRS reported results due to equity accounting for joint ventures.

[3] Head office companies consist mainly of revenue from GlobalConnect Solutions Limited (GlobalConnect), the Group's central financing activities and management fees from segments.

Notes: Year ended 31 March 2021

Figure E.7: MTN's Financial Statements - Fiscal Year 2021-2022

Group income statement

for the year ended 31 December 2022

	Note	**2022 Rm**	2021 Rm
Revenue	2.1; 2.2	**207 003**	181 646
Other income	6.5.5	**410**	677
Direct network and technology operating costs		**(32 854)**	(27 649)
Costs of handsets and other accessories		**(12 055)**	(10 584)
Interconnect and roaming costs		**(11 288)**	(9 622)
Staff costs	2.3	**(12 675)**	(11 716)
Selling, distribution and marketing expenses		**(24 819)**	(22 452)
Government and regulatory costs		**(7 610)**	(6 895)
Impairment and write-down of trade receivables and contract assets	2.3	**(1 579)**	(1 116)
Other operating expenses		**(13 431)**	(12 570)
Depreciation of property, plant and equipment	5.1	**(20 812)**	(21 181)
Depreciation of right-of-use assets	6.5.3	**(7 840)**	(7 216)
Amortisation of intangible assets	5.2	**(5 999)**	(6 243)
Impairment of goodwill and investment in joint ventures	5.2; 9.2	**(625)**	(583)
Gain on disposal of investment in associates	9.4.1.1	**–**	1 212
Loss on deconsolidation of subsidiary	9.4.1.3	**–**	(4 720)
Impairment loss on remeasurement of non-current assets held for sale	9.4.2.4	**(1 263)**	(53)
Finance income	2.4	**2 042**	1 198
Finance costs	2.4	**(19 728)**	(15 646)
Net monetary gain		**1 251**	275
Share of results of associates and joint ventures after tax	9.2	**3 369**	2 054
Profit before tax		**41 497**	28 816
Income tax expense	3.1	**(17 236)**	(11 822)
Profit after tax		**24 261**	16 994
Attributable to:			
Equity holders of the Company		**19 337**	13 750
Non-controlling interests		**4 924**	3 244
		24 261	16 994
Basic earnings per share (cents)	2.5	**1 071**	763
Diluted earnings per share (cents)	2.5	**1 044**	744

Notes: Year ended 31 March 2022

Figure E.8: MTN's Revenue Breakdown - Fiscal Year 2021-2022

Notes to the Group financial statements (continued)

for the year ended 31 December 2022

2 RESULTS OF OPERATIONS (continued)

2.1 Operating segments (continued)

Revenue 2022	Network services Rm	Mobile devices Rm	Inter-connect and roaming Rm	Digital and fintech Rm	Other Rm	Revenue from contracts with customers Rm	Interest revenue Rm	Total revenue Rm
South Africa	32 018	9 792	4 359	2 417	1 573	50 159	481	50 640
Nigeria	65 721	237	6 518	4 087	697	77 260	–	77 260
SEA	12 732	240	872	5 019	479	19 342	–	19 342
Uganda	6 518	90	400	2 932	186	10 126	–	10 126
Zambia	2 096	104	184	869	63	3 316	–	3 316
Other SEA	4 118	46	288	1 218	230	5 900	–	5 900
WECA	35 510	204	2 294	8 920	1 351	48 279	–	48 279
Ghana	12 920	62	590	4 170	289	18 031	–	18 031
Côte d'Ivoire	6 446	46	663	1 116	647	8 918	–	8 918
Cameroon	5 829	28	354	1 422	94	7 727	–	7 727
Other WECA	10 315	68	687	2 212	321	13 603	–	13 603
MENA	5 005	27	1 007	146	27	6 212	–	6 212
Sudan	3 276	19	642	78	17	4 032	–	4 032
Afghanistan	1 729	8	365	68	10	2 180	–	2 180
Major joint venture – Irancell[1]	7 093	183	362	702	206	8 546	18	8 564
Head office companies[2]	1 856	–	6 180	–	15 100	23 136	255	23 391
Eliminations	(957)	(3)	(5 571)	(22)	(13 810)	(20 363)	(242)	(20 605)
Hyperinflation impact	1 988	13	419	49	15	2 484	–	2 484
Irancell revenue exclusion	(7 093)	(183)	(362)	(702)	(206)	(8 546)	(18)	(8 564)
Consolidated revenue	153 873	10 510	16 078	20 616	5 432	206 509	494	207 003

[1] Irancell proportionate results are included in the segment analysis as reviewed by the CODM. This is, however, excluded from IFRS reported results due to equity accounting for joint ventures.

[2] Head office companies consist mainly of revenue from GlobalConnect Solutions Limited (GlobalConnect), the Group's central financing activities and management fees from segments.

Notes: Year ended 31 March 2022

Figure E.9: Orange's Financial Statements - Fiscal Year 2021-2022

Consolidated income statement

(in millions of euros, except for per share data)	Note	2022	2021	2020
Revenue	4.1	**43,471**	**42,522**	**42,270**
External purchases	5.1	(18,732)	(17,973)	(17,691)
Other operating income	4.2	747	783	604
Other operating expenses	5.2	(413)	(700)	(789)
Labor expenses	6.1	(8,920)	(9,917)	(8,490)
Operating taxes and levies	10.1.1	(1,882)	(1,926)	(1,924)
Gains (losses) on disposal of fixed assets, investments and activities	3.1	233	2,507	228
Restructuring costs	5.3	(125)	(331)	(25)
Depreciation and amortization of fixed assets	8.2	(7,035)	(7,074)	(7,134)
Depreciation and amortization of financed assets	8.5	(107)	(84)	(55)
Depreciation and amortization of right-of-use assets	9.1	(1,507)	(1,481)	(1,384)
Impairment of goodwill	7.1	(817)	(3,702)	-
Impairment of fixed assets	8.3	(56)	(17)	(30)
Impairment of right-of-use assets	9.1	(54)	(91)	(57)
Share of profits (losses) of associates and joint ventures	11	(2)	3	(2)
Operating income		**4,801**	**2,521**	**5,521**
Cost of gross financial debt excluding financed assets		(775)	(829)	(1,099)
Interests on debts related to financed assets		(3)	(1)	(1)
Gains (losses) on assets contributing to net financial debt		48	(3)	(1)
Foreign exchange gain (loss)		(97)	65	(103)
Interests on lease liabilities		(145)	(120)	(120)
Other net financial expenses		52	106	11
Finance costs, net	13.2	**(920)**	**(782)**	**(1,314)**
Income taxes	10.2.1	(1,265)	(962)	848
Consolidated net income		**2,617**	**778**	**5,055**
Net income attributable to owners of the parent company		2,146	233	4,822
Non-controlling interests	15.6	471	545	233
Earnings per share (in euros) attributable to parent company	15.7			
Net income				
- basic		0.73	0.00	1.72
- diluted		0.73	0.00	1.71

Notes: Year ended 31 March 2022

Figure E.10: Orange's Revenue Breakdown - Fiscal Year 2021-2022

1.2 Segment revenue

(in millions of euros)	France[1]	Europe				Africa & Middle-East	Enterprise[5]	Totem[1][2]	International Carriers & Shared Services[1][6]	Eliminations	Total telecom activities	Mobile Financial Services	Eliminations telecom activities / mobile financial services	Orange consolidated financial statements
		Spain[1]	Other European countries[3]	Eliminations Europe	Total									
December 31, 2022														
Revenue[4]	**17,983**	***4,647***	***6,329***	***(14)***	**10,962**	**6,918**	**7,930**	**685**	**1,540**	**(2,538)**	**43,480**	**-**	**(9)**	**43,471**
Convergence services	4,857	*1,870*	*959*	-	2,830	-	-	-	-	-	7,687	-	-	7,687
Mobile-only services	2,332	*790*	*2,079*	-	2,869	5,272	659	-	-	(38)	11,093	-	(0)	11,093
Fixed-only services	3,787[7]	*436*	*783*	-	1,219	800	3,466[8]	-	-	(150)	9,121	-	(1)	9,120
IT & integration services	-	*41*	*430*	-	471	40	3,489	-	-	(184)	3,817	-	(6)	3,811
Wholesale	4,938	*878*	*964*	*(14)*	1,828	663	41	685	1,060	(1,859)	7,356	-	-	7,356
Equipment sales	1,323	*632*	*927*	-	1,559	104	275	-	-	(7)	3,255	-	(0)	3,254
Other revenue	746	*1*	*185*	-	187	39	-	-	480	(299)	1,152	-	(2)	1,150
External	*17,238*	*4,586*	*6,219*	-	*10,805*	*6,750*	*7,548*	*113*	*1,017*	-	*43,471*	-	-	*43,471*
Inter-operating segments	*745*	*61*	*109*	*(14)*	*157*	*168*	*383*	*572*	*523*	*(2,538)*	*9*	-	*(9)*	-
December 31, 2021														
Revenue[4]	**18,092**	***4,720***	***5,870***	***(11)***	**10,579**	**6,381**	**7,757**	**n/a**	**1,515**	**(1,795)**	**42,530**	**-**	**(7)**	**42,522**
Convergence services	4,697	*1,870*	*850*	-	2,720	-	-	n/a	-	-	7,417	-	-	7,417
Mobile-only services	2,276	*880*	*2,007*	-	2,887	4,884	636	n/a	-	(31)	10,652	-	(0)	10,652
Fixed-only services	3,872[7]	*435*	*652*	-	1,087	664	3,633[8]	n/a	-	(168)	9,089	-	(1)	9,088
IT & integration services	-	*14*	*338*	-	352	31	3,195	n/a	-	(167)	3,411	-	(4)	3,407
Wholesale	5,313	*900*	*998*	*(11)*	1,886	654	42	n/a	1,056	(1,249)	7,702	-	-	7,702
Equipment sales	1,226	*621*	*869*	-	1,490	112	250	n/a	-	(8)	3,070	-	(0)	3,070
Other revenue	708	*1*	*155*	*0*	157	36	-	n/a	460	(172)	1,188	-	(2)	1,186
External	*17,489*	*4,672*	*5,776*	-	*10,449*	*6,216*	*7,371*	*n/a*	*998*	-	*42,522*	-	-	*42,522*
Inter-operating segments	*603*	*48*	*94*	*(11)*	*131*	*165*	*386*	*n/a*	*517*	*(1,795)*	*7*	-	*(7)*	-
December 31, 2020														
Revenue[4]	**18,461**	***4,951***	***5,638***	***(9)***	**10,580**	**5,834**	**7,807**	**n/a**	**1,450**	**(1,855)**	**42,277**	**-**	**(7)**	**42,270**
Convergence services	4,559	*1,984*	*733*	-	2,717	-	-	n/a	-	-	7,276	-	-	7,276
Mobile services only	2,245	*1,012*	*2,026*	-	3,038	4,420	649	n/a	-	(35)	10,317	-	(0)	10,317
Fixed services only	3,959[7]	*471*	*611*	-	1,083	562	3,851[8]	n/a	-	(177)	9,278	-	(0)	9,277
IT & integration services	-	*8*	*301*	-	310	25	3,086	n/a	-	(164)	3,256	-	(4)	3,252
Wholesale	5,866	*916*	*1,017*	*(9)*	1,924	695	45	n/a	1,038	(1,313)	8,255	-	-	8,255
Equipment sales	1,187	*547*	*828*	-	1,375	89	175	n/a	-	(5)	2,821	-	(0)	2,821
Other revenue	644	*12*	*122*	-	134	43	-	n/a	412	(160)	1,073	-	(2)	1,072
External	*17,794*	*4,908*	*5,559*	-	*10,467*	*5,660*	*7,405*	*n/a*	*944*	-	*42,270*	-	-	*42,270*
Inter-operating segments	*667*	*43*	*79*	*(9)*	*113*	*175*	*402*	*n/a*	*506*	*(1,855)*	*7*	-	*(7)*	-

Notes: Year ended 31 March 2022

Figure E.11: Vodacom's Financial Statements - Fiscal Year 2020-2021

Condensed consolidated income statement

for the year ended 31 March

Rm	Notes	2021 Reviewed	2020 Audited
Revenue	3	**98 302**	90 746
Direct expenses[1]		**(36 269)**	(32 075)
Staff expenses		**(6 990)**	(6 421)
Publicity expenses		**(1 718)**	(1 907)
Net credit losses on financial assets[1]		**(1 078)**	(802)
Other operating expenses		**(12 973)**	(12 024)
Depreciation and amortisation		**(15 117)**	(13 955)
Impairment losses		**(6)**	–
Net profit from associate and joint ventures		**3 501**	4 149
Operating profit		**27 652**	27 711
Net loss on disposal of subsidiaries	4.4	**(70)**	(819)
Finance income		**767**	884
Finance costs		**(4 190)**	(4 702)
Net loss on remeasurement and disposal of financial instruments		**(378)**	(16)
Profit before tax		**23 781**	23 058
Taxation		**(6 710)**	(6 414)
Net profit		**17 071**	16 644
Attributable to:			
Equity shareholders		**16 581**	15 944
Non-controlling interests		**490**	700
		17 071	16 644

1. Net credit losses on financial assets were included in direct expenditure in prior periods. The reclassification had no impact on any reported totals, headline earnings per share or on any amounts presented in the statement of financial position.

Cents	Notes	2021 Reviewed	2020 Audited
Basic earnings per share	4	**978**	939
Diluted earnings per share	4	**956**	923

Notes: Year ended 31 March 2021

Figure E.12: Vodacom's Revenue Breakdown - Fiscal Year 2020-2021

Revenue is further disaggregated into product type below.

Rm	South Africa	International	Corporate and elimination	Total	Safaricom[1]
31 March 2021 – reviewed					
Mobile contract revenue	20 829	1 469	(6)	22 292	3 420
Mobile prepaid revenue	25 359	18 009	(2)	43 366	30 153
Customer service revenue	46 188	19 478	(8)	65 658	33 573
Mobile interconnect	1 742	1 330	(544)	2 528	1 426
Fixed service revenue	3 556	1 233	(390)	4 399	1 429
Other service revenue	4 919	105	(35)	4 989	1 172
Service revenue	56 405	22 146	(977)	77 574	37 600
Equipment revenue	14 672	285	(21)	14 936	1 527
Non-service revenue	5 299	303	(183)	5 419	500
Revenue from contracts with customers	76 376	22 734	(1 181)	97 929	*
Interest income recognised as revenue	296	12	–	308	*
Other[2]	65	–	–	65	*
Revenue	76 737	22 746	(1 181)	98 302	39 627

1. The Group has a 34.94% effective interest in Safaricom Plc (Safaricom) through its subsidiary Vodafone Kenya Limited, which the Group equity accounts for as an investment in an associate at 39.93%. Due to the significance of this investment, and the information available for review by the chief operating decision maker, Safaricom is presented as a separate segment. The above results represent 100% of the results of Safaricom.
2. Other revenue largely represents lease revenues recognised under IFRS 16 "Leases".

* Not reviewed by the chief operating decision maker.

Notes: Year ended 31 March 2021

Figure E.13: Vodacom's Financial Statements - Fiscal Year 2021-2022

Condensed consolidated income statement

for the year ended 31 March

Rm	Note	2022 Reviewed	2021 Audited
Revenue	3	102 736	98 302
Direct expenses		(38 624)	(36 269)
Staff expenses		(7 266)	(6 990)
Publicity expenses		(1 886)	(1 718)
Net credit losses on financial assets		(704)	(1 078)
Other operating expenses		(14 419)	(12 973)
Depreciation and amortisation		(14 657)	(15 117)
Impairment losses		–	(6)
Net profit from associates and joint ventures		3 056	3 501
Operating profit		28 236	27 652
Net loss on disposal of subsidiaries		–	(70)
Finance income		554	767
Finance costs		(4 229)	(4 190)
Net gain/(loss) on remeasurement and disposal of financial instruments		2	(378)
Profit before tax		24 563	23 781
Taxation		(6 829)	(6 710)
Net profit		17 734	17 071
Attributable to:			
Equity shareholders		17 163	16 581
Non-controlling interests		571	490
		17 734	17 071

Cents	Note	2022 Reviewed	2021 Audited
Basic earnings per share	4	1 013	978
Diluted earnings per share	4	984	956

Notes: Year ended 31 March 2022

Figure E.14: Vodacom's Revenue Breakdown - Fiscal Year 2021-2022

Revenue is further disaggregated into product type below.

Rm	South Africa	International	Corporate and elimination	Total	Safaricom[1]
31 March 2022 – reviewed					
Mobile contract revenue	21 985	1 615	(8)	23 592	4 673
Mobile prepaid revenue	25 171	18 294	–	43 465	28 899
Customer service revenue	47 156	19 909	(8)	67 057	33 572
Mobile interconnect	1 703	1 175	(440)	2 438	1 321
Fixed service revenue	3 847	1 011	(325)	4 533	1 508
Other service revenue	5 820	118	(30)	5 908	1 314
Service revenue[2]	58 526	22 213	(803)	79 936	37 715
Equipment revenue	15 838	373	(7)	16 204	1 925
Non-service revenue	5 990	291	(170)	6 111	346
Revenue from contracts with customers	80 354	22 877	(980)	102 251	*
Interest income recognised as revenue	410	11	–	421	*
Other[3]	64	–	–	64	*
Revenue	80 828	22 888	(980)	102 736	39 985

1. The Group has a 34.94% effective interest in Safaricom Plc (Safaricom) through its subsidiary Vodafone Kenya Limited, which the Group equity accounts for as an investment in an associate at 39.93%. Due to the significance of this investment, and the information available for review by the chief operating decision maker, Safaricom is presented as a separate segment. The above results represent 100% of the results of Safaricom.
2. Includes financial services revenue of R2 665 million for South Africa; R4 961 million for International and R14 452 million for Safaricom.
3. Other revenue largely represents lease revenues recognised under IFRS 16 "Leases".
* Not reviewed by the chief operating decision maker.

Notes: Year ended 31 March 2022

Figure E.15: Safaricom's Financial Statements - Fiscal Year 2020-2021

FINANCIAL STATEMENTS FOR THE YEAR ENDED 31 MARCH 2021

STATEMENT OF PROFIT OR LOSS
AND OTHER COMPREHENSIVE INCOME

		GROUP		COMPANY	
	Notes	2021 KShs'm	2020 KShs'm	2021 KShs'm	2020 KShs'm
Revenue from contracts with customers	5(a)	**261,462.3**	260,463.8	**259,296.3**	259,078.7
Revenue from other sources	5(b)	**2,564.2**	2,091.9	**3,153.4**	2,326.8
Total revenue		**264,026.5**	**262,555.7**	**262,449.7**	**261,405.5**
Direct costs	6(a)	**(80,852.8)**	(75,284.9)	**(80,334.1)**	(75,468.7)
Expected credit losses on financial assets	6(b)	**(3,009.7)**	(1,669.6)	**(3,863.7)**	(1,418.7)
Other expenses	7	**(46,034.8)**	(47,559.7)	**(45,168.6)**	(47,023.1)
Earnings before interest, taxes, depreciation and amortisation (EBITDA)		**134,129.2**	**138,041.5**	**133,083.3**	**137,495.0**
Depreciation of property and equipment	18	**(32,624.5)**	(31,964.8)	**(32,570.4)**	(31,925.3)
amortisation – Indefeasible Rights of Use (IRUs)	19	**(406.5)**	(301.0)	**(406.5)**	(301.0)
amortisation – intangible assets	21	**(1,628.5)**	(1,359.1)	**(1,628.1)**	(1,358.0)
amortisation – Right of Use (ROU) assets	22(a)	**(3,304.8)**	(2,922.8)	**(3,304.8)**	(2,922.8)
Operating profit		**96,164.9**	**101,493.8**	**95,173.5**	**100,987.9**
Finance income	8	**2,198.4**	3,518.8	**2,177.0**	3,494.5
Finance cost	9	**(4,220.8)**	(2,596.6)	**(4,405.5)**	(2,585.5)
Share of (loss)/profit of associates	23(b)	**(192.9)**	60.9	**(192.9)**	60.9
Share of (loss)/profit of joint venture	23(b)	**(314.1)**	3,296.1	**(314.1)**	3,296.1
Profit before income tax		**93,635.5**	**105,773.0**	**92,438.0**	**105,253.9**
Income tax expense	12(a)	**(24,959.3)**	(32,115.1)	**(24,481.4)**	(31,969.7)
Profit for the year attributable to the owners of the Company		**68,676.2**	**73,657.9**	**67,956.6**	**73,284.2**
Other comprehensive income		**–**	–	**–**	–
Total comprehensive income for the year attributable to the owners of the Company		**68,676.2**	**73,657.9**	**67,956.6**	**73,284.2**
Basic and diluted earnings per share (KShs per share)	13	**1.71**	**1.84**	**1.70**	**1.83**

Notes: Year ended 31 March 2021

Figure E.16: Safaricom Company's Revenue Breakdown - Fiscal Year 2020-2021

5 Revenue continued

(a) Revenue from contracts with customers continued

Company	31 MARCH 2021 KShs'm At a point in time	31 MARCH 2021 KShs'm Over time	31 MARCH 2021 KShs'm Total	31 MARCH 2020 KShs'm At a point in time	31 MARCH 2020 KShs'm Over time	31 MARCH 2020 KShs'm Total
Voice revenue	–	82,552.0	82,552.0	–	86,529.9	86,529.9
Interconnect revenue from local partners	–	6,175.2	6,175.2	–	5,039.3	5,039.3
Messaging revenue	–	13,602.4	13,602.4	–	15,403.5	15,403.5
Mobile data revenue	–	44,793.2	44,793.2	–	40,157.5	40,157.5
Fixed data revenue	–	9,507.2	9,507.2	–	8,966.8	8,966.8
M-PESA revenue	80,635.8	–	80,635.8	83,135.6	–	83,135.6
Other Services Revenues*	–	7,624.8	7,624.8	–	7,153.9	7,153.9
Mobile Incoming	–	3,295.2	3,295.2	–	3,442.5	3,442.5
Service revenue	80,635.8	167,550.0	248,185.8	83,135.6	166,693.4	249,829.0
Handset revenue	8,511.7	–	8,511.7	6,631.0	–	6,631.0
Connection revenue	–	1,761.1	1,761.1	–	2,034.8	2,034.8
Construction revenue	–	837.7	837.7	–	583.9	583.9
Total revenue	89,147.5	170,148.8	259,296.3	89,766.6	169,312.1	259,078.7

Service revenue streams have been reclassified to align to new Group reporting needs. Appendix 2 shows the comparative based on old revenues classification.

* Other Services Revenues includes Okoa Jahazi fees, roaming revenues, bulk SMS, digital agriculture revenues.

Notes: Year ended 31 March 2021

Figure E.17: Safaricom Group's Revenue Breakdown - Fiscal Year 2021-2022

5 Revenue

(a) Revenue from contracts with customers

The Group has one reportable operating segment whose revenue is presented below.

Group	31 MARCH 2021 KShs'm At a point in time	31 MARCH 2021 KShs'm Over time	31 MARCH 2021 KShs'm Total	31 MARCH 2020 KShs'm At a point in time	31 MARCH 2020 KShs'm Over time	31 MARCH 2020 KShs'm Total
Voice revenue	–	82,552.0	82,552.0	–	86,529.9	86,529.9
Interconnect revenue from local partners	–	6,175.2	6,175.2	–	5,039.3	5,039.3
Messaging revenue	–	13,602.4	13,602.4	–	15,403.5	15,403.5
Mobile data revenue	–	44,793.2	44,793.2	–	40,157.5	40,157.5
Fixed data revenue	–	9,507.2	9,507.2	–	8,966.9	8,966.9
M-PESA revenue	82,647.4	–	82,647.4	84,438.0	–	84,438.0
Other services revenues*	–	7,779.2	7,779.2	–	7,236.5	7,236.5
Mobile Incoming	–	3,295.2	3,295.2	–	3,442.5	3,442.5
Service revenue	82,647.4	167,704.4	250,351.8	84,438.0	166,776.1	251,214.1
Handset revenue	8,511.7	–	8,511.7	6,631.0	–	6,631.0
Connection revenue	–	1,761.1	1,761.1	–	2,034.8	2,034.8
Construction revenue	–	837.7	837.7	–	583.9	583.9
Total revenue	91,159.1	170,303.2	261,462.3	91,069.0	169,394.8	260,463.8

Service revenue streams have been reclassified to align to new Group reporting needs. Appendix 2 shows the comparative based on old revenues classification.

* Other Services Revenues includes Okoa Jahazi fees, roaming revenues, bulk SMS, digital agriculture revenues.

Notes: Year ended 31 March 2021

Figure E.18: Safaricom's Financial Statements - Fiscal Year 2021-2022

FINANCIAL STATEMENTS FOR THE YEAR ENDED 31 MARCH 2022

Statements of Profit or Loss and other Comprehensive Income

		GROUP		COMPANY	
	Notes	**2022 KShs'm**	2021 KShs'm	**2022 KShs'm**	2021 KShs'm
Revenue from contracts with customers	5(a)	**295,441.4**	261,462.3	**292,556.2**	259,296.3
Revenue from other sources	5(b)	**2,636.5**	2,564.2	**3,289.7**	3,153.4
Total revenue		**298,077.9**	**264,026.5**	**295,845.9**	**262,449.7**
Direct costs	6(a)	**(91,467.8)**	(80,852.8)	**(90,613.6)**	(80,334.1)
Expected credit losses on financial assets	6(b)	**(2,361.2)**	(3,009.7)	**(2,602.7)**	(3,863.7)
Other expenses	7	**(55,187.0)**	(46,034.8)	**(49,545.5)**	(45,168.6)
Earnings before interest, taxes, depreciation and amortisation (EBITDA)		**149,061.9**	**134,129.2**	**153,084.1**	**133,083.3**
Depreciation of property and equipment	18	**(34,145.2)**	(32,624.5)	**(33,922.2)**	(32,570.4)
Amortisation – Indefeasible rights of use (IRUs)	19	**(281.3)**	(406.5)	**(281.3)**	(406.5)
Amortisation – Intangible assets	21	**(1,850.0)**	(1,628.5)	**(1,850.0)**	(1,628.1)
Amortisation – Right-of-use (RoU) assets	22(a)	**(3,656.8)**	(3,304.8)	**(3,644.2)**	(3,304.8)
Operating profit		**109,128.6**	**96,164.9**	**113,386.4**	**95,173.5**
Finance income	8	**2,413.4**	2,198.4	**2,050.1**	2,177.0
Finance costs	9	**(8,852.6)**	(4,220.8)	**(8,895.2)**	(4,405.5)
Share of loss of associates	23(b)	**(279.8)**	(192.9)	**(279.8)**	(192.9)
Share of loss of joint venture	23(b)	**(196.2)**	(314.1)	**(196.2)**	(314.1)
Profit before income tax		**102,213.4**	**93,635.5**	**106,065.3**	**92,438.0**
Income tax expense	12(a)	**(34,717.3)**	(24,959.3)	**(34,276.0)**	(24,481.4)
Profit for the year		**67,496.1**	**68,676.2**	**71,789.3**	**67,956.6**
Attributable to:					
Equity holders of the parent		**69,648.1**	68,676.2	**71,789.3**	67,956.6
Non-controlling interests		**(2,152.0)**	–	**–**	–
Other comprehensive loss:					
Items that will subsequently be reclassified to profit or loss					
Exchange differences on translation of foreign operations		**(9,536.3)**	–	**–**	–
Total comprehensive income for year		**57,959.8**	**68,676.2**	**71,789.3**	**67,956.6**
Attributable to:					
Equity holders of the parent		**64,335.4**	68,676.2	**71,789.3**	67,956.6
Non-controlling interests		**(6,375.6)**	–	**–**	–
Total comprehensive income for year		**57,959.8**	**68,676.2**	**71,789.3**	**67,956.6**
Basic earnings per share (KShs per share)	13	**1.74**	**1.71**	**1.79**	**1.70**
Diluted earnings per share (KShs per share)	13	**1.74**	**1.71**	**1.79**	**1.70**

Notes: Year ended 31 March 2022

Figure E.19: Safaricom Company's Revenue Breakdown - Fiscal Year 2021-2022

5 Revenue continued

(a) Revenue from contracts with customers continued

The Group has one reportable operating segment whose revenue is presented below:

	31 MARCH 2022			31 MARCH 2021		
Company	**KShs'm At a point in time**	**KShs'm Over time**	**KShs'm Total**	KShs'm At a point in time	KShs'm Over time	KShs'm Total
Voice revenue	**–**	**83,211.8**	**83,211.8**	–	82,552.0	82,552.0
Interconnect revenue from local partners	**–**	**6,840.6**	**6,840.6**	–	6,175.2	6,175.2
Messaging revenue	**–**	**10,876.7**	**10,876.7**	–	13,602.4	13,602.4
Mobile data revenue	**–**	**48,441.0**	**48,441.0**	–	44,793.2	44,793.2
Fixed data revenue	**–**	**11,242.5**	**11,242.5**	–	9,507.2	9,507.2
M-PESA revenue	**105,218.1**	**–**	**105,218.1**	80,635.8	–	80,635.8
Other services revenues*	**–**	**9,383.8**	**9,383.8**	–	7,624.8	7,624.8
Mobile incoming	**–**	**3,007.6**	**3,007.6**	–	3,295.2	3,295.2
Service revenue	**105,218.1**	**173,004.0**	**278,222.1**	80,635.8	167,550.0	248,185.8
Handset revenue	**12,334.7**	**–**	**12,334.7**	8,511.7	–	8,511.7
Connection revenue	**–**	**1,999.4**	**1,999.4**	–	1,761.1	1,761.1
Construction revenue	**–**	**–**	**–**	–	837.7	837.7
Total revenue	**117,552.8**	**175,003.4**	**292,556.2**	**89,147.5**	**170,148.8**	**259,296.3**

* *Other services revenues include Okoa Jahazi fees, roaming revenues, bulk SMS, and digital agriculture revenues.*

Notes: Year ended 31 March 2022

Figure E.20: Safaricom Group's Revenue Breakdown - Fiscal Year 2021-2022

5 Revenue

(a) Revenue from contracts with customers

The Group has one reportable operating segment whose revenue is presented below:

	31 MARCH 2022			31 MARCH 2021		
Group	**KShs'm At a point in time**	**KShs'm Over time**	**KShs'm Total**	**KShs'm At a point in time**	**KShs'm Over time**	**KShs'm Total**
Voice revenue	–	83,211.8	83,211.8	–	82,552.0	82,552.0
Interconnect revenue from local partners	–	6,840.6	6,840.6	–	6,175.2	6,175.2
Messaging revenue	–	10,876.7	10,876.7	–	13,602.4	13,602.4
Mobile data revenue	–	48,441.0	48,441.0	–	44,793.2	44,793.2
Fixed data revenue	–	11,242.5	11,242.5	–	9,507.2	9,507.2
M-PESA revenue	107,691.8	–	107,691.8	82,647.4	–	82,647.4
Other services revenues*	–	9,795.3	9,795.3	–	7,779.2	7,779.2
Mobile incoming	–	3,007.6	3,007.6	–	3,295.2	3,295.2
Service revenue	**107,691.8**	**173,415.5**	**281,107.3**	**82,647.4**	**167,704.4**	**250,351.8**
Handset revenue	12,334.7	–	12,334.7	8,511.7	–	8,511.7
Connection revenue	–	1,999.4	1,999.4	–	1,761.1	1,761.1
Construction revenue	–	–	–	–	837.7	837.7
Total revenue	**120,026.5**	**175,414.9**	**295,441.4**	**91,159.1**	**170,303.2**	**261,462.3**

Notes: Year ended 31 March 2022

A Data Appendix F - Subsidy

In this Appendix, we summarize all the subsidy programs in the telecommunications sector that were enacted in African countries. As of today, the telecommunications market in 23 African countries have been subsidized. In the Table below, for each subsidy program we provide its name, the year in which it started, and the link to the webpage contaning the documentation describing the program. These subsidies programs are mostly aimed at promoting telecommunications in rural and peri-urban areas; providing access to electronic communications services, in particular fixed and mobile telephony and Internet, in areas not covered; financing initiatives to make universal access available in geographical areas that are difficult to access; ensuring access to telecommunications services at an affordable price for people living in rural or geographically isolated areas; facilitating the provision of universal access to basic telephony for the unserved and underserved communities.

Table F.1: Subsidy programs to telecommunications in African countries

Country	**Year of introduction of subsidy**	**Name of the subsidy program**	**Link**
Algeria	2018	Fonds d'appui du service universel des communications électroniques	Link
Angola	2010	Fundo de Apoio ao Desenvolvimento das Comunicações (FADCOM)	Link
Botswana	2014	Universal Access and Service Fund (UASF)	Link
Cape Verde	2014	Fundo do Serviço Universal e Desenvolvimento da Sociedade de Informação (FUSI)	Link
Cameroon	2012	Fond Spécial des Télécommunications (FST)	Link
Democratic Republic of the Congo	2002	Fonds de développement des services universels (FDSU)	Link
Gabon	2001	Fonds spécial du service universel des télécommunications	Link
Ghana	2006	Ghana Investment Funf for Electronic Communications (GIFEC)	Link
Kenya	2017	Universal Service Fund (USF)	Link
Malawi	2019	Universal Service Fund (USF)	Link
Morocco	2005	Fonds du Service Universel des Télécommunications (FSUT)	Link
Mozambique	2006	Fundo do Serviço de Acesso Universal (FSAU)	Link
Namibia	2009	Universal Service Fund	Link
Nigeria	2006	Universal Service Provision Fund (USPF)	Link
Republic of the Congo	2019	Fonds pour l'Accès et le Service Universels des Communications Électroniques (FASUCE)	Link
Senegal	2011	Fonds de Développement du Service Universel des Télécommunications (FDSUT)	Link
Sierra Leone	2019	Universal Access Development Fund (UADF)	Link
South Africa	1999	Universal Service and Access Fund (USAF)	Link
South Sudan	2019	Universal Service and Access Fund (USAF)	Link
Tanzania	2010	Universal Communications Service Access Fund (UCSAF)	Link
Togo	2001	Fonds du service universel	Link
Uganda	2003	Rural Communications Development Fund (RCDF)	Link
Zambia	2009	Universal Access and Service Fund (UASF)	Link

Emigration Restrictions and Economic Development: Evidence from the Italian Mass Migration to the U.S.

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Abstract

This article studies the impact of immigration restriction policies on technology adoption in countries sending migrants. Between 1920 and 1921, the number of Italian emigrants to the United States dropped by 85% after Congress passed the Emergency Quota Act, a severely restrictive immigration law. In a difference-in-differences setting, we exploit variation in exposure across Italian districts to this large restriction on human mobility. We show that this policy hampered technology adoption and capital investment by using individual-level data on Italian emigration to the US and newly digitized historical censuses. This evidence is consistent with directed technology adoption theory: an increase in the labor supply dampens the incentive for firms to adopt labor-saving technologies. To validate this mechanism, we show that more exposed districts display a sizable increase in overall population and employment in manufacturing. We document that "missing migrants," whose migration was inhibited by the Act, drive this result.

Keywords: Age of Mass Migration, Emigration, Technology Adoption

JEL Codes: N34, O15, O33

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1 Introduction

Technology adoption constitutes a key driver of economic growth in developing countries, which operate far from the technology frontier (Suri, 2011; Bryan et al., 2014).[38] This paper examines how out-migration—a typical feature of industrializing economies—influences the incentive for firms in developing countries to adopt productivity-enhancing technologies. Specifically, we investigate how restrictions to human mobility imposed by immigration countries influence technology adoption in the emigrants' countries of origin.[39]

The effects of out-migration on technology adoption are *ex-ante* ambiguous and potentially conflicting. On the one hand, emigration entails a loss of human capital—a "brain drain"—that may hamper the ability of countries to adopt new technologies (Kwok and Leland, 1982; Gibson and McKenzie, 2011). On the other, however, higher emigration rates may incentivize the adoption of labor-saving technologies by increasing the relative cost of labor (e.g., see Habakkuk, 1962; Hicks, 1932 [1963]). From the directed technical change theory perspective, one can interpret immigration restriction policies (henceforth, IRPs) as "passive" labor market policies that increase the labor supply in targeted countries. These positive labor supply shocks would, in turn, prompt the substitution of capital with more abundant—hence cheaper—labor, thus depressing investment in capital-intensive technologies. Which effect prevails is, ultimately, an empirical question.

We study the Italian mass migration, the largest episode of voluntary migration from one single country in recorded history (Choate, 2008). Between 1876 and 1924, approximately thirteen million emigrants left Italy (nearly 70% of the average Italian population

[38] Economic historians have famously recognized that countries that industrialized relatively late, such as Germany or Italy, relied heavily on innovation produced abroad to catch up with the core industrial countries (Gerschenkron, 1962; Rosenberg, 1982). Recent literature within the tradition of endogenous growth theory embeds technology diffusion dynamics and quantifies its—substantial—contribution to productivity growth (e.g. Eaton and Kortum, 1999; Alvarez et al., 2013; Buera and Oberfield, 2020; Van Patten, 2023).

[39] For brevity, we refer to those policies as immigration restriction policies (IRPs). Data from de Haas et al. (2015) suggest that IRPs have become increasingly common since the 1970s and currently account for 40% of the entire corpus of migration laws.

in 1900); about half never returned. Italy had one of the highest emigration rates and, since the 1890s, it was the leader in sheer emigration numbers (Hatton and Williamson, 1998). On average, 40% emigrants headed toward the United States, the single most common destination country and the focus of this paper. However, the Italian mass migration to the United States abruptly ended in 1921 when Congress passed the first of two restrictive IRPs that we collectively refer to as the "Quota Acts." The Quota Acts defined numerical quotas on yearly arrivals from European countries, which drastically reduced the number of Italians entering the United States.[40] Between 1920 and 1921, the inflow of Italians in the US dropped by 85% and never recovered (see Figure 1). A follow-up tightening policy was imposed in 1924. We exploit variation arising from this sharp and massive restriction to human mobility.

Throughout this period, a group of countries, including Italy, underwent a first wave of industrialization and structural change as part of a broader transformational phenomenon known as the "Second Industrial Revolution" (Mokyr, 1998). The Italian economy, in particular, outperformed the leading industrial countries for the first time between 1895 and 1913. The postwar years, especially the Fascist period, however, were marked by economic stagnation and languishing productivity growth. The economic divide between Northern and Southern areas, which had started to narrow during the economic boom, severely widened during the 1920s and 1930s (Cohen and Federico, 2001). Previous scholarship documents that insufficient investments, especially in the South, hampered the adoption of productivity-enhancing technologies. In this paper, we argue that scarce investments partly came as a consequence of the post-1921 restrictive US immigration policy, which, therefore, plausibly contributed to the widened economic gap between the North and the South of the country and, more generally, to the disappointing performance of the Italian economy.

To identify the effect of the American immigration restriction policy shock on Italian

[40]The 1921 Emergency Quota Act restricted the annual number of immigrants admitted into the US to no more than 3% of the number of residents from that country, as recorded in the 1910 census. The 1924 Johnson-Reed Act reduced the quota to 2% and pegged the reference date to the 1890 census. These laws explicitly targeted Southern and Eastern European countries, which until the early 1900s hardly took part in the Age of Mass Migration and whose immigrants were perceived by the public as a threat to America's economic welfare and cultural values (Higham, 2002).

economic development, we define a district in Italy as more exposed to the Quotas if a larger proportion of its emigrants had moved to the United States before 1921, conditional on the overall number of international emigrants. In a difference-in-differences setting, we thus compare districts located in areas with similar emigration outflows and leverage variation among destination countries.[41] Formally, our identification assumption requires that districts with similar volumes of international emigrant outflows but whose emigrants headed toward different destinations would not have undergone diverging development trajectories in the absence of the Quota Acts. We provide a battery of checks to ensure the plausibility of this assumption, but ultimately, we cannot test the conditional exogeneity of treatment intensity. We thus adapt the shift-share instrumental variable design developed by Card (2001) to construct plausibly random variation in the intensity of exposure to the Quotas across Italian districts. The instrument predicts district-level emigration to the US over time by interacting the initial migration flows between Italian districts and US counties with subsequent non-Italian immigration inflows across US counties. The "naïve" and the instrumented difference-in-differences designs yield quantitatively highly consistent results.

The historical setting allows us to overcome several limitations of contemporary scenarios. First, emigration seldom flows into only a few destinations; hence, observing significant restrictive policy shifts is challenging. Second, migration dynamics are often affected by co-evolving regulations enacted by both receiving and sending countries, which were absent during the period we study (Abramitzky and Boustan, 2017). Third, it is often difficult to retrieve information on emigrants in their home country (Dustmann et al., 2015).

Existing data from official statistics are not suitable for this exercise because (i) digitized US and Italian censuses and complementary historical statistics do not report the origin of Italian migrants at a granular level of spatial aggregation, and (ii) disaggregated indicators of economic performance for Italy remain scarce during this period. We thus construct a dataset that links the administrative records of Italian emigrants who arrived

[41] This intensity-of-treatment design is closely related to the conceptual framework adopted by Abramitzky et al. (2023) to study the effect of the Quota Acts on the US labor market.

at Ellis Island between 1892 and 1930 to their district of origin, we match a subset of these records to the US full-count population census, and we complement it with newly digitized detailed data from industrial and population censuses.

The empirical analysis proceeds in three steps. First, we establish that the Quota Acts had a tangible impact on Italian districts. Theoretically, it is possible that those who would have migrated to the United States in the absence of the policy shift could move to a different country. Looking at aggregate emigration numbers (Figure 1), this seems implausible. Emigration to the United States completely dried up after 1921, but emigration to other countries did not. The total number of emigrants in the 1920s is roughly comparable to that in the 1880s and early 1890s before the US migration gained momentum. We formally test this "imperfect substitution" argument and find that the population in districts that were conditionally more exposed to the Quota Acts increases after 1921. The effect of the Quotas on the Italian population is sizable in magnitude. A 1% increase in the number of US emigrants leads to a 0.04% increase in population. Equivalently, moving from the 50th to the 75th percentile of the distribution of exposure to the policy yields almost 9,000 additional population, relative to an average pre-Quota population of approximately 161,000. This finding is consistent with previous studies documenting the spatial persistence of Italian emigration flows (Gould, 1980b; Brum, 2019; Spitzer et al., 2020). More qualitative cross-country evidence confirms that emigration outflows toward countries that did not promulgate IRPs did not increase. Hence, districts supplying relatively more U.S.-bound emigrants ended up having more "missing" migrants, i.e., people who would have migrated had the Quota Acts not been enacted. This mechanism generates a spatially segmented positive labor supply shock.

Our second finding is that manufacturing firms in provinces more exposed to the Quota Acts substantially decreased investment in capital goods. We consistently estimate adverse effects across several measures of capital goods, ranging from firms with at least one engine to the number of installed engines and the power they generate. For instance, a 1% increase in US emigration yields a 0.126% decrease in the horsepower generated by mechanical engines and a 0.216% drop in the energy generated by electrical ones.

All sectors within manufacturing exhibit similar decreases in capital investment. How can we reconcile the increasing population with the decreasing adoption of productivity-enhancing production technologies? We propose interpreting these findings through the lens of directed technological change theory (Acemoglu, 2002, 2007). As labor becomes a more abundant production input, firms are incentivized to forego investment in capital goods and employ more labor. In Online Appendix A, we develop a simple theoretical framework in the spirit of Zeira (1998) and San (2023) to show why investment in labor-saving technologies would decrease in response to a positive labor supply shock.

To test this interpretation, we study how employment across sectors reacted to the Quota Acts. First, we explore how agriculture and manufacturing employment responded to the policy shock at the district level. We find that manufacturing employment increases in districts more exposed to the IRP shock. Quantitatively, a 1% increase in instrumented US emigration yields a 0.071% increase in manufacturing employment while the effect on agriculture employment—a 0.017% decrease—is not statistically significant. Historical evidence suggests that Italian agriculture in the 1920s was organized as a heavily labor-intensive sector (Cohen and Federico, 2001). It thus seems plausible that manufacturing could be the primary beneficiary of the substantial labor supply shock. Second, we look at how different sectors within manufacturing absorbed the population increase. Analogous to the capital results, we estimate comparable increases in manufacturing employment across industries. Thus, the aggregate and sector-level employment and capital responses to the IRP shock are consistent with the predictions of the directed technical change conceptual framework.

Overall, this paper documents that policies enacted by immigration countries to curtail migrant inflows bear important consequences on countries sending migrants. Foregone emigration, in fact, generates a positive labor supply, which, in turn, dampens technology adoption, thus potentially hampering their long-run prospects of economic growth. Despite the peculiarities of the historical setting, we discuss that the Italian migration to the United States shares similarities with contemporary emigration episodes between developing and developed countries, thus highlighting the policy relevance of our findings.

Related Literature. This paper is related to three streams of literature. First, we speak to the several contributions investigating the impact of emigration on sending countries, as opposed to the larger literature studying the economic and social effects of immigration (Clemens, 2011). Emigration has been shown to impact wages (e.g., Dustmann et al., 2015), attitudes towards democracy and voting (Spilimbergo, 2009; Batista and Vicente, 2011; Ottinger and Rosenberger, 2023) and political change (Chauvet and Mercier, 2014; Kapur, 2014; Karadja and Prawitz, 2019), the diffusion of novel knowledge (Coluccia and Dossi, 2023), entrepreneurship (Anelli et al., 2023), and social norms (Beine et al., 2013; Bertoli and Marchetta, 2015; Tuccio and Wahba, 2018). We inform this literature by showing that emigration fosters the adoption of labor-saving technologies. We emphasize that this channel operates plausibly independently from human capital accumulation. In addition, we document that this mechanism arises in response to restrictive immigration policies enacted by receiving countries.

Second, we contribute to the literature that studies the relationship between technology adoption and the supply of production inputs. Following the seminal contributions by Hicks (1932 [1963]) and Habakkuk (1962), Hornbeck and Naidu (2014), Clemens et al. (2018), and Hanlon (2015) all study historical settings where changes in the availability of labor and other factors of production altered the direction of innovation activity. Lewis (2011) offers similar evidence in a modern setting. Our paper is closest in spirit to Andersson et al. (2022), who show that labor-saving innovation emerged in response to migration-induced labor shortages in 19th-century Sweden. We present several novel findings relative to their paper. First, we show that immigration restriction policies generate a positive labor supply shock in emigration countries because potential emigrants do not fully substitute the restricted destination with other countries. Second, we document that a *positive* labor supply shock depresses investment in capital technology. In principle, since a positive labor supply shock may sustain aggregate demand, its impact on investment is ambiguous. Our results, therefore, highlight the centrality of directed technical adoption incentives for firms' decision-making. Third, instead of innovation, we focus on technology adoption, which is the core driver of economic growth and modernization in developing countries (Suri, 2011; Bryan et al., 2014; Juhász et al., 2020). Finally, the episode we study allows us to implement a difference-in-differences estimation strategy whose identification assumption can be evaluated transparently.

Third, by its setting, this paper adds to the literature that studies technical change and the diffusion of novel technologies during the Age of Mass Migration. A growing number of papers examines the short-run (Arkolakis et al., 2020; Moser and San, 2020; Diodato et al., 2022) as well as the long-run (Akcigit et al., 2017; Burchardi et al., 2020; Sequeira et al., 2020) implications of immigration on US innovation. Moreover, we contribute to studies examining the archetypal Italian case of mass migration. Among those, Hatton and Williamson (1998) study the aggregate determinants of Italian emigration. Spitzer et al. (2020) validate the Gould (1980a) theory, whereby social networks exerted substantial influence on Italian emigration dynamics. Pérez (2021) compares the assimilation dynamics of Italian emigrants to the United States with those who moved to Argentina. Our contribution to this literature is twofold. Methodologically, we present newly digitized district-level data from Italian population and industrial censuses. In terms of new findings, we show that the mass migration was unlikely to have hampered the structural shift toward manufacturing. Our results suggest that the opposite impact prevailed: immigration *restriction* likely hampered economic modernization in Italy.

Outline of the paper. We structure the paper as follows. Section 2 describes the Italian mass migration, the policies that shaped it, and the fundamental economic characteristics of early 20$^{\text{th}}$-century Italy. Section 3 discusses our data-collection contribution and the sources. Section 4 describes the difference-in-differences and instrumental variable strategies. In Section 5, we present our three sets of results. Section 6 concludes.

2 Historical Background

2.1 The Italian Mass Migration

The Italian mass migration (1870–1925) was the largest episode of voluntary migration in recorded history (Choate, 2008). Between 1880 and 1913, 17 million —corresponding to 65% of the Italian population in 1900—emigrated; most headed toward continental Europe and the Americas. Along with Ireland, Italy had the highest per capita emigration rate (Taylor and Williamson, 1997). Even though Bandiera et al. (2013) document that returns rates were equally among the highest in Europe, the Italian mass emigration has long been recognized as a focal feature of the country's development process (Hatton and Williamson, 1998).

2.1.1 A Short History of the Italian Mass Migration

Italy was a latecomer to large-scale mass migration. Northern European countries had been experiencing substantial population outflows since the 1840s. By contrast, Italy and other Southern and Eastern European countries didn't start experiencing mass emigration until the 1880s. The country's migration patterns over 1870–1925 display substantial time variation. Until the 1880s, its emigration rate remained relatively modest, and most migrants hailed from Northern regions. Prohibitively high transportation costs and prevailing poverty in rural Southern areas largely inhibited migration from the *Mezzogiorno*. During the 1880s, Northerners chiefly moved to neighboring countries on a temporary, seasonal basis (Sori, 1979). The widespread adoption of steamships and an agrarian crisis kicked off the Southern mass emigration (Keeling, 1999). A decade later, the script had flipped: most migrants were now coming from Southern regions. Though the share of migrants from Northern regions declined as the share from Southern regions grew, emigration rates from *both areas* rose steadily from 1870 to 1913 (Hatton and Williamson, 1998). By the 1890s, Italy had become the global leader in sheer numbers of emigrants and in emigration rate, which grew from 5‰ in 1880 to a peak of 25‰ in 1913.

Italian emigration collapsed during World War 1 (WW1) but quickly regained momentum in the years immediately following the war. The epoch ended in the early 1920s when the U.S. Congress enacted restrictive immigration policies that effectively halted mass emigration to the United States. Emigration toward other transoceanic and European destinations nonetheless endured until the outbreak of WW2. In Online Appendix Table B.2, we tabulate data from official statistics on regional out-migration to the United

States and other international destinations to gauge the geographical evolution of the Italian mass migration over time.

Internal migration is one last, largely overlooked component of labor mobility in Italy during the Age of Mass Migration. Current data limitations hinder a quantitative study of internal migration from 1870 to 1925. In the rest of this study, we abstract from explicitly accounting for internal migrations for three reasons (beyond data availability). First, Gallo (2012) shows that internal migrants were easily outnumbered by international migration flows, particularly during the Age of Mass Migration. We provide a quantitative assessment of this claim in Online Appendix Table B.3, which confirms that the number of international emigrants is one order of magnitude larger than that of internal migrants. Second, internal mobility was largely temporary and seasonal, inherently different from transoceanic migration (Gallo, 2012). Third, internal migrations reflected historically deep-rooted, persistent economic relationships between regions unlikely to influence our results on economic modernization in the 1930s.

2.1.2 Composition and Determinants of the Migratory Movements

In the 1880s, Italy was a young nation rife with regional disparities spanning cultural and economic dimensions (Smith, 1997). The resulting geographically segmented migratory patterns largely reflected this substantial heterogeneity and provided our empirical strategy's backbone. Until the early 1880s, most migrants from Northern regions moved to European countries. Most of the rest steamed across the Atlantic to Argentina and Brazil. This pattern is completely reversed for Southern migrants, whose primary destination was the United States.

To explain why destinations with low relative wage gaps, such as Argentina and Brazil, received sizeable migration inflows, Gould (1980b) hypothesizes that local emigration dynamics were driven by information diffusion. Information about emigration opportunities required time to spread across the country, and this diffusion accelerated as the volume of emigration increased. Gould (1980b) provides convincing evidence suggesting that declining regional emigration-rate inequality is consistent with this mechanism. An indirect consequence of the Gould hypothesis is that local emigration rates displayed relatively little sensitivity to economic and demographic conditions, instead featuring high persistence (Hatton and Williamson, 1998). Spitzer and Zimran (2023) further provide evidence consistent with Gould's diffusion hypothesis. They show that emigration began in a few districts in the 1870s and 1880s and subsequently spread to nearby districts over time through immigrants' social networks. In Online Appendix A.3.3, we present some evidence that points in the same direction.

2.2 Migration Policy in Italy and the United States

An appealing feature of this context is that migratory flows from Europe to the United States remained essentially unregulated until 1921 (Abramitzky and Boustan, 2017). This section describes the key features of the historical Italian and U.S. systems of migration laws.

2.2.1 Italian Emigration Policy

Newly unified Italy had virtually no emigration policy until 1873. Occasional, largely ineffective provisions were enacted between 1873 and 1887 that reflected the perceived need to deal with labor agents and recruiters, the so-called *padroni*, but did not form a corpus of migration law (Gabaccia, 2013). The first such attempt was the 1888 Crispi-De Zerbi law, which introduced and regulated the emigration contract between the migrant and the migration agency. However, the law was manifestly inadequate to deal with the waves of migration that unfolded starting in the 1890s, and it effectively failed (Foerster, 1919).

As emigration to the United States gained momentum, a new law was passed in 1901 under the renewed understanding that emigration was no artificial phenomenon and could positively affect Italy (Foerster, 1919). As such, the law sought to protect migrants from exploitation rather than restricting their movement. The law established a Commissioner-General of Emigration to oversee the protective institutions and collect migrant data. Only companies licensed by the Commissioner-General could sell tickets, whose rates were reset every three months. Comparatively minor subsequent legislation further protected remittances (1901), strengthened the authority of the Commissioner-General (1910), and regulated citizenship (1913) (Rosoli, 1998).

2.2.2 American Immigration Policy

The United States, for its part, maintained an open border between 1775 and the early 1920s, interrupted only by isolated outbreaks of anti-immigration policy interventions. During the Age of Mass Migration, some 30 million migrants entered the United States. By 1910, 22% of the labor force was foreign-born, the highest share ever since (Abramitzky and Boustan, 2017). In 1907, the United States Congressional Joint Immigration Commission, also known as the Dillingham Commission after its chairman, was formed to study, among other things, immigrants' economic and social conditions. The Commission's 41-volume report favored "old" immigration countries such as England and Germany over "new" ones, mainly Southern and Eastern Europe.

When immigration ramped up again after WWI, nativist demands for restrictions surged, and the Emergency Quota Act was passed in 1921. It was modified by the 1924 Immigration Act, which further tightened immigration restrictions on second-wave countries. The 1921 Emergency Quota Act envisaged a (temporary) annual quota of 360,000 immigrants from Europe.[42] Importantly, for our identification, entry quotas were assigned to each country as 3% of that country's nationals living in the United States in 1910, as recorded in that year's census. The 1924 Immigration Act made the quota system permanent, lowered the inflow from 3% to 2%, and shifted the census baseline year to 1890. The last provision, in particular, targets Southern and Eastern European countries that took part in the Mass Migration starting in the late 1890s, as advised by the report of the Dillingham Commission. Abramitzky et al. (2023) note that the impact of the 1924 Immigration Act on immigration was highly heterogeneous across sending countries. Flows from Southern and Eastern Europe were heavily curtailed because the share of foreign-born individuals from those countries who lived in the United States in

[42] U.S. immigration peaked in 1907 at 1,285,349 entrants. The number of entrants during the 1910s averaged around 800,000.

1890 was very modest. Since the 1890s, the United States had been absorbing 30% to 40% of all Italian emigration, so the Quota Acts represented a significant policy shock for Italy.

2.3 Technology Adoption and Economic Growth in Italy

Italy entered the Age of Mass Migration in the 1880s. The country was amid an agrarian crisis that followed two decades of stagnation (Toniolo, 2014). The period from 1895 to 1913 was the only time until the 1950s "economic miracle" in which Italy outperformed and narrowed the income gap with the leading industrial nations. Still in the 1920s and 1930s, however, during the Fascist period, Italy remained a mainly agricultural country, featuring low income per capita and languishing productivity growth (Cohen and Federico, 2001). During the first half of the Fascist *Ventennio*, economic policy was aimed primarily at fiscal and monetary consolidation. Agricultural policy—which formed an integral part of the Fascist propaganda—centered on boosting agricultural productivity, which had been stagnating since WW1, and draining marshlands. However, sheer numbers attest that agrarian policies resulted in neither substantial intervention nor sizeable progress (Zamagni, 1993). Growth slowed after 1925, and regional disparities widened (Cohen and Federico, 2001). Historical evidence is thus consistent with our finding that following the 1921–1924 U.S. emigration restrictions, Italy underwent a period of economic distress and rising North-South economic inequality.

We relate the migration shock to diminished investment in capital goods, especially technologically advanced ones, and a shift to labor-intensive production routines. Italy operated far from the technological frontier throughout the period, and skill premia *declined* from the 1890s onward (Vasta, 1999). Similarly to contemporary developing countries, Italy lagged behind advanced industrial nations in research-and-development expenditures, and it imported substantial amounts of foreign technology, both patents and machinery. Italian firms bundled different vintages of capital whenever possible, adding new machines to existing ones instead of renovating the whole stock (Cohen and Federico, 2001). The large pool of unskilled workers made it more profitable for Italian entrepreneurs to adopt labor-intensive technologies relative to the highly capital-intensive German and British ones. Consistent with this narrative, the migration policy shock increased the stock of unskilled workers in regions with high emigration. There, firms opted out of investment in capital goods and became more labor-intensive, thus hampering the modernization process they had been undergoing before the Quota Acts.

3 Data

Our analysis spans the years 1881 to 1936. We collect data from several sources; data are organized by census years and analyzed at the *circondario* (henceforth, "district") level if available. Otherwise, the units of observation are provinces.[43] In 1921, there were 216 districts and 69 provinces, each consisting of a variable number of municipalities (see Online Appendix section A.1 for a complete description of the data). Because districts were abolished in 1927, all subsequent district-level data are collected at the municipality level and aggregated at the 1921-district boundaries. We adopt the geographical crosswalk procedure described by Eckert et al. (2020) to ensure that we work with consistent 1921-border district and province geographies. Table 1 reports summary statistics for the variables in our final dataset. Online Appendix Table A.1 lists the source and coverage of each variable in the final dataset.

3.1 Emigration Data

Italian official emigration statistics provide insufficient information because out-migration flows by destination were recorded at the province level (Hatton and Williamson, 1998). This poses a major challenge because we would rather work with more granular geographical units than provinces whenever possible. This limitation precludes the use of

[43] Population censuses were taken in 1881, 1901, 1911, 1921, 1931, and 1936. Manufacturing censuses were taken in 1911, 1927, and 1936. Districts were instituted in 1859 as the middle administrative unit between municipalities and provinces. They had mainly statistical and judiciary purposes and were granted little administrative autonomy. Districts were organized in provinces, which encompassed one to five districts. In the Online Appendix section A.1, we discuss the sources we digitized in more detail and present a visual summary of all the variables we analyze. In Online Appendix A.2, we describe how the final estimation samples are constructed.

official statistics for a spatially-detailed econometric exercise. In addition, official statistics typically relied on issued passports, which were not required to emigrate to the US. We nonetheless digitize province-level emigration outflows from official statistics and use them to construct overall emigration rates and validate the series we derive from the individual dataset we assemble.[44]

To overcome these issues, we collect administrative records of Italians who entered the country between 1890 and 1930 through the Ellis Island immigration station.[45] This was by far the largest, though not the only, immigration gateway during this period.[46] Administrative records report, for most migrants, name and surname, year of arrival, age, municipality of origin, and sailing ship. This study concentrates on the migration year and the municipality of origin. Ultimately, we collected approximately 2.7 million individual observations from 1890 to 1930.

The municipality variable displays frequent coding errors. We perform manual and automated trimming of the raw data and geo-code each municipality to precise geographical coordinates. We can match 1.6 million migrants to their municipality of origin. Among those, 800,000 municipalities are coded with no error. We then map each municipality to the district it belonged to in 1921 through historical GIS boundary files and compute the resulting aggregate U.S. emigration.[47] To the best of our knowledge, the Ellis Island repository is the most comprehensive source spanning the whole Age of Mass Migration for Italy at this level of aggregation.[48] Similar data have been assembled by Gray et al. (2019) and Spitzer and Zimran (2023).[49] Spitzer and Zimran (2018) relied on a small

[44] We construct district-level emigration rates from official statistics. To compute a district's emigration rate, we multiply the province-level number of emigrants by the share of that district's population. In other words, we assume that the emigration rate is constant among districts in the same province.

[45] These records are freely available at `heritage.statueofliberty.org`. We run queries over a comprehensive pool of 20,000 Italian surnames over the 1890–1930 period. In Online Appendix section A.3.2, we document that our constructed series correlates well with existing—albeit less granular—emigration data from official statistics.

[46] According to official U.S. statistics, between 1892 and 1924, a total of 14,277,144 migrants entered the country through Ellis Island, out of a total immigration inflow of 20,003,041 (Unrau, 1984, p. 185). Thus, Ellis Island alone accounted for 71.4% of the total immigrant inflow. Some 95% of all Italian immigrants passed through Ellis Island.

[47] Appendix A.3.1 discusses the methodological details, including the frequency of missing data on immigrants' municipality of origin.

[48] Brum (2019) produced a similar dataset for the pre-1900 period.

[49] Compared to Gray et al. (2019), who list 4.8 million observations, we recover a smaller proportion of migrants because we do not allow for fuzzy matches. This choice is motivated by the fact that the fuzzy

subset of the overall Ellis Island data in their seminal contribution. We validate this dataset with coarser data available from official statistics as detailed in Online Appendix A.3.2. There is a positive, statistically significant, and large correlation between the Ellis Island data and official statistics, which remains stable throughout the estimation period.

To conduct a Bartik-type instrumental variable analysis, we link the individual-level Ellis Island immigration records for 1895–1900 with the full-count US population census (Ruggles et al., 2021). To our knowledge, ours represents the first attempt at linking census records with the Ellis Island administrative data. Concretely, we link individuals with records of Italians who appear in the 1900 census on their name, surname, and immigration year. We detail the procedure in Online Appendix section A.3.4. Using this linked sample, we attach a municipality of origin to Italian migrants, allowing us to compute migration flows from Italian districts to US counties.

Figure 1 plots the overall country-level yearly inflow of immigrants who landed in Ellis Island from 1892 to 1930. Emigration took off in the mid-1890s and peaked between 1905 and 1913. It collapsed during World War 1 (WW1), quickly regained momentum in 1920, and was definitively shut down by the Quota Acts in 1921 and 1924. Our data are consistent with comprehensive U.S. immigration data and overall Italian migration patterns (Brum, 2019; Sequeira et al., 2020). In Figure 2, we plot the geographical distribution of migrants across districts. Panel 2a displays the number of international emigrants across provinces. Panel 2b reports the volume of US out-migration across districts. Out-migration flows exhibit substantial dispersion across provinces and are not clustered in any specific area of the country. Emigration to the United States appears to be more clearly concentrated in Southern districts. Online Appendix A.3.3 presents further stylized facts that the data allows documenting.

match tool provided by the database search engine returns very distant and only vaguely similar results for the given queried surname. By only including exact matches, we ensure that our database does not comprise these (potentially) spurious observations.

3.2 Population and Manufacture Censuses

The Italian Statistical Office (ISTAT) compiled the population of each municipality from the historical population censuses. We aggregate these tabulations by district and province for each census between 1881 and 1936.[50] We compute the k-urbanization rates as (i) the share of the population residing in cities with at least k-thousand inhabitants and (ii) the share of cities with at least k-thousand inhabitants. These tables also contain the altitude and area of each municipality and an indicator variable returning value one for towns near the sea. We collapse the first two at the district and province levels, weighting them by municipality population and tagging districts and provinces with access to the sea.

We construct manufacturing and agriculture employment series from disaggregated data listed in census records. These are available at the district level before 1921 and the municipality level afterward. For consistency, we recast them at the district level throughout the sample period. Employment in agriculture was not reported in the 1931 population census. Until 1921, population censuses contain sector-level employment data for manufacturing firms at the district level. After that, the same variables are reported in the manufacturing census at the province level. Thus, we can observe sector-level manufacturing employment at the province level throughout the sample period.

Manufacturing censuses contain detailed information on the quantity and quality of capital employed in each province by manufacturing firms in 1911, 1927, and 1937. We collect within-manufacturing sector-level data on (i) the number of operating firms, (ii) the number of operating firms employing inanimate horsepower, (iii) the number of mechanical engines, (iv) the number of electrical engines, (v) the amount of horsepower generated by mechanical engines, and (vi) the amount of horsepower generated by electrical engines. We distinguish between electrical and mechanical engines because the former were at the forefront of technological progress (David, 1990). This allows us to disentangle the possibly differential impact of the labor supply shock induced by the migration shock on

[50] Popoulation censuses were taken in 1881, 1901, 1911, 1921, 1927, and 1936. Manufacture censuses were taken in 1911, 1927, and 1936. Data in manufacturing censuses are only available at the province level.

different technology vintages.

3.3 Other Data

Italy participated in WWI between 1915 and 1918. Because the war took place between two census years and ended just three years before the Emergency Quota Act, it can potentially confound our estimates. We, therefore, collect WW1 death records to measure the geographical variation in the cost imposed by the war across districts.[51] The dataset provides rich information on Italian military personnel who died during WWI. Importantly for our analysis, it includes the municipality of origin of each soldier. Because we conduct the analysis at the district level, we collapse the dataset from municipalities to 1921 districts, and we measure the war's severity in a given district as the ratio between deaths and population in 1910.

In robustness checks, we use aggregate information on US GDP and industrial production as further controls. These are constructed by Maddison (2007) and Davis (2004), respectively.

To account for changes in market access, we digitize the entire Italian railway network over the 1839–1926 period.[52] We know all the stations it is connected to for each railway section. Stations are generally labeled according to the municipality in which they are located. Further details are included for stations located in municipalities with more than one station. We also know the exact date when each trunk was built and opened to public use, the distance it covered, and the train's traction system. We use these data to construct the Italian railway network. To capture its evolution over time, we take snapshots of the network at decade frequency.

[51] Death records were compiled by the Fascist regime for propaganda purposes. They are available at cadutigrandeguerra.it. This dataset is maintained by the *Istituto per la storia della Resistenza e della società contemporanea*. Acemoglu et al. (2022) were among the first to use it in the economics literature.

[52] The data come from the volume *Sviluppo delle ferrovie italiane dal 1839 al 31 dicembre 1926*, edited by the Italian Statistical Office (*Ufficio Centrale di Statistica*) in 1927. To our knowledge, this is the first paper to use these data. Compared to Ciccarelli et al. (2021), we do not have access to the geography of historical railway routes as we only digitize the list of stations and the year when each trunk was opened. The advantage of our data is that we can reconstruct the network until 1924, which marks the end of the transatlantic emigration, while previous studies focus on the period until 1913.

4 Empirical Strategy

This section presents the empirical strategy we adopt to identify the effects of the Quota Acts and provides evidence supporting the research design's validity.

4.1 Measuring Exposure to the Quota Acts

The empirical analysis hinges on the observation that areas whose emigrants were more likely to settle in the United States before 1921 would be more exposed to the Quota Acts. This implicitly assumes that emigrants do not perfectly substitute the United States with other—internal or international—destinations. The first step of the analysis validates this assumption.

In principle, districts with more emigrants headed toward the United States before 1921 would be relatively more exposed to the Quota Acts shock. However, if we were to leverage unconditional variation in the number of US emigrants, we would compare districts with very different pre-treatment emigration intensities. If the decision to emigrate were correlated with other—possibly unobserved—characteristics, then the resulting estimates would conflate this underlying spurious association.

Our identification strategy tackles this issue explicitly. To estimate the impact of the Quota Acts on Italian economic development, we compare districts located in provinces with similar volumes of international emigrants and leverage variation in the volume of emigration flows towards the United States. Both variables are computed as the cumulative number of people who emigrated between 1892 and 1921. Before 1892, the officials at Ellis Island did not record the municipality of origin. We set 1921 as the final year because, in 1921, the United States enacted the first restrictive Quota Act.[53] Formally, we thus leverage variation in the number of emigrants towards the United States, conditional on the overall intensity of international emigration outflows.

[53]In several robustness checks, we further restrict the sample period to exclude the years 1892–1900, when municipalities in the Ellis Island dataset are recorded less frequently, the war years (1915–1918), and the post-war period (1915–1924). The results remain quantitatively unchanged through these different sample restrictions.

4.2 Baseline Difference-in-Differences Model

Throughout the paper, we estimate variations of the following double-differences (DiD) Poisson quasi-maximum likelihood model (PQML):[54]

$$\begin{aligned} \ln \mathbb{E}\left(y_{it} \,|\, \mathbf{X}_{it}\right) = \alpha_i + \beta_t + \gamma \times \text{Emigrants}_{p(i)} \times \mathrm{I}(t \geq 1921) + \\ + \sum_{\tau \neq 10} \delta_\tau \times \text{US Emigrants}_i \times \mathrm{I}(t = 1921 - \tau), \end{aligned} \tag{1}$$

where $\mathbb{E}(\cdot)$ denotes the expected value of a generic outcome y conditional on a set of baseline controls $\mathbf{X}$; terms α_i and β_t capture, respectively, unit and time fixed effects, and $\mathrm{I}(\cdot)$ are indicators for each period since the Quota shock. The term (US Emigrants) is the log number of migrants who left district i and moved to the United States between 1892 and 1921. The baseline period is the year of the last census before the Quotas (1911).

In (1), we employ the PQML estimator to account for the non-normality of the outcome and the presence of zeros, particularly when looking at capital investment outcomes. Importantly, equation (1) controls for an interaction term between the cumulative log number of emigrants over the period 1892–1921 ($\text{Emigrants}_{p(i)}$) and a post-Quota indicator variable.[55] This ensures that the DiD estimators $\{\delta_\tau\}$ compare districts located in areas with comparable emigration intensities.[56] In the baseline analysis, $\mathbf{X}$ contains an indicator variable for southern regions interacted with a post-Quota indicator to account for potential diverging North-South trends after the Quotas. In several robustness checks, however, we enrich the included controls. Since districts are quite heterogeneous in population, we weigh them by their 1881 population in all regressions to ensure that very small areas do not drive the results. Standard errors are clustered at the level of the

[54] The key advantage of the PQML estimator is that it remains consistent when dealing with non-negative dependent variables in the presence of fixed effects without requiring to model the underlying distribution explicitly (Correia et al., 2020).

[55] Unfortunately, district-level data on the number of international emigrants, to our knowledge, do not exist. However, controlling for emigration at the province level allows us to mitigate the concern that transatlantic emigration from a given district could be compensated by internal mobility from the other districts in the same province.

[56] All results remain qualitatively unchanged if we estimate the baseline specification (1) as a log-log linear regression instead of a PQML model, and upon normalizing the volume of emigrants by 1881 district population.

treatment relevant to each regression: districts for district-level regressions and provinces for province-level regressions.

The identification assumption that model (1) requires can be stated in terms of conventional parallel trends. Absent the Quotas, units with a conditionally higher number of US emigrants would not have displayed different patterns in y compared with districts with fewer relative US emigrants. While this assumption is not testable, we estimate pre-treatment coefficients that are never statistically different from zero for population (Figure 4) and manufacturing and agriculture employment (Figure 7). These exercises support the parallel trends assumption. We defer a more detailed discussion on the plausibility of the assumption of parallel trends to the following section.

In Table 2, however, we provide one additional exercise to gauge the validity of the research design. In each line, we report the correlation between district-level variables from population censuses (Panel A), province-level manufacturing employment by sector (Panel B), province-level capital variables (Panel C), the number of US emigrants (in columns 1–6), and the instrumental variable defined in (2). In columns (1–2) and (7–8), the variables are measured in 1901; in columns (3–4) and (9–10), they are measured in 1911. Importantly, identification in a difference-in-differences setting requires that the treatment does not correlate with *changes* in pre-determined characteristics, which may impact the outcomes of interest. In columns (5–6) and (11–12), we thus compute the correlation between the growth rate of each variable between 1901 and 1911 and the two treatment indicators. These indicate that observation units appear comparable along a majority of all observed variables in growth rates despite substantial level differences. We cannot repeat this exercise for the capital variables since we do not observe two pre-treatment values. In Panel C, we thus report the correlation between the treatment and their levels in 1911 for completeness.

To avoid the pitfalls of the DiD estimator with continuous treatments reported by Callaway et al. (2021), we always report estimates of model (1) where the intensive margin is coded as a binary variable returning value one for districts above the median value, and zero for districts below the median.

4.3 Instrumental Variable for Quota Exposure

To provide more solid evidence in favor of a causal interpretation of our estimates, we construct a shift-share instrument to predict US emigration across Italian districts. Our approach mirrors a widely employed methodology to estimate the causal impact of immigration (Card, 2001; Tabellini, 2020). The instrument predicts district-level out-migration flows to the United States by interacting the 1895–1900 migration ties between Italian districts and US counties with subsequent county-level immigrant inflows from countries other than Italy. Formally, the actual US emigration is instrumented with

$$\text{US}\ \widehat{\text{Emigrants}}_{it} \equiv \sum_{j} \omega_{ij} \times \text{Immigrants}_{jt}^{-\text{Italy}}, \tag{2}$$

where ω_{ij} denotes the number of immigrants from district i into county j between 1895 and 1900, while the variable ($\text{Immigrants}_{jt}^{-\text{Italy}}$) is the number of non-Italian immigrants who settle in county j in year t, expressed as a share of the overall number of non-Italian immigrants who enter the US in year t. To compute the exposure share terms (ω_{ij}), we rely on our novel dataset that links Ellis Island immigrant records with the full-count US population census (Ruggles et al., 2021). We construct bilateral flows between districts and counties by attaching a municipality of origin to Italian immigrants recorded in the US census. In regression (1), we substitute the baseline treatment with the instrumented number of US emigrants defined in (2) and control for the number of overall international emigrants, as in the baseline case.

Our key identification assumption when using the instrumental variable in the double differences setup is that the initial sorting of emigrants across US counties, weighted by the pull shocks represented by non-Italian immigration inflows, does not correlate with unobserved factors that may impact the *changes* in the outcome variables in the same periods. In contrast to a standard instrumental-variable estimation setting, we do not require that the instrument does not correlate with the *levels* of such variables, as in Anelli et al. (2023). While this assumption cannot be tested, in Table 2, we show that the instrument does not systematically correlate with changes in the outcome variables before the Quotas. This imperfect test supports the validity of this research design.

In Figure 3, we check that actual and predicted US emigration flows are positively correlated. We compute the residualized values of observed and instrumented number of US emigrants by regressing each variable against province-fixed effects, which implicitly control for the province-level emigration rate. We then plot the residuals and highlight the binned values in blue. This exercise reveals a strong, positive, and significant correlation between the instrument and observed US emigration. We provide more detailed tabular evidence in Online Appendix Table B.1.

5 Results

We organize the results in three logically distinct sections. First, we show that the immigration restriction policy generated "missing migrants" who remained in Italy. Second, we explore its effect on technology adoption and investment in physical capital. Finally, we show that immigration restriction policies generate a positive labor supply shock in manufacturing, dampening firms' incentive to invest in labor-saving technologies. We conclude by discussing the limitations of the analysis and possible avenues for future research.

5.1 Population Increases in Districts More Exposed to the Quota Acts

The first step of our argument maintains that areas more exposed to the US Quota Acts experienced an unexpected population increase. Implicitly, this requires that not all those who would have migrated to the United States had the Quotas not been promulgated would settle in a different country. This "imperfect substitution" argument can be tested and quantified empirically. If the US and other countries were perfectly substitutable, we would expect to find no effect of exposure to the Quotas on population.

To assess the validity of the imperfect substitution hypothesis, we estimate model (1) using population as the outcome variable. Table 3 reports the results. We find that districts more exposed to the IRP shock display a larger population after 1921, using the observed exposure to the US quotas (columns 1–2) or the instrument (columns 3–6). Importantly, in columns (2) and (4), we include region-by-time fixed effects to account for time-varying unobserved heterogeneity at the district level. In column (5), we repeat the estimation using a binary treatment for districts below and above the median US emigration rate to avoid issues related to continuous treatment DiD designs. The effect remains quantitatively unchanged if we focus on the sub-sample of Southern districts, where exposure to the Quotas was generally higher (column 6).[57] All these specifications yield quantitatively consistent results. For instance, as shown in column (3), a 1% increase in the number of instrumented US emigration leads to a 0.04% increase in population. Equivalently, moving from the 50th to the 75th percentile of the distribution of predicted US emigration yields 8,850 additional population, compared to a pre-treatment average equal to 161,000.[58]

We also report the coefficient of an interaction between the number of international emigrants over the period 1890–1921 and a post-Quota indicator. While this term cannot be interpreted causally, it remains informative about the validity of the research study. The core observation is that emigration toward countries other than the United States was not restricted. We thus expect that the population in districts with relatively more intense out-migration flows would decrease following the Quotas. The empirical evidence confirms this claim. The coefficient of the interaction term between out-migration and the post-treatment indicator is negative and generally significant, indicating that emigration towards non-US destinations did not generate "missing migrants" in the years following the Quotas.

The validity of the DiD design hinges on a standard assumption of parallel trends. This requires that if the US had not promulgated the Quota Acts, the population would have evolved similarly in districts with relatively more or less intense US emigration. To

[57]By "Southern" districts, we mean areas in the NUTS-2 ITF and ITG regions, which correspond to the former Kingdom of the Two Sicilies.

[58]We employ a PQML estimator and include the log number of US emigrants as the main treatment variable. The coefficient associated with the treatment thus expresses the percentage increase in the dependent variable associated with a 1% increase in the treatment. We compute all magnitudes using the instrument for US emigration. Referring to column (3), all else being equal, a 1% increase in the volume of US emigrants leads to a 0.04% increase in population.

gauge the sensibility of this assumption, we estimate model (1) as a generalized DiD using the instrument interacted with time dummies. Figure 4 reports the estimated dynamic treatment effects. We do not find any statistically significant correlation between predicted US emigration and population before the Quotas were enacted. This pattern supports the parallel trends assumption. We estimate a positive effect of the Quotas already in 1921, which persisted for at least 15 years after the policy shock. The immediacy of the impact of the Quotas is not surprising. As highlighted in Figure 1, US emigration collapsed following WW1. Moreover, the provisions of the Act were immediately enforced (Abramitzky and Boustan, 2017).

5.2 Capital Investments Decrease in Districts More Exposed to the Quota Acts

How did the increased population interact with technology adoption and investment? This section shows that investment in labor-saving and possibly productivity-enhancing technologies decreased in areas more exposed to the shock. To do so, we estimate model (1) using several proxies of capital investment as outcome variables. We distinguish between the overall number of firms, the number of firms with at least one installed engine, mechanical and electrical engines, and the mechanical and electrical horsepower generated by the respective installed engines. The data cover manufacturing firms only.

Table 4 reports the estimated effect of exposure to the Quotas on capital investment. Panel A refers to the observed US emigration, whereas in Panel B, the treatment is the predicted values from (2). We find that investment in physical capital decreased in areas more exposed to the Quotas. This finding is confirmed across all the imperfect proxies available. In particular, we estimate larger treatment effects for electrical engines and horsepower. This is particularly striking, as David (1990), Mokyr (1998), and Reichardt (2024) note that electrical engines stood as a major defining technology of the Second Industrial Revolution, which could yield sizable productivity advantages. Gaggl et al. (2021), moreover, show that electrification in the US was a catalyst for urbanization and structural transformation. In terms of magnitude, the estimated effects are sizable.

Moving from the 50th to the 75th percentile of the distribution of predicted US emigration yields (in parentheses, we indicate the corresponding pre-treatment average value): 537 fewer firms (3,425), 178 fewer firms with engine (668), 42 fewer mechanical engines (583), 417 fewer electrical engines (806), 2901 less mechanical horsepower (11437), and 3110 less electrical horsepower (7154).

Figure 5 displays the associated dynamic DiD coefficients. Unfortunately, the data are available for three points in time only. Of these, 1911 is the only pre-treatment observation. We thus cannot estimate pre-treatment coefficients. Instead, in Table 2, we show that treated and control provinces were similar along all outcome variables except mechanical engines in 1911. All variables decreased in 1927: the effect remains persistent for electrical engines, while it appears to be shorter-lived for mechanical ones.

Thus far, we grouped all manufacturing sectors. Nonetheless, the data allows us to undertake a more disaggregated analysis. We report the results in Figure 6. Each "Capital" panel reports the estimated effect of the Quotas on each capital indicator for a given manufacturing sector. The reaction to the population shock does not exhibit sizable heterogeneity across industries. Capital investment decreases in all sectors except for chemical manufacturing.

5.3 The Quota Acts as Passive Labor Market Policies

Why did investments in capital and technology decrease in areas more exposed to the Quota Acts? We advance and validate the hypothesis that the immigration restriction shock triggered directed technical adoption mechanics *à la* Zeira (1998) and Acemoglu (2002). Under the imperfect substitution hypothesis, which we documented in section 5.1, areas that had been sending relatively more migrants to the United States are, in fact, subject to a larger labor supply shock because a relatively larger fraction of people who would have emigrated are prevented from doing so. This positive labor supply shock decreases wages, which triggers firms' incentive to substitute capital with labor. We formalize this argument in Online Appendix section A.

To test this mechanism more formally, we study how manufacturing and agriculture employment reacted to the shock. We look at manufacturing and agriculture because they account for more than 80% of overall employment. In section 2, we noted that Italian agriculture in this period was labor-intensive and not mechanized (Cohen and Federico, 2001). The directed technical adoption narrative would thus predict that the labor supply shock generated by the Quota Acts would primarily flow into increased manufacturing employment.

In Table 5, we explore the effect of the Quota Acts on manufacturing employment, while in Table 6, we focus on agriculture employment. We find that manufacturing employment increases in areas more exposed to the immigration restrictions shock, while employment in agriculture does not exhibit similarly detectable changes. In both tables, in columns (1–2), we report the results using observed US emigration, while in columns (3–6), we employ the instrumented treatment. Column (5) refers to a binary treatment that codes as treated all districts with above-median US emigration, whereas in the other columns, we employ the continuous measure. For manufacturing employment, the OLS estimates are not statistically significant because, as discussed below, we find a statistically significant correlation between the treatment and the outcome before the treatment period; by contrast, the IV-DD estimates are highly significant with no evidence of similar pre-trends. Importantly, the results remain unchanged when the sample is restricted to the sub-sample of Southern districts (column 6).

Since manufacturing employment increases while agriculture employment does not, the labor supply shock generated by the Quotas prompted a reallocation of labor from agriculture, a largely labor-intensive activity, to manufacturing. Overall, the evidence presented in the table provides solid evidence that manufacturing employment increased in areas more exposed to the Quotas. From a quantitative perspective, moving from the 50th to the 75th percentile of the distribution of predicted US emigration yields 2095 more workers employed in manufacturing (compared to a pre-treatment average equal to 20,390) and 992 fewer agriculture workers (compared to a pre-treatment average of 40,350), although the latter effect is not statistically significant. Crucially, the positive labor supply shock generated by the policy shift did not, however, foster structural change. Employment in agriculture in more exposed areas hardly reacts to the shock. Therefore, the increase in manufacturing employment plausibly reflects the fact that "missing migrants" take jobs in manufacturing rather than a reallocation of jobs from agriculture into manufacturing. It thus appears unlikely that the Quota Acts could prompt the modernization of Italian rural areas.

The historical literature views Italian emigration as a response to over-population in rural areas (Choate, 2008). We evaluate these claims by reporting the coefficient of the interaction between out-migration before the Quotas and a post-treatment indicator. While this term has no causal interpretation, it reveals important patterns related to the motives underlying the migration choice. Employment in manufacturing does not change in districts with relatively more emigrants after the Quota shock. By contrast, agriculture employment decreases. Since out-migration towards countries other than the United States was not curtailed, these patterns appear consistent with the historical literature. Out-migration was prevalent in rural agricultural areas, and thus, agricultural employment decreased in regions with more intense (non-US) out-migration flows after the Quotas.

We report the flexible difference-in-differences estimates in Figure 7. We do not estimate statistically significant pre-treatment coefficients for manufacturing employment, thus providing further solid support for the parallel trends assumption. Manufacturing employment increased after the Quotas. The effect is relatively persistent as it lasted at least until 1931, although it peaks immediately after the immigration restriction shock. We do not find any statistically significant response of agricultural employment, and we thus omit the associated event study.

We can break up manufacturing employment by sector, even though only at the coarser province level of aggregation. As in section 5.2, we do not uncover substantial heterogeneity across sectors. Employment increases in all industries except mining, where geographical constraints may constrain the employment response. These findings confirm that a positive labor supply shock is associated with decreased capital investment in all manufacturing sectors.

5.4 Robustness Checks

This section summarizes the robustness checks in Appendix A. We provide evidence that the baseline estimates are robust to alternative definitions of US emigration, to the inclusion of several covariates controlling for both push and pull factors, to the exclusion of specific parts of the sample, and to using different methods to estimate the standard error.

Since observed US emigration may be subject to mismeasurement, in Tables c.1, c.2, c.3, and c.4 we show that the results are robust to alternative definitions. The first concern is that our results might be driven either by remote migration patterns or by more recent migration closer to the introduction of the quotas. We address these concerns by constructing two measures of US emigration that assign increasing or decreasing weights to more recent out-migration flows to the US. In addition, we also exclude all migrants to the US who left before 1900. As a further test, we construct our measured US emigrations using migration to the US that happened before the first Quota Act in 1921. Last, as discussed in Section 3, though emigration collapsed during WW1, it did not completely dry out. During the war, districts closer to emigration ports are, in fact, disproportionately represented relative to previous shares, possibly because of their geographic position. To control for this, we restrict the sample of US emigration to the years before the outbreak of WWI. In all cases, we find that all our baseline results hold.

In Tables c.5, c.6, c.7, and c.8 we show that our baseline results are robust to the inclusion of a large set of covariates measured before the Acts, interacted with a post-Quota indicator variable, as further controls. These unit-specific control variables are the literacy rate in 1901, measured as the share of people who could read relative to the district's overall population; the urbanization rate in 1901, measured as the share of people living in towns with more than 10,000 inhabitants in the district; the altitude at which the district is located; an indicator variable that returns a value of one if the district has access to the railway network before 1901;[59] the number of deaths due to

[59]For province-level analyses, we use the share of municipalities in the province that had access to the railway network before 1901.

World War One.[60] To control for pull factors, in some specifications, we explicitly control for an interaction term between US GDP, which serves as an indicator of the business cycle, and US emigration. All results remain quantitatively unchanged.

In the above-mentioned Tables, we also document the robustness of our results to these specifications when using the shift-share instrument as treatment. In addition, we test that our results are robust to the exclusion of specific parts of the sample. In Figures c.2 and c.4, we show that the baseline estimates are not driven by any specific region, as regression coefficients remain stable irrespective of the region that we exclude from the sample.

In Figures c.1 and c.3, we compare the baseline estimated standard errors with a battery of alternative estimators. Among others, we employ the correction suggested by Conley (1999) to allow for time and spatial autocorrelation.[61] The significance of the baseline results remains largely unaltered.

5.5 Discussion and Limitations of the Analysis

In this section, we discuss some alternative mechanisms that could be compatible with our findings, and we touch on how data limitations might preclude some additional and potentially relevant analysis. We then briefly elaborate on the external validity of our results.

Human capital spillovers ignited by out-migration have traditionally received sizable attention in the literature. Evidence by Spitzer and Zimran (2018) suggests that Italian emigrants to the United States were positively selected within Southern regions, implying that emigration was exerting a "brain drain" effect on Southern Italy. Under this interpretation, our estimated effects of the Quota Acts would be partially confounded by human-capital dynamics triggered by the IRP shock. More specifically, the drop in capital investment and technology adoption might be driven by substitutability between capital goods and the upper tail of the skill distribution of workers rather than by directed

[60] Shares are expressed relative to the population in 1911 for province-level regression, as 1911 is the first decade of observation for analyses at that level.

[61] Unfortunately, Conley standard errors are not implemented in any available package for PQML estimation. We thus estimate these regressions through OLS on the logged value of each outcome.

technical adoption. Even though this mechanism does not necessarily conflict with the one we propose, we view this as second-order in our setting for two reasons. First, we estimate employment gains and capital investment losses in the First Industrial Revolution, traditionally low-skilled and labor-intensive sectors. Hence, it is unlikely that high-skilled workers would be comparatively more productive there. Second, we run a battery of robustness checks—see Online Appendix Tables c.5, c.6, c.7 and c.8. Results hold when we include the literacy rate as a proxy for average human capital in our regressions.

Besides the brain-drain effect, remittances are a traditionally major research topic within the emigration literature. Despite sizable global flows, Clemens (2011) argues that remittances can have, at best, a second or third-order effect on economic growth in sending countries when compared to the welfare effects of immigration restriction barriers. Building on this insight and given data limitations, we abstracted from including remittances in our analysis. Remittances nonetheless represent a competing mechanism. More exposed districts were receiving more remittances before the Quota Acts. Hence, they suffered the most from the border closure. Since within-household cash transfers result in aggregate savings, remittances may accrue to overall investment dynamics (Rapoport and Docquier, 2006). A large literature has nonetheless documented that remittances are largely spent on consumption and invested in human—rather than physical—capital (for a review, see Yang, 2011). A more sensible interpretation could be that remittances fostered literacy (e.g., Fernández, 2022). Exposed districts would have thus suffered from a relative drop in skilled workers following the Acts, and the labor force would have reshuffled toward unskilled sectors. This pattern would thus move in the opposite direction of the reverse-brain-drain effect. Under this interpretation, this channel does not conflict with the one we propose. If anything, it augments the relevance of exposure to the Quota Acts in generating an excess supply of workers, which triggered the directed technical incentive to abandon investment in physical capital.

One reason precluding a causal interpretation of our estimates would be that—even when conditioning on the decision to emigrate—the choice of *where* to emigrate was systematically correlated with factors inducing an underlying correlation with local economic development. We provide and discuss evidence against this interpretation throughout this paper. Historical scholarship, however, notes that assimilation patterns of Italian immigrants in the United States and Argentina during this period substantially differed (Klein, 1983).[62] If this was caused by pre-migration differences in characteristics, then our identification scheme may fail. Using detailed data from censuses and passenger lists, Pérez (2021) nonetheless documents that the "success" of Italians in Argentina compared to Italians in the United States was unlikely to be caused by pre-migration differences in observable characteristics between the two groups. Emigrants to Argentina and the United States were essentially indistinguishable in terms of occupation and literacy rate, the only difference being that the former chiefly originated from Northern regions. In contrast, the latter mostly came from Southern areas. Selection patterns across the two groups do not display sizable differences, providing solid evidence in favor of our identification assumption.

Data limitations prevent us from studying two additional, potentially interesting variables: wages and output (productivity). Studying wages would be informative because directed technical adoption hinges on relatively more abundant labor becoming relatively cheaper. An analysis of wages could reveal this pattern, which we currently implicitly assume. Unfortunately, geographically disaggregated data on wages do not exist. Productivity would, in turn, be key to investigating the welfare effects of the Quota Acts. However, disaggregated data on output were not recorded until 1936.

It is not obvious that our results lend themselves to further generalization. Some similarities with contemporary settings nonetheless emerge. In terms of emigrant selection, the average Italian emigrant to the United States was slightly positively selected, left a rural area, and took on unskilled industrial jobs once in the United States (Sequeira et al., 2020). This description is remarkably similar to contemporary emigration from poor countries, whereas it is starkly different from emigration from rich countries (e.g., Gibson et al., 2011). While we do not claim that all our findings generalize to contemporary

[62] Argentina and the United States were the two leading destinations for Italian emigrants in this period. Klein (1983), among others, noted that Italian immigrants in Argentina had higher home-ownership rates and were more likely to be employed in skilled occupations compared to Italians in the United States.

migration relationships, the evidence presented in this paper indicates that IRPs should be evaluated in terms of their joint effects on sending and receiving countries beyond remittances and human capital deprivation, as is standard in the existing literature.

6 Conclusions

The adoption of foreign technology is a crucial driver of economic growth for developing countries, which typically operate far from the technology frontier (Eaton and Kortum, 1999; Suri, 2011). This paper explores the relationship between technology adoption and out-migration, a common feature of the development process.

We study the Italian mass migration to the United States between 1892 and 1936 using individual-level data on Italian immigrants and newly digitized census data. Between 1921 and 1924, the U.S. promulgated two immigration restriction policies—the "Quota Acts"—which completely halted the inflow of Italian immigrants. Comparing districts with similar emigration rates but different destinations, we leverage identifying variation in exposure to the Quota Acts to estimate the impact of immigration restriction laws in a difference-in-differences framework. Moreover, we produce a novel sample of Ellis Island immigrants linked to the US full-count population census to construct a shift-share instrumental variable, which confirms the baseline results.

We document three facts. First, we find that the population increased in areas that were comparatively more exposed to the Quota Acts. This finding supports an "imperfect substitution" narrative whereby immigration restriction policies generate foregone emigration because those who would have migrated do not—or cannot—substitute the restricted location with alternative destination countries. We thus interpret immigration restriction policies as "passive" labor market policies that increase the supply of labor in the countries they target. Second, we show that firms in treated locations decreased capital investment and technology adoption, particularly in relatively more advanced technology vintages. How can we reconcile a positive labor supply shock with depressed investment in productivity-enhancing capital? We argue that the immigration restriction policy triggered directed technical change incentives (Zeira, 1998; Acemoglu, 2002). Firms face an incentive to substitute capital with more abundant, hence cheaper labor. To validate this hypothesis, we show that manufacturing employment increased in the districts more exposed to the Quotas. These dynamics operated in each manufacturing sector.

This paper presents novel evidence that out-migration can act as a driver of technology adoption, thus potentially empowering long-run economic growth. We emphasize that this channel operates plausibly independently on "brain drain" effects. It also suggests that immigration restriction policies enacted by immigration—typically developed—countries may hamper the modernization of emigration—typically developing—ones. Our findings thus inform policymakers about the potential long-term consequences of such policies.

Tables

Table 1: Descriptive Statistics

	Mean (1)	Std. Dev. (2)	Median (3)	Min. (4)	Max. (5)	Units (6)	Observations (7)
Panel A. District-Level Variables from Population Censuses (in 10,000 units unless otherwise specified)							
Population	1.704	1.544	1.278	0.250	15.041	211	1235
US Emigrants	0.083	0.094	0.055	0.001	0.852	211	1235
Emigrants	2.036	1.478	1.767	0.126	10.182	211	1235
Manufacturing Employment Share (%)	10.810	6.191	9.170	0.278	38.287	211	1235
Agriculture Employment Share (%)	27.209	8.786	26.803	0.953	77.549	211	1024
Altitude	3.402	2.143	3.302	0.013	9.669	211	1235
Area	1.335	0.831	1.097	0.105	4.982	211	1235
Share of Cities Above 20,000 (%)	5.057	11.287	1.538	0.000	100.000	211	1235
Share of Population in Cities Above 20,000 (%)	20.771	23.277	16.499	0.000	100.000	211	1235
Panel B. Province-Level Manufacturing Employment by Sector (in 10,000 units)							
Agriculture	1.491	1.546	1.103	0.150	11.856	69	343
Chemicals	0.166	0.466	0.046	0.000	5.046	69	343
Construction	1.296	1.176	0.944	0.162	8.077	69	343
Metalworking	0.868	1.651	0.401	0.065	16.876	69	343
Mining	0.145	0.259	0.068	0.000	2.137	69	343
Textiles	2.030	2.736	1.151	0.070	19.988	69	343
Panel C. Province-Level Capital Variables (in 1,000 units)							
N. of Firms	7.665	6.804	5.894	0.000	54.116	71	207
N. of Firms with Engine	1.417	1.880	0.887	0.000	17.404	71	207
N. of Electrical Engines	4.841	13.869	1.410	0.000	158.155	71	207
Electrical Horsepower	35.142	83.486	9.540	0.000	841.094	71	207
N. of Mechanical Engines	0.551	0.395	0.428	0.000	2.079	71	207
Mechanical Horsepower	14.629	16.654	7.875	0.000	84.585	71	207

Notes: This Table reports summary statistics for the main variables used in the paper. Data in Panel A are tabulated from population censuses; data in Panel B and C are digitized from manufacturing censuses. Variables in Panels A and B are reported in 10,000 units unless otherwise specified except population, which is expressed in 100,000 terms; variables in Panel C are reported in 1,000 units. All variables are cross-walked to consistent 1921 district (Panel A) and province (Panels B and C) borders. Referenced on page 1

Table 2: Correlation between Treatment and Pre-period Observable Variables

	Observed Quota Exposure						Shift-Share Instrumental Variable					
	1901		1911		Growth Rate		1901		1911		Growth Rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. District-Level Variables from Population Census												
Population	0.848***	(0.121)	0.962***	(0.147)	0.200*	(0.103)	0.422***	(0.081)	0.483***	(0.097)	0.015	(0.066)
Manufacturing Employment Share	0.449***	(0.089)	0.892***	(0.207)	0.028	(0.079)	0.246***	(0.058)	0.475***	(0.134)	-0.026	(0.050)
Agriculture Employment Share	0.538***	(0.069)	0.748***	(0.100)	0.010	(0.068)	0.147***	(0.048)	0.225***	(0.069)	0.004	(0.043)
Share of Cities Above 20,000 (%)	-0.084	(0.105)	-0.086	(0.107)	0.170	(0.180)	-0.180***	(0.054)	-0.202***	(0.056)	-0.119	(0.093)
Share of Population in Cities Above 20,000 (%)	0.457***	(0.111)	0.456***	(0.113)	0.124	(0.180)	0.196***	(0.071)	0.179***	(0.073)	-0.126	(0.093)
Panel B. Province-Level Manufacturing Employment by Sector												
Agriculture	0.022	(0.291)	-0.003	(0.440)	-0.414	(0.296)	0.149	(0.132)	0.129	(0.202)	-0.257*	(0.134)
Chemicals	-0.015	(0.248)	-0.178	(0.577)	0.613**	(0.312)	0.113	(0.113)	0.428*	(0.259)	0.112	(0.148)
Construction	-0.094	(0.247)	-0.097	(0.419)	0.368	(0.322)	0.048	(0.114)	0.231	(0.190)	0.273*	(0.145)
Metalworking	-0.049	(0.279)	-0.050	(0.558)	0.366	(0.286)	0.222*	(0.125)	0.407	(0.251)	0.259**	(0.129)
Mining	0.385	(0.404)	0.488	(0.328)	0.094	(0.194)	0.236	(0.185)	0.336**	(0.147)	0.006	(0.090)
Textiles	0.046	(0.397)	-0.013	(0.387)	-0.081	(0.218)	0.158	(0.182)	0.177	(0.177)	0.155	(0.098)
Panel C. Province-Level Capital Indicators												
N. of Firms			0.119	(0.465)					0.253	(0.208)		
N. of Firms with Engine			0.194	(0.486)					0.234	(0.218)		
N. of Electrical Engines			0.369	(0.587)					0.260	(0.264)		
Electrical Horsepower			0.013	(0.525)					0.329	(0.233)		
N. of Mechanical Engines			-0.169	(0.264)					0.081	(0.120)		
Mechanical Horsepower			-0.278	(0.411)					0.368**	(0.180)		

Notes: This Table displays the correlation between the observable district- and province-level variables, observed US emigration (columns 1–6), and the instrument (columns 7–12). In columns (1–2) and (7–8), the correlation is between the treatments and the variables in 1901; in columns (3–4) and (9–10), the variables are recorded in 1911. In columns (5–6) and (11-12), we report the correlation between the two treatments and the growth rate of each variable between 1901 and 1911. The absence of any statistically significant correlation between the growth rates and the treatment variables is the crucial test in support of the validity of the research design. In Panel A, the units of observation are districts; in Panel B and C, the units of observation are provinces. Capital variables, displayed in Panel C, are observed in 1911, 1927, and 1937, so we cannot compute the growth rate between two consecutive pre-treatment periods. The outcome variable in each regression is standardized to facilitate the comparisons. Each regression controls for the number of emigrants and region-fixed effects. Units are weighed by their population in 1881. Standard errors are clustered at the district level and are displayed in parentheses. Referenced on pages 2

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table 3: The Response of Population

	Dependent Variable: Population					
	Difference-in-Differences		Instrumented DiD			
	(1)	(2)	(3)	(4)	(5)	(6)
US Emigrants × Post	0.081**	0.049**				
	(0.040)	(0.021)				
$\widehat{\text{US Emigrants}}$ × Post			0.038**	0.029***		0.019*
			(0.015)	(0.011)		(0.011)
I($\widehat{\text{US Emigrants}}$) × Post					0.120**	
					(0.049)	
Emigrants × Post	-0.078**	-0.055*	-0.043*	-0.023	-0.047**	-0.105***
	(0.031)	(0.029)	(0.022)	(0.023)	(0.023)	(0.026)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	–	Yes	–	Yes	Yes
Region-Decade FE	No	Yes	No	Yes	No	No
Regions in Sample	All	All	All	All	All	South
N. of Districts	202	201	192	191	192	85
N. of Observations	1198	1192	1140	1134	1140	502
R^2	0.372	0.377	0.369	0.374	0.369	0.329
Mean Dep. Var.	1.734	1.723	1.788	1.776	1.788	1.599
Std. Beta Coef.	0.151	0.092	0.017	0.013	0.023	0.011

Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on population. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. In columns (1–2), the treatment is an interaction term between US emigration and a post-1921 term. In columns (3–6), the treatment is an interaction between the instrument for US emigration (columns 3–4, 6) or an analogous above-median binary indicator (column 5) and a post-1921 term. In column (6), the sample includes only regions in the South (former Kingdom of Two Sicilies). We include regions-by-time fixed effects in columns (2) and (4). Each regression includes district and time-fixed effects and controls for the emigration rate and an indicator variable for Southern regions; both interacted with a post-1921 indicator. The last row reports the coefficient of the interaction between the number of emigrants and a post-1921 indicator. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page 3

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table 4: The Response of Capital and Technology Adoption

	Dependent Variable: Province-Level Number of... (in 1,000 units)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Firms	Firms with Engines	Mechanical Engines	Electrical Engines	Mechanical Horsepower	Electrical Horsepower
Panel A. Difference-in-Differences Estimates						
US Emigrants × Post	-0.171**	-0.058	-0.198***	-0.335	-0.206**	-0.148
	(0.074)	(0.162)	(0.053)	(0.382)	(0.094)	(0.296)
Emigrants × Post	0.094	-0.137	0.034	0.441	0.022	0.004
	(0.124)	(0.194)	(0.066)	(0.503)	(0.103)	(0.371)
Panel B. Instrumented Difference-in-Differences Estimates						
US $\widehat{\text{Emigrants}}$ × Post	-0.078*	-0.133***	-0.036	-0.257**	-0.126**	-0.216***
	(0.045)	(0.034)	(0.034)	(0.102)	(0.056)	(0.074)
Emigrants × Post	0.028	-0.013	-0.097	0.514	0.004	0.198
	(0.111)	(0.114)	(0.074)	(0.319)	(0.103)	(0.247)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes
N. of Provinces	68	68	68	68	68	68
N. of Observations	204	204	204	204	204	204
R^2	0.436	0.285	0.119	0.672	0.685	0.854

Notes: This Table reports the estimated effect of exposure to the US Quota Acts on capital investment. The unit of observation is a province observed at a census-decade frequency between 1911 and 1936. The dependent variables are the number of firms (column 1), the number of firms with at least one engine (column 2), the number of mechanical engines (column 3), the number of electrical engines (column 4), the horsepower generated by mechanical (column 5) and electrical (column 6) engines. In Panel A, the treatment is an interaction between a post-Quota (1921) indicator variable and the number of US emigrants. In Panel B, the treatment substitutes measured US emigration with the shift-share instrument. Each regression controls for the number of emigrants and an indicator variable for Southern regions, both interacted with a post-1921 indicator. Regressions include province and decade-fixed effects. Units are weighed by their population in 1881. Standard errors clustered at the province level are reported in parentheses. Referenced on page 4

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table 5: The Response of Manufacturing Employment

	Dependent Variable: Manufacturing Employment					
	Difference-in-Differences		Instrumented DiD			
	(1)	(2)	(3)	(4)	(5)	(6)
US Emigrants × Post	0.094*	0.088**				
	(0.056)	(0.045)				
$\widehat{\text{US Emigrants}}$ × Post			0.071**	0.040		0.073**
			(0.032)	(0.031)		(0.029)
I($\widehat{\text{US Emigrants}}$) × Post					0.210***	
					(0.079)	
Emigrants × Post	-0.039	-0.060	-0.022	0.009	-0.033	-0.349***
	(0.083)	(0.066)	(0.062)	(0.047)	(0.065)	(0.068)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	–	Yes	–	Yes	Yes
Region-Decade FE	No	Yes	No	Yes	No	No
Regions in Sample	All	All	All	All	All	South
N. of Districts	202	201	192	191	192	85
N. of Observations	1198	1192	1140	1134	1140	502
R^2	0.597	0.614	0.597	0.613	0.597	0.509
Mean Dep. Var.	2.114	2.098	2.185	2.169	2.185	1.526
Std. Beta Coef.	0.081	0.076	0.014	0.008	0.018	0.024

Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on manufacturing employment. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. In columns (1–2), the treatment is an interaction term between US emigration and a post-1921 term. In columns (3–6), the treatment is an interaction between the instrument for US emigration (columns 3–4, 6) or an analogous above-median binary indicator (column 5) and a post-1921 term. In column (6), the sample includes only regions in the South (former Kingdom of Two Sicilies). We include regions-by-time fixed effects in columns (2) and (4). Each regression includes district and time-fixed effects and controls for the emigration rate and an indicator variable for Southern regions; both interacted with a post-1921 indicator. The last row reports the coefficient of the interaction between the number of emigrants and a post-1921 indicator. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page tab:dd$_{m}anufacture$

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table 6: The Response of Agriculture Employment

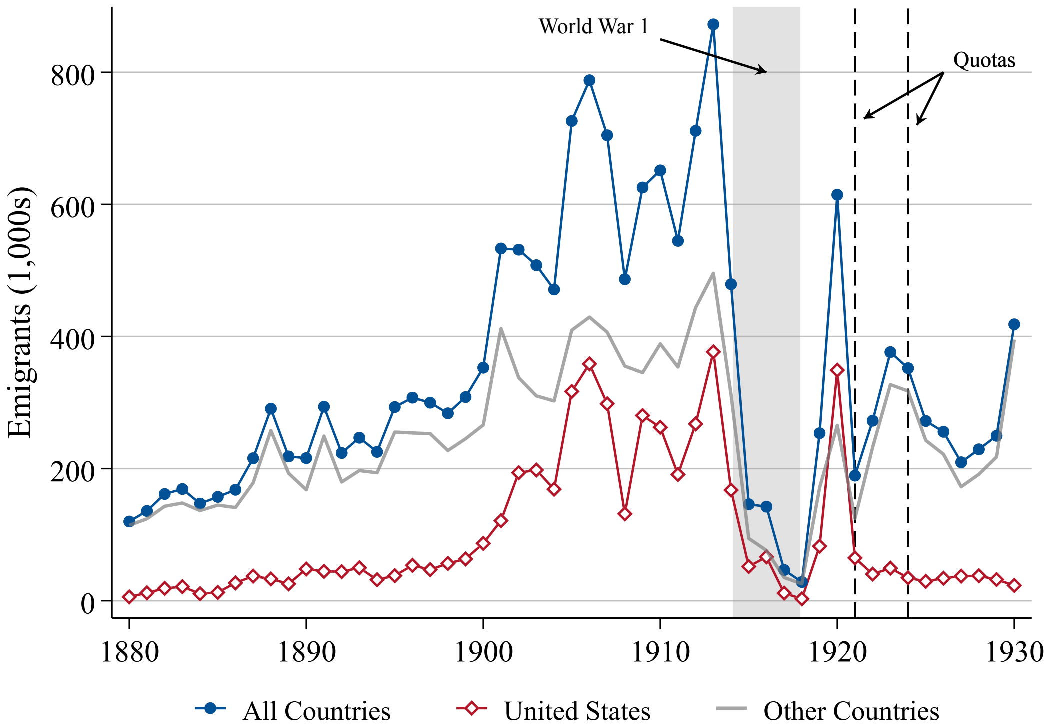
	Dependent Variable: Agriculture Employment					
	Difference-in-Differences		Instrumented DiD			
	(1)	(2)	(3)	(4)	(5)	(6)
US Emigrants × Post	-0.043	-0.049				
	(0.048)	(0.035)				
US $\widehat{\text{Emigrants}}$ × Post			-0.017	-0.032		-0.016
			(0.023)	(0.023)		(0.029)
I(US $\widehat{\text{Emigrants}}$) × Post					-0.054	
					(0.048)	
Emigrants × Post	-0.084**	-0.083**	-0.106***	-0.116***	-0.103***	-0.078*
	(0.039)	(0.035)	(0.027)	(0.030)	(0.031)	(0.044)
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	–	Yes	–	Yes	Yes
Region-Decade FE	No	Yes	No	Yes	No	No
Regions in Sample	All	All	All	All	All	South
N. of Districts	202	201	192	191	192	85
N. of Observations	996	991	948	943	948	417
R^2	0.313	0.315	0.304	0.307	0.304	0.167
Mean Dep. Var.	4.089	4.043	4.215	4.168	4.215	3.766
Std. Beta Coef.	-0.058	-0.068	-0.005	-0.010	-0.007	-0.008

Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on agriculture employment. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. In columns (1–2), the treatment is an interaction term between US emigration and a post-1921 term. In columns (3–6), the treatment is an interaction between the instrument for US emigration (columns 3–4, 6) or an analogous above-median binary indicator (column 5) and a post-1921 term. In column (6), the sample includes only regions in the South (former Kingdom of Two Sicilies). We include regions-by-time fixed effects in columns (2) and (4). Each regression includes district and time-fixed effects and controls for the number of emigrants and an indicator variable for Southern regions; both interacted with a post-1921 indicator. The last row reports the coefficient of the interaction between the number of emigrants and a post-1921 indicator. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page 6

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

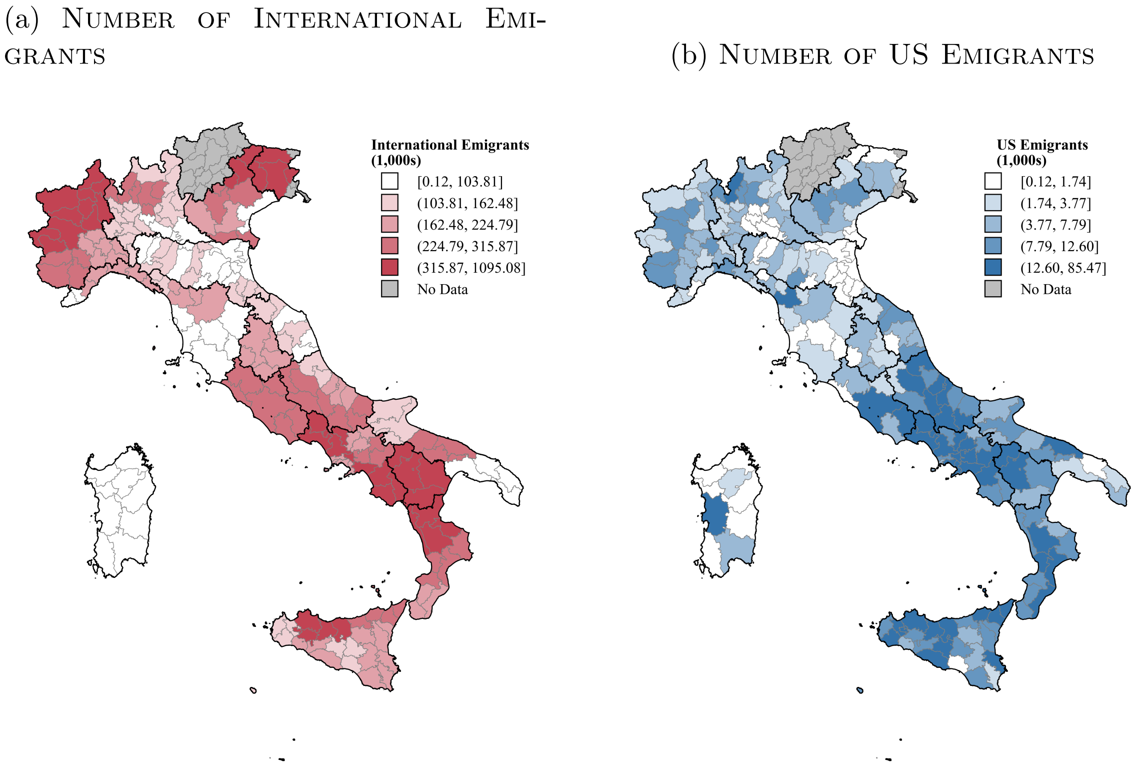
Figures

Figure 1: International Migrants, 1880–1930



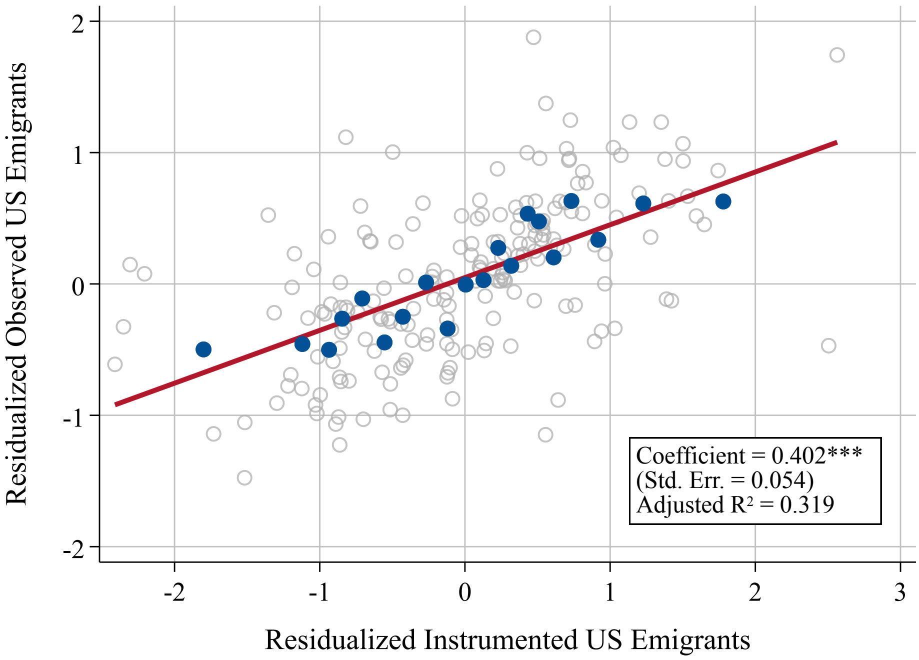
Notes: This figure reports the yearly outflow of international migrants from Italy between 1880 and 1930. Data are digitized from the *Annuario statistico dell'emigrazione italiana dal 1876 al 1925: con notizie sull'emigrazione negli anni 1869-1875* edited by the Italian Statistical Office (1926). The blue line reports the overall number of international migrants; the red line reports the number of migrants to the United States, the single most important destination country over this period; the gray line reports emigrants to every other country. The shaded gray area marks the 1914–1918 war years; the dashed vertical black lines mark the 1921 and 1924 Emergency and (Johnson-Reed) Immigration Quota Acts, respectively. Referenced on pages 1

Figure 2: Spatial Distribution of International Emigration, 1890–1921



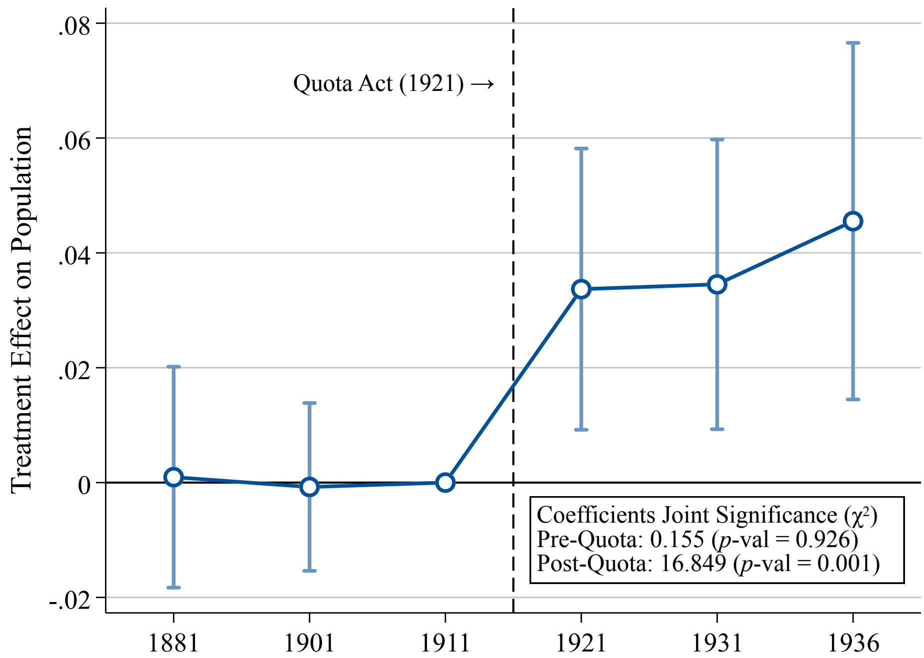
Notes: These figures report the spatial distribution of overall international emigrants (Figure 2a) and emigrants who settle in the United States (Figure 2b) across districts. In each map, the unit of observation is a district. Black lines superimpose region boundaries. The geography is at 1921 borders. The grey areas (today Trentino, Südtirol, Venezia-Giulia and Gorizia) were acquired after the Treaty of Versailles (1918) and are thus excluded from the sample. Panel 2a reports the number of emigrants who leave the Italian territory. The data is at the province level, hence the clustered rendering. Panel 2b displays the number of emigrants who settle in the US and are registered at the Ellis Island immigration station. The data are at the district level and constructed as detailed in the main text. The figures refer to 1890–1921; emigrants are expressed in thousand units. Referenced on page 2

Figure 3: Correlation Between Measured and Predicted US Emigration



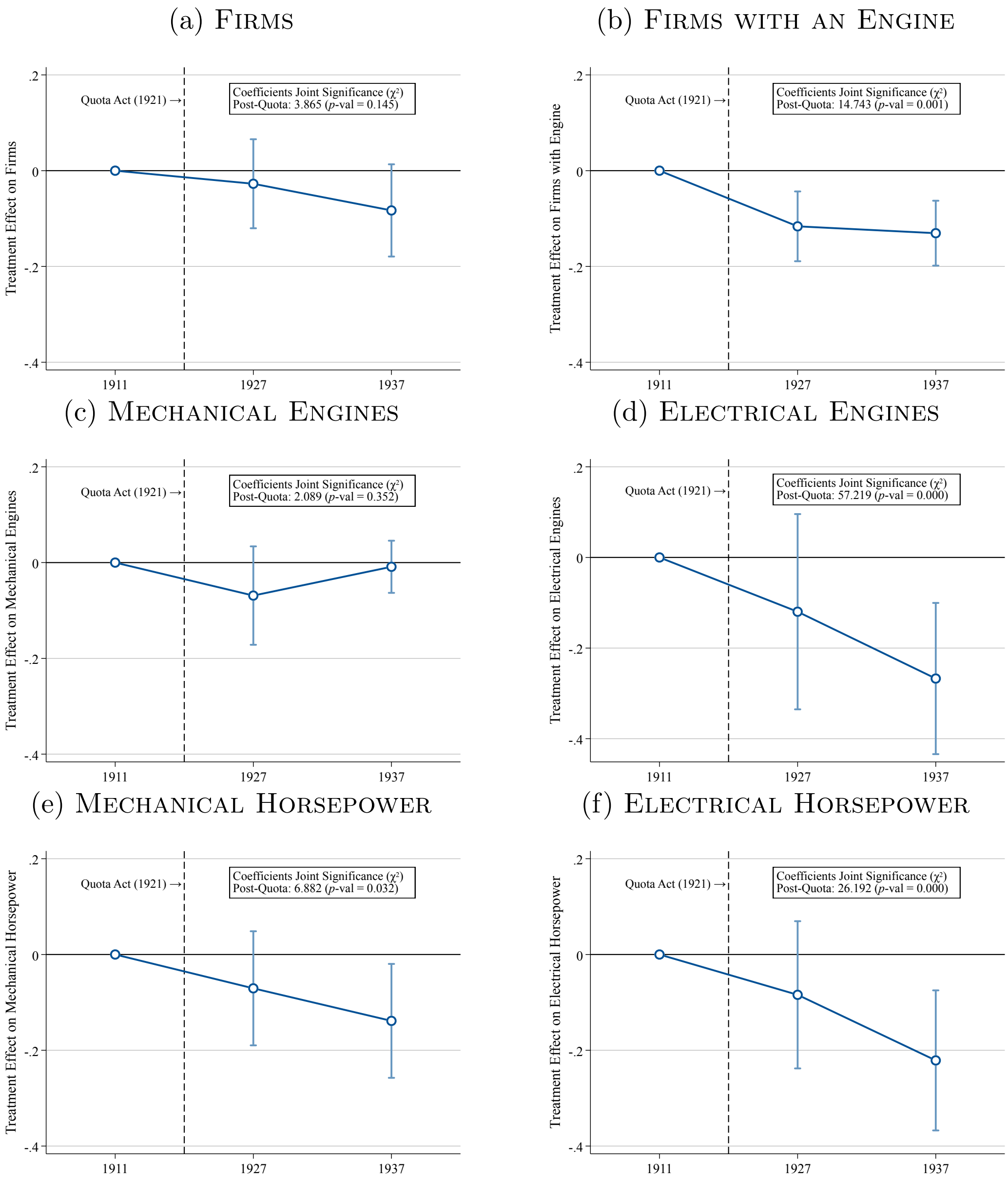
Notes: This Figure reports the "first stage" correlation between the observed Quota Exposure and the shift-share instrument. On the y- and x-axes, we report the residuals of observed US emigration and of the instrument. The residuals are obtained by regressing each variable against province fixed effects, which implicitly also control for an indicator for Southern regions and the number of emigrants, and computing the regression residuals. The unit of observation is a district. Each grey dot refers to one district; the blue dots report the binned scatterplot of the residuals. The red line corresponds to the ordinary least-squares fit. The Figure reports the regression coefficient, its standard error clustered at the district level, and the adjusted coefficient of determination. Referenced on page 3

Figure 4: Effect of Exposure to the Quota Acts on Population



Notes: These figures report the estimated effect of district-level exposure to the US Quota Acts on population. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. The outcome variable is population. Each dot reports the coefficient of an interaction term between period dummies and the cross-sectional instrument of US emigration. The regression includes district and decade-fixed effects and controls for the volume of international migrants and an indicator variable for Southern regions, both interacted with a post-1921 indicator. Units are weighed by their population in 1881. The bands report 95% confidence intervals from standard errors clustered at the district level. The graph reports the values of the Wald statistics of joint significance of pre-treatment and post-treatment coefficients and their respective p-values. Referenced on pages 4

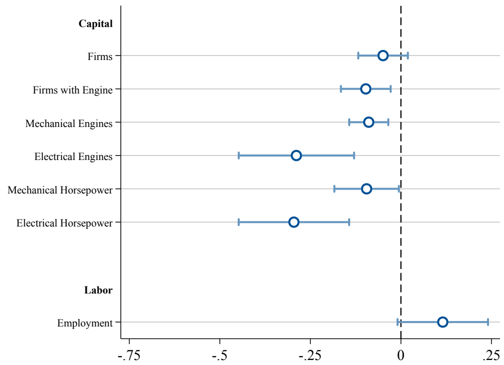
Figure 5: Effect of Exposure to the Quota Acts on Capital Investment



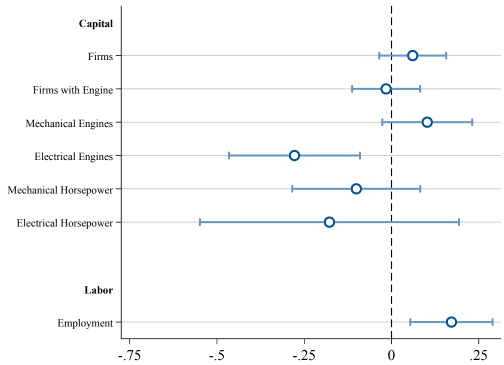
Notes: These figures report the estimated effect of exposure to the US Quota Acts on capital investment over time. The unit of observation is a province observed at a census-decade frequency between 1911 and 1936. The outcome variables are firms (panel 5a), firms with an engine (panel 5b), mechanical (panel 5c) and electrical (panel 5d) engines, mechanical (panel 5e) and electrical (panel 5f) horsepower. Each dot reports the coefficient of an interaction term between period dummies and the cross-sectional instrument of US emigration. Each regression includes province and decade-fixed effects and controls for the emigration rate and an indicator variable for Southern regions, both interacted with a post-1921 indicator. Units are weighed by their population in 1881. Bands report 95% confidence intervals from standard errors clustered at the district level. The graphs report the values of the Wald statistics of joint significance of pre-treatment and post-treatment coefficients and their respective p-values. Referenced on page 5

Figure 6: Effect of the Quota Acts on Capital and Employment by Sector

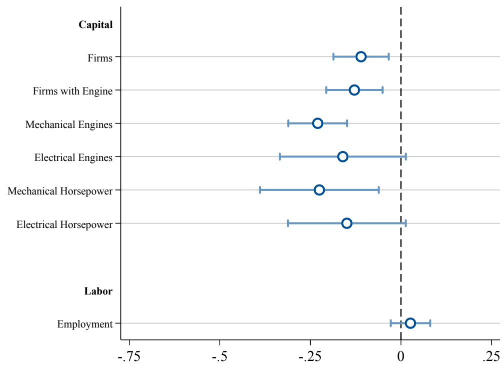
(a) Agriculture



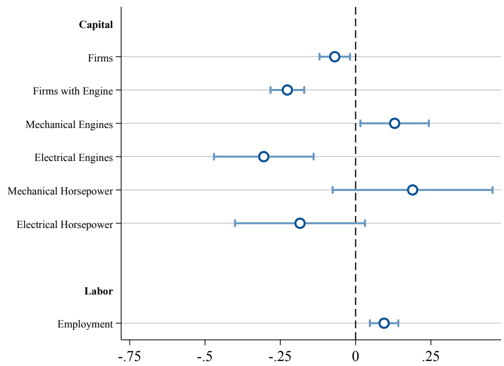
(b) Chemicals



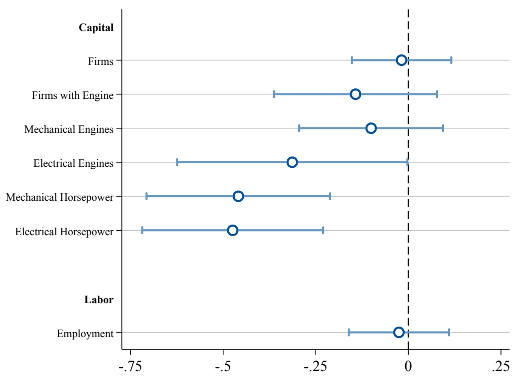
(c) Construction



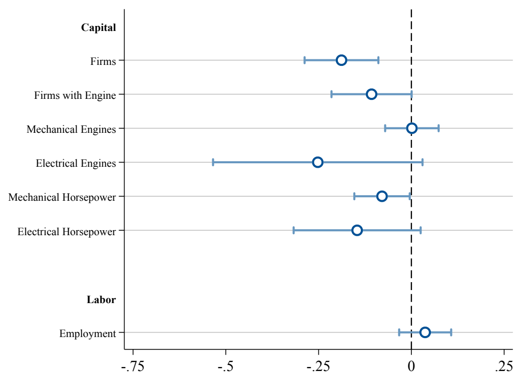
(d) Metalworking



(e) Mining

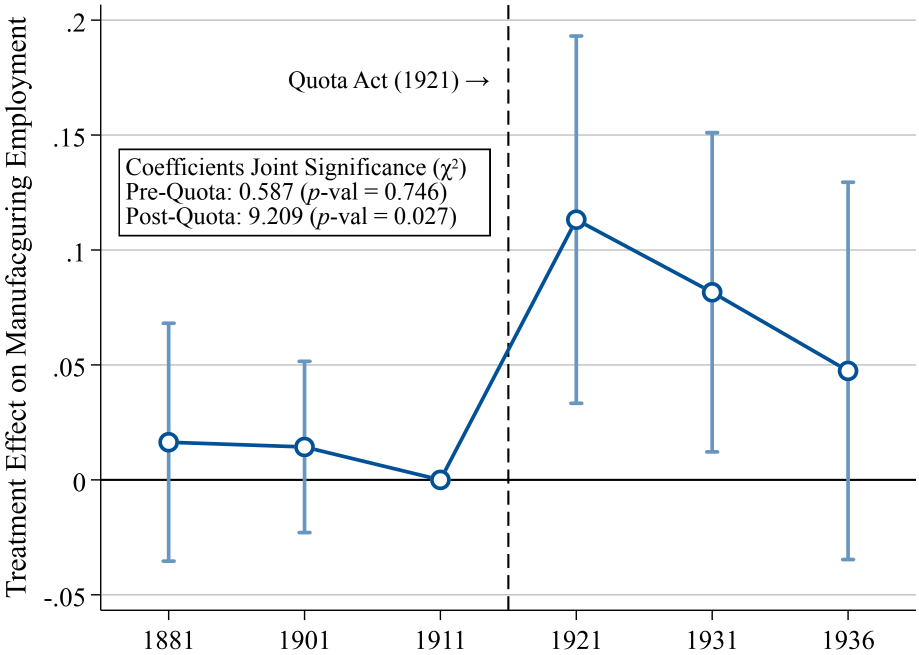


(f) Textiles



Notes: These figures report the estimated effect of exposure to the US Quota Acts on capital and employment by sector over time. The unit of observation is a district observed at a census-decade frequency between 1901 and 1936. Each panel reports the results for a specific manufacturing sector. The outcome variables are listed by row. Each dot reports the coefficient of an interaction between a post-1921 indicator and the instrument of US emigration. Each regression includes district and decade-fixed effects and controls for the volume of emigration and an indicator variable for Southern regions, both interacted with a post-1921 indicator. Units are weighed by their population in 1881. Bands report 90% confidence intervals from standard errors clustered at the province level. Referenced on page 6

Figure 7: Effect of Exposure to the Quota Acts on Manufacturing Employment



Notes: This Figure reports the effect of exposure to the Quota Acts on manufacturing employment. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. The outcome variable is employment in manufacturing. Each dot reports the coefficient of an interaction term between period dummies and the cross-sectional instrument of US emigration. Each regression includes district and decade-fixed effects and controls for the volume of emigration and an indicator variable for Southern regions, both interacted with a post-1921 indicator. Units are weighed by their population in 1881. The bands report 95% confidence intervals from standard errors clustered at the district level. The graph reports the values of the Wald statistics of joint significance of pre-treatment and post-treatment coefficients and their respective p-values. Referenced on pages 7

Appendix
Emigration Restrictions and Economic Development

A Appendix A - Data

A.1 Data Sources

This section lists the sources, methodology, and coverage of the data that we assemble. We defer a more detailed description of the emigration data to section A.3. Table A.1 summarizes the content of this section.

Population Censuses. We extract information from population censuses in 1881, 1901, 1911, 1921, 1931, and 1936. No census was taken in 1891. We digitize district-level information on the number of people employed in all major sectors in 1881–1921 censuses. The same information is available at the municipality level for 1931 and 1936. Hence we aggregate it at the district level. To assign municipalities to districts, we geo-code each municipality and overlay the coordinates to the 1921 district shape file. From population censuses, we also extract information on employment by industry: this is available by districts until 1921 but only by provinces in 1931 and 1936. We thus aggregate industry employment to provinces. Population data have been tabulated by ISTAT for each municipality. We aggregate them at the district and province levels. We also code two types of urbanization variables: the share of the population living in districts with at least k-thousand municipalities and the share of municipalities with at least k-thousand inhabitants. The ISTAT population tables report information on the area, altitude, and access to the sea for each municipality.

Manufacture Censuses. Manufacture censuses were taken in 1911, 1927, and 1937. They report province-level information on the universe of firms. We digitize data on a set of proxies for capital investment: the number of firms, the number of firms with at least one installed engine, the number of installed mechanical and electrical engines, and the number of installed mechanical and electrical horsepower.

World War One Deaths. WW1 deaths are from `cadutigrandeguerra.it`, a dataset maintained by ISTORECO, a branch of the *Associatione Nazionale Partigiani d'Italia* (ANPI). The underlying data were collected by the Fascist regime for propaganda purposes. The honor roll call contains information on 570,355 Italian soldiers who lost their lives during the war. The data appears to be comprehensive since most estimates place the total death toll at 650,000. For each individual, we know the name and surname, the birth year, the municipality of origin—which we map to the municipalities listed in the ISTAT data—, the military rank at death, the regiment, when, where, and why they died, and the decoration, if any. Deaths span the war years (1915–1918). We aggregate them at the district and province levels to have a cross-sectional indicator of mortality.

Railway Data. We reconstruct the network of Italian railways between 1839 and 1926 from a volume curated by the Italian Statistical Office and edited in 1927. This is the first paper using these data. The unit of observation in the data is truck lines connecting two stations. We have information on the precise date when each line opened and the distance it covered, and the name of the station it connected. We geo-code the location of each station and generate a dummy variable that indicates whether a given municipality had at least one station, as well as a count variable returning the number of stations. We also define a variable that returns the number of kilometers that separate every given municipality from the closest transatlantic migration port. Calabrese (2017) suggests that railway access to Genoa, Palermo, or Naples—the only ports with ships sailing toward the United States—was a crucial condition to ignite migration movements. We thus compute the shortest path connecting each municipality with each transatlantic port given the state of the railway network in every given year and take the minimum among the three. We aggregate this variable by district and province, taking a population-weighted average of the shortest railway distances to emigration ports.

A.2 Construction of the Sample

All variables that are not computed from geo-coded data are cross-walked to consistent 1921 district and border geographies using the method described by Eckert et al. (2020). To do so, we use GIS boundary files publicly provided by ISTAT for each census year. Even though this yields quantitatively minor corrections, it is important to ensure that geographies remain consistent because the Fascist regime undertook an extensive revision of local government divisions, which ultimately abolished districts in 1927.

We forcibly exclude areas that were annexed as a consequence of World War One in 1918—Trento and Trieste, Südtirol, Istria, and Zara—because we do not observe pre-Quota outcomes in those regions.

Unlike for US emigrants, we do not have district-level data on overall emigration. To assign province-level emigration to districts, we assume that emigration rates were constant within each province. We then impute district emigration by multiplying province emigration by the share of inhabitants in each district compared to the province population before the mass migration (in 1881).

We assemble three distinct samples (Samples 1, 2, and 3). Sample 1, which comprises population and employment-by-sector data, is at the district level and covers the years 1881, 1901, 1911, 1921, 1931, and 1936. Agriculture employment is not available in 1931. All data in Sample 1 are either digitized from population censuses or are aggregated from data tabulated by ISTAT. Sample 2 runs at the province level, covers capital variables and is available in 1911, 1927, and 1937. Capital variables are retrieved from manufacturing censuses. Sample 3 runs at the province level, covers employment-by-industry variables, and spans the years 1901, 1911, 1921, 1927, and 1936. For the first three decades, the data are from population censuses; for the latter two, we digitize them from manufacturing censuses. Since capital variables exhibit substantial left skewness, we winsorize the top 1% of their distribution.

A.3 Details on the Emigration Data

In this section, we document in detail the emigration data that we collect. The raw data can be found at `https://heritage.statueofliberty.org/`. First, we describe the methodology that we adopt to assemble the data. Second, we show how to validate this dataset with external sources. Last, we present some stylized facts that the new data allow us to document.

This dataset responds to a key limitation of commonly used US census data (Ruggles et al., 2021). These list the country of origin of immigrants residing in the US, but they do not report where immigrants originated from within their home country. This issue applies to all countries. Hence separate papers developed strategies to reconstruct such information for, among others, Norway (Abramitzky et al., 2014) and England (Coluccia and Dossi, 2023). This paper looks at emigrants from Italy, a major emigration country among the so-called "second-wave" nations.

A.3.1 Methodology

We run queries over a comprehensive set of the most common 20,000 Italian surnames between 1890 and 1930. We collect individual-level information on the name and surname of immigrants, their municipality of origin, their immigration year, and whether they can read or write.

The municipality of origin is recorded consistently only between 1892 and 1924. Names, surnames, and municipalities are frequently coded with spelling errors, possibly because they were recorded by American enumerators. In this paper, we are interested in the municipality of origin of immigrants. We tackle this data quality issue in two steps. First, we pick the 1,000 most common origin municipalities in the data, and we correct eventual coding errors in those manually. We also discard entries that are too coarse, such as "Italy" or "Sicily." Then, we geo-code the remaining entries using Google Maps' auto-correction algorithm. Then, we manually checked that the return geo-coded locations are reliable for a subset of 200 municipalities. The algorithm successfully matches 189 out of 200 municipalities. The remaining 11 are impossible to match even by hand. We assess the plausibility of this matching exercise in section A.3.2.

The municipality of origin is missing for a non-negligible sub-sample of immigrants. In Figure A.1, we report graphical evidence. The top panel reports the absolute number of recorded immigrants (in blue) and those that we match to a municipality. The bottom panel reports the share of immigrants with at least one listed origin (in blue) and the share that we match to a municipality. Municipalities after the 1924 Immigration Act were seldom recorded, but we never use this sample period in this paper.

In the analysis, the dataset is aggregated by district or province depending on the part of the analysis using boundaries in 1921 from historical shape files provided by ISTAT.

A.3.2 Validation

The granular nature of the dataset implies that we cannot validate it with existing data at similar levels of aggregation. Our strategy, instead, is to aggregate it at the regional level and compare it with data from official statistics on Italian emigration to the United States collected by the Commissioner General for Emigration. These span the period 1877–1925 and are available by region.

In Table A.2, we report the correlation between the Ellis Island dataset and US emigration as recorded in official statistics. In columns (1–5), we report the correlation between the raw series, while in columns (6–7), we take logs. We find a positive and large unconditional correlation between the two (columns 1 and 6). In particular, Ellis Island migration explains more than 80% of the region-level variation in US emigration as measured in official statistics. This correlation remains conditioning on year (2 and 7), region (3 and 8), and year and region (4 and 9) fixed effects. Importantly it holds within the sub-sample period we use to compute the treatment (5 and 10). Figure A.2 displays the unconditional correlation between the two series (A.2a) and the one absorbing region and year fixed effects (A.2b). These exercises document a positive, large, and statistically significant correlation between the Ellis Island US emigration and data from official statistics. Finally, in Figure A.3, we check that the correlation remains high in each year of the observation sample. Each dot in the figure reports the correlation between the two series in one year between 1892 and 1924. The correlation remains stable, positive, and statistically significant throughout the sample period.

A.3.3 Stylized Facts

Dissecting the specific features of mass emigration to the United States is beyond the scope of this paper. Instead, we present two suggestive facts.

First, in Table A.3, we list the districts that were relatively more exposed to the US migration. In columns (1–3), districts are ranked by the absolute number of emigrants.

In columns (4–6), we rank them by the emigration rate, expressed as the ratio between overall US emigrants and the 1921 population. The vast majority of top-ranked districts are located in Southern regions. Emigration rates are higher in Sicily and Campania. The district of Palermo alone accounts for almost 90,000 emigrants out of a population of 850,000.

We then provide evidence supporting the S-hypothesis advanced by Gould (1980a) and recently analyzed by Spitzer and Zimran (2023). This maintains that local out-migration patterns followed a logistic-type dynamic, with initially low uptake, large increases in a relatively short time period, and subsequent plateau. Gould (1980a) connects these dynamics to information diffusion within the population. To test this hypothesis, we mark the beginning of the mass migration in each district when the US emigration rate exceeded 0.1‰. This generates a setting akin to a staggered treatment roll-out. We then use the method of Borusyak et al. (2022) to estimate the dynamics of US out-migration. Importantly, this approach ensures that we compare emigration districts with areas where the migration had not already begun. We find that emigration followed Gould's S-shaped pattern as documented by Spitzer and Zimran (2023). The event-study figures associated with the resulting model are listed in A.4 and show that out-migration follows an S-shaped pattern as argued by Gould (1980a). We interpret this finding as additional evidence supporting the quality of the underlying data.

A.3.4 Linked Sample

To produce the instrumental variable for Quota Exposure, we require information on the origin district and province of Italian immigrants by US county. This information is not available in the US census or reported in the Ellis Island data. To circumvent this limitation, we link the full-count non-anonymized US population census (Ruggles et al., 2021) and the Ellis Island records. To the best of our knowledge, ours is the first attempt to produce a linked sample between these two uniquely rich sources.

The algorithm builds on similar automated linking procedures (e.g., Abramitzky et al., 2021). First, we translate the names of Italian-born individuals recorded in the US census to their Italian version.[63] For each record in the Ellis Island dataset i who immigrates in year t_i, we pick the set of Italian-born individuals J in the 1900 US census whose initial name and surname Soundex-adjusted letters are the same as i's and whose immigration year recorded in the US census is in the window $[t_i - 1, t_i + 1]$.[64] We then compute the Monge-Elkan similarity with Jaro-Winkler inner word distance between the name and surname of i and those of the individuals in J. Among those, we pick the j's with the highest name and surname similarity as potential matches. If both the maximal name and surname similarities are above a given quality threshold, which in the baseline exercise is set at .9, the match(es) is (are) accepted; otherwise, they are discarded.

In Figure A.5, we report the distribution of name and surname similarities for the sample of individuals with at least one potential match. There is substantial mass at 1, where matches are literal. In Figure A.6, we report the share of Ellis Island records with at least one match, in blue, and one *accepted* match, in red. The gross matching rate remains constant throughout the sample at approximately 50%. There are several reasons why someone recorded at Ellis Island may not appear in the 1900 census. First, that person may have left before 1900. Second, women could change their surname. Alternatively, Italians could choose to change their surname as an assimilation effort. If the name change did not simply consist of a translation, we would fail to detect this practice. Finally, the immigration year in the census may be coded with errors. Of the 50% fraction with at least one match, between one-third and one-half presents at least one accepted match with sufficiently high quality. The resulting 22% matching rate is not very distant from benchmark rates for intergenerational linked samples using US census data (Abramitzky et al., 2021).

A key concern for the empirical strategy is that the probability of matching individuals from the Ellis Island data is correlated with their area of origin. This possibility would induce selection in the resulting linked sample, thus ultimately invalidating the rel-

[63] For instance, we convert "Peter" to "Pietro." This procedure ensures that Anglicizations of Italian names that occur in the US census but not in the Ellis Island records do not artificially deflate our matching rate.

[64] We use the Soundex-adjusted algorithm to ensure that different spellings with similar phonetics are treated in the same way. For instance, the Soundex-adjusted initial of "Katherine" and "Catherine" is encoded as the same hard "c."

evance of the shift-share instrument. While we provide quantitative evidence to support the relevance of the first stage, we can check whether any systematic selection pattern emerges directly from the linked data. In Figure A.7, we report the correlation between the probability of matching and the origin region (panel A.2a) and province (panel A.2b) of immigrants. There appears to be no systematic selection pattern. Individuals from Calabria and Sicily are marginally more likely to be matched, even though this difference likely reflects a larger sample size of emigrants from those regions. Overall, the resulting instrumental variable retains a considerable correlation with the observed emigration outflows.

A.4 Tables

Table A.1: Summary of the Data Sources and Coverage

Variable (1)	Observation Unit (2)	Source (3)	Observed Years (4)
Panel A. Demographics			
Population	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Area	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Urbanization	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Literacy	Municipality	Population Censuses	1881-1936, excl.1891
Panel B. Employment, by Sector			
Manufacture	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Agriculture	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Trade	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Liberal Professions	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Public Administration	District (1881-1921), Municipality (1931-1936)	Population Censuses	1881-1936, excl.1891
Panel C. Capital			
Firms	Province	Manufacture Censuses	1911, 1927, 1937
Firms with Engine	Province	Manufacture Censuses	1911, 1927, 1937
Mechanical Engines	Province	Manufacture Censuses	1911, 1927, 1937
Electrical Engines	Province	Manufacture Censuses	1911, 1927, 1937
Mechanical Horsepower	Province	Manufacture Censuses	1911, 1927, 1937
Electrical Horsepower	Province	Manufacture Censuses	1911, 1927, 1937
Panel D. Manufacturing Employment, by Industry			
Agriculture	District (1901–1921), Province (1927–1936)	Population Censuses, Manufacture Census	1901–1936
Chemicals	District (1901–1921), Province (1927–1936)	Population Censuses, Manufacture Census	1901–1936
Construction	District (1901–1921), Province (1927–1936)	Population Censuses, Manufacture Census	1901–1936
Metalworking	District (1901–1921), Province (1927–1936)	Population Censuses, Manufacture Census	1901–1936
Mining	District (1901–1921), Province (1927–1936)	Population Censuses, Manufacture Census	1901–1936
Textiles	District (1901–1921), Province (1927–1936)	Population Censuses, Manufacture Census	1901–1936
Panel E. Emigration			
US Emigration	Municipality	Ellis Island Data	1892-1924
Overall Emigration	Province, imputed to Districts	Official Statistics of the Commissioner General	1877-1925
Panel F. Other			
WW1 deaths	Municipality	ISTORECO, ANPI	1915-1918
Railways	Municipality	ISTAT	1839-1926
US GDP	National	Maddison (2007)	
Panel G. GIS Files			
Shapefiles	District, Provinces	ISTAT	1881–1936, excl. 1891

Notes: This table reports all variables used in the paper. Column (2) returns the level of aggregation at which the variable is measured. Column (3) displays the type of source the raw data are extracted from. Further references to original sources can be found in the text's main body. Column (4) reports the years when the raw data is available. ISTAT: Italian Statistical Office or previous denominations. ISTORECO: Istituto per la storia della Resistenza e della società contemporanea, part of the Associazione Nazionale Partigiani Italiani (ANPI). Referenced on pages A.1

Table A.2: Correlation Between Ellis Island and Official Statistics US Emigration

	Official Statistics Emigrants					ln(1+Official Statistics Emigrants)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ellis Island Migrants	0.906***	0.906***	0.591***	0.591***	0.578***					
	(0.108)	(0.112)	(0.067)	(0.070)	(0.110)					
ln(1+Ellis Island Migrants)						0.957***	1.034***	0.835***	0.618***	0.722***
						(0.048)	(0.087)	(0.045)	(0.059)	(0.143)
Region FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Year FE	No	Yes	No	Yes	Yes	No	Yes	No	Yes	Yes
Sample Years	All	All	All	All	1900–1914	All	All	All	All	1900–1914
N. of Regions	16	16	16	16	16	16	16	16	16	16
N. of Observations	527	527	527	527	240	527	527	527	527	240
R^2	0.820	0.820	0.971	0.971	0.982	0.820	0.882	0.894	0.955	0.972

Notes: This Table compares the number of US emigrants recorded in Italian official statistics with data from the Ellis Island Foundation dataset. The unit of observation is a region at a yearly frequency. The sample period spans 1892 to 1925. In columns (1–5), the dependent and independent variables are the number of emigrants recorded in official statistics and at Ellis Island, respectively. In columns (6–10), both variables are taken as log(1+). Columns (1) and (6) display the unconditional correlation; in columns (2) and (7), (3) and (8), and (4) and (9), we include year, region, and year and region fixed effects. In columns (5) and (10), we restrict the observation sample to the years 1900–1914, which is the period with a lower share of missing municipalities. Standard errors are always clustered at the region level and are displayed in parentheses. Referenced on page A.2

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table A.3: Most Common Emigration Districts

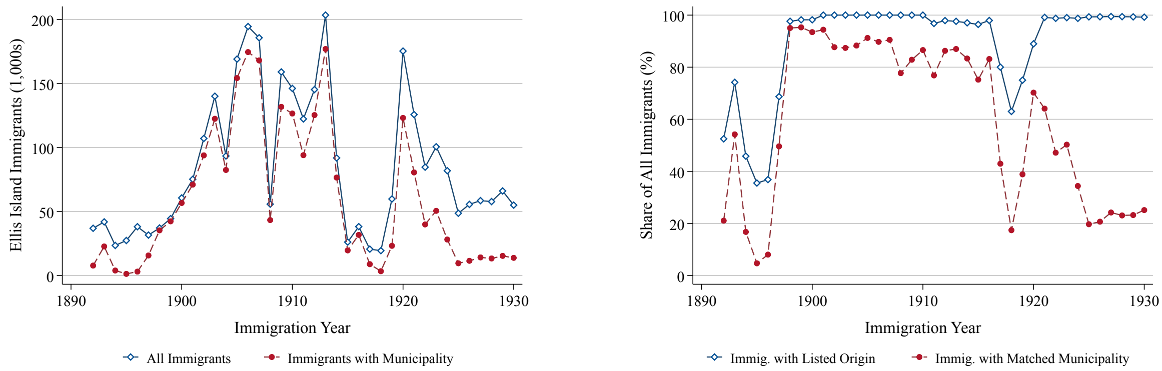
	Most Common Origin Districts					
	Absolute Number of Emigrants			Emigration Rate		
	(1) District	(2) Emigrants	(3) Emigration Rate (‰)	(4) District	(5) Emigrants	(6) Emigration Rate (‰)
1	Palermo	89546	14.097	Termini Imerese	26069	26.358
2	Caserta	40586	11.970	Piedimonte d'Alife	11256	22.794
3	Cosenza	38821	16.673	Campobasso	26965	21.390
4	Bari delle Puglie	37918	8.485	Avellino	37422	18.932
5	Avellino	37422	18.932	Sulmona	18928	18.294
6	Girgenti	34467	12.135	Cefalù	19185	17.604
7	Salerno	33096	10.414	Cosenza	38821	16.673
8	Frosinone	29422	13.111	Isernia	22900	16.466
9	Campobasso	26965	21.390	Asiago	5214	16.429
10	Termini Imerese	26069	26.358	Sant'Angelo de' Lombardi	21404	16.020
11	Messina	25765	8.735	Cerreto Sannita	13676	15.582
12	Napoli	24625	2.479	Nola	17583	15.566
13	Isernia	22900	16.466	Corleone	9192	15.482
14	Sant'Angelo de' Lombardi	21404	16.020	Nicastro	19631	15.360
15	Gerace Marina	21094	13.711	Benevento	18385	14.410
16	Catanzaro	20535	11.606	Palermo	89546	14.096
17	Gaeta	20329	11.228	Gerace Marina	21094	13.711
18	Potenza	19792	12.651	Mistretta	8763	13.612
19	Nicastro	19631	15.360	Cotrone	11811	13.593
20	Cefalù	19185	17.604	Campagna	14273	13.572
21	Sulmona	18928	18.294	Bivona	10908	13.390
22	Aquila degli Abruzzi	18562	12.411	Melfi	13898	13.231
23	Benevento	18385	14.410	Sala Consilina	10458	13.143
24	Caltanissetta	17715	10.747	Frosinone	29422	13.111
25	Lucca	17626	4.748	Castroreale	15883	13.047
26	Nola	17583	15.566	Potenza	19792	12.650
27	Oristano	17183	12.268	Aquila degli Abruzzi	18562	12.411
28	Castellammare di Stabia	16420	7.290	Oristano	17183	12.268
29	Castroreale	15883	13.047	Bovino	6784	12.224
30	Roma	15831	1.616205	Patti	15739	12.18462

Notes: This Table reports the districts with the largest number of US emigrants (columns 1–3) and US emigration rates relative to the 1921 population (columns 4–6). We list the top 30 origin districts in each category. Emigration rates are expressed in per-thousand units. Referenced on page A.3

A.5 Figures

Figure A.1: Missing Origin in the Ellis Island Dataset

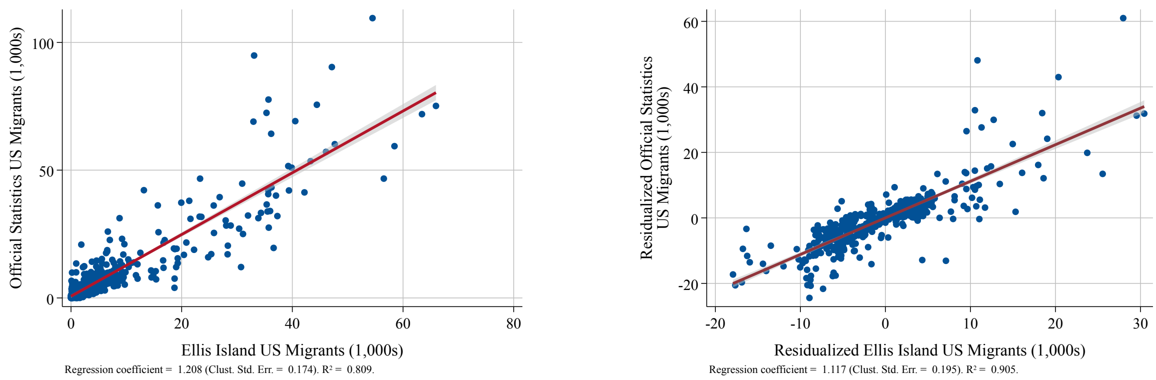
(a) Number of US Immigrants (b) Share of US Immigrants



Notes: This Figure reports data on the missing municipality of origin in the Ellis Island dataset. In Panel A.1a, we display the absolute number of immigrants (in blue) and immigrants for whom we can assign a municipality of origin (in red). In Panel A.1b, we display the share of immigrants with at least one listed place of origin (in blue) and those for whom we can assign the listed origin to a municipality. Referenced on page A.1

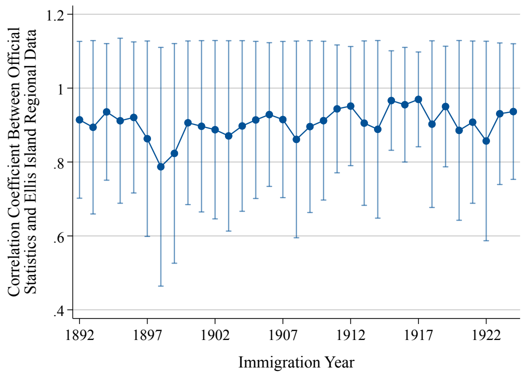
Figure A.2: Correlation between Official Statistics and Ellis Island US Emigration

(a) Unconditional Correlation (b) Conditional Correlation



Notes: This Figure reports the correlation between the number of US emigrants recorded in the Italian official statistics and the number of Italian immigrants recorded in the Ellis Island dataset. The unit of observation is a region at a yearly frequency between 1892 and 1925. In Panel A.2a, we report the unconditional correlation. Panel A.2b displays the correlation between the variables after residualizing region and year-fixed effects. Both graphs report the fitted values of a linear regression between the variables. Referenced on page A.2

Figure A.3: Year-by-Year Correlation Between Ellis Island and Official Statistics US Emigrants

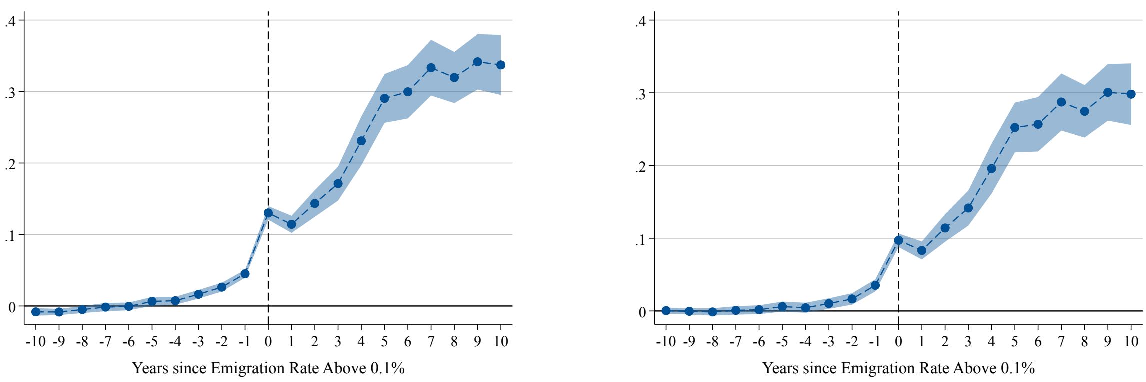


Notes: This Figure reports the correlation between the number of US emigrants recorded in the Italian official statistics and the number of Italian immigrants recorded in the Ellis Island dataset. Each dot reports the correlation between the two variables in one specific year between 1892 and 1925. In each dot, the unit of observation is a region. Both variables are standardized to have zero mean and unitary standard deviation in each year for readability. The bars report 95% confidence intervals from standard errors clustered at the regional level. Referenced on page A.3

Figure A.4: Testing the S-Shaped Hypothesis

(a) Unconditional Emigration

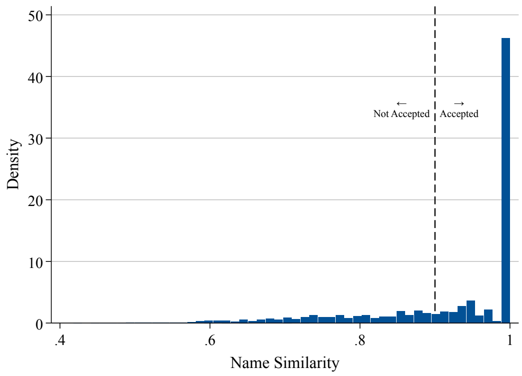
(b) Emigration Net of Fixed Effects



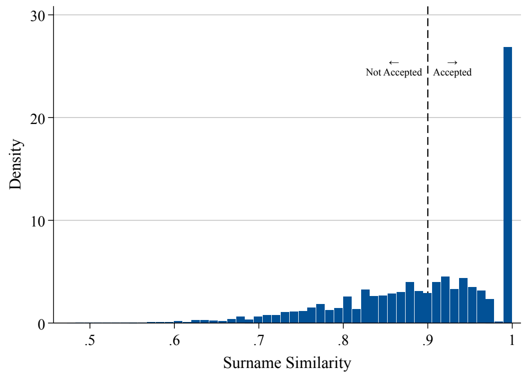
Notes: These figure test the S-shape emigration hypothesis of Gould (1980a). The dependent variable is US emigration, observed at the district level every year between 1892 and 1924. For each district, we define an indicator variable that returns the number of years since the ratio between US emigrants and population in 1921 exceeds 0.1%. We report the estimated difference-in-differences coefficients obtained using the method of Borusyak et al. (2022) around this threshold. Panel A.4a does not include any fixed effect in the regression; in Panel A.4b, we include district and year fixed effects. Standard errors are clustered at the district level; bands report 99% confidence intervals. Referenced on page A.4

Figure A.5: Name and Surname Similarity in the Linked Ellis Island–US Census Sample

(a) Name Similarity

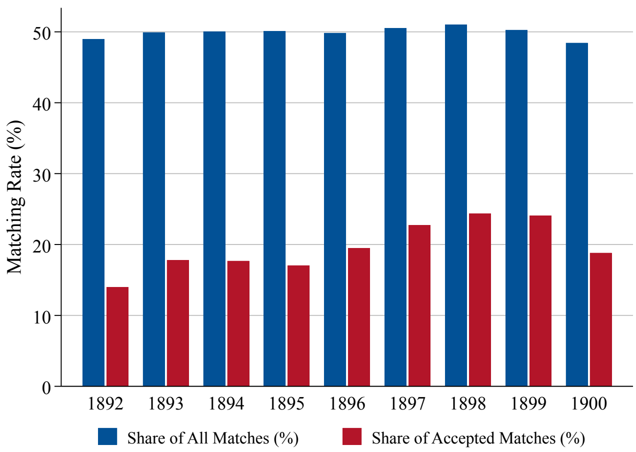


(b) Surname Similarity



Notes: These figures reports the name (panel A.5a) and surname (panel A.5b) similarities between the records of Ellis Island and those that appear in the US census. To compare name and surname matches, we adopt the Monge-Elkan method with the embedded Jaro-Winkler word measure. The resulting values are normalized between zero and one, with values closer to one indicating closer comparisons. For each name and surname recorded in the Ellis Island data, we select the individual in the US census with the highest name and surname similarity among those whose initial Soundex-adjusted letter is the same as the Ellis Island record to be matched. The dashed lines mark the quality thresholds below which we reject the matches as uncertain. Referenced on page A.5

Figure A.6: Matching Rate in the Linked Ellis Island–US Census Sample

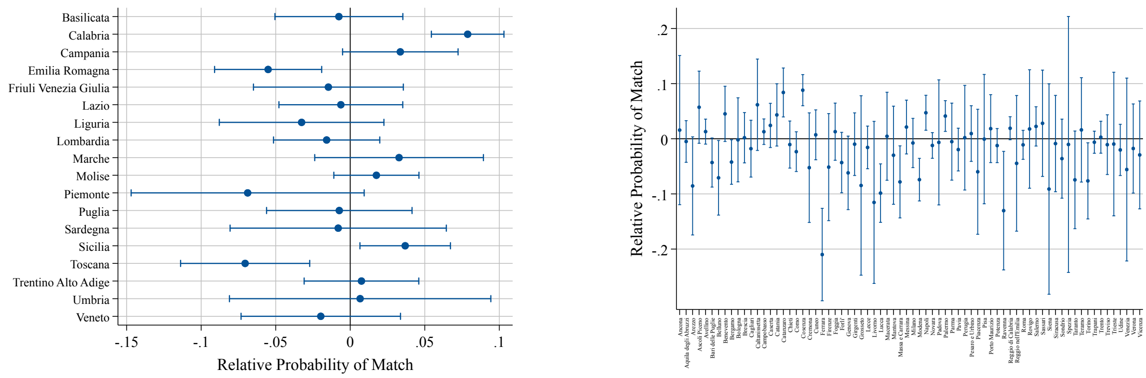


Notes: This Figure reports the matching rate in the linked sample between the Ellis Island data and the records of Italians living in the US as recorded in the population census. The blue bars report the share of individuals with at least one match in the US census. The red bars report the share of individuals with at least one acceptable match—i.e., with name and surname similarity above 0.9—in the US census. Matching rates are expressed in percentage terms and by immigration year. Referenced on page A.6

Figure A.7: Probability of Match: Breakdown by Origin of Ellis Island Immigrants

(a) Correlation by Region of Origin

(b) Correlation by Province of Origin



Notes: These figures report the correlation between the matching status and the region (panel A.7a) and the province (panel A.7b) of origin in the Ellis Island–US Census linked sample. The sample comprises all individuals who appear in the Ellis Island dataset who immigrated between 1892 and 1900. The dependent variable is an indicator equal to one if the individual has at least one accepted match in the linked sample and zero otherwise. The right-hand side consists of a series of indicator variables which tag regions, in panel A.7a, or provinces, in panel A.7b, of origin. Standard errors are clustered at the year level, and the bands report the associated 95% confidence intervals. Referenced on page A.7

A Appendix B - Additional Facts and Results

B.1 Tables

Table B.1: First-Stage Regressions

	Dependent Variable: Measured US Emigrants							
	Weighed				Unweighed			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predicted US Emigrants	0.495***	0.304***	0.341***	0.402***	0.554***	0.377***	0.371***	0.402***
	(0.054)	(0.044)	(0.046)	(0.065)	(0.044)	(0.044)	(0.050)	(0.063)
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Region FE	No	No	Yes	–	No	No	Yes	–
Province FE	No	No	No	Yes	No	No	No	Yes
N. of Districts	192	192	191	177	201	201	201	190
R^2	0.504	0.678	0.767	0.822	0.536	0.663	0.735	0.814
Mean Dep. Var.	8.608	8.608	8.607	8.636	8.548	8.548	8.548	8.569
Std. Beta Coef.	0.710	0.436	0.489	0.580	0.795	0.542	0.533	0.581

Notes: This Table reports the correlation between the number of US emigrants and the shift-share instrument constructed from equation (2). The units of observation are districts. Each district is observed once, and the outcome and the dependent variables are aggregated over time. The outcome variable is measured exposure to the US Quota Acts. In columns (1–4), districts are not weighed by population; in columns (5–8), districts are weighed by 1881 population. Columns (1) and (5) report the unconditional correlation; in columns (2) and (6), we include the number of emigrants and an indicator for southern regions as controls; in columns (3) and (7), we include region fixed effects; columns (4) and (8) control for province fixed effects. Standard errors clustered at the district level are reported in parentheses. Referenced on page B.1

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table B.2: Regional US and Overall Emigration, 1876–1925

	Emigrants to US					Emigrants to all destinations					Share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	76-87	88-99	00-12	13-25	Total	76-87	88-99	00-12	13-25	Total	
Abruzzi e Molise	26.9	68.0	371.0	161.6	627.4	58.3	164.1	585.7	241.6	1049.7	59.8
Basilicata	28.4	53.3	108.1	38.5	228.3	74.1	106.5	179.8	70.5	431.0	53.0
Calabria	15.0	58.5	457.7	125.1	656.3	74.1	178.5	539.8	253.6	1046.1	62.7
Campania	44.3	157.5	637.8	241.5	1081.2	131.3	339.6	871.0	360.7	1702485	63.5
Emilia Romagna	1.3	8.4	62.0	24.0	95.8	60.5	137.7	422.4	178.7	799.2	12.0
Lazio	0.02	2.3	109.4	50.1	161.9	0.4	14.0	151.4	72.9	238.6	67.8
Liguria	8.2	10.8	27.2	10.6	56.8	63.0	51.1	89.0	92.9	296.1	19.2
Lombardia	4.4	11.0	56.7	28.6	100.8	237.9	259.7	675.8	441.6	1615.2	6.2
Marche	0.2	2.0	62.0	30.6	94.8	12.7	48.0	280.6	131.1	472.3	20.1
Piemonte	5.2	12.3	109.8	43.4	170.8	353.3	332.5	697.2	527.9	1910.8	8.9
Puglie	1.3	12.9	164.7	107.9	286.9	8.1	37.2	283.4	172.4	501.2	57.2
Sardegna	0.01	0.03	8.5	5.7	14.2	1.3	6.2	72.8	43.9	124.1	11.5
Sicilia	12.6	117.2	687.7	356.1	1173.6	26.8	170.9	946.5	516.4	1660.6	70.7
Toscana	3.3	12.9	89.6	42.0	147.8	110.7	157.5	412.4	230.6	911.2	16.2
Umbria	0.1	0.5	24.1	11.8	36.6	0.5	6.0	129.9	59.4	195.7	18.7
Veneto	1.0	6.0	52.7	48.4	108.1	486.3	1197.6	1298.2	651.0	3633.1	3.0
Total	152.1	533.9	3029.1	1326.0	5041.3	1699.3	3206.9	7635.8	4045.4	16587.4	30.4

Notes: This Table reports regional emigration towards the US and total emigration from 1876 to 1925. Figures are in thousands. Column (11) indicates the percentage of total emigrants towards US relative to all emigrants from the given region in the whole period 1876-1925. Referenced on page B.2

Source: our elaboration on data from the *Annuario statistico dell'emigrazione italiana dal 1876 al 1925: con notizie sull'emigrazione negli anni 1869-1875*, Italian Statistical Office (ISTAT), Roma, 1926.

Table B.3: Internal and International Migrations, 1921–1931

	Absolute numbers			Share over Population	
	(1)	(2)	(3)	(4)	(5)
	Population	Internal Migrants	Emigrants	Internal Migrants	Emigrants
Abruzzo	1317.2	19.3	170.3	1.5	12.9
Basilicata	524.5	5.6	52.4	1.1	10.0
Calabria	1257.9	8.2	219.4	0.7	17.4
Campania	2896.6	1.2	248.4	0.0	8.6
Emilia Romagna	2183.4	78.7	165.3	3.6	7.6
Lazio	903.5	-133.8	88.2	-14.8	9.8
Liguria	892.4	-60.5	112.7	-6.8	12.6
Lombardia	3680.6	-198.0	460.6	-5.4	12.5
Marche	939.3	25.2	99.2	2.7	10.6
Piemonte	3070.3	-111.9	469.3	-3.6	15.3
Puglia	1589.1	52.9	117.8	3.3	7.4
Sardegna	682.0	2.8	27.7	0.4	4.1
Sicilia	2927.9	31.7	333.4	1.1	11.4
Toscana	2208.9	27.2	198.0	1.2	9.0
Umbria	572.1	-1.0	37.1	-0.2	6.5
Veneto	2814.2	139.8	639.8	5.0	22.7

Notes: This Table reports internal migration and out-migration flows over the period 1921-1931. Column (1) reports the population in 1881. Column (2) is the net internal migrant flow. To compute net internal migration flows, we take the difference in the outflow of people leaving a given region and the inflow of people arriving in that region during the decade 1921-1931. Since Census data only report the stock of people born in a given region living in another region in 1921 and 1931, to compute the outflow of people leaving a region during that decade, we take the difference across years of the total number of people born in that region and living in any other Italian region. Similarly, to compute the inflow of people arriving in a region during that decade, we take the difference across years of the total number living in that region who were born in any other Italian region. Positive (negative) figures imply a net population loss (gain) due to internal migrations. Column (3) reports the number of international emigrants. Figures are in thousands. Columns (4–5) report net internal and international migration figures relative to the 1881 population. Figures are in percentage terms. Referenced on page B.3

Source. Our elaboration on data from the *Annuario statistico dell'emigrazione italiana dal 1876 al 1925: con notizie sull'emigrazione negli anni 1869-1875*, Italian Statistical Office (ISTAT), Roma, 1926, and from *Censimento della Popolazione Italiana*, Italian Statistical Office (ISTAT), Roma, 1921 and 1931.

A Appendix C - Robustness Checks

c.1 Tables

Table c.1: Exposure to the US Quota Acts and Population

	Difference-in-Differences					Instrumented DiD				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US Emigrants × Post (Increasing weight)	0.077**					0.038**				
	(0.034)					(0.015)				
US Emigrants × Post (Decreasing weight)		0.080*					0.038**			
		(0.041)					(0.015)			
US Emigrants × Post (Between 1900 and 1924)			0.077*					0.038**		
			(0.042)					(0.015)		
US Emigrants × Post (Between 1900 and 1920)				0.077*					0.038**	
				(0.041)					(0.015)	
US Emigrants × Post (Between 1890 and 1910)					0.075**					0.037**
					(0.036)					(0.015)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions in Sample										
N. of Districts	202	202	202	202	202	192	192	192	192	192
N. of Observations	1198	1198	1198	1198	1198	1140	1140	1140	1140	1140
R^2	0.372	0.372	0.372	0.372	0.372	0.369	0.369	0.369	0.369	0.369
Mean Dep. Var.	1.734	1.734	1.734	1.734	1.734	1.788	1.788	1.788	1.788	1.788
Std. Beta Coef.	0.117	0.127	0.144	0.142	0.133	0.021	0.023	0.067	0.067	0.067

Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on population. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. Each column represents the estimates of a regression where the treatment is an interaction between a post-Quota (1921) indicator variable and the district-level number of US emigrants. We use five different approaches to compute US emigration, constructed using different weighting of the number of emigrants to the US or computing the number of US emigrants over different periods. In columns 1 and 2, we assign a higher weight to emigrants who departed closer to the Quota Acts date and much earlier: for both measures, we adopt an exponential weighting of factor 0.9. In columns 3, 4, and 5, we construct the Quota Exposure using the number of emigrants to the US who departed between 1900 and 1924, between 1900 and 1920, and between 1890 and 1910. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. We replicate the analysis in columns 6-10, substituting the measured US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.1
***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.2: Exposure to the US Quota Acts and Capital Investment

	Observed Quota Exposure						Instrumented Quota Exposure					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Firms	Firms with Engines	Mechanical Engines	Electrical Engines	Mechanical Horsepower	Electrical Horsepower	Firms	Firms with Engines	Mechanical Engines	Electrical Engines	Mechanical Horsepower	Electrical Horsepower
Panel A. Increasing weight												
US Emigrants × Post	-0.168**	-0.090	-0.190***	-0.390	-0.252**	-0.212						
	(0.073)	(0.122)	(0.068)	(0.321)	(0.103)	(0.253)						
IV US Emigrants × Post							-0.054*	-0.092***	-0.011	-0.109	-0.069**	-0.102**
							(0.029)	(0.021)	(0.021)	(0.071)	(0.034)	(0.052)
Panel B. Decreasing weight												
US Emigrants × Post	-0.203**	-0.062	-0.199***	-0.391	-0.171	-0.173						
	(0.081)	(0.136)	(0.077)	(0.348)	(0.109)	(0.269)						
IV US Emigrants × Post							-0.054*	-0.093***	-0.011	-0.113	-0.067*	-0.103**
							(0.029)	(0.022)	(0.021)	(0.071)	(0.034)	(0.052)
Panel C. US emigrants between 1900 and 1924												
US Emigrants × Post	-0.170**	-0.051	-0.198**	-0.320	-0.188*	-0.131						
	(0.073)	(0.131)	(0.077)	(0.336)	(0.112)	(0.262)						
IV US Emigrants × Post							-0.054*	-0.093***	-0.011	-0.112	-0.068**	-0.103**
							(0.029)	(0.022)	(0.021)	(0.071)	(0.034)	(0.052)
Panel D. US emigrants between 1900 and 1920												
US Emigrants × Post	-0.161**	-0.045	-0.198***	-0.295	-0.189*	-0.116						
	(0.071)	(0.129)	(0.077)	(0.331)	(0.112)	(0.260)						
IV US Emigrants × Post							-0.054*	-0.093***	-0.011	-0.112	-0.068**	-0.103**
							(0.029)	(0.022)	(0.021)	(0.071)	(0.034)	(0.052)
Panel E. US emigrants between 1890 and 1910												
US Emigrants × Post	-0.151**	-0.067	-0.183***	-0.329	-0.229**	-0.162						
	(0.068)	(0.121)	(0.069)	(0.318)	(0.105)	(0.251)						
IV US Emigrants × Post							-0.054*	-0.092***	-0.011	-0.109	-0.069**	-0.101**
							(0.029)	(0.021)	(0.021)	(0.071)	(0.034)	(0.052)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Provinces	68	68	68	68	68	68	68	68	68	68	68	68
N. of Observations	204	204	204	204	204	204	204	204	204	204	204	204
Mean Dep. Var.	7.263	1.252	0.544	3.437	14.079	24.240	7.263	1.252	0.544	3.437	14.079	24.240

Notes: This Table reports the estimated effect of exposure to the US Quota Acts on capital investment. The unit of observation is a province observed at a census-decade frequency between 1911 and 1936. The dependent variables are the number of firms (column 1), the number of firms with at least one engine (column 2), the number of mechanical engines (column 3), the number of electrical engines (column 4), the horsepower generated by mechanical (column 5) and electrical (column 6) engines. The treatment is an interaction between a post-Quota (1921) indicator variable and US emigration. In the five panels, we construct US emigration using different approaches. In Panel A and B we respectively assign a higher weight to emigrants departed closer to the Quota Acts date and much earlier in time: for both measures we adopt an exponential weighting of factor 0.9. In Panel C, D, and E, we respectively construct the Quota Exposure using the number of emigrants to the US who departed, respectively, between 1900 and 1924, between 1900 and 1920, and between 1890 and 1910. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. In columns (7–12), we replicate the same analysis but substitute the observed values of US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.2
***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.3: Exposure to the US Quota Acts and Manufacture Employment

	Difference-in-Differences					Instrumented DiD				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US Emigrants × Post (Increasing weight)	0.111**					0.070**				
	(0.052)					(0.032)				
US Emigrants × Post (Decreasing weight)		0.077					0.071**			
		(0.054)					(0.032)			
US Emigrants × Post (Between 1900 and 1924)			0.079					0.071**		
			(0.056)					(0.032)		
US Emigrants × Post (Between 1900 and 1920)				0.078					0.071**	
				(0.056)					(0.032)	
US Emigrants × Post (Between 1890 and 1910)					0.102*					0.070**
					(0.054)					(0.032)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions in Sample	All	All	All	All	All	All	All	All	All	All
N. of Districts	202	202	202	202	202	192	192	192	192	192
N. of Observations	1198	1198	1198	1198	1198	1140	1140	1140	1140	1140
R^2	0.597	0.597	0.597	0.597	0.597	0.597	0.597	0.597	0.597	0.596
Mean Dep. Var.	2.114	2.114	2.114	2.114	2.114	2.185	2.185	2.185	2.185	2.185
Std. Beta Coef.	0.078	0.057	0.068	0.067	0.084	0.018	0.020	0.058	0.058	0.057

Notes: This Table reports the estimated effect of exposure to the US Quota Acts on manufacturing employment. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. Each column represents the estimates of a regression where the treatment is an interaction between a post-Quota (1921) indicator variable and the number of US emigrants. We use five different approaches to compute the number of US emigrants. In columns 1 and 2, we assign a higher weight to emigrants who departed closer to the Quota Acts date and much earlier: for both measures, we adopt an exponential weighting of factor 0.9. In columns 3, 4, and 5, we construct the Quota Exposure using the number of emigrants to the US who departed between 1900 and 1924, between 1900 and 1920, and between 1890 and 1910. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. We replicate the analysis in columns 6-10, substituting the measured US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.3

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.4: Exposure to the Quota Acts and Agriculture Employment

	Difference-in-Differences					Instrumented DiD				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
US Emigrants × Post (Increasing weight)	-0.039					-0.017				
	(0.045)					(0.022)				
US Emigrants × Post (Decreasing weight)		-0.050					-0.017			
		(0.049)					(0.022)			
US Emigrants × Post (Between 1900 and 1924)			-0.042					-0.017		
			(0.049)					(0.022)		
US Emigrants × Post (Between 1900 and 1920)				-0.041					-0.017	
				(0.048)					(0.022)	
US Emigrants × Post (Between 1890 and 1910)					-0.036					-0.017
					(0.045)					(0.022)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions in Sample	All	All	All	All	All	All	All	All	All	All
N. of Districts	202	202	202	202	202	192	192	192	192	192
N. of Observations	996	996	996	996	996	948	948	948	948	948
R^2	0.313	0.313	0.313	0.313	0.313	0.304	0.304	0.304	0.304	0.304
Mean Dep. Var.	4.089	4.089	4.089	4.089	4.089	4.215	4.215	4.215	4.215	4.215
Std. Beta Coef.	-0.043	-0.058	-0.057	-0.055	-0.046	-0.007	-0.007	-0.022	-0.022	-0.022

Notes: This Table reports the estimated effect of exposure to the US Quota Acts on agriculture employment. The unit of observation is a district observed at a census-decade frequency between 1881 and 1936. Each column represents the estimates of a regression where the treatment is an interaction between a post-Quota (1921) indicator variable and the number of US emigrants. We use five approaches to compute the number of US emigrants. In columns 1 and 2, we assign a higher weight to emigrants who departed closer to the Quota Acts date and much earlier: for both measures, we adopt an exponential weighting of factor 0.9. In columns 3, 4, and 5, we respectively construct the Quota Exposure using the number of emigrants to the US who departed, respectively, between 1900 and 1924, between 1900 and 1920, and between 1890 and 1910. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. We replicate the analysis in columns 6-10, substituting the measured US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.4
***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.5: Exposure to the US Quota Acts and Population

	Difference-in-Differences						Instrumented DiD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
US Emigrants $\times$ Post	0.078**	0.039	0.085**	0.079*	0.040	0.081**						
	(0.039)	(0.034)	(0.040)	(0.041)	(0.044)	(0.040)						
US $\widehat{\text{Emigrants}}$ $\times$ Post							0.037***	0.027**	0.037**	0.037**	0.029*	0.038**
							(0.014)	(0.013)	(0.015)	(0.015)	(0.017)	(0.015)
Literacy $\times$ Post	0.074						0.018					
	(0.097)						(0.087)					
Urbanization $\times$ Post		0.282***						0.292***				
		(0.064)						(0.067)				
Altitude $\times$ Post			-0.028						-0.019			
			(0.020)						(0.023)			
Railway $\times$ Post				0.074**						0.098***		
				(0.035)						(0.036)		
WW1 deaths $\times$ Post					0.000**						0.000***	
					(0.000)						(0.000)	
Emigrants $\times$ US GDP growth						-0.000						-0.001
						(0.001)						(0.001)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions in Sample												
N. of Districts	202	202	202	202	202	202	192	192	192	192	192	192
N. of Observations	1198	1198	1198	1198	1198	1198	1140	1140	1140	1140	1140	1140
R^2	0.372	0.373	0.372	0.372	0.373	0.372	0.369	0.370	0.369	0.369	0.369	0.369
Mean Dep. Var.	1.734	1.734	1.734	1.734	1.734	1.734	1.788	1.788	1.788	1.788	1.788	1.788
Std. Beta Coef.	0.146	0.074	0.159	0.148	0.075	0.151	0.016	0.012	0.016	0.016	0.013	0.017

Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on population. Each column includes the interaction between the post-quota indicator variable and a district- or country-specific variable as one further control. In column 1, we use the district's literacy rate in 1901; in column 2, the urbanization rate in 1901, measured as the share of people living in towns with more than 5'000 inhabitants in the district; in column 3, the altitude at which the district is located; in column 4 an indicator variable specifying whether the district was connected to the railway network before 1901; in column 5 district's number of deaths caused by WW1. In column 6, we use the US GDP growth, which we interact with the emigration volume. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. We replicate the analysis in columns 7-12, substituting the measured US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.5
***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.6: Exposure to the US Quota Acts and Capital Investment

	Observed Quota Exposure						Instrumented Quota Exposure					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Firms	Firms with Engines	Mechanical Engines	Electrical Engines	Mechanical Horsepower	Electrical Horsepower	Firms	Firms with Engines	Mechanical Engines	Electrical Engines	Mechanical Horsepower	Electrical Horsepower
Panel A. Control: Literacy × Post												
US Emigrants × Post	-0.167**	-0.032	-0.192***	-0.328	-0.207**	-0.136						
	(0.070)	(0.142)	(0.058)	(0.341)	(0.101)	(0.277)						
IV US Emigrants × Post							-0.034	-0.110**	-0.025	-0.089	-0.178**	-0.192**
							(0.046)	(0.046)	(0.045)	(0.117)	(0.079)	(0.097)
Panel B. Control: Urbanization × Post												
US Emigrants × Post	-0.178**	-0.059	-0.197***	-0.368	-0.203**	-0.145						
	(0.076)	(0.165)	(0.054)	(0.441)	(0.096)	(0.320)						
IV US Emigrants × Post							-0.104***	-0.135***	-0.033	-0.294**	-0.125**	-0.212**
							(0.038)	(0.035)	(0.034)	(0.148)	(0.055)	(0.093)
Panel C. Control: Altitude × Post												
US Emigrants × Post	-0.220**	-0.054	-0.176***	-0.649	-0.163	-0.262						
	(0.104)	(0.194)	(0.057)	(0.495)	(0.118)	(0.375)						
IV US Emigrants × Post							-0.087*	-0.137***	-0.020	-0.356***	-0.114*	-0.263***
							(0.048)	(0.046)	(0.034)	(0.125)	(0.065)	(0.092)
Panel D. Control: Railway access × Post												
US Emigrants × Post	-0.170**	-0.057	-0.196***	-0.315	-0.182**	-0.149						
	(0.072)	(0.163)	(0.053)	(0.372)	(0.085)	(0.296)						
IV US Emigrants × Post							-0.077*	-0.136***	-0.034	-0.233**	-0.111**	-0.224***
							(0.043)	(0.031)	(0.034)	(0.104)	(0.055)	(0.069)
Panel E. Control: WW1 death rate × Post												
US Emigrants × Post	-0.009	0.071	-0.190***	0.339	-0.147	0.248						
	(0.069)	(0.167)	(0.054)	(0.340)	(0.106)	(0.293)						
IV US Emigrants × Post							-0.026	-0.102***	-0.028	-0.169**	-0.107*	-0.153**
							(0.039)	(0.038)	(0.035)	(0.077)	(0.055)	(0.074)
Panel F. Control: US GDP growth × I(Quota Exposure) × Post												
US Emigrants × Post	-0.143*	-0.090	-0.298***	-0.275	-0.204**	-0.117						
	(0.084)	(0.165)	(0.075)	(0.364)	(0.094)	(0.274)						
IV US Emigrants × Post							-0.078*	-0.133***	-0.036	-0.258**	-0.125**	-0.216***
							(0.045)	(0.034)	(0.034)	(0.101)	(0.056)	(0.074)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N. of Provinces	68	68	68	68	68	68	68	68	68	68	68	68
N. of Observations	204	204	204	204	204	204	204	204	204	204	204	204
Mean Dep. Var.	7.263	1.252	0.544	3.437	14.079	24.240	7.263	1.252	0.544	3.437	14.079	24.240

Notes: This Table reports the effect of the Quotas on capital investment. In the five panels, we add a different control, given by the interaction between the post-quota indicator variable and a province-specific variable. We use, respectively, the literacy rate in 1901, the urbanization rate in 1901 (share of people in towns with more than 5'000 inhabitants), the altitude, the share of municipalities connected to the railway network before 1901, the number of deaths caused by WW1; the US GDP growth interacted with the province's number of emigrants. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. In columns (7–12), we replicate the exercises but substitute measured US emigration with the shift-share instrument. Standard errors clustered at the province level are reported in parentheses. Referenced on page c.6
***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.7: Exposure to the US Quota Acts and Manufacture Employment

	Difference-in-Differences						Instrumented DiD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
US Emigrants × Post	0.063	0.045	0.096*	0.090	0.071	0.094*						
	(0.044)	(0.052)	(0.058)	(0.056)	(0.063)	(0.056)						
US $\widehat{\text{Emigrants}}$ × Post							0.042	0.057*	0.071**	0.070**	0.067*	0.071**
							(0.031)	(0.034)	(0.032)	(0.032)	(0.035)	(0.032)
Literacy × Post	0.683***						0.601***					
	(0.172)						(0.180)					
Urbanization × Post		0.288**						0.259**				
		(0.146)						(0.126)				
Altitude × Post			-0.013						0.002			
			(0.035)						(0.030)			
Railway × Post				0.179*						0.190*		
				(0.096)						(0.111)		
WW1 deaths × Post					0.000						0.000	
					(0.000)						(0.000)	
Emigrants × US GDP growth						-0.000						-0.001
						(0.004)						(0.004)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions in Sample												
N. of Districts	202	202	202	202	202	202	192	192	192	192	192	192
N. of Observations	1198	1198	1198	1198	1198	1198	1140	1140	1140	1140	1140	1140
R^2	0.599	0.598	0.597	0.597	0.597	0.597	0.597	0.597	0.597	0.597	0.597	0.597
Mean Dep. Var.	2.114	2.114	2.114	2.114	2.114	2.114	2.185	2.185	2.185	2.185	2.185	2.185
Std. Beta Coef.	0.054	0.039	0.083	0.078	0.061	0.081	0.008	0.011	0.014	0.014	0.013	0.014

Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on population. In each column, we control for the interaction between the post-quota indicator variable and a district- or country-specific variable. In column 1, we use the district's literacy rate in 1901; in column 2, the urbanization rate in 1901, measured as the share of people living in towns with more than 5'000 inhabitants in the district; in column 3, the altitude at which the district is located; in column 4 an indicator variable specifying whether the district was connected to the railway network before 1901; in column 5 district's number of deaths caused by WW1. In column 6, we use the US GDP growth interacted with the volume of international emigrants. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. In columns (7–12), we replicate the analysis by substituting the measured US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.7

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

Table c.8: Exposure to the Quota Acts and Agriculture Employment

	Difference-in-Differences						Instrumented DiD					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
US Emigrants × Post	-0.037	-0.033	-0.038	-0.043	-0.049	-0.043						
	(0.049)	(0.045)	(0.049)	(0.049)	(0.046)	(0.048)						
US $\widehat{\text{Emigrants}}$ × Post							-0.002	-0.020	-0.016	-0.017	-0.017	-0.018
							(0.021)	(0.023)	(0.023)	(0.023)	(0.022)	(0.023)
Literacy × Post	-0.450***						-0.454***					
	(0.118)						(0.105)					
Urbanization × Post		-0.105						-0.134				
		(0.075)						(0.093)				
Altitude × Post			-0.029						-0.030*			
			(0.018)						(0.018)			
Railway × Post				0.014						-0.001		
				(0.043)						(0.041)		
WW1 deaths × Post					0.000						0.000	
					(0.000)						(0.000)	
Emigrants × US GDP growth						-0.007***						-0.007***
						(0.002)						(0.003)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decade FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regions in Sample												
N. of Districts	202	202	202	202	202	202	192	192	192	192	192	192
N. of Observations	996	996	996	996	996	996	948	948	948	948	948	948
R^2	0.314	0.313	0.313	0.313	0.313	0.313	0.306	0.305	0.305	0.304	0.304	0.305
Mean Dep. Var.	4.089	4.089	4.089	4.089	4.089	4.089	4.215	4.215	4.215	4.215	4.215	4.215
Std. Beta Coef.	-0.051	-0.045	-0.052	-0.059	-0.067	-0.059	-0.000	-0.006	-0.005	-0.005	-0.005	-0.005

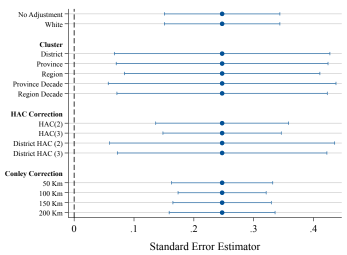
Notes: This Table reports the estimated effect of district-level exposure to the US Quota Acts on population. In each column, we control for the interaction between the post-quota indicator variable and a district- or country-specific variable. In column 1, we use the district's literacy rate in 1901; in column 2, the urbanization rate in 1901, measured as the share of people living in towns with more than 5'000 inhabitants in the district; in column 3, the altitude at which the district is located; in column 4 an indicator variable specifying whether the district was connected to the railway network before 1901; in column 5 district's number of deaths caused by WW1. In column 6 we use the US GDP growth interacted with the volume of international emigrants. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. In columns (7–12), we replicate the analysis, substituting the measured US emigration with the shift-share instrument. Units are weighed by their population in 1881. Standard errors clustered at the district level are reported in parentheses. Referenced on page c.8

***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.10$

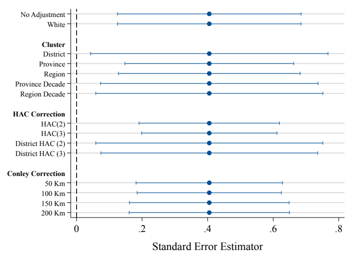
c.2 Figures

Figure c.1: Alternative Standard Errors: District-Level Regressions

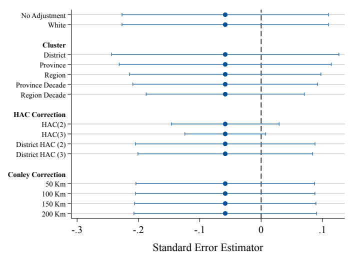
(a) Population



(b) Manufacturing Employment



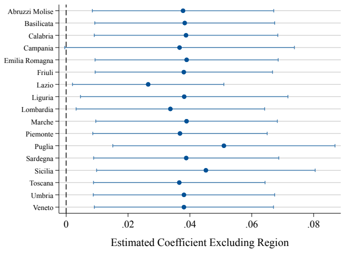
(c) Agriculture Employment



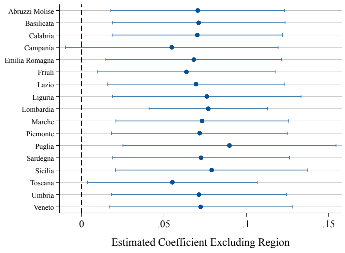
Notes: This Figure reports alternative estimators of the standard errors in the baseline district-level regressions. The unit of observation is a district, at a decade frequency between 1881 and 1936. The dependent variable is population (Panel c.1a), manufacturing employment (Panel c.1b), and agriculture employment (Panel c.1c). Regressions are estimated through OLS and include district and decade fixed effects. The treatment is an interaction term between the instrumented US emigration and a post-1921 term. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. Units are weighed by their population in 1881. Bands report 90% confidence intervals. Referenced on page c.1

Figure c.2: Excluding one region at the time: District-Level Regressions

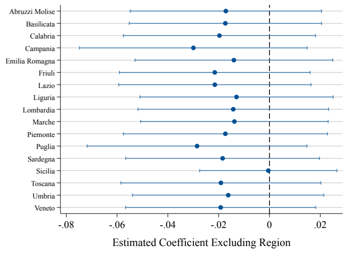
(a) Population



(b) Manufacturing Employment



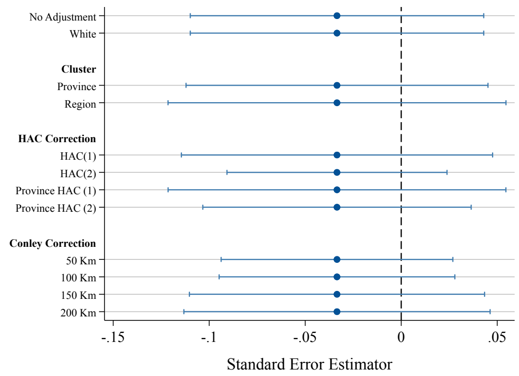
(c) Agriculture Employment



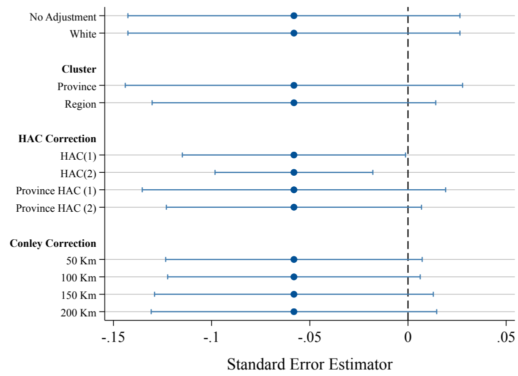
Notes: This Figure reports the estimates of the baseline district-level regressions when excluding one region. The unit of observation is a district, at a decade frequency between 1881 and 1936. The dependent variable is population (Panel c.2a), manufacturing employment (Panel c.2b), and agriculture employment (Panel c.2c). Regressions include district and decade-fixed effects. The treatment is an interaction term between the instrumented US emigration and a post-1921 term. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. The left axis indicates the excluded region. Units are weighed by their population in 1881. Bands report 95% confidence intervals. Standard errors clustered at the district level. Referenced on page c.2

Figure c.3: Alternative Standard Errors: Province-Level Regressions

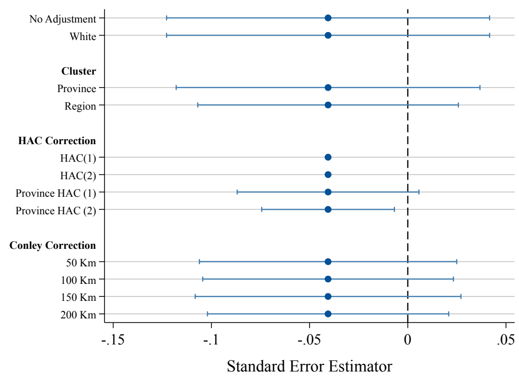
(a) Firms



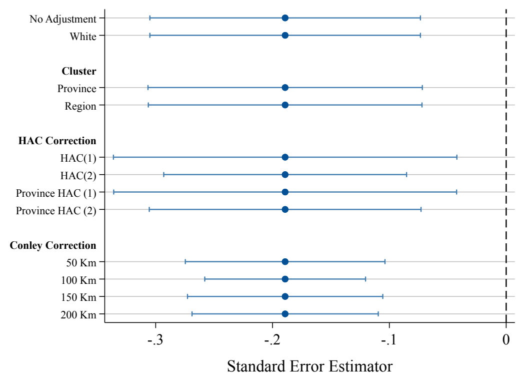
(b) Firms with Engine



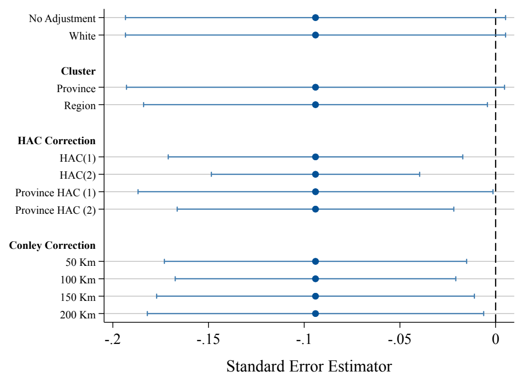
(c) Mechanical Engines



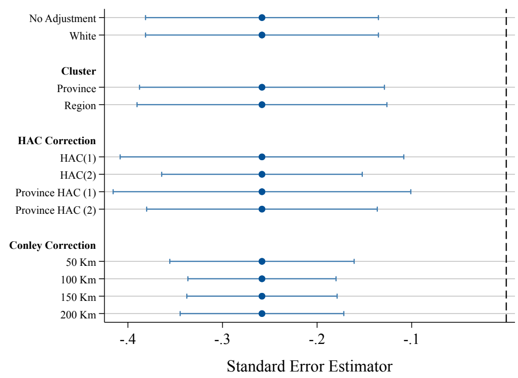
(d) Electrical Engines



(e) Mechanical Horsepower

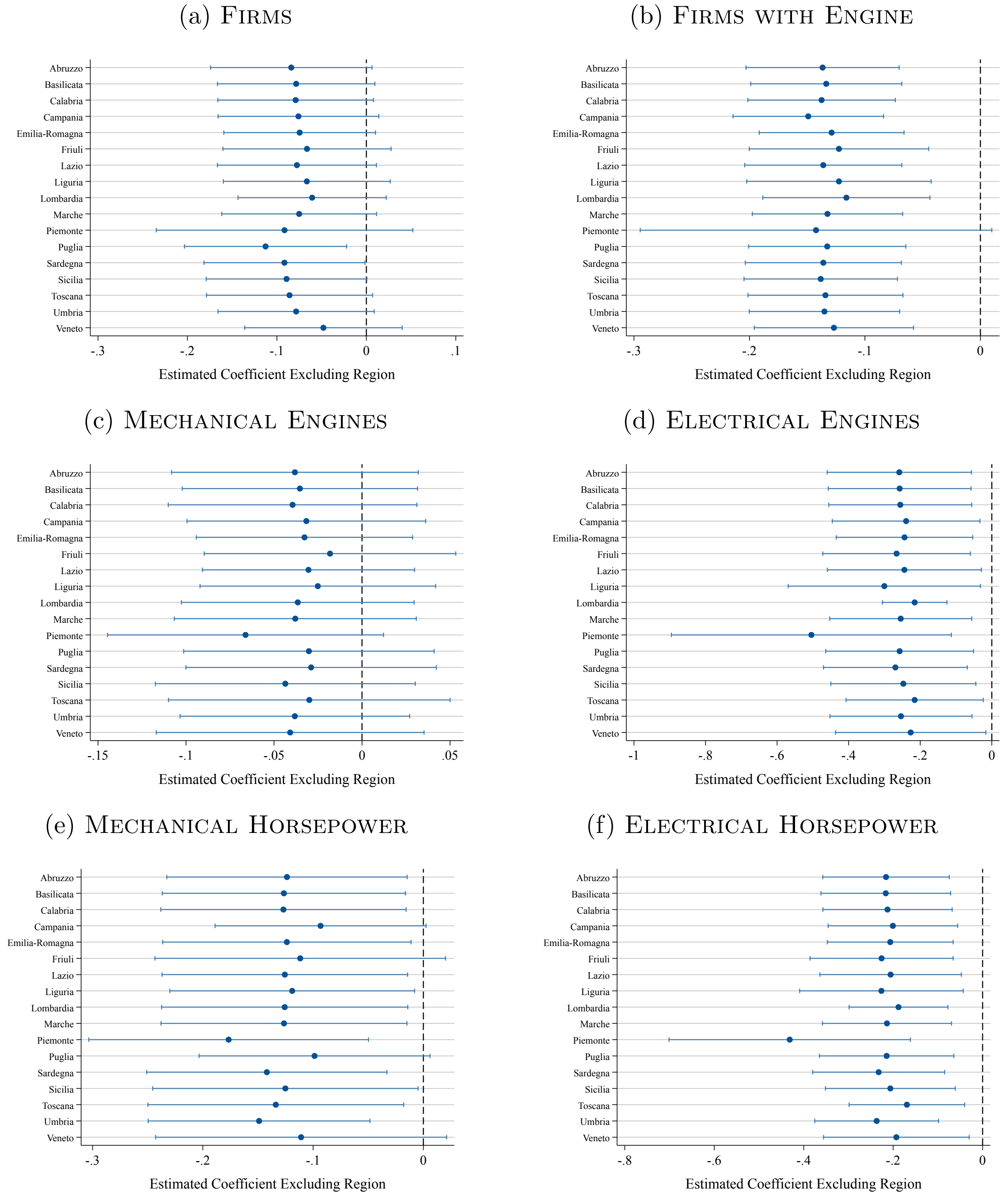


(f) Electrical Horsepower



Notes: This Figure reports alternative estimators of the standard errors in the baseline province-level regressions. The unit of observation is a province, at a decade frequency between 1911 and 1937. Regressions are estimated through OLS on the logged outcomes and include province and decade fixed effects. The treatment is an interaction term between the instrumented US emigration and a post-1921 term. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. Units are weighed by their population in 1881. Bands report 90% confidence intervals. Referenced on page c.3

Figure c.4: Excluding one region at the time: Province-Level Regressions



Notes: This Figure reports the estimates of the baseline province-level regressions when excluding one region. The unit of observation is a province, at a decade frequency between 1911 and 1937. Regressions include province and decade fixed effects. The left axis indicates the excluded region. The treatment is an interaction term between the instrumented US emigration and a post-1921 term. Each regression controls for the number of emigrants and an interaction term between an indicator variable for Southern regions and a post-1921 indicator. Units are weighed by their population in 1881. Bands report 95% confidence intervals. Standard errors clustered at the province level. Referenced on page c.4

A Appendix D - A Model of Directed Technological Adoption

In this section, we develop a simple framework to rationalize our main findings in the context of labor-saving technical change theory. Proofs and further analytical insights on the baseline environment can be found in section D.3.

D.1 Theoretical Framework

In this section, we develop a simple analytical framework inspired to zeira$_w orkers_1 998andsan_l abor_2 023to$
$--hereafter, machines---substitutelaborasaproductioninput. Wethusimplicitlyrestricttechnologic$
$saving, asinacemoglu_d irected_2 002, acemoglu_e quilibrium_2 007. The decision of the firm to adopt productivi$
$enhancingmachineswilldependontheirpricerelativetothecostoflabor. Intheequilibrium, alaborsupplysh$
$--suchastheoneinducedbyIRPs---dampenstheincentivetoadoptmachinesbecauseitpushesdownthe$

Consider a closed economy with one consumption good and a representative household supplying labor. The consumption good is produced by a continuum of tasks $j \in [0, 1]$. Each task can be performed with either labor or machines. The amount of machines in task j is denoted by $x(j)$, whereas the amount of labor employed is $e(j)$. Note that each task can be fulfilled with either machines or labor, but not both. This is intended to model in a stylized manner labor-saving machines. To simplify the analysis and following **?** we assume that machines fully depreciate at the end of the period, hence the model is essentially static.

The final consumption good is produced by identical, perfectly competitive firms with the following production function:

$$Y = A\left[\int_0^{\iota} m x(j)^{\alpha}\, dj + \int_{\iota}^{1} e(j)^{\alpha}\, dj\right], \tag{3}$$

where A is a technology parameter, m is the relative productivity of machines and $\alpha \in (0, 1)$ is a production parameter. We assume $m \in (0, 1)$ following san$_l abor_2 023, andrestrictmachinestobe$
$[0, 1]$ denotes *industrialization* defined as the share of automatized tasks, which are those

fulfilled by machines. We assume that tasks are ordered by degree of complexity. Because the marginal cost of producing machines—which we define below—is increasing in complexity, the price of machines is non-decreasing in j. It is therefore without loss of generality to assume that the first ι tasks are automatized. This is because the final good producer will first automatize tasks whose machine costs the least since the relative productivity of machines is constant across tasks. We assume that there is a fixed stock of labor $L > 0$ which is supplied inelastically by the household.

The problem of the representative final good producer is, therefore, to choose the industrialization level ι, and input quantities $x(j)$ and $e(j)$ for each task to maximize profits

$$\max_{\iota, \{x(j), e(j)\}_{j \in [0,1]}} Y - \int_0^{\iota} p(j)x(j)\, dj - w \int_{\iota}^{1} e(j)\, dj, \tag{4}$$

where $p(j)$ is the price of a machine for task j, w is the nominal wage, subject to the technology constraint (3). Note that the price of the consumption good is implicitly normalized to one. In section D.3, we formally show that the demand schedules for machines and labor are given by the following demand schedules:

$$x(j) = p(j)^{-\frac{1}{1-\alpha}} (\alpha A m)^{\frac{1}{1-\alpha}} \quad \forall j \in [0, \iota], \tag{5a}$$

$$e(j) = w^{-\frac{1}{1-\alpha}} (\alpha A)^{\frac{1}{1-\alpha}} \quad \forall j \in [\iota, 1]. \tag{5b}$$

Combining (5a)-(5b) with the first order condition for the industrialization rate, it follows that in the equilibrium ι^* is pinned down by the following:

$$m = \left[\frac{p(\iota^*)}{w}\right]^{\alpha}. \tag{6}$$

The economic intuition behind condition (6) is that at the marginal task, *i.e.* the last automatized task, the price of the machine fulfilling the task must be equal to the cost of labor, adjusted by the technology parameter and the relative productivity of machines.

Each machine is produced by a monopolist, following zeira$_{w}orkers_{1}998.Themachineproducerwillsee$

is increasing in the complexity of tasks, *i.e.* $\psi'(\cdot) > 0$. Moreover, we assume that the marginal cost function satisfies basic Inada conditions.[65] This is intended to capture the idea that machines substituting low-skill tasks are not as expensive as those replacing tasks on the right side of the skill distribution of workers. The problem of the machine producer is therefore

$$\max_{p(j)} \left[p(j) - \psi(j)\right] x(j), \tag{7}$$

subject to (5a). In section D.3, we show that the first-order conditions imply

$$p(j) = \min\left\{mw, \frac{\psi(j)}{\alpha}\right\}, \tag{8}$$

where the minimum descends from the observation that because each task can be performed by labor as well as by machines, setting a price greater than the productivity-adjusted wage simply pushes the final goods producer not to automatize the task. We now obtain two technical results to ensure the existence and uniqueness of the equilibrium. The formal definition of the competitive equilibrium in this economy, as well as the proofs of all lemmas and propositions, can be found in section D.3. In the equilibrium, the marginal task ι^* is such that $p(\iota^*) = \psi(\iota^*)/\alpha = wm^{1/\alpha}$. Combining this result with the equilibrium conditions of the final goods producer, we derive the following strong existence result.

Proposition 1 *There exists one and only one* $\iota^* \in [0, 1]$ *which solves the problem of the final good producer* (5a)-(5b)-(6) *as well as the problem of the machine producers* (8) *and verifies labor market clearing. In particular, the equilibrium industrialization* ι^* *is the solution to the following:*

$$\psi(\iota^*) = L^{\alpha-1}(1-\iota^*)^{1-\alpha}\alpha^2 A m^{1/\alpha}.$$

This concludes our analytical characterization of the environment. We now exploit the

[65]In this setting, this simply boils down to $\lim_{j\uparrow 1} \psi(j) = +\infty$ and $\lim_{j\downarrow 0} \psi(j) = 0$. The economic intuition behind these is that it is never profitable for the representative firm to automatize all tasks. Similarly, there is always at least one task that is automatized. Note that while these assumptions are sufficient for the existence of an equilibrium, they are not necessary.

model to deliver a number of testable predictions which will guide our empirical analysis.

D.2 Empirically Testable Implications

Having established the existence of the equilibrium, we can now derive two key empirical implications of this directed technical adoption setting. First, note that Lemma D.1 conveys the basic intuition of the model. In particular, we have $\psi(\iota^*) = \alpha m^{1/\alpha} w$, hence an increase in the nominal wage induces industrialization to rise because $\psi'(\cdot) > 0$ by assumption. The economic intuition behind this result is that if the cost of labor increases, then the final good producer will seek to automatize more tasks in order to avoid paying the increase in the wage. This is summarized in the following implication statement. Following an exogenous increase (resp. decrease) in the nominal wage w, the share of tasks performed by machines ι^* increases (resp. decreases). A similar comparative static result follows considering an increase in the labor stock. To see it, notice that because the nominal wage is invariant across tasks, from (5b) and labor market clearing the total labor stock L is evenly allocated across the $(1 - \iota^*)$ non-automated tasks. Using this insight, we obtain the following empirical prediction. Following an exogenous increase (resp. decrease) in the labor supply stock L, the share of tasks performed by machines ι^* decreases (resp. increases). This is the key implication of the model that we test in the paper. In our setting, we provide evidence that immigration restriction policies induce positive labor supply shocks, hence increasing the labor stock. We show that firms operating in districts that were more exposed to the Quota Acts decreased investment in machinery—section 5.2—and increased employment—-section 5.3. These findings are fully in line with the empirical predictions D.2 of the model and hence provide evidence in favor of labor-saving directed technical adoption.

D.3 Proofs of Analytical Results

Solution of the problem of the final good producer.. Plugging the technology constraint into problem (4), the problem of the final good producer reads out as follows:

$$\max_{\iota,\{x(j),e(j)\}_{j\in[0,1]}} A\left[\int_0^\iota m x(j)^\alpha\, dj + \int_\iota^1 e(j)^\alpha\, dj\right] - \int_0^\iota p(j)x(j)\, dj - w\int_\iota^1 e(j)\, dj.$$

The—necessary and sufficient—first-order conditions with respect to labor and capital in the generic task j are

$$\begin{aligned} x(j) &= p(j)^{-\frac{1}{1-\alpha}}(\alpha A m)^{\frac{1}{\alpha}} \quad \forall\, j \in [0,\iota], \\ e(j) &= w^{-\frac{1}{1-\alpha}}(\alpha A)^{\frac{1}{\alpha}} \qquad \forall\, j \in [\iota, 1]. \end{aligned}$$

To obtain the first-order condition for the optimal industrialization rate, apply the Leibniz integral rule with respect to ι to get:

$$x(\iota^*)\left[m x(\iota^*)^{\alpha-1} - p(\iota^*)\right] = e(\iota^*)\left[e(\iota^*)^{\alpha-1} - w\right].$$

Plugging (5a)-(5b) into the expression above we get $m = (p(\iota^*)/w)^\alpha$. ■

Solution of the problem of the monopolist.. The solution is trivial upon plugging (5a) into the objective function (7). ■

Proof of Lemma D.1. From (8) and (6), it is

$$\begin{aligned} p(\iota^*) &= \min\left\{\frac{\psi(\iota^*)}{\alpha}, mw\right\}, \\ p(\iota^*) &= m^{1/\alpha} w \end{aligned}$$

Hence, we have

$$m = \left[\frac{\min\left\{\frac{\psi(\iota^*)}{\alpha}, mw\right\}}{w}\right]^\alpha.$$

We can distinguish two cases. Assume $mw \leq \psi(\iota^*)/\alpha$. This implies that $m = m^\alpha$, which is only verified if $m = 1$ or $m = 0$. Since by assumption $m \in (0,1)$, this can never hold. We are left with the case $mw > \psi(\iota^*)/\alpha$. We show that this is consistent with all the parameter restrictions. Note first that since $m \in (0,1)$, it must be $\psi(\iota^*)/\alpha < w$, since otherwise it would be $m \geq 1$. We therefore have $\psi(\iota^*)/\alpha < w$ and $\psi(\iota^*)/\alpha < mw$. Because $m < 1$, the only binding constraint is $\psi(\iota^*)/\alpha < mw$. It is

$$m = \left[\frac{\psi(\iota^*)}{\alpha} \cdot \frac{1}{w}\right]^{\alpha},$$

which implies $\psi(\iota^*)/\alpha = wm^{1/\alpha}$. Because $m \in (0,1)$, $m^{1/\alpha} < m$ since $\alpha \in (0,1)$, and therefore $\psi(\iota^*)/\alpha = wm^{1/\alpha} < wm$. This implies that the solution is acceptable. Hence, $p(\iota^*) = \psi(\iota^*)/\alpha$ and this concludes the proof. ■

Proof of Proposition 1. Because $w(j) = w$ for all $j \in [0,1]$, from (5b) we get that $e(j)$ does not depend on j and:

$$e(j) = e = w^{-\frac{1}{1-\alpha}}(\alpha A)^{\frac{1}{1-\alpha}} = \frac{L}{1-\iota^*},$$

where the last equality holds by labor market clearing, which requires $(1-\iota^*)e = L$. From Lemma D.1, it is $w = \psi(\iota^*)/(\alpha m^{1/\alpha})$. Plugging this into the previous equation, we get

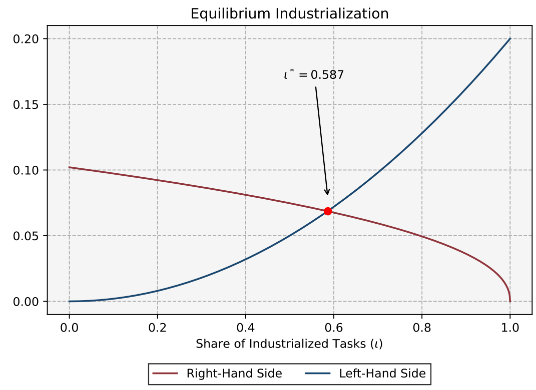
$$\begin{aligned}
\left(\frac{\psi(\iota^*)}{\alpha m^{1/\alpha}}\right)^{-\frac{1}{1-\alpha}}(\alpha\beta)^{\frac{1}{1-\alpha}} &= \frac{L}{1-\iota^*} \\
\frac{\psi(\iota^*)}{\alpha m^{1/\alpha}}(\alpha\beta)^{-1} &= \left(\frac{L}{1-\iota^*}\right)^{-1+\alpha} \\
\psi(\iota^*)L^{1-\beta} &= (1-\iota^*)^{1-\alpha}\alpha^2 A m^{1/\alpha}.
\end{aligned}$$

Because $\psi'(\cdot) > 0$, the left-hand side is strictly increasing in ι^*. Moreover, because $\alpha \in (0,1)$, the right-hand side is strictly decreasing in ι^*. By the Inada conditions, $\lim_{z\uparrow 1}\psi(z) = +\infty$ and $\lim_{z\downarrow 0}\psi(z) = 0$. If $\iota^* = 0$, the right-hand side is strictly positive, whereas it is zero if $\iota^* = 1$. Hence, because both are trivially continuous, by the intermediate value theorem, there exists at least one ι^* which verifies the equation. Since both are strictly monotone, ι^* is unique. ■

Proof of Implication D.2. From Lemma D.1, it is $m^{1/\alpha} = \psi(\iota^*)/(\alpha w)$, or

$$\alpha w m^{1/\alpha} = \psi(\iota^*).$$

Notes. This figure plots the equilibrium of the model. The blue and red lines, respectively, display the left and right-hand sides of the final equation of the proof of Proposition 1. We assume $\psi(j) = \gamma j^2$ even though quadratic costs do not verify the Inada conditions.
Parametrization: $\alpha = .55$, $\beta = .45$, $\gamma = .2$, $A = .5$, $L = 1$, $m = .5$.



Because $\psi'(\cdot) > 0$, an increase in w in the equilibrium implies an increase in $\psi(\iota^*)$, hence in ι^*. ■

Proof of Implication D.2. First note that because w is invariant across tasks, then by (5b) $e(j) = e$ for all j. Moreover, since the productivity of labor is constant across tasks, it is optimal to divide evenly L across the $(1 - \iota^*)$ non-automatized tasks. Therefore, by labor market clearing $e = L/(1 - \iota^*)$. Plug this in the left-hand side of (5b), yielding

$$w^{-\frac{1}{1-\alpha}}(\alpha A)^{\frac{1}{1-\alpha}} = \frac{L}{1 - \iota^*}.$$

Using Lemma D.1 into the previous equation we get

$$\begin{aligned} \frac{\psi(\iota^*)}{\alpha m^{1/\alpha}} &= \left(\frac{L}{1 - \iota^*}\right)^{\alpha - 1} \alpha A \\ L^{1-\alpha} &= \frac{(1 - \iota^*)^{1-\alpha}}{\psi(\iota^*)} \alpha^2 A m^{1/\alpha}. \end{aligned}$$

Because $\alpha \in (0, 1)$ and $\psi'(\cdot) > 0$, the right-hand side is decreasing in ι^*. Therefore, an exogenous increase in L leads to an increase in the right-hand side, hence a decrease in ι^*. Following an increase in the labor supply, the share of automatized tasks decreases. ■

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