Customer Data Access and Fintech Entry: Early Evidence from Open Banking†

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Abstract

Open banking (OB) empowers bank customers to share transaction data with fintechs and other banks. New cross-country data shows 49 countries have adopted OB policies, privacy preferences predict policy adoption, and adoption spurs investments in fintechs. UK microdata shows that OB enables: i) consumers to access both financial advice and credit; ii) SMEs to establish new lending relationships. In a calibrated model, OB universally improves welfare through entry and product improvements when used for advice. When used for credit, OB promotes entry and competition by reducing adverse selection, but higher prices for costlier or privacy-conscious consumers partially offset these benefits.

Keywords: Open banking, banks, fintech, entry, financial innovation, data access, data rights, data portability, Big Data, financial regulation

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The increasing ease with which data is collected, stored, and analyzed has made it a critical input in economic decision-making. Data's growing importance has led to an active discussion about who should control the data generated through private economic activity: A firm or its customers. This issue is particularly salient in financial services, where banks' provision of financial products inherently generates useful customer data. Periodic direct deposits, overdrafts, and late payments help predict a potential borrower's riskiness. Account balances and transactions allow firms to learn about a customer's needs and offer tailored financial advice or other products. A small business's transaction data could inform lenders about its health and help a fintech deliver financial management services.

Historically, a customer's financial data has been under her bank's exclusive control, giving that bank an advantage in pricing and customizing financial services.[1] However, banks' exclusive access to this data is being upended by a movement known as open banking (OB). OB empowers bank customers to share their financial transactions data with other financial service providers. For example, OB allows a bank customer to easily share her bank account history with a potential lender (which can analyze her income and spending habits to underwrite her credit) or with a financial management app (to help her manage her money).

While some banks have implemented OB of their own accord, many governments are promoting or even mandating it. As of October 2021, regulators in 80 countries have taken at least some steps to encourage the adoption of OB. 49 of the 80 have already adopted their key OB policies. Through OB, policymakers aim to boost innovative entry, competition, and financial inclusion. Policymakers reason that allowing bank customers to share their transaction data will allow fintech entrants and other banks to better compete for business.

In this paper, we explore the causes and consequences of government policies to promote OB. In doing so, we make four key contributions. First, we assemble the first comprehensive, standardized dataset of government-led OB policies. Using this data, we document the ubiquity of OB government policies around the world and examine their drivers. Second, we use data from the UK—an early adopter of OB—to provide evidence on how OB policies impact consumers and small and medium enterprises (SMEs). Third, we examine the global impact of OB policies on financial innovation using our country-level OB policy data. Finally, we provide a quantitative modeling framework for customer data sharing, which measures the overall and distributional effects of OB.

We begin by assembling a comprehensive dataset on government policies to promote OB for the world's 168 largest countries—representing more than 99% of world GDP. We uncover vast heterogeneity in OB policy choices. For example, countries in the European Union (EU)

[1] As a motivating example, Appendix Figure A1 Panel (a) shows non-banks and fintech lenders, which lack such customer data, overwhelmingly use standardized underwriting models such as FICO when originating US residential mortgages. Banks are much more likely to use non-standard credit models, allowing them to exploit their customer data. These non-standard models lead to more individualized pricing: Panel (b) shows that non-standard models lead to more dispersed interest rate residuals than standard models.

have adopted OB regimes that require sharing only data from transaction accounts. In contrast, countries in other regions typically mandate sharing a broader set of data. We also examine the drivers of OB policies and show that consumer trust in sharing data with fintechs predicts OB policy adoption: Intuitively, willingness to share data increases the potential benefit of these policies. Other country characteristics are less predictive, including economic and financial development, levels of innovation, or the quality of local institutions.

The prevalence of OB policies motivates further study of the economic effects of these policies. We first focus on he UK where granular microdata offers direct evidence on the adoption and economic impact of OB for both consumers and SMEs. For consumers, we use a survey by the UK Financial Conduct Authority to document two main distinct reasons consumers share data: Financial planning and management (advice OB) and borrowing (which we term credit OB). There is little overlap between users of advice and credit OB, and consumers are more likely to use both OB products if they are willing to share their data, are employed, or have missed bill payments. We find suggestive evidence that OB use improves consumer outcomes: Advice OB is associated with greater financial knowledge and credit OB is associated with greater credit access.

For SMEs, UK panel data allows us to estimate the causal impact of OB on borrowers, measure whether banks or non-banks provide new loans, and examine OB's financial inclusion implications. We exploit the fact that the commercial OB-related policy applied only to SMEs with annual sales below £25 million. This cutoff provides quasi-random variation and allows us to compare outcomes for eligible and non-eligible SMEs following the policy implementation. SMEs eligible to share data form more new lending relationships with non-bank lenders (e.g., fintechs). In terms of distributional effects, we find that treated firms with prior lending relationships are more likely to get new loans and those SMEs that form new lending relationships with non-banks pay less interest.

We next provide global evidence on the effect of OB on fintech entry, which regulators regard as a key mechanism through which OB can improve innovation and competition. We measure fintech entry using data on venture capital (VC) investment in fintech startups. Using the staggered implementation of OB policies across countries in a difference-in-differences design, we show that the VCs investment in fintechs surge following OB policy adoption. Event studies show a discontinuous increase in fintech activity after the introduction of OB policies, with no pre-trends. Countries whose residents place more trust in sharing data with fintechs see greater post-OB fintech VC investment, suggesting that consumer preferences for data sharing play an important role in OB's impact. Importantly, we observe increases in fintech activity across many financial products (e.g., financial advice apps, credit, payments, regtech), consistent with our UK survey evidence that OB data has a wide range of use cases.

While our empirical results offer valuable descriptive and causal evidence regarding OB use, they fall short of addressing several key economic and policy questions related to OB.

First, they are largely silent on the mechanisms by which access to OB data increases entry across the two distinct use cases—financial advice and credit—highlighted by our UK consumer results. Second, our differences-in-differences tests have little to say on welfare, equilibrium effects, or distributional consequences. Third, while the consumer and SME microdata is informative about the UK case, our cross-country results highlight the importance of customer preferences for sharing data, which raises questions about how OB might look in countries with different social attitudes towards fintechs and privacy.

We tackle these questions directly using a quantitative model of data usage. This model incorporates consumer data use into a standard IO model of consumer choice with heterogeneous consumers. In our model, data about a bank's customer—interpreted as either an individual or a business—reveals her preferences (allowing the creation of better products for advice OB) and costliness to serve (allowing screening for credit OB). A relationship bank always sees her data, while other firms see it only if she shares it via OB. We calibrate the model to the two use cases using our reduced-form results and pre-OB estimates from the literature. In our credit use case, we calibrate to mortgage products, where data is informative about consumer risk. In our financial advice use case, we calibrate to investment advice, where data is informative about particularized customer needs. OB spurs innovation and competition in both cases, but through different channels. In the credit OB case, unequal data access discourages entry by giving relationship banks an underwriting advantage and creating adverse selection for entrants. Allowing data sharing reduces this adverse selection, makes entrants more profitable, and, in equilibrium, increases entry. In the advice OB case, unequal data access impairs fintechs' ability to offer customized products, and enabling customers to share their data leads to better-customized products, higher customer demand, and, again, increased entrant profitability and entry.

While OB unambiguously increases competition and innovative entry, our model also shows how these goals can sometimes, but not always, come into conflict with the financial inclusion goal of OB. The distributional effects of OB depend critically on how the data is used. All customers benefit in the advice OB use case, where the data is used to provide higher-quality or more tailored products. In contrast, the credit OB use case can have negative distributional consequences because OB increases entry precisely by enabling entrants to better exclude unprofitable (higher risk) customers. Users who share unfavorable data lose directly. Users who opt out of sharing are inferred to have strategically hidden unfavorable data, even when opting out due to strong privacy preferences. Thus, consistent with our reduced-form findings in the SME analysis, the customers who benefit the most may be those who already have credit access. Customers who opt out still gain from increased entry and competition, but lose because they are now inferred to be higher risk. Our quantitative model allows us to weigh this tradeoff, a particularly important question for policymakers concerned with the distributional consequences of OB.

Our model shows that societal preferences for privacy (i.e., unwillingness to share data) not only drive the impact of OB (consistent with our cross-country results), but also play an important role in explaining these distributional effects. The financial transaction data shared through OB differs from credit registry data not simply because of its utility for generating financial advice, but also because it is by nature more sensitive and many customers are reluctant to share it, as highlighted by our UK consumer data. In our model, strong societal preferences for privacy blunt the impact of OB as few customers opt in to data sharing and so few firms enter. However, societal preferences for privacy have a silver lining because they cause customers to opt out of data sharing for privacy reasons, which means that opting out sends only a weak signal about ones riskiness. In fact, under reasonable parameters—including those obtained in our UK calibration—OB is welfare-improving for all customers even when data is used for screening. The negative inference lenders draw against opt-outs is more than offset by the benefits that these customers derive from increased entry and innovation. Consequently, incorporating privacy preferences and the implications of different use cases is an important part of an OB implementation, highlighting an important distinction between credit registries and OB data sharing.

To summarize, we document that government policies to promote OB are prevalent: About half of countries have some OB efforts. Our empirical analyses and the quantitative model show that OB data can have beneficial economic effects. Our work suggests that the potential implications of OB for industry, society, and policymakers are large. By giving customers the ability to share their financial transaction data, OB promises to upend the organization of the financial sector. The welfare and distributional effects of this, however, depend crucially on specific uses of customers' data and their willingness to share data. Our paper proceeds as follows. In Section 1, we situate our contribution in the literature. In Section 2, we describe our data. In Section 3, we examine the effects of OB policies, and in Section 4, we provide an economic framework for evaluating our results. Section 5 concludes.

1 Related Literature

Our paper contributes to several strands of literature. First, our research question and methodology connect to the broader literature on cross-country bank regulation. In the wake of the financial crisis, much of this literature focuses on regulation and bank risk, for example, Laeven and Levine (2009), Beck et al. (2013), and Ongena et al. (2013). Our paper is closer to research on regulation and competition, such as that by Claessens and Laeven (2004) who argue contestability and regulation are key drivers of bank competition, or Barth et al. (2004) who argue for the role of disclosure and private incentives. We contribute by showing that government policies to promote bank customer data sharing foster entry into the financial sector across many financial products and potentially improves bank customer outcomes.

Second, we engage with the fundamental question, originating with Diamond and Dybvig (1983) and Diamond (1984), over what makes banks special. While fintechs and other non-depository institutions have gained significant market share in transaction-oriented functions like origination and servicing (e.g., Gopal and Schnabl (2022); Buchak et al. (2024b)), they have been slower to replace banks in deeper intermediation roles like underwriting, monitoring, and balance sheet lending. Importantly, banks appear to derive significant value from engaging in multiple intermediation activities simultaneously, as in Egan et al. (2022), Aguirregabiria et al. (2019), or Benetton et al. (2022), suggesting there are significant barriers that limit the growth of new single-product competitors. Information lies at the heart of relationship banking (Ramakrishnan and Thakor, 1984; Boot and Thakor, 1997) and our paper directly addresses the idea that aggregating data across multiple business lines leads to informational advantages. This explanation dates to Petersen and Rajan (1994), Petersen and Rajan (1995), and, more recently, Granja et al. (2022) and Blickle et al. (2023). Recent empirical work by Ghosh et al. (2022) shows a direct effect of transaction data on screening quality for commercial loans. Berg et al. (2020) and Di Maggio et al. (2022b) show the value of alternative data more generally. Banks' informational advantages are challenged with OB, paving the way for an analysis of how important these advantages are.

Third, we add to the nascent literature on the economic effects of data ownership and access. Theoretical work typically views data as either an input to production or a way to address information asymmetries. Mandated data sharing generates complex competitive interactions that depend on how the data is used. Taking the production-input view, Jones and Tonetti (2020) show that a firm may suboptimally hoard product-improving data to prevent entry, motivating the reallocation of data property rights from firms to consumers. Farboodi et al. (2019) model data as valuable for forecasting and suggest that large firms generate more data and benefit from it. Emphasizing the information economics view, He et al. (2023) and Parlour et al. (2022) highlight how data sharing and portability can increase the quality of lending while having ambiguous effects on consumer welfare and bank profits. Goldstein et al. (2022) emphasize the theoretical connection between liquidity transformation and lenders' access to information. He et al. (2024) study how the hardening of soft information, which can result from policies like open banking, affects competition in lending markets. Empirically, Babina et al. (2024) show that larger firms—that naturally generate more data—benefit more from their investments in Artificial Intelligence (AI) and AI use is associated with increased industrial concentration, suggesting that a current status quo (where firms own their customers' data) can stifle entry and weaken competition.

We build on this largely theoretical literature in several ways. OB policies weaken bank data monopolies and give consumer the power to share their data, offering a valuable opportunity to study the economic effects of change in data ownership policies. To the best of our knowledge, we provide the first empirical study on the impact of government policies that open access to rich customer-level transaction data. While conceptually related to credit registries, e.g., Djankov et al. (2007) and Hertzberg et al. (2011), OB policies differ in important respects. They typically cover consumers regardless of their credit usage and are designed from the outset to facilitate ease of data access by potential bank competitors, including non-banks. The richer data that OB covers lends itself to uses beyond screening; however, this very richness creates greater privacy concerns than a standard credit file.[2] We show these aspects of OB are important in driving its effects. Thus, our paper provides evidence of the effects of adopting data-sharing policies more generally. Beyond that, we provide a quantitative framework for studying the use of consumer data in the context of OB. Building on common tools in the IO/finance literature (e.g., Egan et al. (2017), Di Maggio et al. (2022a), Buchak et al. (2024a)), we connect data to information about consumer heterogeneity around marginal costs and desired customization. Through these channels, we synthesize both the input-to-production and information economics views of data and highlight their quantitative importance across particular applications. In contrast to, e.g., He et al. (2023) and Parlour et al. (2022), our model emphasizes entry and innovation, which are key policy goals of OB. Moreover, our analysis complements this literature by highlighting the importance of consumer preferences over data privacy shown by, e.g., Acquisti et al. (2016), Tang (2019), and Bian et al. (2021) by explicitly incorporating privacy preferences into our structural model.

Fourth, our structural model allows us to broaden the literature around the industrial organization of the financial sector. This literature has studied the role of banks and the increased competition they face from non-depository institutions, e.g., Buchak et al. (2018), Fuster et al. (2019), Jiang et al. (2020) (mortgages), Erel and Liebersohn (2022), Gopal and Schnabl (2022) (small business lending in the US), Di Maggio and Yao (2021), De Roure et al. (2022) (personal loans), and Buchak et al. (2021) (deposits). These papers typically highlight the interplay between technology and regulation and how they interact with the comparative advantages of depository and non-depository institutions.[3] Our results also connect to the growing literature on financial system structure and financial inclusion (e.g., Claessens and Rojas-Suarez (2016), Bartlett et al. (2022), or Philippon (2019)).

Finally, our paper is connected to the literature on the drivers of innovation and entrepreneurship. We document the importance of data access for innovation: We show a large effect of OB policies on innovative entry, which adds to a literature that has shown mixed results on whether policymakers are able to promote high-growth entrepreneurship (Acs et al. (2016); Denes et al. (2023); Bai et al. (2022); Babina et al., 2023b)).[4]

[2] For example, Nam (2022) looks at a German OB fintech and shows that the vast majority of its credit report-sharing applicants are unwilling to also share their OB data.

[3] Literature reviews on the impact of technology in finance can be found in Stulz (2019), Vives (2019), Allen et al. (2021), Thakor (2020), Berg et al. (2022), and Boot et al. (2021).

[4] Other work shows the positive impact of less entry regulation (Klapper et al., 2006; Mullainathan and Schnabl, 2010), more optimistic beliefs (Puri and Robinson, 2007), VC availability (Kaplan and Lerner, 2010),

2 Institutional Background and Descriptive Analysis

This section describes the institutional background of OB policies, details our data collection process, shows the global importance of OB policies, and examines their drivers.

2.1 Institutional Background on Open Banking

OB describes a broad trend where, upon customer request, financial intermediaries share—willingly or by regulatory fiat—access to their customers' data with other financial service providers. There are two primary non-mutually exclusive ways in which OB is spreading around the world: Market-led, where banks and fintechs adopt OB without government intervention, and government-led, where regulators institute policies to promote the adoption of OB by the financial sector. This paper focuses on government-led OB policies, which typically apply to a bank's individual customers and sometimes also apply to business customers.

While the specifics of government OB efforts vary, the UK's Open Banking Initiative is an instructive introduction: In 2017, the UK's Competition and Markets Authority (CMA) introduced one of the first OB regulations—commonly known as the CMA Open Banking Order—with the aim of increasing innovation and competition in the retail banking sector. The initiative required that by 2018, banks *"give their personal and business customers the ability to access and share their account data on an ongoing basis with authorized [by the government] third parties."*[5] Here, third parties refer to both fintechs and other banks. Additionally, banks were required to allow customers to authorize third parties to make payments from their accounts—a practice called payment initiation. OB differs significantly from the UK's existing private sector credit bureaus: It covers richer data (in particular, information on transaction accounts), it gives banks' customers control over their data, it is free to the requester, and banks are forced to participate. These are common features of OB policies around the world and mean that OB goes beyond traditional credit bureaus.

Data access and payment initiation typically occur through a bank-provided Application Programming Interface (API). APIs are a technology that allows two computer systems (e.g., a bank's and a fintech's) to speak to each other over a network. OB APIs are published by the data provider and are a set of standardized, programmatic commands that allow data users to interact with the provider's customer database and to perform financial services on customers' behalf. The particulars are regime-specific, but API functionality in OB typically allows read access (e.g., querying account data) and sometimes allows write access (e.g.,

R&D subsidies (Babina and Howell, 2024), and competition policies (Phillips and Zhdanov, 2017; Babina et al., 2023).)

[5]Page 11 of "Open Banking, Preparing for Lift off" document. See the official policy document. A related data-sharing policy focusing exclusively on SME bank customers was introduced in 2015 and implemented in 2017. We discuss this policy in detail in Section 3.2 and Appendix D.

payment initiation).[6] In Appendix B, we show that in countries that implement OB policies, banks are indeed more likely to provide APIs for customer data sharing.

By opening bank data, regulators aim to create an environment where financial intermediaries—both incumbents and entrants—can create new or improved financial services for bank customers and better compete with existing services. The prototypical use case of OB is a financial advice product, such as financial account aggregation, which works as follows. A consumer might have financial accounts scattered across several financial intermediaries: Her bank account, several credit cards, a mortgage, an investment account, and so on. With OB, fintechs can access, aggregate, and analyze these separate accounts to provide customized financial advice. She may find it helpful to monitor these accounts in a single place to understand her spending habits and get advice on budgeting, savings, and credit management. Another use case of OB is credit, where potential lenders can access the otherwise private information that a consumer's home bank has about her. For example, with customer permission, a fintech lender could use the data on a bank's customer to query her bank account transactions to help price her a loan. Beyond financial advice and credit, many other use cases have emerged, including identity verification, payments, and insurance.

Even without government OB policies, fintechs have gained access to customer bank data through financial aggregators such as Yodlee and Plaid that collect data via a combination of bilateral agreements and "screen scraping" (web scraping using user-provided passwords). In practice, although these market-based solutions are improving, they are expensive for fintechs and offer incomplete coverage.[7] Incumbent banks' reluctance to voluntarily offer widespread data sharing suggests that they lose monopoly rents—an intuition crystallized in our model—and that there are significant contracting frictions that prevent them from capturing surpluses. For example, bank customer stickiness or a lack of customer sophistication prevents banks from extracting the value of data sharing from customers, and coordination problems around large numbers of (merely hypothetical) fintech entrants prevents a Coasaan solution. Importantly, because banks are data monopolists, standard economics predicts that a straightforward arrangements where the bank sells information access to fintechs will lead to markups and an inefficiently low quantity of data access. Thus, government involvement in data sharing appears to be an important force in its widespread adoption.

[6] While API-enabled OB is currently mainstream, fintechs have historically achieved somewhat similar functionality through what is known as "screen scraping" where a customer gives her login credentials for each of her financial institutions to the fintech (e.g., Mint.com). The fintech's software then uses the customer's credentials to log in to each financial institution (as if it were the customer) and extract account data from the financial institution's webpage. Although screen scraping accomplishes similar results to accessing an OB API, screen scraping has numerous weaknesses, including security risks, privacy issues, inefficiency, and unreliability. The API-enabled OB approach addresses these issues.

[7] For example, financial aggregator pocketsmith.com reports a median connection success rate of 44% for Yodlee among the Canadian banks it claims to cover as of mid-2023. In the US, Fidelity and PNC dropped support for Plaid in late 2023 (see here).

2.2 Data Collection Methodology for Open Banking Around the World

We create a comprehensive, hand-collected database of OB government policies (or the lack thereof) for the largest 168 countries (covering over 99% of global GDP). This section describes our methodology; Appendix C provides further detail. We base our sample on countries with at least one million people according to the IMF 2018 data or at least 10 VC-backed companies.[8] For each country, we manually search for official OB policy documents using Google, and when those are not available, for descriptions of government-led OB initiatives from law firms, research papers, journalists, and industry participants. We classify these policies on multiple dimensions, giving preference to official policy documents (laws, regulations, policy papers, and official statements) to classify the various dimensions of OB policies into standardized categorical variables.

We ensure accuracy by performing multiple cross-checks. First, two authors independently classify each country's OB regime and jointly reconcile any discrepancies. Second, we use automated news topic searches to uncover any material potentially missed in our manual searches. Third, we reconcile our results against a database of OB regulations maintained by Platformable,[9] an OB advocacy group.

2.3 Summary Statistics on Open Banking Government Policies

Table 1 provides summary statistics on our hand-collected OB data both overall and by region.[10] As of October 2021, 80 of the 168 countries in our sample have at least a nascent government OB effort and 49 have adopted their key OB policies. There is significant heterogeneity by region. 80% of countries in Europe and Central Asia have conducted at least some government OB policies. OB is less present in other regions but all regions in the world have seen at least some government OB effort.

OB regulators frequently cite one or more justifications for implementing OB regimes in their official statements. The three most common are to promote innovation, competition, and financial inclusion. Table 1 shows that 97% of regulators cite innovation as a policy goal; 82% cite competition, and 29% cite financial inclusion. There is significant regional heterogeneity in financial inclusion being an OB policy goal: Only 10% of countries in Europe & Central Asia cite financial inclusion, whereas other regions are much more likely to do so.

Finally, we note that the EU adopted and implemented a common OB framework known as the Revised Payment Services Directive (PSD2, EU Directive 2015/236). PSD2 obligated participating countries to implement its provisions in their respective banking regulations. In the country-level summary statistics in this section, we keep the participating countries

[8] The IMF data is from here. The VC data is from PitchBook and is described later.

[9] Platformable's data is described here.

[10] Following World Bank geographic terms, regions are Africa, Middle East & North Africa; Europe & Central Asia; Latin America & the Caribbean; North America; South Asia, East Asia & Pacific.

separate. For our analyses in Sections 2.4 and 3.3, we weight all countries covered by PSD2 as a single pooled observation.

Implementation Status and Key Dates of Government-led Policies We categorize a country's OB maturity in terms of its implementation status on a 0 to 7 scale, where 0 denotes no effort toward OB, 1–2 correspond to ongoing policy discussions, 3–5 correspond to being in the process of implementation, and 6–7 correspond to full implementation.[11]

Panel (a) of Figure 1 shows the geographical distribution of government-led OB initiatives based on their maturity. As of October 2021, among countries with a government-led approach to OB, 31 (38%) are at the discussion stage, 14 (18%) are in the process of implementation, and 35 (44%) are fully implemented or already seeing follow-on policies. We refer to the 49 countries in the latter two groups as having implemented OB. To provide three examples along the implementation timeline, OB discussion is underway in the US,[12] Brazil is in the process of implementing OB (see here), and the UK has fully implemented its Open Banking Initiative and is considering a follow-on "open finance" regulation.[13] Figure 1 Panel (b) shows the passage year of countries' major OB government policies.

Requirements Set by the Regulator OB government policies differ in what they require of market participants, and indeed, whether they require anything at all. The UK, for example, places explicit de jure legal requirements on banks to participate. Other examples with binding regulatory approaches are Australia, Bahrain, Brazil, the EU, and Israel. In contrast, regulators in Singapore, Malaysia, and Russia do not explicitly mandate data sharing and instead facilitate the adoption of OB by mediating industry discussion, providing technical standards or infrastructure for data sharing.

As shown in Table 1, among the countries whose OB initiatives have advanced sufficiently for these issues to be decided, we find that 88% require banks to share data (variable "Required data sharing"). In addition to requiring incumbent banks to share data, some OB regimes also require reciprocal sharing by new entrants (e.g., fintechs): Our data shows that only 18% of regimes have data sharing reciprocity (variable "Data reciprocity"). Finally, 39% of countries' regulators lay out technical specifications for data sharing (variable "Regulator

[11] Specifically, the stages are (1) pre-discussion (some government interest is announced but no actual law or policy implementation is taking place); (2) discussion (the actual law has been discussed or rulemaking is taking place); (3) pre-implementation (the major policy-making has concluded but nothing is yet binding or implemented); (4) early implementation (some data sharing requirements are binding, e.g., bank-level product information, but not personal account/transactions); (5) mid-implementation (personal account/transaction data sharing is binding or OB infrastructure/technical standards have been put in place, but not all planned elements are in place); (6) fully implemented (full implementation as described in the law/rulemaking/policy documents); (7) follow-on regulation or policies (OB is implemented, and regulators are actively working on related policies, such as open finance or open data, or building new infrastructure for OB).

[12] The Consumer Financial Protection Bureau (CFPB) is looking into whether to create regulation based on Dodd-Frank's Section 1033 that gives consumers the right to their financial data, but which was never codified into rulemaking and, hence, is not legally binding. See here.

[13] This policy would broaden data access beyond transaction accounts. See here.

provides tech specs"), while the remainder do not. There is significant regional variation in government-led approaches regarding mandatory data sharing and technical specifications: Figure 2 Panels (a) and (b) show these differences graphically for mandatory data sharing and regulator-set technical specifications, respectively.

Open Banking Scope: Covered Services and Functions OB government policies differ in what financial products are covered. By definition, all OB regimes cover at least transaction accounts (checking accounts, credit cards, and digital wallets). Some regimes include a broader set of core consumer finance products: Savings accounts, investments, and loans. Still broader regimes, called "open finance," cover all financial services. Fewer then 34% of countries cover non-transaction accounts (variable "Beyond transaction accts"). Regarding regional heterogeneity, Europe & Central Asia OB policies tend to be very narrow in scope, with only 3% covering non-transaction accounts. In contrast, OB policies in other regions are much broader, with 90% going beyond transaction accounts.

Regarding functionality, OB data sharing can, in theory, be used both to read data (e.g., pull customer account information) and to write data (e.g., initiate transactions). Some OB regimes focus on data sharing only, and some on both. Our data shows that among those countries where this issue has been decided (variables under "Functionality scope"), only 5% focus on data sharing only, none on payments only, and 95% on both.

Open Banking Strength Index Using our hand-collected data on OB policies, we construct an OB Strength Index, which measures the comprehensiveness of OB policies. The index averages the four key OB policy dimensions discussed above: Whether the regulators have set policies that (i) mandate banks to share data, (ii) require financial service providers (such as fintechs) who use data to share data in return, (iii) cover a wide range of financial products, and (iv) set technical standards for data sharing. This index ranges from 0 (all four dimensions are not yet mandated) to 1 (yes on all four dimensions).

2.4 Drivers of Open Banking Government Policies

We next examine what factors drive countries to adopt OB policies around the world. In the spirit of Kroszner and Strahan (1999) or Cornelli et al. (2020), we examine what predicts OB policy adoption using a broad set of country characteristics as summarized in Panel (a) of Table A1. We start with basic country-level data, including per capita GDP in thousands of US dollars and population in millions from the World Bank. Given the importance of consumer wiliness to share data for OB adoption, we use the measure of consumer trust in sharing data with fintechs from Chen et al. (2023). From the World Bank, we also add standard measures of country-level financial sector development, including the quantity of private sector credit to GDP, the number of bank branches per 100k people, and the financial sector's Lerner Index (which captures the market power of banks). We take the percentage of banks that are foreign owned from Claessens and Van Horen (2013). To capture the quality of institutions, we use the Rule of Law Index from the Cato Institute. Finally, to measure innovation, we add data on VC deals from PitchBook, widely acknowledged as one of the best VC data sources for more recent years.[14]

Using our cross-country data, we then test the association between the time of OB policy implementation and these country characteristics using a Cox proportional hazards model:

$$h_i(t) = h_0(t)\exp(X_i'\beta + Region_r) \tag{1}$$

where $h_i(t)$ represents the hazard function for the occurrence of the OB outcome (implementation of OB policies through 2021) in year t in country i. This hazard function can be interpreted as the risk of the event happening at time t given it has not yet occurred. X_i' is a vector of country-level characteristics. $Region_r$ are region fixed effects. Data availability causes the number of observations to fluctuate across specifications.

We supplement this regression with a cross-country regression on OB characteristics. We use both the 0 to 7 OB implementation status (the measure of how far government OB policy has progressed) and the 0 to 1 OB Strength Index (the measure of comprehensiveness of OB policies) based on key OB policy dimensions. These regressions take the following form, where OB_i denotes the two measures of OB policy for country i as of 2021:

$$OB_i = X_i'\beta + Region_r + \epsilon_i \tag{2}$$

Table 2 presents the determinants of OB adoption speed (columns 1–5), implementation status (columns 6–7), and policy strength (columns 8–9). Columns 1 to 5 use Equation (1). Since low overall levels of economic development could be associated with the introduction of OB policies in all columns we control for both GDP per capita (and its square) and log population. However, neither a country's GDP nor its population robustly predicts the introduction of OB government policies. Column 1 shows that consumer trust in sharing their data with fintechs is associated with earlier implementation of OB policies, despite the limited number of observations available for only 27 countries for the trust in fintech data. The effect is economically meaningful: A one standard deviation (0.15) increase in trust is associated with a significantly higher rate of OB policy adoption, with the hazard (or event occurrence) rate nearly quadrupling.

[14]The data on trust in sharing data with fintechs is based on the survey underlying the EY Global Fintech Adoption Index. Specifically, it measures trust as the portion of survey respondents in each country who "agree" or "strongly agree" that they are comfortable with their main bank to securely share their financial data with fintechs. The trust in fintechs variable is based on surveys conducted in February and March of 2019, as earlier survey vintages had very low coverage. All other variables are as of 2013, with that year chosen because it predates the earliest OB regimes and because it is the final year that comprehensive Lerner Index data is available from the World Bank.

Other country characteristics are only weakly associated with OB. Column 2 shows that measures of financial development do not predicts government-led efforts to promote OB. Column 3 shows that OB policies are somewhat more likely to be adopted in countries with more non-fintech VC deals in 2013, but that fintech VC deals are not predictive of adoption. In column 4, we find weak and statistically insignificant associations between the adoption of OB policies and both the Rule Law variable and the fraction of foreign-owned banks. In column 5, we include both our trust in fintechs measure and non-fintech VC deals as those were the significant predictors: The coefficient on trust in fintechs is unchanged, while the coefficient on non-fintech VC becomes statistically insignificant.

Columns 6 to 9 present estimates of Equation (2). Trust in fintechs is again associated with the OB implementation, with a one standard deviation increase in trust being associated with about two steps of increase on our seven-step scale (column 6). The coefficient is unchanged when we control for non-fintech VC deals (column 7). Columns 8 and 9 show trust in fintechs is associated with our OB Strength Index with borderline significance. Overall, consumer trust in sharing data with fintechs is associated with the adoption of OB policies. Trust increases the potential benefit of these policies, as people being willing to share their financial data is crucial to the operation of OB.[15]

3 The Economic Effects of Open Banking

Next, we examine the economic effects of OB. We first focus on the UK (one of the first countries to adopt OB policies): We show that OB enables consumers to access both financial advice and credit (Section 3.1) and leads SMEs to form new lending relationships (Section 3.2). We then examine the global impact of OB policies on financial innovation using our country-level OB policy data (Section 3.3).

3.1 Evidence from UK Microdata on Consumers

We analyze the use of OB by UK consumers and their financial outcomes using data from the Financial Lives Survey (FLS). The FLS is a representative survey of UK consumers conducted by the Financial Conduct Authority (FCA)—one of the main regulators of the UK financial services industry. The survey provides information about consumers' demographics, attitudes towards managing their money, financial product usage, and experiences engaging with financial services firms. We use the February 2020 survey which covers usage of OB products for the first time.[16] Table A2 provides summary statistics.

[15] A potential concern is reverse causality, as the trust in fintechs was based on a survey conducted in early 2019. However, since consumer trust is likely persistent, this concern is unlikely to be of first-order importance.

[16] See the survey questionnaire here.

This data has three advantages. First, the survey asks consumers whether they use financial services based on OB, providing novel evidence on uptake. Second, its demographic information allows us to examine what type of consumers adopt OB. Finally, the survey covers consumer financial outcomes so we can examine their association with OB use.

We begin with consumers' uptake of OB. The survey asked 4,310 consumers who report having a day-to-day bank account (necessary to use OB) about their use of OB products. The survey splits these products into two broad categories: Advice OB and credit OB. Advice OB is applications that provide information or services to users, such as financial advice apps: Apps that aggregate data from several financial accounts or help users with savings. Credit OB is applications that offer credit, either directly (e.g., lending) or indirectly (e.g., credit ratings or price comparison).[17]

Among consumers who report knowing whether they use these types of services, Table A2 shows that 8.6% report the use of advice OB and 5.5% of credit OB. The high use of advice OB shows that OB data is valuable for more than just credit provision, consistent with our findings in subsequent sections of an OB-led increase in VC fintech investment across a wide range of financial product categories. Surprisingly, we find little association between these two types of OB services. Only 13% of advice OB users also use credit OB, while 20% of credit OB users use advice OB. Overall, the total rate of (unique) OB users is 13%.

Table A3 shows the cross-sectional association between the use of each type of OB and consumer characteristics. We regress whether a consumer used advice OB (column 1) and credit OB (column 2) on consumer characteristics, while including location fixed effects. People who have concerns about sharing their OB data are less likely to use both types of OB. Employed people are more likely to share, in line with standard models of voluntary disclosure (e.g., Grossman (1981)) as employment status is information absent from credit reports but shareable via OB. People who miss bill payments are also more likely to share, suggesting more demand for both advice and credit for this financially vulnerable group.

We next test whether OB usage is associated with consumer financial outcomes. Table 3 relates OB usage to financial knowledge (column 1) and credit product usage (columns 2 to 5). We control for all the consumer characteristics from Table A3 and location fixed effects. In column 1, we find that consumers who use advice OB report 0.16 of a standard devia-

[17] The question we use to proxy for financial advice OB is "RB102c" which asks about the use of financial aggregation apps that allow consumers to see the accounts they hold with different banks in one place (e.g., Money Dashboard, Yolt, MoneyHub) and savings-related apps that help build savings by monitoring consumer current accounts and automatically transferring funds (e.g., Chip, Cleo, Moneybox, Plum). The question we use to proxy for credit OB is "RB102d" which asks about the use of credit products, such as firms offering lending products, credit reference agencies (which use OB to provide alternative credit scores), or price comparison websites (which use OB to prequalify borrowers or match them to lenders). The survey questions ask about specific OB products being used to address the fact that consumers might be unaware of exactly what OB is. In practice, this means OB use will be somewhat under-reported and these rates are a lower bound on the share of consumers using OB services.

tion higher knowledge about financial matters, potentially suggesting advice OB improves consumers' financial education and awareness. Here, a key concern is that financially savvy people could be more eager to use advice OB. However, another study of UK consumers shows that those who use advice OB are less financially confident ex-ante and report better financial awareness and decision-making ex-post (see here). Interestingly, credit OB use is not associated with improved financial knowledge, potentially because these applications, by design, do not aim to improve consumer financial literacy.

In columns 2 to 5, we look at the link between credit OB use and credit access.[18] We exploit the fact that OB data might be more used for some products than others. Credit cards and personal loans are unsecured credit products likely to benefit from data informative about credit worthiness. Credit OB users are more than 10% more likely to get both credit cards (column 2) and personal loans (column 3).[19] We use student loans and pawnbroking as placebo products that are ex-ante unlikely to benefit from OB. Due to UK regulation, student loan underwriting does not depend on consumer creditworthiness (see here), while pawnbroking is backed by physical collateral and low-tech. As expected, neither student loans (column 4) nor pawnbroking (column 5) are associated with credit OB use.[20] These results show that credit OB use is robustly associated with access to credit products that are ex-ante expected to benefit from OB underwriting.

Overall, the data on UK consumers shows that OB enables consumers to access financial advice and credit and is associated with improved consumer financial outcomes.

3.2 Evidence from UK Microdata on SMEs

Data on the 2017 launch of the UK's SME-focused OB policy—the "Commercial Credit Data Sharing" (CCDS)—allows us to estimate how OB impacted SMEs' ability to obtain new loans (from banks and non-banks) and test OB's financial inclusion implications. The CCDS is an SME-focused analog of the UK's main OB policy (which covers individual bank customers). The CCDS mandated banks to share information on their SME customers, with client approval. Specifically, it required that the nine largest UK banks share detailed information on the transaction accounts, loan repayments, and corporate credit cards of their

[18] Unfortunately, we cannot observe interest rates on credit products because we do not have this data for the sample of OB respondents in the FLS data.

[19] We do not provide analysis for the other major credit product—mortgages—because, due to the institutional and regulatory features of the UK mortgage market, it was not ex-ante clear whether this market would benefit from OB. However, in unreported results, we do find that there is an increased probability of getting a mortgage among credit OB users.

[20] Our credit access results could be partially driven by consumers seeking credit from OB lenders signing up for OB too. Although this still shows an active role for OB, we can mitigate this concern by controlling for credit demand. Table A4 shows that our credit effects are robust to controlling for credit use as proxies for demand (columns 1 to 4; measured as the number of other credit products a consumer has) or tests with person-level fixed effects (column 5; the specification is run on product-by-person-level data).

SME clients with other lenders. Since previous initiatives had made SME credit histories available through credit bureaus, the CCDS principally revealed information about SMEs' transaction accounts (i.e., cash flows). Thus, the information shared on SMEs is analogous to the information individual bank customers share under OB. We briefly describe our analysis of this policy's effect on SME lending, with Appendix D providing more detail on the CCDS policy, summary statistics, and robustness tests.

The CCDS initiative applied only to SMEs with annual sales below £25 million, which creates quasi-random variation that we exploit for identification. We compare SMEs just below the cutoff (treated) to SMEs just above the cutoff (control) for the three years prior to (2014–2016) and following (2017–2019) the implementation of the policy.[21] We then test how the CCDS policy affects SMEs' ability to form relationships with new lenders. An increased ability to switch or add lending relationships is a direct benefit of greater data sharing and a key channel through which OB is theorized to increase competition and innovation. Following Ioannidou and Ongena (2010), we consider a firm as forming a new relationship if, in a given year, it borrows from at least one lender that is not part of the set of lenders from whom the firm had borrowed in the previous three years. $Any\ New\ Lender_{i,t}$ is an indicator variable equal to one if firm i forms a relationship with a new lender in year t.

Firms in the UK are required to report all claims ("charges") lenders have against their assets, including lender (bank or non-bank) names, the date the claim commenced, and when the charge ceases, to Companies House (the UK firm Registrar).[22] The information on charges in the Companies House is collected by Bureau Van Dijk (BvD) and provided in their FAME database. BvD data also provides annual firm-level financial information matched to charge-holders information.[23] Hence, we observe firms' lending relationships as well as their balance sheet and income statement information over time.

Figure 3 presents binned scatterplots of new borrowing relationship formation against firm sales before and after the reform. Panel (a) shows no evidence of a change in the propensity for SMEs to form new lending relationships around the £25 million in sales threshold before

[21]While the CCDS was due to go live in April 2016, technical issues meant that data sharing started only in the second half of 2017. Therefore, we include 2016 in the period prior to the reform. We exclude 2020 from the sample because of the potential confounding effects of the COVID-19 pandemic.

[22]These reports are similar to Uniform Commercial Code (UCC) data on SME lending in the US where lenders make filings on all secured loans to preserve priority in bankruptcy (Gopal and Schnabl, 2022). The charge can be against a specific asset or it can be a charge covering the entirety of the firm's balance sheet or its outstanding invoices in the case of invoice financing. There are strong incentives to ensure this data is accurately reported. Lenders have 21 days to formally register their claim (or face legal barriers to repossessing the assets). Borrowers have an incentive to declare when a charge is satisfied to unencumber their assets. We do not observe unsecured claims. However, the overwhelming majority of loans to UK SMEs are collateralized and hence this data provides a highly representative and timely view of a firm's lending relationships.

[23]BvD data is well known for suffering from survivorship bias and various issues with constructing consistent historical panels (Kalemli-Ozcan et al., 2023). To alleviate this concern and maximize coverage of historical observations, we use annually sampled archived vintages of the FAME database, as in Bahaj et al. (2020), to compile our final panel dataset.

the policy, while Panel (b) shows a discontinuity at that threshold appearing after the policy. Firms below the threshold are more likely to establish a new lending relationship than firms above the threshold after the policy but not before.[24]

We formally estimate the effect of the policy on new lending relationships using a difference-in-differences (DiD) design with a linear probability model:

$$Any\ New\ Lender_{i,t} = \beta \times Treated\ SME_i \times Post_t + \eta X_{i,t-1} + \alpha_i + \gamma_{s,t} + \eta_{g,t} + \nu_{r,t} + \varepsilon_{i,t} \quad (3)$$

We focus on firms with 2016 sales between £10 million and £40 million to cleanly identify the effect of the new data-sharing policy. The treatment indicator variable $Treated\ SME_i$ equals one for firms with sales below £25 million in 2016. $Post_t$ is an indicator variable equal to one in the years after the policy went live (2017 and later). β measures the focal policy effect. $X_{i,t-1}$ is a lagged vector of firm controls: The log of total assets, cash to total assets, leverage ratio, and credit risk. We include a rich set of fixed effects, including firm (α_i), sector-by-year ($\gamma_{s,t}$), region-by-year ($\eta_{g,t}$), and lending relationship-stage-by-year ($\nu_{r,t}$).[25] Regions correspond to the 124 UK postcode areas and industry sectors are based on one-digit SIC codes. Standard errors are clustered at the firm level.

Table 4 reports our results. The first four columns show consistently positive effects of the data-sharing policy on SMEs' propensity to borrow from new lenders. In column 1, where we control for year fixed effects only, the $TreatedSME \times Post$ interaction coefficient is positive and statistically significant, showing the policy increased the probability of SMEs forming new borrowing relationships. We find a 1.36 percentage point increase for treated firms after the policy, a 25% increase from the sample mean relationship formation rate of 5.3%. Adding firm fixed effects (column 2) and our richer set of fixed effects and controls (column 3) slightly increases these estimates.

In column 4, we use an even tighter identification strategy that leverages the fact that the CCDS initially only required the nine largest UK banks to share data. We interact the Treated SME $\times$ Post term with both an indicator variable equal to one if SME i had pre-CCDS borrowing relationships with one of the nine banks required to share data under the CCDS ($Prior\ CCDS\ relationship_i$) and an equivalent indicator variable for SMEs that did not have a prior relationship with the nine banks but had a relationship with another lender ($Prior\ non-CCDS\ relationship_i$). The treatment effect is entirely concentrated among clients of the banks required to share SME data.

Our data allows us to observe whether new lending relationships are with banks (columns

[24] The overall downward trend in the new relationship formation rate over time arises mechanically because we fix our sample of firms at the beginning of the period in order to have a balanced panel. This means that the firms in Panel (b) are somewhat older and thus less likely to form new relationships.

[25] Relationship stages are calculated as the deciles of the relationship duration (in months) an SME has with its lenders up to year t.

5 and 7) or non-banks (6 and 8). The coefficient is positive but not statistically significant for new relationships formed with banks, and is both larger and statistically significant for new relationships formed with non-banks (e.g., fintechs). The effect is concentrated among clients of the banks required to share data (the triple interaction with $Prior\ CCDS\ relationship_i$ in columns 7 and 8). This shows that access to customer bank data leads to non-bank entry into the SME lending market, consistent with the increased fintech entry in Section 3.3. In Table D4, we present an additional analysis of the policy's effects on SME interest expenses and balance sheets. We find that treated firms with new non-bank relationships see declining interest expenses after the policy (suggesting lower interest rates on new loans), as well as more short-term liabilities and assets (suggesting more borrowing).

Figure 4 presents event-study plots for lending relationship formation (Panel (a)) and lending relationship formation with non-bank lenders (Panel (b)) using our main specification in Equation (3). This figure illustrates that treated and non-treated firms were on approximately parallel trends prior to the policy, with a divergence starting in 2017 (the first year of data sharing). Post-policy in 2017, the coefficient turns positive and significant, especially for non-banks, and it remains positive for the whole duration after the policy.

Finally, since financial inclusion is a key objective expressed by many policymakers, we examine the distributional effects of the data-sharing policy by comparing firms with and without prior lending relationships. It is not ex-ante obvious whether OB will be of greater benefit to those customers who already had credit or those who did not. Presumably, firms with no prior lending relationship have the most to gain from outside lenders obtaining non-standard data that could be useful in underwriting. Pushing against this is a countervailing selection mechanism. Customers whose transactions reveal them to be low risk are both more likely to get credit from their relationship lender prior to the policy (because it sees they are low risk) and more able to establish new lending relationships after the policy (because a non-relationship lender can now see they are low risk). We examine the policy's extensive margin effects in column 9 of Table 4 by testing how prior lending relationships mediate the rate of new lending relationship formation. We interact our DiD coefficient with indicator variables for whether a firm had a single or multiple prior lending relationships, with the baseline DiD coefficient capturing the effects for firms with no prior lending relationships. Sharing data makes firms with prior lending relationships more likely to form new lending relationships. We do not find an effect for firms without prior lending relationships. This gives support for the selection mechanism rather than the hypothesis that sharing data increases financial inclusion for previously unserved SME borrowers. As we show in Section 4, this is consistent with our model's distributional predictions.

3.3 OB Government Policies and Financial Innovation around the World

Out last set of results focuses on the global consequences of OB policies around the world, broadening our UK-specific analysis. We test whether increased data access spurs financial innovation, which is the most common goal of OB policies. Regulators hope that giving bank customers the ability to share their financial data with fintechs will spark the creation of new firms that offer innovative financial products and increase competition. We use data on VC investment into startups as a proxy for innovative entry, as past research has shown that VC-backed startups are generally innovative, fast-growing entrants (Puri and Zarutskie, 2012; Gornall and Strebulaev, 2021). This proxy is a forward-looking measure of profit-motivated investors' expectations. We use a standard panel event-study design:

$$FintechVC_{i,t} = \sum_{k \neq 0} \beta_k \times OBLag(k)_{i,k,t} + Country_i + Region_r \times Year_t + \epsilon_{i,t}, \tag{4}$$

where $FintechVC_{i,t}$ is a measure of fintech VC activity in country i and year t, measured as either the number of deals or the millions of US dollars invested using data from PitchBook.[26] $OBLag(k)_{i,k,t}$ is an event time indicator, equal to 1 if country i's adoption of OB government policy occurred k years from time t and zero otherwise.[27] We normalize the year of the OB policy's passage to zero so that the coefficient β_k measures changes in fintech VC activity k years before or after OB policy passage relative to the year of its passage. $Country_i$ and $Region_r \times Year_t$ are country and region-by-year fixed effects. Standard errors are clustered at the country level.

VC data poses two challenges. First, VC activity is skewed, with the US having far more VC investments than any other country. We correct for this using a $\log(1+x)$ transformation of our VC activity measures, which means our tests measure relative increases or decreases in VC activity, which is common in the VC literature (e.g., Gompers and Lerner (1998) or Li and Zahra (2012)). Second, the lack of central VC investment registries in most countries makes collecting VC data challenging. Table A5 summarizes our data and shows that PitchBook, despite being one of the best VC databases, has significant gaps in its international coverage. Due to a combination of data collection and low VC activity, only one-quarter of our post-2000 country-years have any fintech VC deals and more than half have no VC deals at all. To reduce

[26] The staged nature of VC investments means that deal counts tend to measure earlier-stage investment and dollar amounts tend to measure later-stage investment. Since our interest lies in financial innovation, we split the VC deals in each country-year into fintech deals and non-fintech deals, with fintech deals being the deals PitchBook places in the "Financial Software" sub-industry or the "Fintech" vertical. Because of the cryptocurrency boom and bust cycles and the fact that digital assets are not related to OB, we reclassify digital assets startups as non-fintech for our main analysis, although this does not have any impact on our results.

[27] For countries in the sample that never adopt OB, $OBLag(k)_{i,k,t}$ is zero everywhere; these countries help identify region-by-year fixed effects.

the biases created by using log-transformed variables in the presence of zeros and VC data coverage issues, we restrict our attention to countries with active PitchBook coverage. As our first government OB policy passage occurs in 2016 or later and PitchBook coverage improves over time, we restrict our analysis of VC activity to the 2011–2021 period. In addition, we consider only countries that PitchBook already covered before our regression sample period by focusing on countries with five or more fintech deals in the 2000-2010 pre-period, which we refer to as high-coverage countries.[28] Our focus on high-coverage countries and our tests using VC dollars, which load on large and hard-to-miss deals, help attenuate concerns that PitchBook coverage improvements are correlated with the passage of OB government policies.[29] Because we condition on pre-period deals, our results mostly speak to countries that already have developed VC markets.[30] Because our filter drops a large number of country-years that *never* had OB, identification in this specification comes chiefly (though not entirely) through the staggered adoption of OB within countries. Intuitively, our regression is comparing VC activity in countries at time t to other countries in the region that will adopt OB but have not adopted it yet. The key identifying assumption is that, absent the treatment, countries within a region would have been on parallel trends.

Figure 5 presents the results from the event-study specification in Equation (4) and shows a relative absence of pre-trends in fintech VC activity in the number of deals in Panel (a) and the amount invested in Panel (b). In both panels, there is a clear inflection point around the year of the OB policy passage and a change of large economic magnitude: Deals increase by almost half a log point and dollars by about a full log point. The sharp increase in fintech VC investments following OB policy adoption is a natural consequence of the uncertainty reduction around the timing of OB policy passage combined with VCs' fast reactions to new investment opportunities.[31]

Table 5 uses a difference-in-differences design to quantify the relationship between OB

[28]Specifically, we consider Australia, Belgium, Brazil, Canada, China, Germany, Denmark, Finland, France, India, Ireland, Israel, Japan, the Netherlands, Norway, Poland, Russia, Spain, Sweden, the United Kingdom, and the United States of America.

[29]Although only 13% of countries are high-coverage, they include 91% of the VC deals and 94% of the investment value. Thus, our analysis of OB policies on fintech VC activity uses the sample of high-coverage countries in the 2011-2021 period. 99% of these high-coverage country-years have at least one fintech deal, dramatically reducing the econometric issues associated with log-transforming zeros.

[30]The results in Table 5 continue to hold with similar coefficients for the entire sample of countries; however, the large number of zeros makes it hard to interpret the results.

[31]For example, OB has been in the works in the US since the 2010 Dodd-Frank Act specified that consumers should own their financial transaction data, yet over a decade later, it has not been codified into regulation and hence does not bind on banks. VCs target at least 30% returns and so see timing as a crucial factor for their financial performance (Gompers et al., 2020). High required returns and a desire to move fast mean that the VC industry is characterized by dramatic year-over-year changes in investment in response to perceived opportunities (Gompers et al., 2008).

policies and fintech VC activity:

$$FintechVC_{i,t} = \beta \times OB_{i,t} + Country_i + \gamma \times Non-fintechVC_{i,t} + Region_r \times Year_t + \epsilon_{i,t}, \quad (5)$$

where $OB_{i,t}$ is an indicator variable equal to one if OB was adopted in country i before year t and other variables are as in Equation (4). We are interested in the coefficient β which measures log change in fintech VC activity following the introduction of government OB policies. Alternative specifications remove the control for non-fintech VC, add the interaction of our trust in fintechs measure with OB passage ($\gamma \times OB_{i,t} \times Trust_i$), use year fixed effects instead of region-by-year fixed effects ($Year_t$), or include additional controls for potentially time-varying importance of trust in fintechs ($Trust_i \times Year_t$).

Across specifications, fintech companies receive significantly more VC investment following the adoption of OB policies. Using our preferred specification from Equation (5), we find a 0.31 increase in log fintech VC deals (column 4 of Table 5) and a 0.87 increase in log fintech VC dollars (column 9). These estimates are robust to different combinations of controls and fixed effects (columns 1, 3, 6, and 8). The median country-year in this data has 19 fintech VC deals worth \$89 million and so our estimates of β translate into an additional 7 deals and \$125 million annually for the median country. Although these investments are small in absolute terms, small investments in companies with the potential to become large is a defining property of the VC industry.[32]

In Section 2.4, we identified consumer trust in sharing their data with fintechs as a potential driver of OB government policies. We next examine if trust in fintechs mediate the effect of OB on VC investments in fintech. In columns 2 and 7, we provide suggestive evidence that trust amplifies the effect of OB policies on fintech VC activity, with the coefficient on the interaction between OB passage and trust in fintechs being positive and significant at the 10% level for fintech VC deals and positive and insignificant for dollars invested. These relationships are tentative given that our trust measure is only estimated for a small number of countries and our VC data is inherently noisy. A potential confounder in this setting is that countries that had high trust in fintechs experience both increases in fintech VC activity and the passage of OB policies. However, our country controls absorb a time-invariant relationship between trust and fintechs. Moreover, in columns 5 and 10 we show that our results persist while controlling for trust-by-year fixed effects: This addresses a concern that trust was more important for fintechs in the later part of the sample and countries happened to be passing OB laws around the same time. In Appendix E, we present additional robustness tests and show that OB policies that force banks to share their customers' data drive these results.

[32]For example, less than \$3 billion was invested by US VCs up to 1981 (Gompers et al., 2008), yet that investment included a \$1 million investment in Microsoft and a \$150 thousand investment in Apple (Gornall and Strebulaev, 2021).

We also test if OB spurs fintech entrants offering different financial products. This allows us to shed light on whether the new data made available by OB is used for many financial products or only used for credit underwriting. Since Pitchbook lacks more granular product classifications, we overcome this by using PitchBook's keywords feature to define seven subindustries of fintech: alternative lending, consumer finance, financial IT, payments, regtech (i.e., the use of technology to address regulatory processes), wealth management, and digital assets. Details of our classification are in Appendix E. Using Equation (5), Table 6 considers VC investments in companies targeting specific use cases as dependent variables. Alternative lending shows a 0.66 log point increase; consumer finance, financial IT, payments, and regtech show increases of between 0.48 and 0.61 log points; and wealth management shows a statistically insignificant 0.43 log point increase. The notable and reassuring exception to this trend is digital assets, where we see an insignificant negative effect. This is intuitive and serves as a placebo test: Digital assets, such as cryptocurrency, are largely unrelated to OB functionality. Although the size of each of these subindustries is small,[33] we find a broad-based increase in fintech activity, which suggests VCs anticipate OB data as offering value not just for credit issuance but for a variety of fintech use cases. This is consistent with our findings in Section 3.1 that UK consumers use many OB-data-reliant products, such as financial advice and credit.

4 An Economic Framework for Open Banking

We build on the empirical facts documented in the previous section to develop a structural model of how wider access to bank customers' data affects entry, competition, and welfare. Our empirical results illustrate the importance of both credit OB and advice OB. Our model allows us to examine the distinct economic mechanisms that underlie these different data uses. We calibrate our model by linking our novel results on OB firm entry and customer OB adoption with off-the-shelf estimates of financial product markets from the relevant literature. This allows us to assess the welfare and distributional consequences of OB and to extend the insights from our UK microdata to different environments, including countries with different privacy preferences for sharing data.

Our model is tailored to speak to three issues. First, we model the two use cases of OB identified in our empirical work: Credit and advice. For credit, we use a standard setup where data provides a signal of borrower quality, whereas for advice we use and adapt models with product (e.g., Jones and Tonetti (2020)) or business practice (e.g., Farboodi et al. (2019)) improvements to capture data improving financial products. Second, reflecting the goal of OB in promoting financial innovation and competition, we explicitly model new entry on

[33] Specifically, the median (mean) subindustry-year sees 4 (15) deals worth \$9 million (\$300 million).

the extensive margin together with product and price improvements on the intensive margin. Third, our consumer OB use and fintech entry results confirm that privacy considerations are central to the uptake of the policy. Our model builds off this result and considers data-sharing choices as a trade-off between privacy preferences and the better products or lower prices a customer could obtain from revealing her data.

4.1 Model

The model extends a standard discrete choice framework by explicitly considering consumer data usage. For expositional purposes, we use the term "consumer," which we interpret generically as applying to either an individual or an SME. Consumer data allows competing firms to improve their products or pricing by learning about the characteristics of heterogeneous consumers. For example, the pricing of a loan is improved using data from a transaction account that reveals a consumer's credit risk, as shown by Ghosh et al. (2022) and our SME analysis in Section 3.2. Alternatively, a financial planning app uses balances and transactions from a consumer's financial accounts to offer her customized financial and tax advice.

We model two data access regimes that determine which firms can use a consumer's data. In the relationship banking regime, which is the pre-OB status quo, only a consumer's incumbent relationship bank can use her data. In the OB regime, each consumer chooses whether to opt in to data sharing, and if she does, all firms providing the financial product can use her data regardless of whether they are her relationship bank. If she opts out of data sharing, all firms observe that she opted out, and only the relationship bank can use her data.

4.1.1 Consumer Data and Market Structure

A mass m of heterogeneous consumers, indexed by i, can purchase a financial product. Products are offered by I incumbent firms (i.e., banks) and an endogenous number, N, of new entrants (i.e., fintechs). All firms offer a single product to each consumer, who chooses a single product among the available offerings.

Each consumer is endowed with a vector of characteristics, χ_i, that is known to the consumer and revealed to firms that can access that consumer's data. Which firms can access the consumer's data depends on the policy regime. Under the relationship banking regime, only a single relationship bank can access the data and learn χ_i, and all other firms only know the unconditional distribution $dF(\chi_i)$. Under the OB regime, the relationship bank still knows χ_i, but, additionally, the consumer decides whether to share her data with all other firms. Let $S_i \in \{0, 1\}$ denote consumer i's (endogenous) choice of whether to opt in to data sharing. If consumer i opts to share data ($S_i = 1$), all firms observe χ_i. If the consumer does not ($S_i = 0$) the non-relationship firms observe only that the consumer opted out of data sharing and consequently infer the endogenous conditional type distribution $dF(\chi_i|S_i = 0)$.

To account for both advice OB and credit OB use cases, we assume that χ_i provides information on both the consumer-specific marginal cost (mc_i)[34] paid by the lender to provide the product and consumer-specific customization needs (f_i), which if precisely met, provide additional utility to the consumer. Thus, $\chi_i \equiv (f_i, mc_i)$. Marginal cost covers both usage cost (will they exploit credit card bonuses or incur late fees?) and risk (will they default?) and is most linked to credit OB. Customization needs cover product tailoring (how can we set up a financial plan for a particular customer?) and creation (how can we communicate their spending to them or help them save?) and is most linked to advice OB.

4.1.2 Consumer Demand

Consumer i makes a discrete choice of firm j's product from among the $I+N$ competing firms. Product ij is characterized by $\nu_{ij} \equiv (p_{ij}, g_{ij})$, where p_{ij} is price and g_{ij} are non-price characteristics, e.g., whether the offered advice is customized or whether the firm had a relationship with consumer i in the prior period. Consumer i receives the following indirect utility from product ij:

$$u(\nu_{ij}, \chi_i) \equiv -\alpha p_{ij} + (\theta + \lambda)R_{ij} + \lambda(1 - R_{ij})S_i + \epsilon_{ij}. \tag{6}$$

Here, α is the consumer's price sensitivity and p_{ij} is the price. R_{ij} is an indicator for whether firm j is the relationship bank for consumer i, and θ represents the consumer's utility from obtaining the product from her relationship bank, e.g., due to a desire to obtain financial services from a convenient one-stop shop. λ is the extra utility the consumer gets from a financial institution that can provide customization, e.g., by being offered more relevant financial advice. S_i is an indicator for whether the consumer shares her data with outsiders. When a consumer obtains a product from her relationship bank, she receives both the additional relationship utility θ as well as the customization utility λ. When a consumer obtains a product from an outsider, she only obtains the customization utility and only if she shares her data. u is implicitly a function of χ_i because χ_i contains the consumer's desired customization.

Finally, ϵ_{ij} is a horizontal taste shock whose i.i.d. realization is known to the consumer at the time of making the product choice (and only after deciding whether to share her data) but unknown to the firms, creating differentiation and giving individual firms market power. Importantly, these ϵ shocks prevent the unraveling of pure strategy equilibria by obscuring whether a consumer chooses an uninformed offer because she is a high-cost type with high-price offers from insiders, or because she is a low-cost type with a high idiosyncratic preference

[34] We interpret variance in mc_i as the residual *conditional* on observables, e.g., residual variation after controlling for a consumer's publicly available credit score. For example, in countries where credit scores are more informative, we would expect our modeled variance in mc_i to be smaller relative to a country that has no credit scores. We discuss this in more detail in Appendix F.

for the outsider's product (see, e.g., Crawford et al. (2018)).

Among the offerings and an outside option, u_0, the consumer chooses the product that offers the highest indirect utility. Let $s_j(\boldsymbol{\nu}_i, \chi_i)$ denote the probability that a consumer with characteristics χ_i chooses firm j's product given all product offerings, including the outside option, $\boldsymbol{\nu}_i$. This quantity is obtained by integrating the consumer's optimal choice over the consumer-firm taste shocks, $\boldsymbol{\epsilon_i}$:

$$s_j(\boldsymbol{\nu}_i, \chi_i) = \int \mathbb{I}\left\{u(\nu_{ij}, \chi_i) > u(\nu_{ik}, \chi_i),\ \forall k \neq j\right\} dF(\boldsymbol{\epsilon_i}). \tag{7}$$

4.1.3 Consumer Opt-in to Data Sharing

Under the OB regime, each consumer chooses whether to opt in to data sharing.[35] If she shares her data, all $I + N$ firms observe her consumer-specific χ_i. If she does not share her data, her relationship bank observes χ_i, and the other firms observe only that she opted out of data sharing. Let $\boldsymbol{\nu}_i^S$ and $\boldsymbol{\nu}_i^{\sim S}$ denote the set of offers she receives if she opts in to or out of data sharing, respectively. Let $Eu(\boldsymbol{\nu}_i)$ denote the consumer's expected utility of the discrete choice problem in Equation (7) for a given set of offers, with

$$Eu(\boldsymbol{\nu}_i) = \int \max_j \left\{u(\nu_{ij}, \chi_i)\right\} dF(\boldsymbol{\epsilon_i}). \tag{8}$$

The consumer makes her data-sharing decision by comparing her expected utility if she shares her data to her expected utility if she does not. We enrich this decision by incorporating a consumer-specific preference for privacy, reflecting both aggregate preferences for privacy and consumer-level heterogeneity.[36] In the same discrete choice framework, we model the consumer's indirect utility of sharing or not sharing her data as follows:

$$u_i^S = -\phi + Eu(\boldsymbol{\nu}_i^S, \chi_i) + \epsilon_i^S \tag{9}$$

$$u_i^{\sim S} = Eu(\boldsymbol{\nu}_i^{\sim S}, \chi_i) + \epsilon_i^{\sim S}. \tag{10}$$

Here, ϕ represents a society-wide hedonic privacy preference and ϵ_i^S and $\epsilon_i^{\sim S}$ represent a consumer-specific i.i.d. privacy preference shocks.[37] Based on her characteristics and privacy preference, the consumer chooses the greater of these utilities, which yields an endogenous

[35] For simplicity, we assume the consumer either shares her data with all the firms or no firms (besides the relationship bank, which already has it). This assumption is nearly without loss of generality because if a consumer is made better off by sharing her data with one extra firm, she is made even better off by sharing her data with all firms. The only exception to this would be if the consumer has increasing hedonic disutility from sharing data with more firms.

[36] See, for example, Tang (2019), Bian et al. (2021), and Ben-Shahar and Schneider (2011).

[37] The variance of these shocks being greater than zero precludes a cutoff strategy of opt in versus opt out.

probability of disclosure for each set of consumer characteristics χ_i given by ψ_i:

$$\psi_i = \int \mathbb{I}\left\{u_i^S > u_i^{\sim S}\right\} dF(\epsilon_i^S, \epsilon_i^{\sim S}). \tag{11}$$

Finally, the conditional distribution of types who opt out of data sharing is

$$dF(\chi_i|S_i = 0) = \frac{(1-\psi_i)dF(\chi_i)}{\int_i (1-\psi_i)dF(\chi_i)}. \tag{12}$$

4.1.4 Firms

Entrant firms pay a fixed cost c to enter. Conditional on entry, firms compete in a differentiated Bertrand structure. Firm j's marginal cost for consumer i is the sum of two parts. First, mc_j, a firm-specific cost common to all of j's potential customers, which is known to firms and assumed in our calibration to differ only by incumbent versus new entrant. Second, mc_i, a consumer-specific cost that is common to all firms selling to consumer i, known by the relationship bank and by new entrants only if data is shared by the consumer:

$$mc_{ij} \equiv mc_j + mc_i. \tag{13}$$

Firms are informed about consumer i's characteristics, χ_i, if (1) they are consumer i's relationship bank or (2) the economy is in the OB regime and consumer i has opted into data sharing. Uninformed firms know only the distribution of consumer types not sharing data, which in the relationship banking regime is the unconditional consumer distribution, $dF(\chi_i)$, and in the OB regime is the consumer distribution conditional on opting out of data sharing, $dF(\chi_i|S_i = 0)$. Firms set prices and product characteristics to maximize profits, with informed firms setting consumer-specific prices and products (ν_{ij}) and uninformed firms offering a single product and price to all consumers:

$$\Pi_{ij} = \begin{cases} \max_{\nu_{ij}} s_j(\boldsymbol{\nu}_i, \chi_i)(p_{ij} - mc_{ij}) \text{ for firms with data} \\ \max_{\nu_j} \int s_j(\boldsymbol{\nu}_i, \chi_i)(p_j - mc_{ij})dF(\chi_i) \text{ for firms without data under relationship banking} \\ \max_{\nu_j} \int s_j(\boldsymbol{\nu}_i, \chi_i)(p_j - mc_{ij})dF(\chi_i|S_i = 0) \text{ for firms without data under OB.} \end{cases} \tag{14}$$

Each firm's profit is equal to its profit across all its customers, including both profit from offering targeted products and pricing to customers whose data they know (due to OB data sharing or relationships, if any) and profit from offering an uncustomized product at a single price to the customers whose data they do not know:

$$\Pi_j = \int_i \Pi_{ij} di - c. \tag{15}$$

The entry cost of c implies that in equilibrium, $\Pi_j = c$ for the marginal entrant.

4.1.5 Equilibrium

Events proceed as follows in the relationship banking regime. First, firms choose whether to enter. Second, firms simultaneously set prices and products for both the consumers whose data they have and the consumers whose data they do not have. Third, consumers choose products and consume them. The OB regime has a similar structure but has an added first stage where consumers choose whether to share their data.

We focus on symmetric equilibria within firm types where all informed firms charge the same consumer-specific price and all uninformed firms charge the same price to observably equivalent consumers. For a given regime, an equilibrium consists of a set of prices and product customization choices, $\boldsymbol{\nu}_i$, a number of new entrants, consumer product choices, and consumer data-sharing choices. The endogenous choices satisfy the optimal firm entry and profit maximization conditions, optimal consumer product and data sharing choice, and firms' consistent beliefs over consumer choices by type.

4.1.6 Model Calibration

We breathe life into the model using simple calibrations based on two products: US non-Government-Sponsored Enterprise (GSE) residential mortgages and financial planning advice. We use these products as representative examples of the credit OB and advice OB use cases described previously. Both calibrations are intended to be quantitatively realistic illustrations of the economic forces affecting two real-world applications of OB.

The non-GSE residential mortgage calibration is an example of where consumer data is useful for underwriting, as the relevant dimension of heterogeneity is in default risk.[38] This market is well studied and there exists estimates for several key parameters in the literature for calibration. The financial advice calibration is an example of the data allowing for a product more tailored to the consumer's needs: The relevant dimension of heterogeneity is what the optimal savings, investment, and tax strategy would be given the consumer's particular financial situation.

We detail our calibration exercise in Appendix F. Broadly, our key objects for calibration are the variance of unobserved marginal costs (for mortgages), the value of customized advice (for financial advice), and consumer preferences for privacy (for both cases). We calibrate these parameters through the simulated method of moments, utilizing empirical moments from our earlier reduced-form analysis, including the difference-in-differences estimates of

[38] We focus in particular on the non-GSE sector because GSEs' guarantees mostly render default risk irrelevant.

fintech entry (described in Section 3.3) and consumer adoption of OB from the UK consumer survey (described in Section 3.1). Other parameter estimates, such as consumer price sensitivity and lender marginal costs, are taken from the relevant mortgage (Buchak et al. (2024a)) and financial advice (Di Maggio et al. (2022a)) literature.

4.2 Consequences of OB

Using our calibrated model, we first look at the aggregate and distributional effects of OB (Section 4.2.1) before moving on to the role of society-wide privacy preferences (Section 4.2.2). Additional discussion showing the interaction between credit registries and OB is presented in Appendix F.3.

4.2.1 Aggregate and Distributional Consequences of OB

Figure 6 Panel (a) compares equilibrium outcomes under OB to those under relationship banking for our financial advice (magenta) and credit (cyan) calibrations. Across both calibrations, entry rises and the quantities of financial services provided increase, although these increases are more dramatic in the advice case. We decompose these aggregate quantity changes into quantity changes from relationship banks (columns "Quantities (relationship)") and other providers (columns "Quantities (outsiders)"). Outsider (e.g., fintech) quantities increase and relationship bank quantities decrease for both products. The substantial increases in quantities offered by outsiders for both financial products are consistent with our findings on large increases in fintech entry in Section 3.3. Average prices in both cases are largely unchanged, although the modest aggregate price changes in the credit case mask dramatic heterogeneity along the distribution of borrower types. Incumbent profits fall and consumer surplus increases in both cases, although the surplus increase is larger for the advice case despite lower entry.

Panels (b) through (e) provide greater insight into the distributional effects of credit OB across the distribution of borrower marginal cost. Here, we focus on the comparison between the no-OB status quo in red and the calibrated OB regime in green.[39] Panel (b) shows the fraction of borrowers opting into data sharing. In the no-OB status quo, no consumers share data. Once in the OB regime, the green line shows that the propensity to share data is decreasing in the borrower's unobserved MC: Roughly 60% of borrowers with the lowest MC share, while essentially no borrowers with medium or higher MC share data.[40]

[39] We return to a counterfactual with a smaller consumer preference for privacy below (in blue).

[40] Note that this proportion is smoothly decreasing in MC due to borrowers' idiosyncratic preferences for privacy. This smoothness prevents a full (Grossman, 1981) unraveling, and is in contrast to many theoretical signaling models where stark cutoff strategies are common. Importantly, opting out of data sharing does not fully reveal the borrower's type. However, based on the results in Panel (b), it is clear that opting out of data sharing in the OB regime is at least partially revealing, and indeed, the distribution conditional on opting out, $dF(\chi_i|S_i = 0)$ has a higher expected MC than the unconditional distribution $dF(\chi_i)$.

Turning to price and quantity outcomes, Panel (c) shows that in the no-OB status quo (red line) average interest rates are only weakly increasing in MC. The relationship is weak because average interest rates are a combination of informed insider rates, which only partially track borrower MC due to information rents, and the uninformed pooled interest rate, which is invariant. In the OB regime (green line), low-MC borrowers opt in to data sharing and reveal their type to outside lenders. These borrowers are offered lower rates from both outsiders and the insider, who now faces greater competition. These lower rates lead to more borrowing, Panel (d), and to outsiders gaining market share among the lowest-MC borrowers, Panel (e).

In contrast, high-MC borrowers, who choose not to opt in to data sharing, partially reveal to outside lenders their type, although hedonic privacy preferences partially obscure this inference. Therefore, uninformed outsiders charge slightly higher rates as compared to the status quo. This result is consistent with our findings in the SME analysis in Section 3.2: Under OB firms with prior lending relationships are more likely to get new loans and those firms that form new lending relationships with non-banks pay less interest. Importantly, however, because information revelation reduces the adverse selection faced by outsiders, entry rises and in our calibration, entry's positive effect through product variety more than offsets the negative effect of higher prices, even among the highest-MC borrowers. Thus, the quantity of credit provided increases for all borrowers under the OB regime.

Finally, consider the financial advice calibration. Here, consumer "type" represents the idiosyncratic needs for financial advice. All types are made better off under OB. This arises because customers that share data benefit through outsiders' ability to offer fully customized advice. Furthermore, there is an increase in competition which benefits everyone including customers that do not share their data due to privacy concerns. Since, in contrast to credit OB, no negative information is revealed by sharing data, consumers are more likely to opt in to OB in the advice case than the credit case. Intuitively, all customers benefit from providing more data to their financial advisor, while only customers with low MC directly benefit from providing more data to their loan underwriter. This helps to explain the greater uptake of advice OB than credit OB observed in the UK survey data in Section 3.1.

4.2.2 Consumer Attitudes Towards Privacy

We conclude our analysis of the model by examining how consumer attitudes towards privacy impact the equilibrium outcomes of OB. Figure 7 shows the impact of varying consumers' mean preference for privacy. The x-axis shows the value of privacy as a multiple of the calibrated value for the UK such that consumers' aversion to data sharing is increasing in the x-value. The lines with circle markers show the fraction of consumers opting into data sharing. The x marks show the fraction of consumers (regardless of whether they opt in to OB) who are made *worse* off by OB in a utility sense. The red lines and marks show outcomes for the financial advice calibration, and the blue lines and marks show outcomes for the credit calibration.

Unsurprisingly, the fraction of consumers opting into data sharing is decreasing in their preference for privacy. However, our finding in Section 3.1 that more consumers opt in to OB for financial advice than for credit is sustained across counterfactual privacy preferences. Next, while in the credit case, high MC borrowers who do not share do not benefit directly from OB, they do experience two indirect effects: They benefit from increased lender entry and are harmed by their opt-out decision partially revealing their high MC. For societies with weak privacy preferences, the act of not sharing data reveals strong negative information about their type, and so the harm outweighs the benefits of increased entry. In contrast, in societies with privacy preferences similar to the UK, the negative inference from not sharing data is relatively weak, and so the competition and product variety benefits of increased entry outweigh the signaling costs. Our plot showing the fraction of customers made worse off by OB makes this clear. For advice, for the reasons described, all types of consumers are better off at all levels of societal preference. For credit, we see a distinct threshold at about 85% of our calibrated UK privacy preference, below which the signaling cost for high-MC types outweighs the benefit of new entry and a positive number of borrowers are made worse off.

We confirm this intuition by revisiting Figure 6 Panels (b) through (e). Here, the dashed blue lines reflect a counterfactual where the privacy preference is decreased by 25%—corresponding to 0.75 on the x-axis of Figure 7. These panels show that as more borrowers opt in to OB (Panel (b)), rates decrease more for low-MC borrowers and increase more for high-MC borrowers (Panel (c)). This leads to greater quantities of credit for low-MC borrowers, but less credit for high-MC borrowers, both overall and from outsiders, relative to the no-OB status quo (Panels (d) and (e)).

4.2.3 Summary

The bottom line from our model is that a serious quantitative evaluation of OB, and not merely a theoretical one, is necessary for policymakers when thinking about the aggregate and distributional consequences of OB.

The complex interplay between use cases, consumer heterogeneity, and societal preferences for privacy leads us to a range of important predictions for the impact of OB on the market for financial products. The advice OB case has little ambiguity. All customers benefit from the option to share either directly through better products when sharing data or indirectly through increased competition when they are privacy conscious. In contrast, the results in the credit OB, are far more nuanced. Customers with favorable data and low privacy preferences share data and benefit from improved loan terms. Firm entry increases as potential entrants face less adverse selection. Customers with unfavorable data or strong privacy preferences do not share, which partially signals to outsiders that they are costly to serve, leading to higher prices. These negative effects for non-sharing customers are potentially offset by increased entry and competition. Thus, while on the surface there appears to be an inherent conflict between OB's stated goals of increased competition and innovation with financial inclusion, it is not ex-ante obvious which force dominates for high-cost or privacy-conscious customers.

We find that the societal desire for privacy plays an important role in pinning down distributional consequences of credit OB. More privacy-conscious consumers shield high-MC borrowers from scrutiny: Lenders cannot infer from opting out of OB that the borrower is not sharing because she has a high-MC type. As the preference for privacy decreases, opting out is a more precise signal that the consumer is a costly borrower to serve and lenders charge higher rates. This has the effect of potentially leaving privacy-conscious consumers and those with a high marginal cost worse off.

5 Conclusion

Our paper examines the dramatic rise of OB, which is now present in some form in roughly 80 countries. Using a hand-collected dataset of OB government policies around the world, we document significant heterogeneity in these policies' timing, purpose, and implementation. Granular microdata on UK consumers shows they use OB for credit but also for financial advice, with that usage associated with credit use and greater financial knowledge, respectively. Data on UK SMEs affected by OB shows they form more new lending relationships, especially with non-banks. These new relationships are driven by SMEs with prior lending relationships. Large increases in VC fintech investments across different financial products (e.g., financial advice applications, credit, payments, regtech) follow OB policy implementations, suggesting consumer financial transactions data are valuable across many financial applications.

We interpret these results through a general framework of data use and sharing, focusing on the contrasting implications of using data for underwriting (in credit OB) and using data to improve products (in advice OB). OB increases entry in both use cases through very different channels: For credit, data allows entrants to underwrite more effectively and reduce adverse selection; while for product improvements, data allows entrants to improve their product quality. Although our results suggest OB is achieving its innovation-promotion goals, our framework highlights how OB-enabled credit underwriting can harm consumers whose data would indicate their riskiness. Being able to opt out offers only partial protection to these consumers, as the act of opting out itself sends a signal from which lenders draw a negative inference. Moreover, these consumers are likely to be on the margins of the financial system, and thus precisely those whose financial inclusion policymakers are interested in facilitating. These results are at odds with the financial inclusion goals of OB policies but consistent with our finding that the SMEs who benefited the most from OB are those who already had credit access.

Importantly, these potential negative distributional effects are not present when OB data is used for product improvements rather than for screening, and preliminary evidence suggests that product improvements are an equally—if not more—quantitatively relevant OB application. Additionally, social privacy preferences can ameliorate some of the worst distributional effects and prevent a stigma from non-sharing. In our quantitative calibration on UK data, the benefits of entry and innovation more than offset the losses from information revelation for even the riskiest borrowers, with many borrowers seeing major benefits. This result is specific to our calibration and our estimates of UK privacy preferences, highlighting the importance of quantitative models like ours for evaluating the impacts of OB.

As policymakers set the path of future banking regulation, our paper helps put these tradeoffs in perspective. Data lies at the heart of relationship banking, and large financial institutions benefit from their special ability to aggregate huge amounts of customer data. Because of that, removing banks' monopoly on customer data has the potential to transform the very nature of relationship banking. If opening data reduces banks' economies of scope, the entire banking ecosystem could reorganize around more specialized and interconnected firms. The large reaction of fintech investment to OB policy implementations shows the potential for disruption and just how valuable innovators perceive this data to be, while our results on non-bank SME borrowing document real disruption to an important market.

More generally, the role that data ownership and access plays in endogenously creating and maintaining market power is a first-order question in an increasingly data-driven economy, sectors that are dominated by a small number of data-intensive firms. Opening data to potential competitors and innovators in order to spur innovation, increase competition, and ultimately raise welfare is a natural policy response, and our paper is the first to provide a global comparative analysis of such policy initiatives. Our work aims to set the stage for future research on OB and the use of data in finance and beyond by highlighting why it matters and the key tradeoffs it raises. However, this potentially profound disruption and restructuring of the financial system is still in its infancy. Important empirical and theoretical questions remain about how these policies will impact the behavior and outcomes of consumers, businesses, and financial firms.

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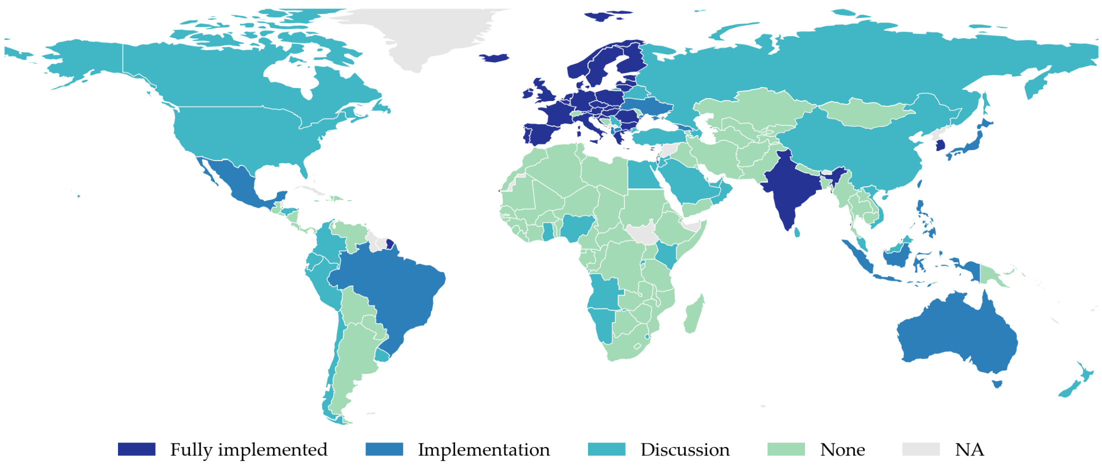
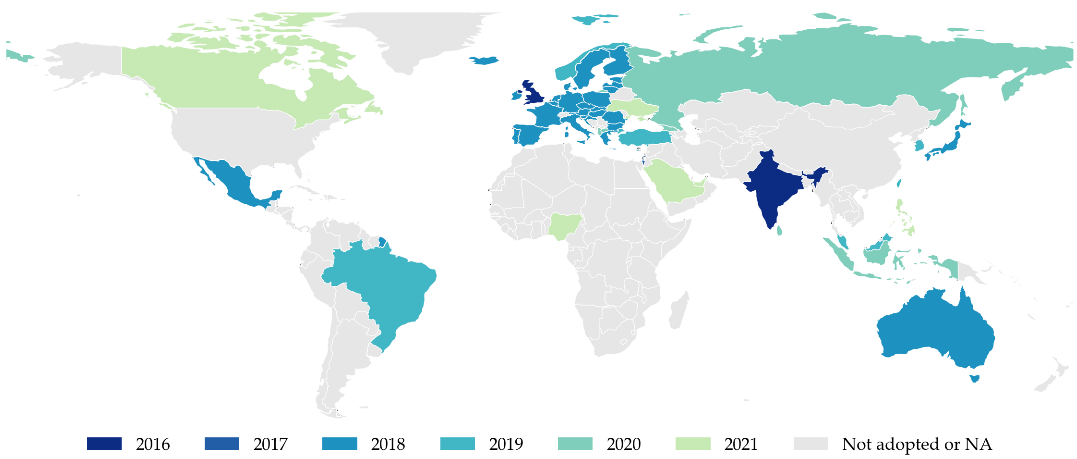
Figure 1: Government-led Open Banking Regimes Around the World

Note: These maps show the current implementation status of government-led open banking policies and the year in which the major open banking policy was passed. Panel (a) shows the implementation status of their government open banking policies. Fully implemented corresponds to countries that have implemented open banking government policies; Implementation to those that have determined the specifics of the open banking approach and are currently implementing it; Discussion to those either considering implementing open banking policies or discussing that implementation; None to those with no government open banking approach; and NA to those where we have not collected data. Panel (b) shows the passage year of countries' major open banking policies. Data on government open banking policies is current as of October 2021.



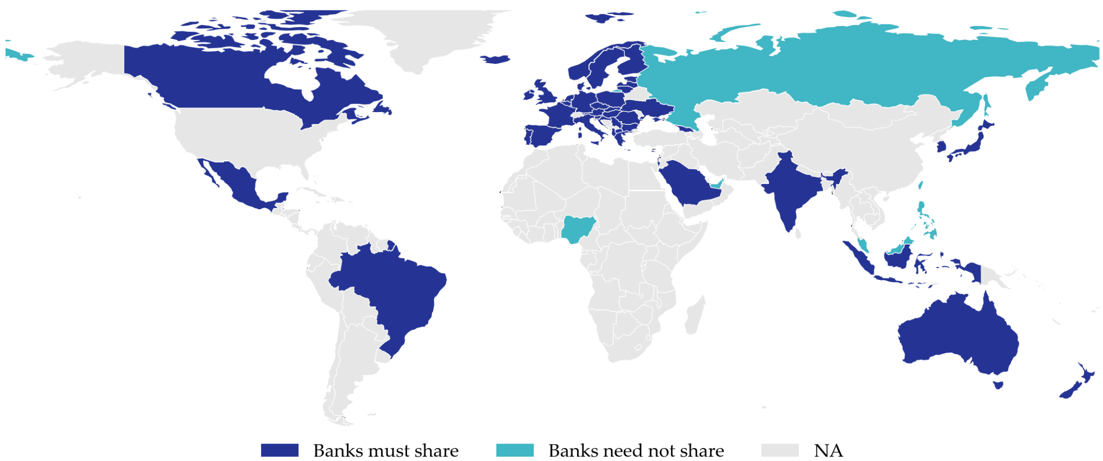
(a) Government open banking policy implementation status



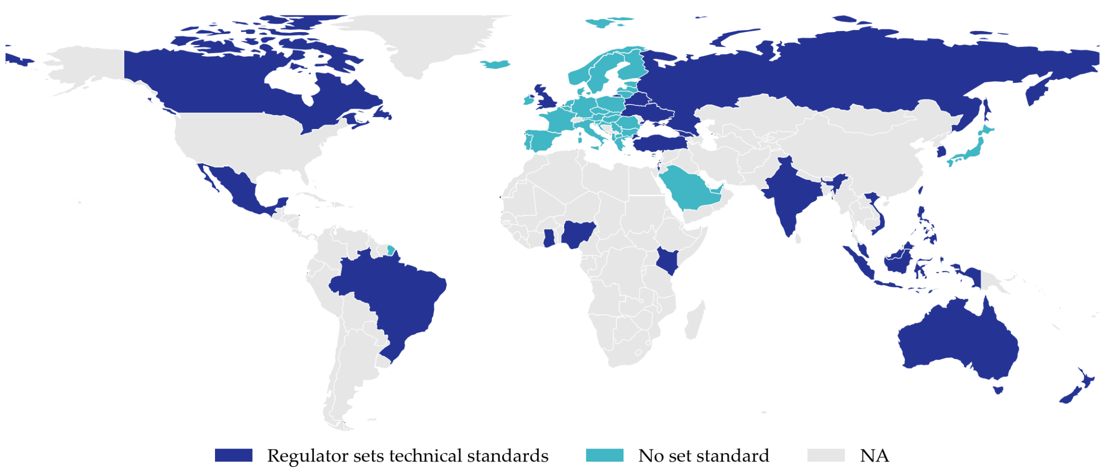
(b) Timeline of open banking adoption

Figure 2: Open Banking Government Policy Dimensions

Note: These maps show mandated data sharing and technical specifications among countries with government-led open banking efforts developed enough to specify those policy dimensions. Panel (a) shows whether the current or proposed policy requires banks to share data upon customer request. Panel (b) shows whether the regulator sets a technical standard for open banking application programming interfaces—the technology used to share bank customer data. Countries marked NA either have no government-led open banking regime, are too early in discussion for the issue to be decided, or were excluded from our data collection. Data on government open banking policies is current as of October 2021.



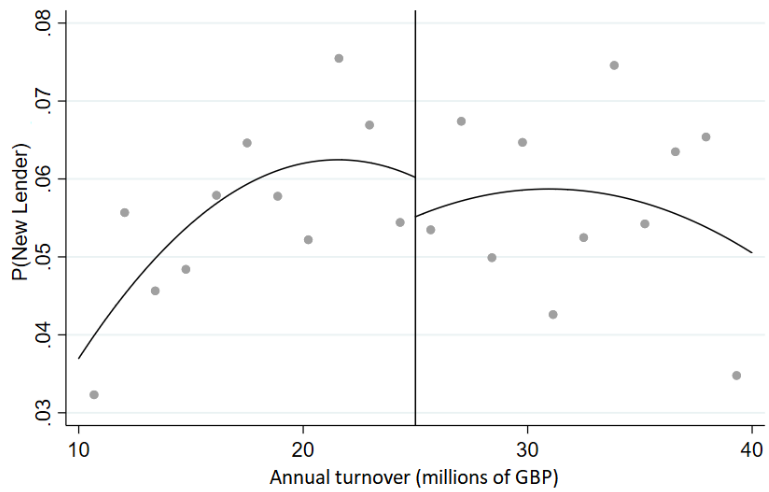
(a) Banks must share data upon customer request



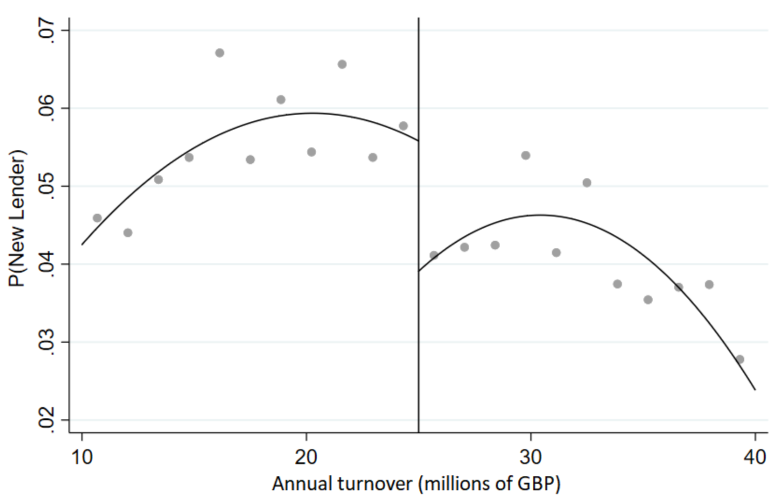
(b) Regulator sets technical standards

Figure 3: New SME Lending Relationships around CCDS Eligibility Threshold

Note: This figure shows the association between new lending relationship formation and firm sales before and after the implementation of the Commercial Credit Data Sharing (CCDS) policy. The underlying data is company-year data on secured loans for UK firms from Companies House. Panel (a) presents observations from before the implementation of the CCDS (2014-2016) and Panel (b) presents observations after the policy (2017-2019). Each dot is the fraction of firms forming new lending relationships (y-axis) among firms in a given sales bucket (x-axis). We use 22 equally sized buckets from £10 million to £40 million of 2016 firm sales. A firm establishes a new relationship when it gets a loan from a lender that it had not borrowed from in the preceding three years. The vertical line denotes the cutoff firm sales for data sharing under the policy (£25 million), with firms to the left of the line in Panel (b) being treated by the policy and firms to the right of the threshold serving as the control group. The solid curves plot best-fit quadratic polynomials for lending relationship propensity, separately estimated above and below the policy cutoff.



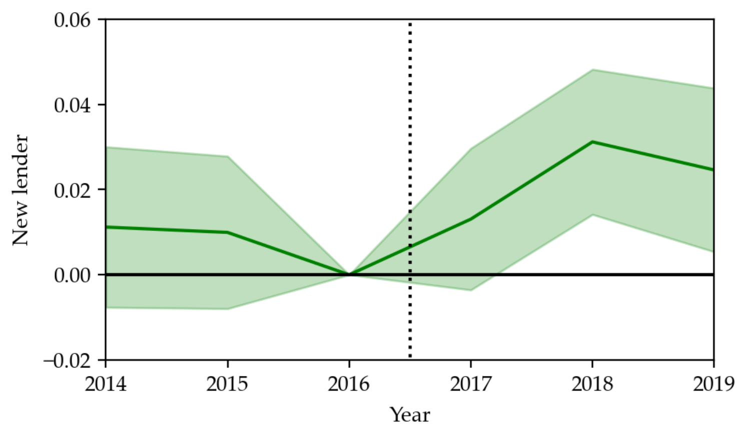
(a) New lenders by SME sales before data-sharing policy (2014-2016)



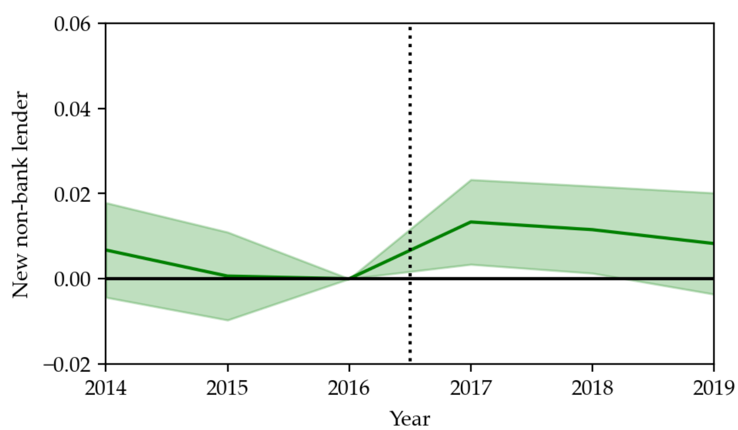
(b) New lenders by SME sales after data-sharing policy (2017-2019)

Figure 4: Event-study of SME Data Sharing and New Lending Relationships

Note: This figure shows changes in new lending relationship formation for SMEs treated by the UK Commercial Credit Data Sharing (CCDS) policy using a panel event-study analysis. The underlying data is company-year data on secured loans for UK firms with 2016 sales between £10 million and £40 million from Companies House via Bureau van Dijk for the 2014–2019 period. Firms are classified as treated if their 2016 sales is below the CCDS's £25 million eligibility threshold, with firms above the threshold serving as the control group. Panel (a) shows an event-study on the rate of new lending relationships with any lender for treated firms, while Panel (b) shows an event-study on the rate of new lending relationships with non-banks. The event-study specification is estimated using one period lagged firm-level control variables of the log of total assets, a low credit risk dummy, cash to total assets, and leverage ratio, as well as firm, sector-by-year, region-by-year, and relationship stage-by-year fixed effects. Low credit risk is defined as a QuiScore above 80, sectors are defined based on 1-digit 2003 UK SIC codes, regions are the 124 postcode areas, and relationship stage is the decile of the average relationship length the firm has with its lenders. The shaded regions denote 95% confidence intervals calculated using standard errors clustered at the firm level.



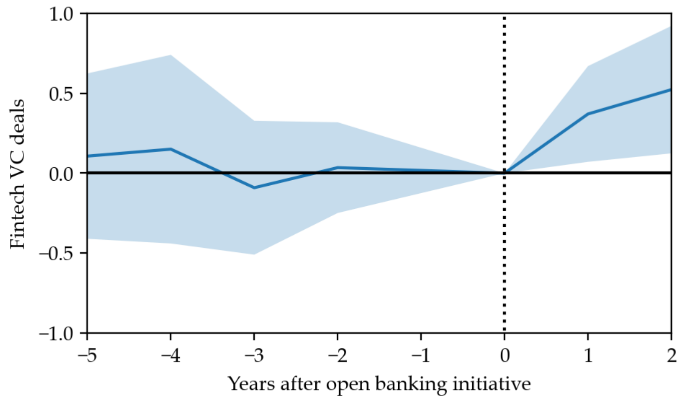
(a) New lending relationships



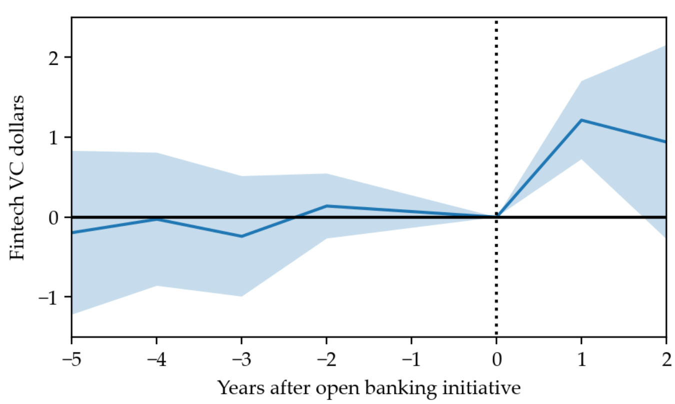
(b) New lending relationships with non-banks

Figure 5: Event-study of Fintech Investment After Open Banking Government Policies

Note: This figure shows changes in fintech venture capital (VC) activity around the passage of open banking government policies using a panel event-study analysis. We perform this analysis on our high-coverage Pitchbook panel of 2011-2021 data for the 21 countries with at least five fintech VC deals in the 2000–2010 period. Panel (a) shows an event study on the log of one plus the number of fintech VC deals, and Panel (b) shows an event study on the log of one plus the millions of US dollars invested in fintech VC deals. Year 0 is the passage year of each country's major open banking initiative. The coefficient for year 0 is set to zero and other coefficients are presented net of country fixed effects and region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. The shaded regions denote 95% confidence intervals calculated using standard errors clustered at the country level.



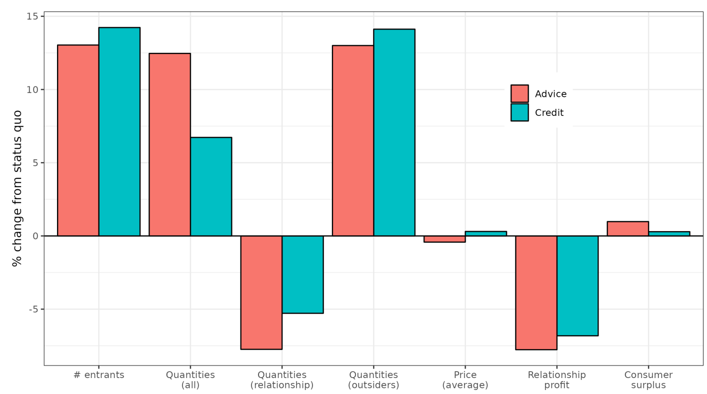
(a) Log number of fintech VC deals



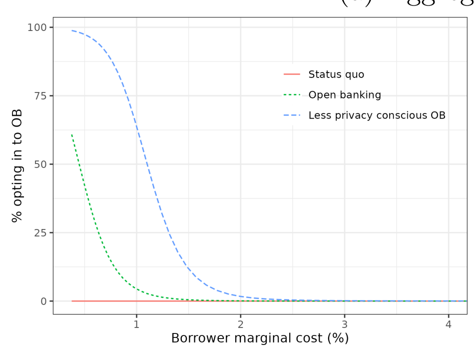
(b) Log amount of fintech VC investment in millions of US dollars

Figure 6: Aggregate and Distributional Outcomes of Open Banking

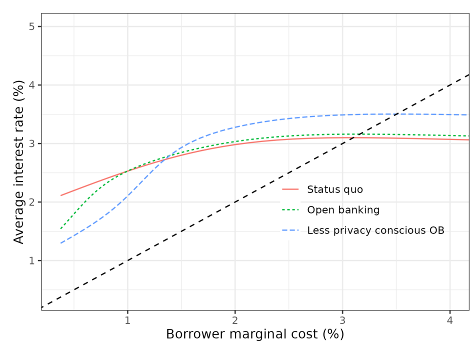
Note: Panel (a) presents model-implied aggregate changes after open banking (OB), with each bar showing the percentage change in the relevant outcome caused by moving from the status-quo relationship banking regime to the OB regime. Magenta and cyan bars show outcomes for the financial advice and non-GSE residential mortgage calibrations, respectively. # entrants is the number of new entrants. Quantities (all) is the population fraction obtaining the financial service, which we further split into Quantities (relationship), i.e., relationship bank, and Quantities (outsiders), i.e., fintechs. Price (average) is the average fee or rate charged. Relationship profit is relationship banks' profits. Panels (b)–(e) show the distributional outcomes of OB in the credit case. x-axes show borrowers with different marginal costs. Red lines and dotted green lines indicate outcomes for the relationship banking and calibrated OB regime, respectively. Dashed blue lines indicate outcomes in a counterfactual simulation where borrowers' privacy preference is 25% lower. Panel (b) shows the fraction of the population opting into data sharing. Panel (c) shows the average interest rate. Panel (d) shows the fraction of the population obtaining credit. Panel (e) shows the outsiders' market share.



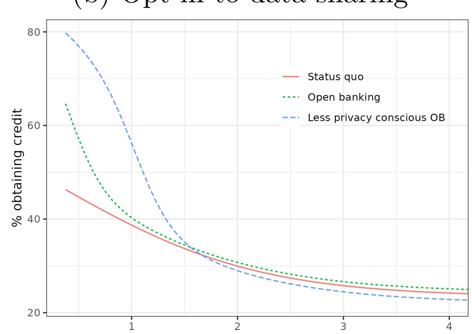
(a) Aggregate outcomes



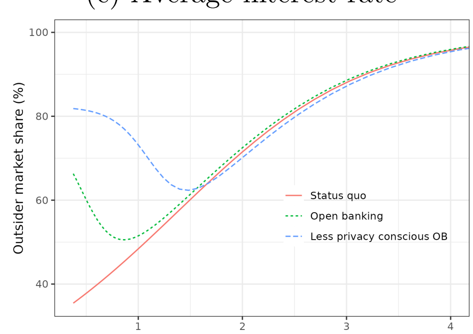
(b) Opt in to data sharing



(c) Average interest rate



(d) Fraction obtaining credit



(e) Market share of outsiders

Figure 7: Effect of Societal Privacy Preferences on Open Banking Equilibria

Note: This figure shows how the impact of open banking (OB) varies as societal privacy preferences vary under the model of Section 4. Specifically, it shows outcomes (y-axis) for the advice (red) and credit (blue) OB as population preferences for privacy vary (x-axis). The solid lines with circle indicators show the fraction of the population opting into open banking. The x markers show the fraction of the population made worse under open banking. Privacy preferences are presented as a multiple of the baseline calibration, with a lower value corresponding to individuals being more willing to share data.

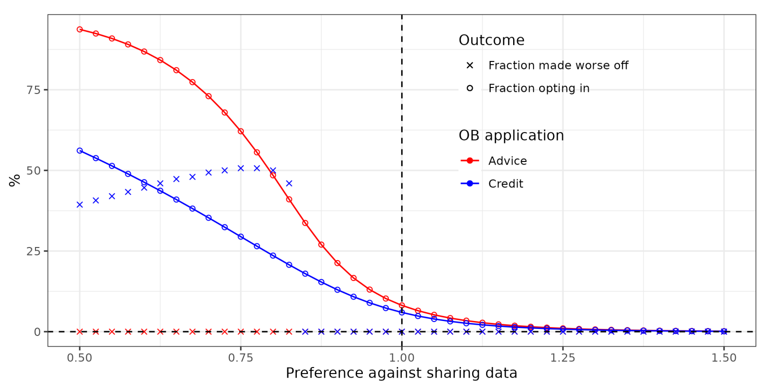


Table 1: Open Banking Government Policies Summary Statistics

Note: This table presents summary statistics on open banking government policies for 168 countries. The first number in each column is the percentage of countries fitting the given criteria and the number in parentheses is the number of countries under consideration. Government-led open banking presence considers all countries in the respective region for which data were collected, while the other categories (policy mandates, status, participation, product scope, and functionality scope) consider only those countries with a government-led open banking approach that has advanced far enough that the issue in question has been (at least preliminarily) decided. Columns split the sample into regions, with geographic terms following the World Bank definitions.

Variable	Worldwide	Africa, Middle East & North Africa	Europe & Central Asia	Latin America & the Caribbean	North America	South Asia, East Asia & Pacific
Government-led open banking presence	48% (168)	25% (65)	80% (50)	32% (25)	67% (3)	56% (25)
Policy justification						
Innovation	97% (65)	100% (9)	97% (39)	100% (3)	100% (1)	92% (13)
Competition	82% (65)	67% (9)	87% (39)	100% (3)	0% (1)	77% (13)
Inclusion	29% (66)	40% (10)	10% (39)	100% (3)	100% (1)	54% (13)
Status						
Discussion	38% (80)	75% (16)	12% (40)	75% (8)	100% (2)	36% (14)
Mid-implementation	18% (80)	6% (16)	12% (40)	25% (8)	0% (2)	43% (14)
Implemented	44% (80)	13% (16)	75% (40)	0% (8)	0% (2)	21% (14)
Policy strength						
Required data sharing	88% (57)	67% (6)	97% (37)	100% (2)	100% (1)	64% (11)
Data reciprocity	18% (56)	33% (6)	0% (36)	100% (2)	100% (1)	45% (11)
Regulator provides tech specs	39% (62)	63% (8)	15% (39)	100% (2)	100% (1)	83% (12)
Beyond transaction accts	34% (56)	80% (5)	3% (36)	100% (3)	100% (1)	91% (11)
Functionality scope						
Data sharing only	5% (58)	0% (6)	0% (38)	50% (2)	100% (1)	9% (11)
Payments only	0% (58)	0% (6)	0% (38)	0% (2)	0% (1)	0% (11)
Both	95% (58)	100% (6)	100% (38)	50% (2)	0% (1)	91% (11)

Table 2: Drivers of Open Banking Government Policies

Note: This table shows whether ex-ante country characteristics predict the implementation of open banking government policies. Columns 1–5 consider Cox proportional hazards models testing the adoption year of open banking based on the period up to October 2021. Columns 6–7 consider a cross-country OLS regression of the status of a country's open banking (OB) regulation, expressed as a zero-to-seven score of each country's open banking implementation progress as of October 2021, with 0 being no action, 1–2 being increasingly serious levels of discussion, and 3–7 being levels of implementation progress. Columns 8–9 consider our OB Strength Index, a zero-to-one measure of the strength of each countries' open banking regime equal to the average of four indicators of policy strength (banks needing to share data, data-using firms needing to share data, regulators setting technical standards, and coverage of financial products beyond transaction accounts). The independent variables are country characteristics. Trust in fintechs is the portion of survey respondents who report being willing to share their financial data with fintechs, as reported by Chen et al. (2023). Bank branches per 100k people, Private sector credit to GDP, and Financial sector Lerner index are from the World Bank. The Lerner index measures markups over marginal costs, ranges between 0 and 1, and captures the market power of banks, with higher values denoting less competition. Non-fintech VC deals and Fintech VC deals are from PitchBook and are used after taking the log of one plus the number of VC deals. Foreign-owned banks is the share of banks that are foreign-owned and are from the Claessens and Van Horen (2013) foreign bank ownership data. The Rule of Law Index is from the Cato Institute and is on a zero-to-ten scale with higher numbers denoting more favorable conditions. OB adoption year is the calendar year of OB adoption. All specifications include GDP per capita in thousands of US dollars, the square of GDP per capita in hundreds of thousands of US dollars, and the log of population based on World Bank data, as well as region fixed effects for i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. All independent variables are as of 2013, except for the trust in fintechs measure which is from early 2019. The regressions are cross-sectional, where each country in the sample corresponds to a single data point. European Union member states are weighted to count as a single country for estimates and standard errors. Robust standard errors are in parentheses. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Open banking adoption					OB implementation (0-7)		OB Strength Index (0-1)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Trust in fintechs	9.755*				8.803**	15.130***	14.006***	5.403*	4.836*
	(5.284)				(4.044)	(3.939)	(4.079)	(2.471)	(2.436)
Branches per 100k people		-0.007							
		(0.020)							
Private sector credit to GDP		-0.001							
		(0.005)							
Financial sector Lerner index		0.246							
		(1.301)							
Non-fintech VC deals			0.311**		0.540		0.488		0.144
			(0.135)		(0.438)		(0.659)		(0.148)
Fintech VC deals			0.098						
			(0.271)						
Foreign-owned banks				-0.150					
				(0.463)					
Rule of Law Index				0.049					
				(0.126)					
OB adoption year								0.231	0.256
								-0.207	(0.164)
Per capita GDP ($k)	0.202***	0.067	0.021	0.047**	0.139***	0.442***	0.330*	0.072	0.056
	(0.065)	(0.042)	(0.021)	(0.023)	(0.053)	(0.096)	(0.180)	(0.069)	(0.071)
Per capita GDP ($100k) squared	-20.218***	-6.516	-2.869	-4.696**	-14.530***	-43.110***	-32.951*	-4.409	-3.234
	(5.707)	(4.100)	(2.120)	(2.235)	(4.725)	(8.154)	(16.022)	(5.957)	(6.116)
Log population	-0.086	0.011	-0.095*	0.027	-0.232**	0.044	-0.159	0.216**	0.121
	(0.133)	(0.042)	(0.057)	(0.092)	(0.106)	(0.176)	(0.308)	(0.085)	(0.145)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27	86	163	130	27	27	27	19	19
Concordance index	0.893	0.882	0.924	0.895	0.917				
Adjusted R^2						0.698	0.696	0.789	0.800

Table 3: Consumers' Open Banking Usage and Their Financial Knowledge and Credit Access

Note: This table shows the association between financial knowledge, credit product usage, and open banking (OB) usage using person-level responses to the Financial Conduct Authority's 2020 Financial Lives Survey in the UK. We use a cross-sectional OLS specification. The dependent variable in column 1 is the respondent's answer to the question "How knowledgeable would you say you are about financial matters?" on a 0 (not at all knowledgeable) to 10 (very knowledgeable) scale. The dependent variables in columns 2 to 5 are indicator variables equal to one if the respondent currently holds the credit product in question or held it in the last 12 months. Advice OB is an indicator variable equal to one if the respondent uses OB for financial advice products, i.e., answers yes to using financial aggregation apps that allow consumers to see the accounts they hold with different banks in one place (e.g., Money Dashboard, Yolt, MoneyHub) or savings-related apps that help build savings by monitoring consumer current accounts and automatically transferring funds (e.g., Chip, Cleo, Moneybox, Plum). Credit OB is an indicator variable equal to one if the respondent uses OB for credit products, i.e., answers yes to using firms offering customized lending products, credit reference agencies (which can personalize credit reports), or price comparison websites (e.g., rates offered by different lenders). Respondent controls are indicator variables for being unwilling to share data (respondent gives a score of 3 or below on a 0-to-10 scale to the question "Thinking about Open Banking, how willing would you be to give your bank permission to securely access your banking information?"), being employed (working full- or part-time), missing bill payments (reports missing bill payments in at least three of the last six months or finds keeping up with domestic bills and credit commitments to be a heavy burden), having high risk aversion (gives a score of 3 or below on a 0-to-10 scale to the question "Are you a person who is generally willing to take risks?"), having at least some post-secondary education, being aged 18–39 years, being male, being of white ancestry, and being married or in a registered civil partnership. All specifications control for county (UK local authority) fixed effects and estimate robust standard errors (reported in parentheses). *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

		Credit product ownership			
	Financial knowledge	Credit card	Personal loan	Student loan	Pawnbroking loan
	(1)	(2)	(3)	(4)	(5)
Advice OB	0.370***	0.039	0.020	-0.030	0.006
	(0.143)	(0.034)	(0.026)	(0.026)	(0.004)
Credit OB	0.019	0.126***	0.108***	0.002	0.001
	(0.197)	(0.040)	(0.035)	(0.034)	(0.005)
Respondent controls	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Observations	3,098	3,104	3,104	3,104	3,104
Adjusted R^2	0.158	0.167	0.089	0.325	0.025

Table 4: SME Data Sharing and New Lending Relationships

Note: This table shows changes in new lending relationship formation for SMEs treated by the UK Commercial Credit Data Sharing (CCDS) policy. The table uses a difference-in-differences design on firm-year data on secured loans for UK firms with 2016 sales between £10 million and £40 million from Companies House via Bureau van Dijk for the 2014–2019 period. A firm is classified as a Treated SME if its 2016 sales is below the CCDS's £25 million eligibility threshold. Post is an indicator variable equal to one after the CCDS was implemented in 2017. Prior CCDS relationship equals one if the firm had an existing lending relationship in 2016 with one of the nine banks required to share SME data under the CCDS, while Prior non-CCDS relationship is an equivalent indicator variable for SMEs that did not have a prior relationship with the nine banks but had a relationship with another lender. Single relationship and Multiple relationships are indicator variables equal to one if in 2016 the firm had loans from one lender or loans from multiple lenders, respectively. The dependent variable in columns 1–4 and 9 is an indicator variable equal to one if the firm takes a loan in the year in question from a lender that it had not borrowed from in the preceding three years. The dependent variable in columns 5 and 7 is an indicator variable equal to one if the firm similarly takes a new loan and that loan is from a bank, while in columns 6 and 8 the indicator variable is equal to one if the loan is from a non-bank. Firm controls are the log of total assets, a low credit risk dummy, cash to total assets, and leverage ratio, all lagged one year. Low credit risk is defined as a QuiScore above 80, sectors are defined based on 1-digit 2003 UK SIC codes, regions are the 124 postcode areas, and relationship stage is the decile of the average relationship length the firm has with its lenders. Standard errors are clustered at the firm level and are in parentheses. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Any new lender				New bank	New non-bank	New bank	New non-bank	Any new lender
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated SME × Post	0.0136***	0.0156***	0.0153***	0.0003	0.0061	0.0093***	0.0008	0.0005	0.0003
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
Treated SME	-0.0021								
	(0.004)								
Treated SME × Post × Prior CCDS relationship				0.0228***			0.0067	0.0146***	
				(0.009)			(0.007)	(0.006)	
Treated SME × Post × Prior non-CCDS relationship				0.0064			0.0046	0.0017	
				(0.013)			(0.010)	(0.009)	
Treated SME × Post × Single relationship									0.0129*
									(0.008)
Treated SME × Post × Multiple relationships									0.0279**
									(0.012)
Firm controls			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes							
Firm FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Relationship stage-by-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-by-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE			Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,089	39,089	39,089	39,089	39,089	39,089	39,089	39,089	39,089
Adjusted R^2	0.00	0.058	0.063	0.064	0.020	0.076	0.021	0.076	0.071

Table 5: Fintech Investment After Open Banking Government Policies

Note: This table shows changes in fintech venture capital (VC) investment following the implementation of open banking (OB) government policies. The table uses a difference-in-differences design on our high-coverage Pitchbook panel of country-year data spanning 2011-2021 for the 21 countries with at least five fintech deals in the 2000–2010 period. The dependent variable in columns 1 to 5 is the log of one plus the number of fintech deals in a country-year, and in columns 6 to 10 it is the log of one plus the amount invested in millions of US dollars. The main independent variable is After OB initiative which is an indicator variable equal to one if the year in question is after the year major open banking policy was passed in the country in question. Columns 2 and 7 include After OB initiative × trust in fintechs which interacts that term with country-level trust in fintechs variable equal to the portion of survey respondents who report being willing to share their financial data with fintechs, as measured for the EY Global Fintech Adoption Index and reported by Chen et al. (2023). Columns 4 and 9 include a control for non-fintech VC activity using Pitchbook data, transformed the same way as fintech VC activity. All specifications control for country fixed effects; columns 1, 2, 6, and 7 contain controls for year fixed effects; and columns 3, 4, 5, 8, 9 and 10 control for region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. Columns 5 and 10 additionally offer time-varying controls for the trust-in-fintech measure, with the coefficient on the control variable being estimated separately for each calendar year. European Union member states are weighted to count as a single country for estimates and standard errors. Standard errors (reported in parentheses) are clustered at the country level. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Fintech VC deals					Fintech VC dollars				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
After OB initiative	0.214*	0.101	0.416**	0.308**	0.432*	0.746**	0.802*	1.058**	0.874**	0.949*
	(0.111)	(0.164)	(0.159)	(0.125)	(0.205)	(0.267)	(0.390)	(0.415)	(0.368)	(0.487)
After OB initiative × Trust in fintechs		0.594*					0.041			
		(0.280)					(0.784)			
Non-fintech VC deals				0.498***						
				(0.139)						
Non-fintech VC dollars									0.338***	
									(0.105)	
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes				Yes	Yes			
Region-by-year FE			Yes	Yes	Yes			Yes	Yes	Yes
Fintech trust-by-year FE					Yes					Yes
Observations	231	176	231	231	176	231	176	231	231	176
Adjusted R^2	0.919	0.918	0.930	0.937	0.925	0.877	0.869	0.894	0.898	0.888

Table 6: Fintech Investment After Open Banking Government Policies by Fintech Product Area

Note: This table shows changes in fintech venture capital (VC) investment by different product areas following the implementation of government open banking policies. The table uses a difference-in-differences design on our high-coverage Pitchbook panel of country-year data spanning 2011-2021 for the 21 countries with at least five fintech deals in the 2000–2010 period. The dependent variable in each specification is the log of one plus the number of VC deals in a country-year and given subsector of fintech, where subsectors are defined based on Pitchbook keywords as described in Appendix E. The independent variable is an indicator variable equal to one if the year in question is after the year major open banking policy was passed in the country in question. We use Equation (5) which controls for the log of one plus the number of non-fintech VC deals, country fixed effects, and region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. Standard errors (reported in parentheses) are clustered at the country level. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

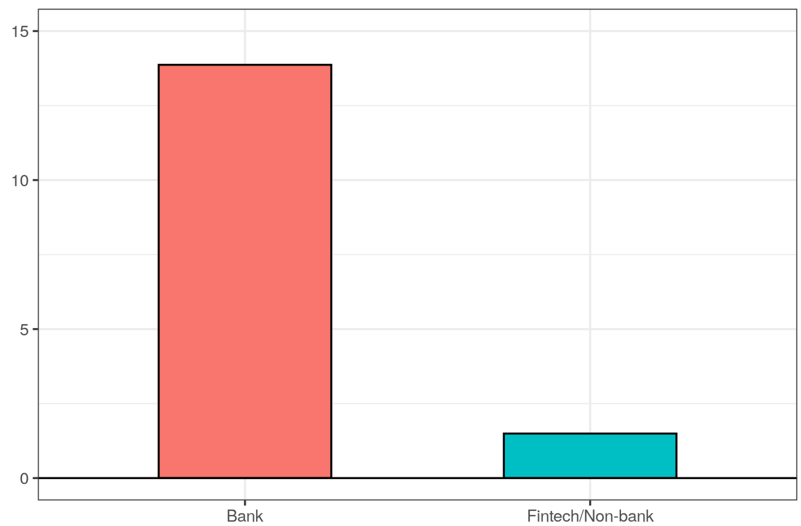
	Alternative lending	Consumer finance	Financial IT	Payments	Regtech	Wealth management	Digital assets
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
After OB initiative	0.656**	0.480***	0.608***	0.409*	0.503**	0.432	-0.136
	(0.296)	(0.140)	(0.140)	(0.209)	(0.187)	(0.293)	(0.259)
Non-fintech VC control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231	231	231	231	231	231	231
Adjusted R^2	0.872	0.835	0.882	0.871	0.882	0.887	0.835

Appendix

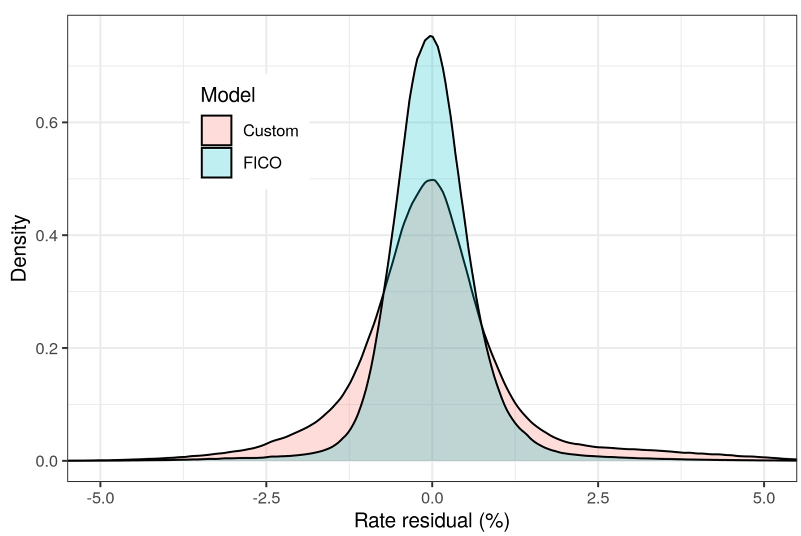
A Additional Tables and Figures

Figure A1: Data Use by Banks and Non-banks/Fintechs in the US Mortgage Market

Note: This figure shows the use of credit-scoring models by banks and non-banks and interest rate residuals in the US residential mortgage market. Panel (a) shows the fraction of mortgages originated using a credit scoring model besides standardized Equifax, Experian, FICO, or Vantage Score for depository (red) and non-depository (blue) institutions. Panel (b) shows the distribution of interest rate residuals for custom (red) and standardized (blue) credit scoring models after controlling for interacted LTV, loan purpose, lien status, loan type, debt-to-income ratio, whether the loan is a reverse mortgage, open-end line of credit, made for a business purpose, HOEPA status, construction method, occupancy type, and conforming status fixed effects, plus year-MSA fixed effects. Data is from HMDA for 2018 and 2019, merged with the Avery file to identify lender type.



(a) Percentage of mortgages originated using alternate credit scoring methods



(b) Mortgage interest rate residuals by credit scoring method

Table A1: Country-level Data Summary Statistics

Note: This table presents summary statistics on our country-level variables. Panel (a) reports values for a cross-section of country characteristics for all countries for which we have collected open banking (OB) data; we use this sample to examine which country characteristics predict OB policy adoption. Panel (b) reports values for 2011–2021 panel data for our high-VC-coverage sample of countries that have at least five fintech venture capital (VC) deals in the 2000–2010 period; we use this sample for panel regressions of open banking's impact on fintech VC activity. For each variable, we present the number of observations, the average value, the standard deviation, and assorted percentiles. The first set of variables (under "Open banking variables") concerns the status of open banking policies as of October 2021. After open banking (OB) initiative equals one in country-years after a major open banking policy was passed (in Panel (b)). In both panels, the next three variables are set at the country level based on that country's OB policies: OB implemented is an indicator variable equal to one if the open banking policy was implemented or is in the pre-implementation stage, OB implementation is a 0-7 rating of the open banking policy progress where higher numbers denote more progress toward regulation, and the OB Strength Index is our 0-1 measure of open banking policy strength. All other variables, except "Trust in fintechs", are measured in 2013, which we use for pre-open banking country characteristics for our cross-country regressions; Trust in fintechs is measured in 2019—the earliest available year with comprehensive data. VC deals, non-fintech VC deals, and fintech VC deals are presented next and are from PitchBook and used after taking the log of one plus the number (and are hence different from Table A5). Per capita GDP in thousands of US dollars, the square of per capita GDP in hundreds of thousands of US dollars, the log of population (in millions), private sector credit to GDP, bank branches per 100k people, and the financial sector Lerner index are from the World Bank. Trust in fintechs is the proportion of survey respondents who report being willing to share their financial data with fintechs, as reported by Chen et al. (2023) The Lerner index ranges between 0 and 1 and measures the market power of banks, with higher values denoting less competition. Foreign-owned banks are from the Claessens and Van Horen (2013) foreign bank ownership data. The Rule of Law Index is from the Cato Institute and is on a 0 to 10 scale with higher numbers denoting more favorable conditions.

Panel (a) Cross-sectional data for 168 country sample

	Count	Mean	Std. dev.	10th pct.	25th	50th.	75th	90th
Observations	168							
Open banking variables								
OB implemented	168	0.29	0.45	0.00	0.00	0.00	1.00	1.00
OB implementation	168	1.83	2.46	0.00	0.00	0.00	4.00	6.00
OB Strength Index	168	0.15	0.26	0.00	0.00	0.00	0.25	0.50
Venture capital variables								
VC deals	168	1.58	1.97	0.00	0.00	0.69	2.79	4.79
Non-fintech VC deals	168	1.54	1.95	0.00	0.00	0.69	2.66	4.68
Fintech VC deals	168	0.56	1.03	0.00	0.00	0.00	0.69	1.99
Other explanatory variables								
Per capita GDP ($k)	163	14.65	20.66	0.75	1.38	5.58	18.35	45.54
Per capita GDP ($100k) squared	163	0.06	0.17	0.00	0.00	0.00	0.03	0.21
Log population	156	2.48	2.09	0.60	1.35	2.33	3.39	4.33
Trust in fintechs	27	0.23	0.15	0.09	0.12	0.16	0.33	0.42
Private sector credit to GDP	149	54.19	47.37	11.08	18.70	39.79	70.53	124.82
Branches per 100k people	155	17.30	15.63	2.72	4.94	12.48	23.54	37.15
Financial sector Lerner index	94	0.31	0.13	0.17	0.23	0.29	0.37	0.47
Foreign-owned banks	134	0.43	0.28	0.03	0.20	0.42	0.66	0.80
Rule of Law Index	146	5.18	1.56	3.43	3.94	4.77	6.47	7.56

Table A1: Country-level Data Summary Statistics (continued)

Panel (b) Panel data for 21 countries with high-VC-coverage sample

	Count	Mean	Std. dev.	10th pct.	25th	50th.	75th	90th
Observations	231							
Open banking variables								
After open banking initiative	231	0.32	0.47	0.00	0.00	0.00	1.00	1.00
OB implemented	231	0.81	0.39	0.00	1.00	1.00	1.00	1.00
OB implementation	231	4.81	1.89	1.00	4.00	6.00	6.00	6.00
OB Strength Index	231	0.43	0.34	0.25	0.25	0.25	0.50	1.00
Venture capital variables								
VC deals	231	5.75	1.22	4.47	4.92	5.53	6.31	7.46
Non-fintech VC deals	231	5.67	1.21	4.36	4.82	5.42	6.21	7.29
Fintech VC deals	231	3.19	1.38	1.61	2.30	3.00	3.88	5.10
Other explanatory variables								
Per capita GDP ($k)	231	40.26	22.00	6.78	27.13	44.27	52.62	62.73
Per capita GDP ($100k) squared	231	0.21	0.18	0.00	0.07	0.20	0.28	0.39
Log population	231	4.40	4.00	1.69	2.27	3.64	4.85	5.80
Trust in fintechs	176	0.19	0.16	0.07	0.10	0.14	0.15	0.56
Private sector credit to GDP	199	107.33	44.47	51.88	65.25	105.49	141.13	167.65
Branches per 100k people	197	24.86	13.72	8.92	14.79	21.86	32.93	38.36
Financial sector Lerner index	72	0.27	0.12	0.11	0.18	0.28	0.34	0.41
Foreign-owned banks	231	0.27	0.24	0.02	0.08	0.20	0.40	0.58
Rule of Law Index	126	7.08	1.44	4.35	6.78	7.45	8.18	8.61

Table A2: Consumer Data Summary Statistics

Note: This table presents summary statistics from the Financial Conduct Authority's 2020 Financial Lives Survey. For each variable, we present the number of observations, the average value, the median value, and the standard deviation. Observation counts vary as we exclude "don't know" and/or "prefer not to say" responses. Advice OB is an indicator variable equal to one if the respondent uses open banking for financial advice products, i.e., answers yes to using financial aggregation apps that allow consumers to see the accounts they hold with different banks in one place (e.g., Money Dashboard, Yolt, MoneyHub) or savings-related apps that help build savings by monitoring consumer current accounts and automatically transferring funds (e.g., Chip, Cleo, Moneybox, Plum). Credit OB is an indicator variable equal to one if the respondent uses open banking for credit products, i.e., answers yes to using firms offering customized lending products, credit reference agencies (which can personalize credit reports), or price comparison websites (e.g., rates offered by different lenders). Unwillingness to share data equals one if the respondent gives a score of 3 or below on a 0 to 10 scale to the question "Thinking about Open Banking, how willing would you be to give your bank permission to securely access your banking information?". Employed equals one if the respondent reports working full- or part-time. Missing bill payments equals one if the respondent reports missing bill payments in at least three of the last six months or finds keeping up with domestic bills and credit commitments to be a heavy burden. Risk aversion equals one if the respondent gives a score of 3 or below on a 0 to 10 scale to the question "Are you a person who is generally willing to take risks?". Higher education equals one if the respondent has completed at least some post-secondary education. Young equals one if the respondent is aged 18–39. Male equals one if the respondent reports being male. White equals one if the respondent is of white ancestry. Married equals one if the respondent is married or in a registered civil partnership. Financial knowledge is the respondent's answer to the question "How knowledgeable would you say you are about financial matters?" on a 0 (not at all knowledgeable) to 10 (very knowledgeable) scale. Credit card, personal loan, student loan, and pawnbroking loan are indicator variables equal to one if the respondent currently holds the credit product in question or held it in the last 12 months. The number of other credit products variables are the count of credit products the respondent reports owning, excluding the product in question.

	Count	Mean	Median	Std. dev.
Open banking usage				
Advice OB	3,923	0.086	0	0.281
Credit OB	3,943	0.055	0	0.227
Respondent characteristics				
Unwillingness to share data	3,940	0.524	1	0.499
Employed	4,281	0.453	0	0.498
Missing bill payments	4,234	0.141	0	0.348
Risk aversion	4,257	0.371	0	0.483
Higher education	3,963	0.518	1	0.5
Young	4,310	0.406	0	0.491
Male	4,253	0.451	0	0.498
White	4,188	0.916	1	0.277
Married	4,172	0.452	0	0.498
Financial knowledge and credit product ownership				
Financial knowledge	4,266	6.545	7	2.272
Credit card	4,310	0.536	1	0.499
Personal loan	4,310	0.107	0	0.309
Student loan	4,310	0.182	0	0.386
Pawnbroking loan	4,310	0.004	0	0.066
Number of other credit products				
Excluding credit cards	4,310	1.054	1	1.302
Excluding personal loans	4,310	1.483	1	1.368
Excluding student loans	4,310	1.408	1	1.456
Excluding pawnbroking	4,310	1.585	1	1.49

Table A3: Determinants of Consumer Open Banking Usage in the UK

Note: This table shows the association between open banking (OB) usage and demographic variables using person-level responses to the Financial Conduct Authority's 2020 Financial Lives Survey in the UK. We use a cross-sectional OLS specification. The dependent variable in column 1 indicates if the respondent uses open banking for financial advice products, i.e., answers yes to using financial aggregation apps that allow consumers to see the accounts they hold with different banks in one place (e.g., Money Dashboard, Yolt, MoneyHub) or savings-related apps that help build savings by monitoring consumer current accounts and automatically transferring funds (e.g., Chip, Cleo, Moneybox, Plum). The dependent variable in column 2 indicates if the respondent uses open banking for credit products, i.e., answers yes to using firms offering customized lending products, credit reference agencies (which can personalize credit reports), or price comparison websites (e.g., rates offered by different lenders). Other variables are dummy variables measuring person-level characteristics. Unwillingness to share data equals one if the respondent gives a score of 3 or below on a 0 to 10 scale to the question "Thinking about Open Banking, how willing would you be to give your bank permission to securely access your banking information?". Employed equals one if the respondent reports working full- or part-time. Missing bill payments equals one if the respondent reports missing bill payments in at least three of the last six months or finds keeping up with domestic bills and credit commitments to be a heavy burden. Risk aversion equals one if the respondent gives a score of 3 or below on a 0 to 10 scale to the question "Are you a person who is generally willing to take risks?". Higher education equals one if the respondent has completed at least some post-secondary education. Young equals one if the respondent is aged 18–39. Male equals one if the respondent reports being male. White equals one if the respondent is of white ancestry. Married equals one if the respondent is married or in a registered civil partnership. All specifications control for county (UK local authority) fixed effects and estimate robust standard errors (reported in parentheses). *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Advice OB (1)	Credit OB (2)
Unwillingness to share data	-0.022**	-0.037***
	(0.010)	(0.009)
Employed	0.039***	0.024***
	(0.011)	(0.009)
Missing bill payments	0.043**	0.049***
	(0.017)	(0.015)
Risk aversion	-0.000	-0.010
	(0.010)	(0.008)
Higher education	-0.000	0.022***
	(0.010)	(0.009)
Young	0.047***	0.017
	(0.013)	(0.011)
Male	-0.002	-0.013
	(0.010)	(0.008)
White	-0.014	0.021
	(0.023)	(0.017)
Married	0.001	0.005
	(0.011)	(0.009)
County FE	Yes	Yes
Observations	3,217	3,232
Adjusted R^2	0.035	0.025

Table A4: Consumers' Open Banking Usage and their Financial Knowledge and Credit Access with Credit demand Controls

Note: This table shows the association between credit product ownership and open banking (OB) usage using person-level responses to the Financial Conduct Authority's 2020 Financial Lives Survey in the UK. We use a cross-sectional OLS specification. The dependent variables in columns 1 to 4 are indicator variables equal to one if the respondent currently holds the credit product in question or held it in the last 12 months. In column 5, we run a similar specification at the person-by-product level with each person entering the data four times, once for each potential credit product, and the omitted category is student loans. Credit OB is an indicator variable equal to one if the respondent uses open banking for credit products, i.e., answers yes to using firms offering customized lending products, credit reference agencies (which can personalize credit reports), or price comparison websites (e.g., rates offered by different lenders). Number of other credit products is the total number of all credit products that the respondent holds other than the credit product in the respective column. Columns 1 to 4 control for county (UK local authority) fixed effects and demographic controls. Column 5 controls for the interaction between the credit product and respondents' (demographic) controls as well as person fixed effects. Respondent controls are indicator variables for unwillingness to share, employed, missing bill payments, risk aversion, higher education, young, male, white, and married. Unwillingness to share data equals one if the respondent gives a score of 3 or below on a 0 to 10 scale to the question "Thinking about Open Banking, how willing would you be to give your bank permission to securely access your banking information?". Employed equals one if the respondent reports working full- or part-time. Missing bill payments equals one if the respondent reports missing bill payments in at least three of the last six months or finds keeping up with domestic bills and credit commitments to be a heavy burden. Risk aversion equals one if the respondent gives a score of 3 or below on a 0 to 10 scale to the question "Are you a person who is generally willing to take risks?". Higher education equals one if the respondent has completed at least some post-secondary education. Young equals one if the respondent is aged 18–39. Male equals one if the respondent reports being male. White equals one if the respondent is of white ancestry. Married equals one if the respondent is married or in a registered civil partnership. All specifications estimate robust standard errors (reported in parentheses). *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Credit card (1)	Personal loan (2)	Student loan (3)	Pawnbroking loan (4)	Product level (5)
Credit OB	0.071*	0.068**	0.006	-0.002	
	(0.039)	(0.033)	(0.033)	(0.005)	
Credit card × Credit OB					0.119**
					(0.047)
Personal loan × Credit OB					0.089**
					(0.044)
Pawnbroking loan × Credit OB					-0.010
					(0.038)
Number of other credit products	0.101***	0.061***	-0.004	0.005**	
	(0.008)	(0.005)	(0.005)	(0.002)	
Respondent controls	Yes	Yes	Yes	Yes	
County FE	Yes	Yes	Yes	Yes	
Product-Respondent controls FE					Yes
Person FE					Yes
Observations	3,232	3,232	3,232	3,232	12,928
Adjusted R^2	0.223	0.146	0.32	0.043	0.412

Table A5: PitchBook Data Summary Statistics

Note: This table presents summary statistics on our PitchBook venture capital (VC) deal data for 168 countries from 2000–2021. The first column presents statistics on the entire dataset, the next two columns present data for 2000–2010 and 2011–2021 for low-coverage countries, and the final two columns present data for 2000-2010 and 2011-2021 for high-coverage countries. High-coverage countries are those with five or more fintech VC deals in the 2000–2010 period, while countries with fewer than five are low-coverage countries. The first set of rows presents the number of countries in each sample, both those with open banking implemented or in the pre-implementation stage as of October 2021 and those that have not reached that stage. The second set of rows presents the number of country-year observations in each sample, both those that are after an open banking policy was passed in that country and other observations. The third set of rows presents statistics on country-year VC investment: any VC deals indicates the percentage of country-years with a VC deal, mean and median raw VC deals present the average number of deals in country-years, and mean and median raw VC dollars ($m) presents the average value of VC deals in a country-year in millions of US dollars. The fourth set of rows presents similar statistics on country-year fintech VC investment.

	All countries	Low-coverage countries		High-coverage countries	
	2000-2021	2000-2010	2011-2021	2000-2010	2011-2021
Countries					
Count of countries	168	147	147	21	21
Countries with open banking implemented	49	32	32	17	17
Countries without open banking implemented	119	115	115	4	4
Country-year observations					
Count of country-year observations	3,696	1,617	1,617	231	231
Country-years after open banking passed	139	0	84	0	55
Country-years before open banking passed	3,557	1,617	1,533	231	176
Country-year VC activity					
Any VC deals (%)	44.6	23.4	50.1	99.1	100.0
Mean raw VC deals	74.5	1.1	13.0	212.7	880.6
Median raw VC deals	0.0	0.0	1.0	38.0	251.0
Mean raw VC dollars ($m)	718.1	6.3	85.8	1,725.2	9,119.4
Median raw VC dollars ($m)	0.0	0.0	0.0	170.6	1,109.9
Country-year fintech VC activity					
Any fintech VC deals (%)	25.3	3.2	31.4	64.1	98.7
Mean raw fintech VC deals	6.0	0.0	1.8	8.4	74.8
Median raw fintech VC deals	0.0	0.0	0.0	1.0	19.0
Mean raw fintech VC dollars ($m)	81.2	0.1	20.9	66.8	1,085.9
Median raw fintech VC dollars ($m)	0.0	0.0	0.0	1.3	88.6

B Government-led Open Banking and Incumbent Banks' Data Sharing

In this appendix, we analyze whether banks indeed share customer data following OB government policies. Since APIs are the main technology used for data sharing under OB, we test whether these policies are associated with the prevalence of bank API offerings. We use bank API data from Platformable, which is a global leader in data on OB APIs.[41].

Table B1 shows the results of a cross-country regression of the prevalence of bank APIs in each country against our measures of that country's government OB implementation:

$$BankAPIs_i = \beta \times OB_i + X_i'\gamma + Region_r + \epsilon_i, \tag{16}$$

where $BankAPIs_i$ is the log-transformed number of banks with APIs (columns 1 to 3) or the percentage of the top 10 banks in each country that offer APIs (columns 4 to 6). OB_i is one of three types of OB outcomes. First, we use a 0/1 indicator for whether the government has already implemented OB policies in a country as of October 2021 (columns 1 and 4). Second, we use a continuous measure of how far the implementation of government OB policy has progressed, with 0 denoting none and 7 denoting fully implemented with follow-on regulation (columns 2 and 5). Third, we use the interaction between our 0/1 OB policy indicator and our 0 to 1 OB Strength Index (columns 3 and 6), which is described at the end of Section 2.3. $Region_r$ are region fixed effects, and X_i' is a vector of ex-ante basic economic country characteristics (GDP per capita and population).

There is a strong positive association between OB policies and bank API offerings. Column 1 shows that countries with OB policies have about twice as many banks offering APIs, with columns 2, 4, and 5 yielding qualitatively similar numbers. Columns 3 and 6 show that these effects are driven by more comprehensive OB policies. These results provide the first systematic evidence that government policies to promote OB might have already had a significant effect on data sharing in the financial service industry, and that counties that have more comprehensive OB policies (as measured by our OB Strength Index) are likely to see more data sharing. These results also suggest that banks are not voluntarily sharing data.

[41] Platformable collects industry data on OB and open finance by systematically identifying API providers and consumers using bank and fintech website sources, fintech registers such as EUCLID (EU) and FCA (UK), assessing API consumers and providers from fintech association membership lists, and by surfacing new initiatives from newsletters and industry alerts. Data is collected on a rolling basis, with each entity assessed at least once every three months.

Table B1: Open Banking Government Policy and Bank API Offerings

Note: This table shows the association between government open banking policies and banks' open application programming interfaces (APIs) using an OLS specification. The sample includes the sample of countries for which we have collected open banking (OB) data (168 countries) and could also obtain bank data (158 countries). The dependent variable in columns 1 to 3 is the log of one plus the number of banks offering APIs and in columns 4 to 6, it is the percentage of the top 10 banks in each country (as ranked by 2020 assets in Bureau van Dijk) that offer APIs as of the end of 2021. APIs are the technology used to share bank customer data under open banking. The independent variable of interest in columns 1 and 4 is Open banking implemented (0/1) which is an indicator variable equal to one if open banking was implemented in the country in question as of October 2021; in columns 2 and 5 it is Open banking implementation (0–7) which is a 0–7 rating of the extent of open banking government policy implementation progress as of October 2021, with 0 being no action, 1–2 being increasingly serious levels of discussion, and 3–7 being levels of implementation progress; and in columns 3 and 6 it is the interaction of the open banking implemented (0/1) indicator variable with our Open Banking Strength Index which is a measure of policy strength. The open banking implemented indicator corresponds to being in or after the pre-implementation stage or equivalently to a level of 3 or above. All specifications include GDP per capita in thousands of US dollars, the square of GDP per capita in hundreds of thousands of US dollars, and the log of population, all based on World Bank data as of 2013. Region fixed effects are for Africa, Middle East & North Africa; Europe & Central Asia; Latin America & the Caribbean; North America; South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. All specifications estimate robust standard errors. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Banks with APIs			% of top 10 banks with APIs		
	(1)	(2)	(3)	(4)	(5)	(6)
Open banking implemented (0/1)	0.794***		-0.286	0.218***		-0.005
	(0.245)		(0.224)	(0.072)		(0.053)
Open banking implementation (0-7)		0.233***			0.058***	
		(0.046)			(0.013)	
OB Strength Index × OB implemented			1.238***			0.256***
			(0.341)			(0.087)
Per capita GDP ($k)	0.031**	0.016	0.027**	0.004	0.000	0.003
	(0.012)	(0.011)	(0.012)	(0.003)	(0.003)	(0.003)
Per capita GDP ($100k) squared	-0.893	0.404	-0.612	-0.023	0.266	0.035
	(1.705)	(1.475)	(1.610)	(0.447)	(0.394)	(0.433)
Log population	0.164***	0.145**	0.162***	0.025**	0.021**	0.025**
	(0.060)	(0.056)	(0.059)	(0.010)	(0.009)	(0.010)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	158	158	158	158	158	158
Adjusted R^2	0.577	0.629	0.596	0.461	0.509	0.476

C Open Banking Data Collection and Variable Definitions

This appendix describes the construction of our OB government policies dataset and defines variables. Each observation in the dataset corresponds to a country's OB approach as of the collection date.[42]

C.1 What Is an "Approach" and What Makes an Approach "Open Banking"?

A government-led OB approach does not need to be a single law or policy; many countries' OB approaches are in fact composed of several separate policies. Rather, an approach encompasses the totality of the country's OB government efforts.

The line between OB policies and related but non-OB policies can be unclear, and a single simple definition cannot encompass all cases. For our purposes, there are two reasons for us to classify a regulatory approach as OB:

1. **Functional**: Does the regulator's approach have the key functional elements of OB? Specifically, does it facilitate programmatic access (e.g., through an API) to financial intermediaries' customers' data for the purposes of data sharing or payments?

2. **Nominal**: Do regulators, journalists, or industry groups refer to the regulation as "open banking"?

The functional approach is more objective and can be applied to countries that have progressed sufficiently far down the pathway of discussing and implementing OB policies. The nominal approach is useful in cases where regulators have only recently been discussing OB but none of the functional elements have yet been formalized. The following two regulations may be similar to OB but we do not consider them to be OB policies and we list them as illustrative counterexamples:

1. General Data Protection Regulation (GDPR): This EU law grants consumers certain privacy rights over their data. However, GDPR is not an OB law because it does not mandate that commercial entities (specifically, banks) in possession of the data share it upon customer request. Note, however, that the EU does have an OB law, the PSD2.

2. Regulation related to central bank digital currencies (CBDC): Movements to create payment systems utilizing CBDC are payments regulations but are not open payments regulations, as they do not mandate open data sharing between market participants.

[42] Most recently, October 2021.

There have been many payments-related regulations (CBDC and others) that modernize payments but are not "open" in any sense, aside from, for example, reporting requirements to regulators.

Having defined what constitutes an "approach" and what makes an approach an "open banking" approach, we now define in detail the variables we collect and the classification decision rules. With each data category, we provide notes to clarify decision rules and address common questions.

C.2 Data Categories and Variable Definitions

C.2.1 Open Banking Approach and Regulatory Mandate

- **government_led_initiative**: Is there a government-led initiative around OB?
  - **Yes.**
  - **No.**
- **regulatory_entity_type**: Which type of regulator is leading the OB effort?
  - **Monetary authority**: A financial regulator, e.g., a central bank.
  - **Competition authority**: A regulator tasked with anti-trust or other competition-related enforcement, e.g., the Competition and Markets Authority in the UK.
  - **Consumer protection authority**: A regulator tasked with consumer protection, e.g., the Consumer Financial Protection Bureau in the US or a data privacy authority.
- **innovation_mandate**: Is increasing innovation a proffered policy mandate?
  - **Yes**: Spurring the creation or adoption of new financial products or technologies is either discussed or explicitly stated as policy goals.
  - **No**: Otherwise.
- **competition_mandate**: Is increasing competition a proffered policy mandate?
  - **Yes**: Increasing entry, increasing competition, decreasing markups, or related issues are either discussed or explicitly stated as policy goals.
  - **No**: Otherwise.
- **inclusion_mandate**: Is increasing financial inclusion a proffered policy mandate?

– **Yes**: Increasing access to the financial system, serving the unbanked, fighting inequality, or related issues are either discussed or explicitly stated as policy goals.

– **No**: Otherwise.

How do we denote efforts coordinated between both regulators and market participants?

We define these as government-led efforts. The justification for this is that almost all major government policies involve some level of collaboration or input from industry. In the US, for example, there are open comment periods and meetings with industry and lobbyists. Fundamentally, however, these initiatives work through the government, and so to the extent that the government has any authoritative hand in leading the regulation, we consider it as government led.

Which agency type do we select in cases where several are responsible?

We select the regulator most aligned with the proffered mandate or rationale for OB. For example, in the case of Australia, we select the Australian Competition and Consumer Commission because the country's OB policy mandate is most closely aligned with that of a "competition authority".

C.2.2 Timeline and Initiative

- **initiative_name**: Name of the government-led policy initiative.

- **initiative_passed_date**: Date that the OB legislation is signed into law, or date when the first non-regulation government major effort to promote OB goes into effect (e.g., for Singapore we use November of 2016—the date when the Monetary Authority of Singapore (MAS) published a comprehensive roadmap: API Playbook—which, in effect, set the gold standard for regulatory advice on the topic in Asia: see here). For efforts that have not yet been signed into law or resulted in a major government policy, this field is TBD.

- **data_sharing_date**: First date at which the legal mandate on customers' data sharing begins to bind, or (in cases of non-legally binding policies) when the government sets up the infrastructure that allows customer data sharing.

- **oct_21_status**: Implementation status as of October 2021.

  – **Nothing**: No government-led OB.

  – **Pre-discussion**: Some government interest but no actual law or implementation is taking place.

- **Discussion**: The actual law has been introduced or passed and rulemaking is taking place.
- **Pre-implementation**: The law is passed and rules have been set, but nothing is yet binding.
- **Early implementation**: Some data sharing requirements are binding (e.g., bank-level product information), but not personal account/transactions.
- **Mid implementation**: Personal account/transaction data sharing is binding, but not all planned elements are in place (e.g., not all planned API functionality exists.)
- **Fully implemented**: Full implementation as described in the law/rulemaking.
- **Follow-on regulation**: OB is implemented, and regulators are actively working on related regulation such as open finance or open data more broadly.

Which government effort do we focus on when there are several?

We focus on the first major government OB effort.[43] For example, in the United States, several regulatory bodies have expressed interest in OB (e.g., the Treasury/OCC and the Consumer Financial Protection Bureau (CFPB)). The CFPB's effort through Dodd-Frank Section 1033 is the most important US regulatory effort. In the UK, the 2017 CMA9 order was the first major open banking law, although it is subject to pending follow-up regulation to broaden its scope.

What if the precise date is unavailable?

In cases where the precise date cannot be found or is ambiguous for some reason, we use the most precise date that can be inferred from the data. For example, if the best information for a country that can be located says the law passed in "the second half of 2020," we will assign the date as July 1, 2020.

What event defines the data sharing date?

In cases where data sharing is mandated, this is the date. In cases where data sharing is not mandated but, for example, the regulator sets API standards, we use the date at which the API standards go into force. In cases where the regulation initially applies only to a subset of later planned entities (e.g., the UK Open Banking Initiative applies to 9 large banks), we use the date at which the requirements first apply to any entity.

[43] Given the recency of the OB trend, this is almost always also the latest OB approach with the exceptions being the United Kingdom and Sweden. These two countries had earlier, abortive OB attempts that we exclude due to their limited implementation.

C.2.3 Standards

- **regulatory_technical_specifications**: Does the regulator set technical specifications for data sharing / payments?
  - **Yes.**
  - **No.**

  What happens when regulators and industry collaborate on technical specifications?

  This field is "Yes" if technical standards are either developed internally by the regulator, arrived at through collaboration of the regulator with industry participants, or mandated by the regulator to be developed by industry participants.

C.2.4 Open Banking Scope

- **financial_services_scope**: How wide is the set of financial products covered under OB?
  - **Narrow**: Transaction accounts only.
  - **Broad**: Transaction accounts and other "core" financial products (e.g., loans).
  - **Very broad**: Above products plus "non-core" financial products (e.g., insurance).
- **transaction_accounts_covered**: Does the regulation cover transaction accounts?
  - **Yes.**
  - **No.**
- **nontransaction_accounts_covered**: Does the regulator cover financial products aside from transaction accounts?
  - **Yes.**
  - **No.**
- **share_account_data**: Does the regulator either require or facilitate the sharing of customers' transaction account data?
  - **Yes.**
  - **No.**
- **payment_initiation**: Does the regulator require or facilitate technology to allow the initiation of customer payments by third parties?

  - **Yes.**
  - **No.**

What do we include in transaction accounts?

Any financial account that allows for cash-like transactions, e.g., checking accounts, debit cards, credit cards, and digital wallets.

What are core and non-core financial products?

Core products are consumer financial products that banks typically offer, including, e.g., loans or investment services. Non-core products are either consumer finance products that banks do not typically offer, e.g., insurance, or financial products that are not "consumer" finance products, such as small business loans.

Is a payment service like Venmo or Alipay an OB transaction service?

No, these services do not rely on open APIs interfacing with banks. See the definition of an OB approach above.

C.2.5 Sharing Scope and Reciprocity

- **data_holders_share**: Do data holders (e.g., banks) have to share their customers' data (upon customer request)?
  - **Yes.**
  - **No.**
- **data_users_share**: Do data users (e.g., fintechs) have to share their customers' data (upon customer request)?
  - **Yes.**
  - **No.**

C.2.6 Miscellaneous

- **PSD2**: Is this country a party to Europe's PSD2?
  - **Yes.**
  - **No.**

C.3 Miscellaneous Notes

How do we define scope, sharing rules, and so on in cases where the regulators have not yet decided on an approach?

We denote these cases as "TBD" and exclude them from sections of the analysis where we split or condition on these variables.

D Open Banking Use by SMEs and Their Financial Outcomes

Institutional Background for the SME Data-Sharing Policy The UK's headline open banking policy was introduced in 2017 by the UK's Competition and Markets Authority (CMA) as one of the first national OB policy initiatives. This policy is what we refer to as the UK's OB policy in our cross-country analysis and required that, by 2018, banks provide their personal and business customers with the ability to access and share their current account data on an ongoing basis with authorized third parties, such as fintechs and other banks.

However, the UK set the stage for a related policy targeting banks' SME customers two years earlier. In November 2015, concerned with the high concentration of its national banking market, the UK Government enacted the "Small Business Enterprise & Employment Act 2015" (the Act). The intention of the Act was to lower entry barriers for alternative credit providers in the SME credit segment, thereby stimulating competition. The Act's initiative related to OB-related data sharing is the Commercial Credit Data Sharing (CCDS) scheme.[44] We describe this initiative in detail next.

The CCDS regulation required nine UK banks to share current account data (i.e., data from transaction accounts with a bank), as well as the up-to-date performance of loans and corporate credit cards, of all their SME customers with other lenders, including both banks and non-banks, via four designated Credit Reference Agencies (CRAs).[45] When other lenders join the scheme, they commit to sharing their own SME portfolio data with the designated CRA within one year under a reciprocity rule. SMEs were affected if they had annual sales below £25 million. As of 2017,[46] each CRA receives raw financial transaction data on a monthly basis and consolidates that data into a common format so that it can be easily delivered to any credit provider that is considering lending to a prospective borrower. Lenders receive data from the CRAs about an SME only if that SME both consents to the CCDS program and submits a loan application, and so this scheme can be regarded as credit OB. While SMEs' credit histories were widely available through credit bureaus even prior to the CCDS, the new policy supplemented these credit files with data on SMEs' cash flows using the monthly snapshots of their current accounts.

The CMA Order to promote open banking (OB) and the CCDS can be thought of as twin OB policies: Both allow bank customers to share their current account data (with bank customers' approval) with third parties. The main differences between the two policies are the following. First, the CCDS only applied to SMEs, while the OB applied to both businesses and consumers. Second, the technical implementation of data sharing is different. The CCDS mandated banks to share SME data with CRAs (who then shared that data

[44] A full summary of all the initiatives related to credit market access is available here.

[45] These are Experian, Equifax, Dun & Bradstreet, and Creditsafe.

[46] While the CCDS was due to go live in April 2016, technical issues delayed the actual data sharing to 2017.

onward), while the OB mandated banks to share customer data directly with third parties via APIs. Third, the type of data being shared is slightly different. The OB provides more detail as it offers real-time transaction-level current account information, while the CCDS only provides a month-end summary of current accounts (e.g., max/min/average balance, credit/debit sales, and rejected payments). Fourth, while both policies offer bank customers a choice of sharing their data, the CCDS offers a bank-account-level option to opt out of sharing, while the OB provides a more granular data-using-application-level option to opt in. Since among business customers, anecdotally SMEs benefited most from the main OB initiative, our results could be interpreted as the combined effect of both the CCDS and the OB.

SMEs were eligible for the scheme if they had an annual sales below £25 million. This threshold can be regarded as quasi-exogenous. It differs from the typical UK definition of an SME that is used in official statistics and that determines Companies House reporting standards (i.e., 250 employees or £36 million in sales). It also does not match with key thresholds in the tax system (e.g., VAT is only payable on sales over £80k).

Sample and Summary Statistics Our UK firm panel data comes from Bureau Van Dijk (BvD), which offers firm financial data as well as data on all claims ("charges") against firms' assets by lenders (i.e., secured loans) from Companies House. We match charges to firm financials via the Companies House ID number and to lenders using charge holder names. We classify lenders as banks (including foreign banks) or non-banks using the Bank of England's Historical Banking Regulatory Database (HBRD) and the Financial Conduct Authority's Financial Services Register (FSR). Unmatched lenders are classified based on their name.[47]

This data allows us to observe firms' lending relationships as well as their balance sheet and income statement information over time, although we do not observe the interest rates or amounts borrowed for individual loans. To construct our final sample, we restrict our attention to limited liability firms and exclude both subsidiaries and companies whose primary industry is mining (UK SIC codes 1010-1450), utilities (4011-4100), finance and insurance (6511-6720), public administration (7511-7530), or education and health (8010-8540). We focus on firms with 2016 sales between £10 million and £40 million to identify the effect of the CCDS on SMEs near the £25 million threshold. We consider only firms reporting both sales and our baseline control variables (total assets, non-equity liabilities, cash holdings, and QuiScore, a measure of credit risk) for at least one year in each of the pre- and post-treatment time windows. This leaves us with a sample of 39,089 observations on 6,886 unique firms.

Table D1 presents summary statistics. All ratios are Winsorized at the 1% level. As described in the main paper, we consider a firm as having established a new lending relationship if it obtains a loan from a lender with whom it did not have a relationship in the preceding

[47] Information on the HBRD can be found here and the FCA FSR here. We classify unmatched lenders with "bank" in their name as banks and other unmatched lenders as non-banks.

three years. The probability that an SME establishes a new lending relationship in a given year is 5.3%. Over the entire sample period, SMEs are more likely to switch to bank lenders than to non-bank lenders, although this may simply reflect the fact that there are more bank relationships than non-bank relationships in the SME lending market. An indicator variable "Prior CCDS relationship" shows that 57% of our firms have an existing loan from one of the 9 banks required to share under the data-sharing policy. A significant number of firms (21%) have no secured credit relationships (i.e., there is no lien against their assets in the Companies House data), and 44% have only one lender at the time of the policy introduction. The average firm in our sample is 24 years old and has a leverage ratio (defined as the ratio of total non-equity liabilities to total assets) of 59%. Additionally, the average QuiScore in our sample is 90.3 (higher values mean lower risk), and the largest proportion of firms comes from the manufacturing, services, and retail sectors, a mix broadly in line with the aggregate economy.[48]

We next assess the comparability of treated and control firms in 2016, the year in which the policy was passed (noting that actual data sharing only started in 2017). Table D2 tests for differences between the sample means of our variables for the treated and the control groups. In the first three rows, we can see that both groups have a similar rate of switching to a new lender, both overall and to bank or non-bank lenders in particular. When it comes to financial characteristics, treated firms are smaller than control firms, but that is mechanically driven by the definition of treatment, which is based on sales size. Control firms (above £25 million in sales) hold slightly more cash and have higher leverage ratios. These differences are statistically significant but small in economic magnitude. Our baseline specification controls for these potentially important differences. However, the two groups are almost identical in terms of credit risk, firm age, and lending relationship characteristics (number and length). Finally, the distribution of the two groups in terms of industry slightly differs, but these differences are absorbed by sector-by-year fixed effects in our main specification.

Robustness We conduct several robustness tests on our main SME specification (column 3 of Table 4), which we present in Table D3. First, the CCDS policy does not specify which year the sales eligibility threshold refers to. Although firm sales is persistent over time and we include firm fixed effects in the regression, the cutoff may be measured with some error in 2016. Thus, in the first column of Table D3, we assign treatment based on firm sales in 2017 instead of 2016. We observe that our key test coefficient remains positive and statistically significant, with a comparable magnitude to our baseline results.

Second, although our identification strategy helps alleviate concerns about the compara-

[48] We define sectors following the 2003 UK Standard Industrial Classification (SIC) of Economic Activities. Specifically, manufacturing firms are firms with UK SIC codes between 1511 and 3720; real estate between 7011 and 7032, or between 4511 and 4550 (construction); wholesale between 5010 and 5190; retail 5211-5274; transport 6010-6340, or 6410-6412; services 7411-7490, or 5510-5552 (hotel and restaurants), or 7210-7260 (computer), 9211-9310 (other services), or 6420 (telecommunications); and everything else is other sector.

bility between treated and control firms, we retest our baseline specification using a matching strategy. As shown in the balance test in Table D2, the treated and control groups differ slightly from one another in terms of some observable characteristics (cash and leverage, other than obvious differences in size). Therefore, in column 2 we reestimate our specification after matching each firm in the control group to at most four firms in the treated group based on 2016 values of lagged total assets, leverage, cash-to-asset ratio, a credit risk indicator, sector, and location. The difference-in-differences coefficient remains similar in magnitude and statistically significant.

In the next two columns, we shrink the sales window (£10-£40 million) we used for the firm sample to £15-£35 million (column 3) or £20-£30 million (column 4). While standard errors increase due to the reduced sample size, the point estimates remain very similar to the baseline coefficient, confirming the positive effect of the policy on the probability of establishing new borrowing relationships.

Finally, the last two columns change the window used to identify the existing lending relationships a firm has in previous years. We move from the baseline window (3 years) to 1 year (column 5) or 5 years (column 6). In both cases, our coefficient of interest remains statistically significant and similar in magnitude to our baseline result.

Real effects After determining the effect of the policy on the SMEs' new borrowing relationships, we analyze whether and how firm real and financial outcomes are affected in Table D4. In the first column, we explore the loan pricing effect of the policy.[49] We find that only loans from new non-bank lenders, rather than those from bank lenders, are associated with lower total firm interest expenses.

In the next two columns of Table D4, we investigate the effects on firm liabilities. We focus on the triple interaction between treated SMEs meeting the revenue cutoff, the post-period, and firms that took a new non-bank loan, as that is where the policy has stronger effects (i.e., see Table 4). We show that short-term liabilities increase for treated firms after the policy, especially when switching to non-banks. The coefficient on the triple interaction is positive not statistically significant for long-term liabilities. These results suggest that non-banks use new data to gain customers and provide short-term credit, consistent with the policy opening access to non-traditional short-term sources of finance (e.g., factoring). Finally, we see that the asset side of the firm balance sheet expands, as new credit through data sharing likely leads to an increase in total assets (column 4).

[49] Interest-paid is not a well-reported item in BvD. For each firm, we address this issue by replacing missing values with the average interest expenses over its pre- or post-reform period.

Table D1: SME Lending Data Summary Statistics

Note: This table presents summary statistics on our sample of UK SMEs with £10m–£40m in 2016 sales. Each data point is an SME-year for the 2014–2019 period (with variables denoted as $t-1$ being lagged one year). Our data is from Bureau Van Dijk and covers secured borrowing and company financials. Any new lenders is an indicator variable equal to one if the SME received a new loan in the year in question from a lender that they did not have a loan from in the preceding three years. New bank lenders and New non-bank lenders are similarly equal to one if the SME has received a new loan from a new bank or non-bank lender, respectively. Log Total assets, Cash / Total assets, and Leverage are the respective accounting variables. Low risk is a dummy variable equal to one if the firm has a BvD QuiScore above 80. For other characteristics, the 2016 value is used for all firm years. Sales is the SME's revenue in 2016 in millions of British pounds. Treated SME is an indicator variable equal to one if the SME's 2016 sales was below £25 million. No relationship, single relationship, and multiple relationships are indicator variables equal to one if, in 2016, the SME had no loans, loans from one lender, or loans from multiple lenders, respectively. Prior CCDS relationship equals one if the SME had an existing lending relationship in 2016 with one of the nine banks required to share SME data under the CCDS, while Prior non-CCDS relationship is an equivalent indicator variable for SMEs that did not have a prior relationship with the nine banks but had a relationship with another lender. Relationship length is the log of one plus the number of months the SME's average lending relationship has lasted, as of 2016. Firm age is the SME's age in years as of 2016. Manufacturing, Services, Real estate, Retail, Wholesale, Transportation, and Other sector are indicator variables defined based on UK SIC codes as described in Appendix D. All variables are Winsorized at the 1% level. The number of observations, mean, standard deviation, and percentiles are presented for each variable.

	Count	Mean	SD	10th pct.	25th	50th.	75th	90th
New lending relationships								
Any new lender$_{i,t}$	39,089	0.053	0.224	0	0	0	0	0
New bank lender$_{i,t}$	39,089	0.036	0.186	0	0	0	0	0
New non-bank lender$_{i,t}$	39,089	0.020	0.140	0	0	0	0	0
Accounting variables								
Log Total assets$_{i,t-1}$	39,089	9.259	0.817	8.400	8.738	9.152	9.652	10.239
Cash / Total assets$_{i,t-1}$	39,089	0.685	0.258	0.288	0.511	0.738	0.911	0.977
Leverage$_{i,t-1}$	39,089	0.587	0.272	0.242	0.391	0.584	0.762	0.904
Low risk$_{i,t-1}$	39,089	0.915	0.279	1	1	1	1	1
Firm characteristics								
Sales$_i$	39,089	19.500	7.337	11.534	13.506	17.496	24.255	30.675
Treated SME$_i$	39,089	0.771	0.420	0	1	1	1	1
No relationships$_i$	39,089	0.214	0.410	0	0	0	0	1
Single relationship$_i$	39,089	0.436	0.496	0	0	0	1	1
Multiple relationships$_i$	39,089	0.350	0.477	0	0	0	1	1
Prior CCDS relationship$_i$	39,089	0.571	0.495	0	0	1	1	1
Prior non-CCDS relationship$_i$	39,089	0.215	0.411	0	0	0	0	1
Relationship length$_i$	39,089	8.860	9.677	0	1.499	6.086	12.630	21.847
Firm age$_i$	39,089	23.550	20,767	5	10	17	31	50
Firm sectors								
Manufacturing$_i$	39,089	0.198	0.399	0	0	0	0	1
Services$_i$	39,089	0.305	0.461	0	0	0	0	1
Real estate$_i$	39,089	0.141	0.348	0	0	0	0	1
Retail trade$_i$	39,089	0.049	0.216	0	0	0	0	0
Wholesale trade$_i$	39,089	0.205	0.404	0	0	0	0	1
Transportation$_i$	39,089	0.053	0.225	0	0	0	0	0
Other sector$_i$	39,089	0.047	0.212	0	0	0	0	0

Table D2: SME Sales Threshold Balance Tests

Note: This table presents the results of a balance test on our sample of UK SMEs with £10m–£40m in 2016 sales. We compare treated (2016 sales≤£25 million) with control (2016 sales>£25 million) SMEs as of 2016. Our data is from Bureau Van Dijk and covers secured borrowing and company financials. Any new lenders is an indicator variable equal to one if the SME received a new loan in the year in question from a lender that they did not have a loan from in the preceding three years. New bank lenders and New non-bank lenders are similarly equal to one if the SME has received a new loan from a new bank or non-bank lender, respectively. Log Total assets, Cash / Total assets, and Leverage are the respective accounting variables for 2015. Low risk is a dummy variable equal to one if the firm has a BvD QuiScore above 80 for 2015. Sales is the SME's 2016 revenue in millions of British pounds. No relationship, single relationship, and multiple relationships are indicator variables equal to one if, in 2016, the SME had no loans, loans from one lender, or loans from multiple lenders, respectively. Prior CCDS relationship equals one if the SME had an existing lending relationship in 2016 with one of the nine banks required to share SME data under the CCDS, while Prior non-CCDS relationship is an equivalent indicator variable for SMEs that did not have a prior relationship with the nine banks but had a relationship with another lender. Relationship length is the log of one plus the number of months the SME's average lending relationship has lasted, as of 2016. Firm age is the SME's age in years as of 2016. Manufacturing, Services, Real estate, Retail trade, Wholesale trade, Transportation, and Other sector are indicator variables equal to one for firms in these sectors defined based on UK SIC codes as described in Appendix D. All variables are Winsorized at the 1% level. The number of observations, mean, and standard deviation are presented for each group and cross-group differences are tested using a t-test.

	Control			Treated			
	Count	Mean	SD	Count	Mean	SD	Difference
New lending relationships							
Any new lender$_i$	1,656	0.061	0.239	5,230	0.054	0.226	-0.007
New bank lender$_i$	1,656	0.042	0.201	5,230	0.038	0.191	-0.004
New non-bank lender$_i$	1,656	0.019	0.138	5,230	0.018	0.133	-0.001
Accounting variables							
Log Total assets$_{i,t-1}$	1,656	9.598	0.818	5,230	9.085	0.766	-0.513***
Cash / Total assets$_{i,t-1}$	1,656	0.697	0.256	5,230	0.679	0.259	-0.018**
Leverage$_{i,t-1}$	1,656	0.614	0.268	5,230	0.591	0.266	-0.023***
Low risk$_{i,t-1}$	1,652	0.913	0.282	5,219	0.907	0.291	-0.007
Firm characteristics							
Sales$_i$	1,656	30.801	4.205	5,230	16.287	4.019	-14.515***
No relationships$_i$	1,656	0.222	0.416	5,230	0.209	0.406	-0.014
Single relationship$_i$	1,656	0.432	0.495	5,230	0.441	0.497	0.009
Multiple relationships$_i$	1,656	0.346	0.476	5,230	0.350	0.477	0.004
Prior CCDS relationship$_i$	1,656	0.575	0.494	5,230	0.572	0.495	-0.003
Prior non-CCDS relationship$_i$	1,656	0.202	0.402	5,230	0.219	0.414	0.017
Relationship length$_i$	1,656	8.431	9.476	5,230	8.824	9.561	0.393
Firm age$_i$	1,656	23.367	21.148	5,230	23.113	20.302	-0.254
Firm sectors							
Manufacturing$_i$	1,656	0.171	0.377	5,230	0.203	0.403	0.032***
Services$_i$	1,656	0.332	0.471	5,230	0.306	0.461	-0.026**
Real estate$_i$	1,656	0.146	0.353	5,230	0.140	0.347	-0.006
Retail trade$_i$	1,656	0.050	0.217	5,230	0.050	0.217	0.000
Wholesale trade$_i$	1,656	0.219	0.414	5,230	0.200	0.400	-0.019*
Transportation$_i$	1,656	0.043	0.204	5,230	0.054	0.226	0.010*
Other sector$_i$	1,656	0.039	0.193	5,230	0.047	0.212	0.008

Table D3: Alternative Tests on SME Data Sharing and Lending

Note: This table shows changes in new lending relationship formation for SMEs treated by the UK Commercial Credit Data Sharing (CCDS) policy tested using alternative specifications. Each specification builds off of our baseline test that uses a difference-in-differences design on company-year data on secured loans for UK SMEs with 2016 sales between £10 million and £40 million from the UK Companies House via Bureau van Dijk for the 2014–2019 period. An SME is classified as a Treated SME if its 2016 sales is below the CCDS's £25 million eligibility threshold and, therefore, is potentially affected by the data-sharing policy. Post is an indicator variable equal to one after the CCDS was implemented in 2017. The dependent variable is an indicator variable equal to one if the SME takes a loan in the year in question from a lender that they had not dealt with in the preceding three years. In column 1, we vary the baseline specification by defining treatment based on 2017 sales rather than 2016 sales. In column 2, we match each firm in the control group to at most four firms in the treated group based on 2016 values of lagged total assets, leverage, cash-to-asset ratio, a credit risk indicator, sector, and location. In columns 3 and 4, we restrict the sample to firms with 2016 sales in the given range. In columns 5 and 6, we classify relationships as new based on a shorter or longer lookback time, respectively. Firm controls are the log of total assets, a low credit risk dummy, cash to total assets, and leverage ratio, all lagged one year. Low credit risk is defined as a QuiScore below 80, sectors are defined based on 1-digit 2003 UK SIC codes, regions are the 124 postcode areas, and relationship stage is the decile of the average relationship length the firm has with its lenders. Standard errors are clustered at the firm level and are in parentheses. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	2017 Sales		Sales Window		Relationship Window	
	for Threshold	Matched	£15-35m	£20-30m	1-year	5-year
	(1)	(2)	(3)	(4)	(5)	(6)
Treated SME × Post	0.0199***	0.0138**	0.0129**	0.0126	0.0137***	0.0148***
	(0.005)	(0.006)	(0.006)	(0.009)	(0.005)	(0.005)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Relationship stage-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,089	22,638	23,587	11,052	39,089	39,089
Adjusted R^2	0.064	0.069	0.069	0.078	0.067	0.063

Table D4: Real Effects of SME Data-sharing

Note: This table shows changes in financial outcomes for SMEs treated by the UK Commercial Credit Data Sharing (CCDS) policy. We use a difference-in-differences design on company-year data on secured loans for UK SMEs with 2016 sales between £10 million and £40 million from the UK Companies House via Bureau van Dijk for the 2014–2019 period. An SME is classified as a Treated SME if its 2016 sales is below the CCDS's £25 million eligibility threshold and, therefore, is potentially affected by the data-sharing policy. Post is an indicator variable equal to one after the CCDS was implemented in 2017. New non-bank relationship and New bank relationship are indicator variables equal to one if the SME has a new borrowing relationship in the year in question and that relationship is with a non-bank or a bank, respectively. New refers to relationships with lenders the SME did not have a loan from in the preceding three years. The dependent variable in column 1 is the ratio of interest expenses to total assets. The dependent variables in columns 2 to 4 are the logarithm of short-term (ST) liabilities (2), long-term (LT) liabilities (3), and total assets (4). Firm controls are the log of total assets, a low credit risk dummy, cash to total assets, and leverage ratio, all lagged one year. Low credit risk is defined as a QuiScore above 80, sectors are defined based on 1-digit 2003 UK SIC codes, regions are the 124 postcode areas, and relationship stage is the decile of the average relationship length the firm has with its lenders. Standard errors are clustered at the firm level and are in parentheses. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Interest / Assets (1)	Log (ST liabilities) (2)	Log(LT liabilities) (3)	Log(Total assets) (4)
Treated SME × Post × New non-bank relationship	-0.0123* (0.007)	0.1409** (0.071)	0.2891 (0.285)	0.1756*** (0.050)
Treated SME × Post × New bank relationship	0.0042 (0.003)	0.0678 (0.049)	0.2040 (0.209)	0.0074 (0.031)
Treated SME × Post	0.0005 (0.000)	0.0255** (0.010)	0.0402 (0.046)	0.0214*** (0.005)
Firm FE	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Pairwise interactions	Yes	Yes	Yes	Yes
Relationship stage-by-year FE	Yes	Yes	Yes	Yes
Sector-by-year FE	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes
Observations	30,530	35,101	34,710	35,115
Adjusted R^2	0.528	0.837	0.831	0.955

E Open Banking and Venture Capital Fintech Investments

E.1 Supplemental Venture Capital Analysis

The substantial cross-country policy we document in Section 2.3 leads naturally to the question of what policies are most effective at fostering innovation. In Table E1, we answer this by testing the relationship that fintech activity has with OB policy choices (columns 1–4) and the overall comprehensiveness of OB policies (as measured by our OB Strengths Index in column 5). We find tentative evidence that OB policies that force banks to share their customers' data drive our results; however, the power of these tests is limited due to small sample.

Beyond that, we show that our key results hold under a variety of alternative specifications. First, following the recent econometric literature on biases created by difference-in-differences regressions with staggered treatment and heterogeneous treatment effects (see, for example, Goodman-Bacon (2021) or Sun and Abraham (2021)), in Figure E1 we show our results are essentially unchanged when we rerun our event studies using the methodology from Gardner (2022) which addresses this concern.

Second, we perform a number of tests to address potential concerns about confounding factors. In Figure E2 and Figure E3 we run two placebo tests: First, shifting the event dates and windows five years earlier, and, second, replacing fintech deals with non-fintech deals as the dependent variable in our main specification, as another precaution against a general rise in innovation causing our results. Reassuringly, we see no effect in either test. In Figure E4 we control for contemporaneous non-fintech VC deals as a proxy for innovation more generally and find that our baseline results are robust. This addresses a potential concern that OB adopters enacted broader innovation-promoting policies. In Table E2 we show our effects persist when we rerun our tests while excluding first each country in turn, then Germany and France together (the two countries powerful enough to have an impact on the passage of OB government policy in the EU), and finally the three countries that did not implement OB in our sample (Canada, China, and the United States).

Finally, in Table E3, we show that our results hold under other transformations of fintech VC activity. We first repeat our baseline specification (columns 1 and 2) for comparison purposes. We then follow Jeng and Wells (2000) and consider fintech VC deals (or millions of US dollars invested) scaled by trillions of US dollars of GDP (columns 3 and 4). Next, we consider fintech VC activity divided by total VC activity (columns 5 and 6) and finally the inverse hyperbolic sine transformation of fintech VC activity (columns 7 and 8). Across specifications, we see statistically significant and economically meaningful effects.

E.2 Classification of Fintech Startups

PitchBook groups tens of thousands of startups into the "Financial Software" subindustry and the "Fintech" vertical, but does not offer a more granular industry definition. We overcome this using PitchBook's keywords feature with categories from PitchBook's 2021Q1 fintech market map and keywords derived from those startups. PitchBook's fintech market map divides recent fintech financing rounds into eight broad categories: alternative lending, capital markets, consumer finance, digital assets, financial services IT, payments, regtech, and wealthtech. Importantly, these categories were designed around use cases and without OB in mind.

Although innovative startups are by nature often hard to classify, these categories roughly span the current fintech market. Alternative lending includes retail and commercial lending. Capital markets includes institution-focused capital market applications, including trading, data, and capital management. Consumer finance encompasses digital banking, rewards programs, and credit cards. Digital assets covers cryptocurrency and related applications. Financial services IT includes both APIs and enterprise architecture. Regtech includes risk management and compliance startups. Wealth management includes investment advisory and brokerage services.

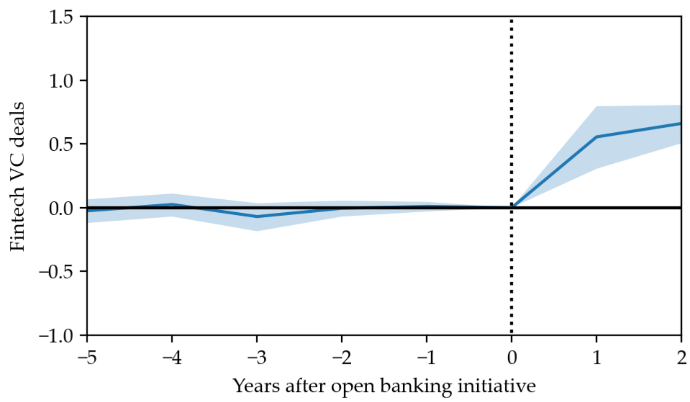
For each of those categories, we derive a list of keywords used by the startups in that category. These keywords were assigned by PitchBook analysts covering the company, with the typical company having four keywords. Keywords range from general to specific, for example, the most frequently used keywords for companies in the regtech segment of the market map are regtech vertical, fraud detection, fraud detection platform, regulatory compliance, fintech, artificial intelligence, and risk management.

We find the relative frequency of each keyword within each category. For example, the regtech vertical keyword accounts for 3% of the keywords used by startups in the regtech category and less than 1% for all the other categories. A keyword is distinctive to a category if it is in the top 25 keywords for that category and its usage rate in that category is twice the sum of its usage rates in the other categories. Regtech vertical, fraud detection, fraud detection platform, and regulatory compliance are all distinctive keywords for the regtech category. Fintech, artificial intelligence, and risk management are not because they are commonly used across categories. The capital markets category focuses on institutional services and lacks distinctive keywords (its top keywords are financial technology, financial software, financial platform, and financial services) and so we drop it.

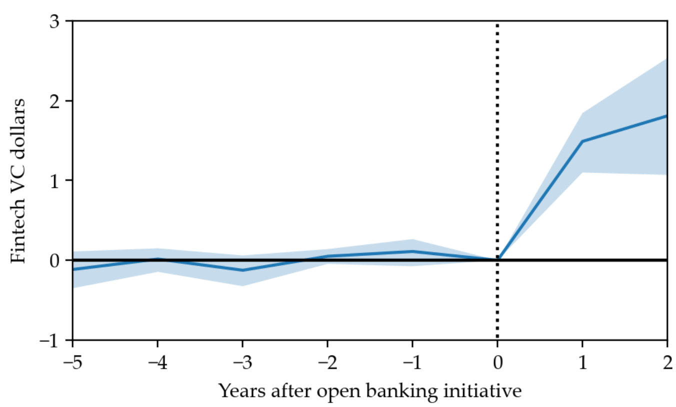
We assign fintech startups into categories using the distinctive keywords for each category. A startup is classified as a regtech startup if it is marked with regtech vertical, fraud detection, fraud detection platform, regulatory compliance, or other distinctive keywords for the regtech category. Fintech companies often offer a broad scope of services and can be hard to assign to a single category. Our keyword-based classification system accommodates this by allowing companies to be in multiple categories. For example, the US company SeedFi offers packages of borrowing and saving to lower-income customers placing it in both the alternative lending and consumer finance categories. The resulting categories are relatively balanced, with the largest categories (wealth management, financial IT) being about two-and-a-half times as large as the smallest category (consumer finance).

Figure E1: Event-study of Fintech VC and Open Banking Using Gardner (2022) TWFE

Note: This figure replicates our main event study (Figure 5) of changes in fintech venture capital (VC) activity around the passage of open banking (OB) government policies but follows the two-way fixed-effect (TWFE) specification of Gardner (2022). We use the default specification provided by the R did2s package available here. We perform this analysis on our high-coverage Pitchbook panel of 2011-2021 data for the 21 countries with at least five fintech VC deals in the 2000–2010 period. Panel (a) shows an event study on the log of one plus the number of fintech VC deals, and Panel (b) shows an event study on the log of one plus the millions of US dollars invested in fintech VC deals. Year 0 is the passage year of each country's major open banking initiative. The coefficient for year 0 is set to zero and other coefficients are presented net of country fixed effects and region-by-year fixed effects for Africa, Middle East & North Africa; Europe & Central Asia; Latin America & the Caribbean; North America; South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. The shaded regions denote 95% confidence intervals calculated using standard errors clustered at the country level.



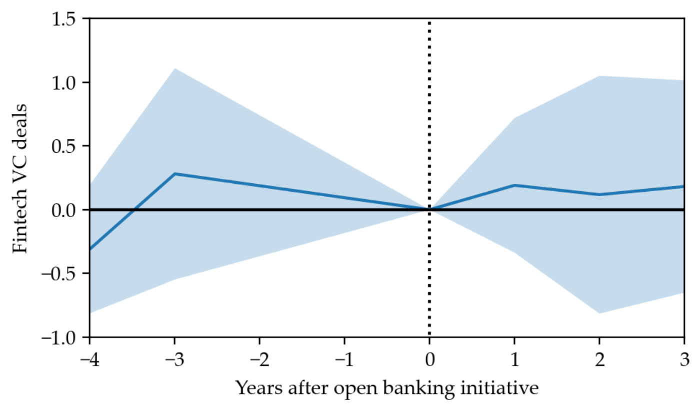
(a) Fintech VC deals following Gardner (2022)



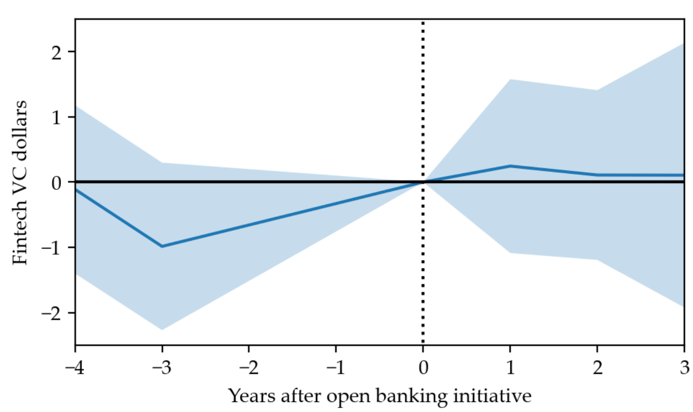
(b) Fintech VC dollars following Gardner (2022)

Figure E2: Placebo Test Event-study of Fintech VC Five Years Before Open Banking

Note: This figure conducts a placebo test of our main event study (Figure 5) of changes in fintech venture capital (VC) activity around the passage of open banking (OB) by shifting all events and windows five years earlier. We perform this analysis on a Pitchbook panel of 2006-2016 data for the countries with at least five fintech VC deals in the 1995–2005 period. Panel (a) shows an event study on the log of one plus the number of fintech VC deals, and Panel (b) shows an event study on the log of one plus the millions of US dollars invested in fintech VC deals. Year 0 is five years before the passage year of each country's major open banking initiative. The coefficient for year 0 is set to zero and other coefficients are presented net of country and region-by-year fixed effects for Africa, Middle East & North Africa; Europe & Central Asia; Latin America & the Caribbean; North America; South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. The shaded regions denote 95% confidence intervals calculated using standard errors clustered at the country level.



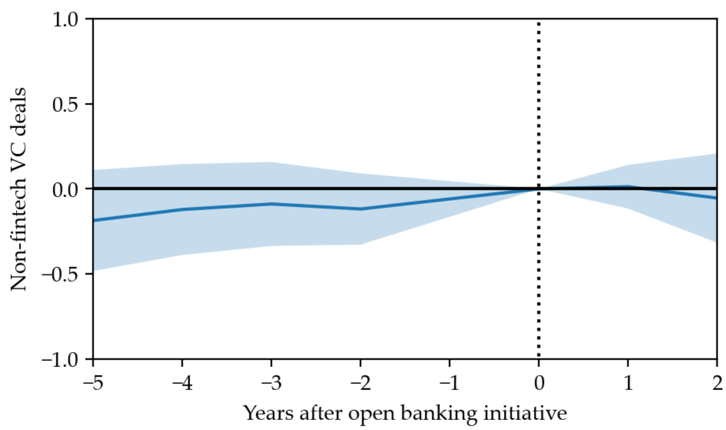
(a) Placebo test of fintech VC deals five years before passage of OB



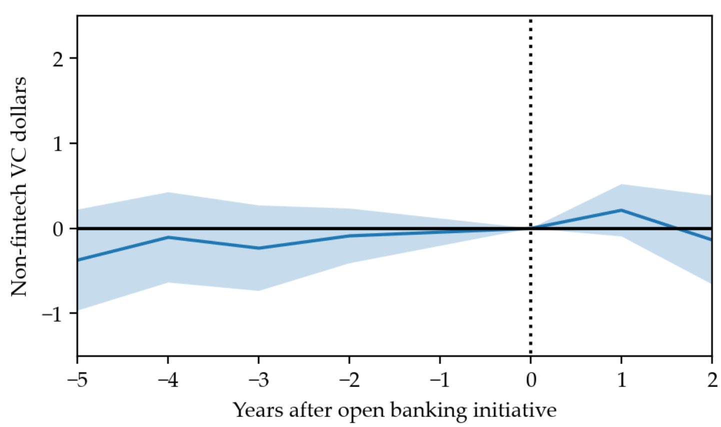
(b) Placebo test of fintech VC dollars five years before passage of OB

Figure E3: Placebo Test Event-study of Non-fintech VC After Open Banking

Note: This figure conducts a placebo test of our main event study (Figure 5) by switching non-fintech VC deals and fintech VC deals (and likewise for dollars) for our regression specification and sample construction. We perform this analysis on a Pitchbook panel of 2011-2021 data for the countries with at least five non-fintech VC deals in the 2000–2010 period. Panel (a) shows an event study on the log of one plus the number of non-fintech VC deals, and Panel (b) shows an event study on the log of one plus the millions of US dollars invested in non-fintech VC deals. Year 0 is five years before the passage year of each country's major open banking initiative. The coefficient for year 0 is set to zero and other coefficients are presented net of country and region-by-year fixed effects for Africa, Middle East & North Africa; Europe & Central Asia; Latin America & the Caribbean; North America; South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. The shaded regions denote 95% confidence intervals calculated using standard errors clustered at the country level.



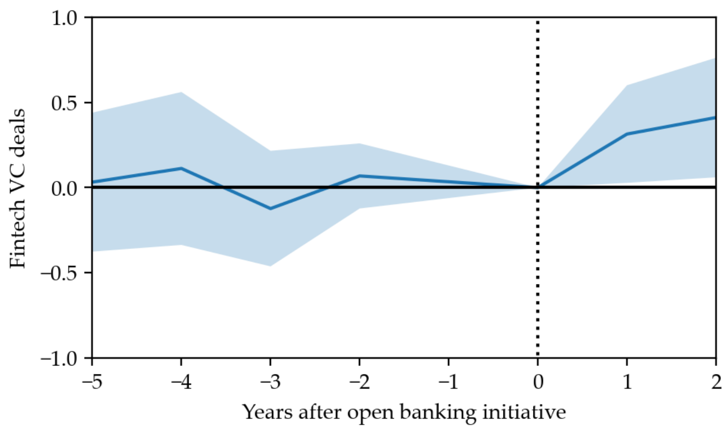
(a) Placebo test of non-fintech VC deals



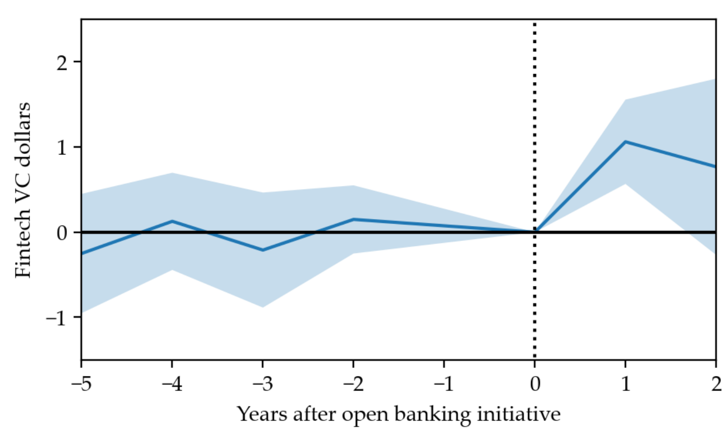
(b) Placebo test of non-fintech VC dollars

Figure E4: Event-study of Fintech Investment Controlling for Non-fintech VC deals

Note: This figure provides a robustness check to our main event study (Figure 5) by adding a control for non-fintech VC activity. We perform this analysis on a Pitchbook panel of 2011-2021 data for the countries with at least five fintech VC deals in the 2000–2010 period. Panel (a) shows an event study on the log of one plus the number of fintech VC deals while controlling for non-fintech VC deals. Panel (b) shows an event study on the log of one plus the millions of US dollars invested in fintech VC deals while controlling for the log of one plus the millions of dollars invested in non-fintech VC deals. Year 0 is five years before the passage year of each country's major open banking initiative. The coefficient for year 0 is set to zero and other coefficients are presented net of country and region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. The shaded regions denote 95% confidence intervals calculated using standard errors clustered at the country level.



(a) Fintech VC deals after controlling for non-fintech VC



(b) Fintech VC dollars invested after controlling for non-fintech VC

Table E1: Effect of Open Banking Government Policy Characteristics on Fintechs

Note: This table shows changes in fintech venture capital (VC) investment activity following the implementation of different types of open banking policies by governments around the world. The table uses a difference-in-differences design on our high-coverage Pitchbook sample of country-year data spanning 2011-2021 for the 21 countries with at least five fintech deals in the 2000–2010 period. The dependent variable in each specification is the log of one plus the number of fintech VC deals in each country-year. The independent variables are different characteristics of open banking government policies interacted with an indicator variable equal to one if the year in question is after the year major open banking laws were passed in the country in question. In column 1 we indicate whether banks are mandated to share the data with other financial service providers upon consumer request; in column 2 whether there is data reciprocity between banks and other financial service providers (e.g., if fintechs have to share customer data with banks); in column 3 whether regulators set technical standards for open banking implementation; and in column 4 whether, in addition to bank payment accounts, open banking policies cover other financial products and services (e.g., mortgages, insurance). In column 5, we interact with the Open Banking Strength Index, which we define as the average of those four policy dimensions used in columns 1 to 4. All specifications have a control for non-fintech VC activity, country fixed effects, and region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. Standard errors are clustered at the country level (reported in parentheses). *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Fintech VC Deals				
	(1)	(2)	(3)	(4)	(5)
Banks must share × after OB	0.284**				
	(0.124)				
Users must share × after OB		0.264			
		(0.173)			
Regulated specifications × after OB			0.179		
			(0.142)		
Beyond transactions × after OB				0.141	
				(0.308)	
OB Strength Index × after OB					0.488
					(0.370)
After OB initiative	0.037	0.220	0.208	0.247	0.030
	(0.156)	(0.146)	(0.184)	(0.171)	(0.273)
Non-fintech VC control	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes	Yes
Observations	231	231	231	231	231
Adjusted R^2	0.937	0.937	0.937	0.936	0.937

Table E2: Leave-one-out Country Effect of Open Banking Government Policy on Fintechs

Note: This table shows how our estimate of the effect of open banking (OB) on fintech VC deals estimated using Equation (5) varies when we exclude countries from our data. Each row corresponds to a data sample that is equal to our high-coverage Pitchbook panel data of country-year data spanning 2011-2021 for the 21 countries with at least five fintech deals in the 2000–2010 period, but excluding each country one at a time in the first 21 rows, excluding France and Germany (the two largest EU countries) together in the next row, and excluding Canada, China, and the USA together (the three countries that did not pass OB laws in our sample period) in the final row. The Coefficient column presents the coefficient on post-OB (parameter on After OB initiative) estimated using a difference-in-differences design on that sample, with the Standard error, t stat. and p-value columns similarly presenting their respective statistics. All specifications have a control for non-fintech VC activity, country fixed effects, and region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors. Standard errors are clustered at the country level. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Coefficient	Standard error	t stat.	p-value
Excluding AUS	0.294***	0.092	3.201	0.009
Excluding BEL	0.300**	0.114	2.637	0.023
Excluding BRA	0.299**	0.111	2.685	0.023
Excluding CAN	0.301**	0.114	2.630	0.025
Excluding CHN	0.172*	0.094	1.826	0.098
Excluding DEU	0.301**	0.115	2.626	0.024
Excluding DNK	0.300**	0.115	2.617	0.024
Excluding ESP	0.296**	0.115	2.570	0.026
Excluding FIN	0.298**	0.115	2.588	0.025
Excluding FRA	0.298**	0.114	2.603	0.025
Excluding GBR	0.329*	0.156	2.112	0.061
Excluding IND	0.357**	0.131	2.717	0.022
Excluding IRL	0.304**	0.115	2.646	0.023
Excluding ISR	0.299**	0.111	2.685	0.023
Excluding JPN	0.310*	0.144	2.162	0.056
Excluding NLD	0.297**	0.116	2.559	0.027
Excluding NOR	0.264*	0.123	2.135	0.058
Excluding POL	0.297**	0.117	2.543	0.027
Excluding RUS	0.355*	0.169	2.102	0.062
Excluding SWE	0.295**	0.115	2.570	0.026
Excluding USA	0.301**	0.114	2.630	0.025
Excluding DEU and FRA	0.301**	0.115	2.608	0.024
Excluding CAN, CHN, and USA	0.176*	0.095	1.856	0.096

Table E3: Effect of Open Banking Government Policy on Fintechs Using Other Transformations

Note: This table shows changes in fintech venture capital (VC) investment following the implementation of open banking government policies. The table tests our main difference-in-differences regression specification (Equation 4) on our high-coverage Pitchbook panel data of country-year data spanning 2011-2021 for the 21 countries with at least five fintech deals in the 2000–2010 period. Odd columns consider dependent variables based on the number of fintech deals, while even columns consider dependent variables based on the value of fintech deals in millions of US dollars. Each pair of columns considers different transformations of these measures, with columns 1 to 2 considering the log of 1 plus the measure of fintech activity (our main specification), columns 3 and 4 considering the ratio of fintech activity to trillions of dollars of GDP, columns 5 and 6 considering the ratio of fintech VC activity to total VC activity in the country-year, and columns 7 and 8 considering the inverse hyperbolic sine (IHS) of fintech VC activity in a country-year. The independent variable is a dummy variable equal to one if the year in question is after the year major open banking laws were passed in the country in question. The mean of the dependent variables, the standard deviation of the dependent variables, and Cohen's d values are presented to aid in the interpretation of the effect sizes under the different transformations. Cohen's d is the ratio between the regression coefficient on After OB initiative and the standard deviation of the dependent variable. All specifications have a control for non-fintech VC activity, country fixed effects, and region-by-year fixed effects. Regions are i) Africa, Middle East & North Africa; ii) Europe & Central Asia; iii) Latin America & the Caribbean; iv) North America; v) South Asia, East Asia & Pacific, following World Bank geographic terms. European Union member states are weighted to count as a single country for estimates and standard errors (reported in parentheses). Standard errors are clustered at the country level. *** denotes p-value < 0.01, ** denotes <0.05, and * denotes <0.1.

	Log (1 + Fintech VC)		Fintech VC / GDP		Fintech VC / Total VC		IHS Fintech VC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Deals	Dollars	Deals	Dollars	Deals	Dollars	Deals	Dollars
After OB initiative	0.308**	0.874**	17.758*	298.962***	0.027**	0.079**	0.303*	0.868*
	(0.125)	(0.368)	(9.438)	(24.498)	(0.009)	(0.026)	(0.146)	(0.403)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Non-fintech VC control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	231	231	200	200	231	231	231	231
Adjusted R^2	0.937	0.898	0.752	0.452	0.754	0.621	0.923	0.89
Std. of dependent variable	1.38	2.33	23.52	328.21	0.04	0.11	1.47	2.44
Mean of dependent variable	3.19	4.58	25.51	194.18	0.08	0.11	3.80	5.20
Cohen's d	0.22	0.38	0.75	0.91	0.62	0.74	0.21	0.36

F Model Solution, Calibration, and Additional Comparative Statics

This appendix section details the solution method and calibration of our structural models of (1) US non-GSE residential mortgages (primarily jumbo mortgages) and (2) consumer financial advice. In both cases, we impose common structural assumptions on consumer heterogeneity. The horizontal taste shocks ϵ_{ij} follow a type-one extreme value distribution.[50] We assume the privacy taste shocks ϵ_i^S follow the same distribution and normalize their variance to 1.

F.1 Model Solution

The model solution requires solving for equilibrium interest rates, firm entry, and each consumer type's probability of sharing data. Optimal firm pricing gives a series of first-order conditions that pin down rates. Firm entry is pinned down by the zero-profit condition. Data sharing probabilities are pinned down through consumer privacy preferences. While each equilibrium object to solve for impacts all others, we find the fixed point by solving a large system of non-linear equations given by the preceding equilibrium conditions. Code to solve the model is available upon request.

F.2 Model Calibration

In both contexts, the parameters to calibrate are as follows: (1) the value of customization λ, (2) distributional parameters of marginal costs, which we assume are log-normally distributed with a mean and variance to be calibrated, (3) preferences for the incumbent relationship lender, (4) the outside option utility of not buying a product, (5) the entry cost of new firms, (6) the MC advantage (or disadvantage) for incumbents, (7) the sensitivity to interest rates and prices, and (8) the hedonic value of privacy. This yields 17 parameters: 8 in each context plus a common value of privacy.

We first assume that the unobserved marginal cost variance is zero for financial advice and the value of customization is zero in the mortgage context. Next, where possible, we take estimates available from the literature or industry reports for these parameters. The sources for these are reported in Table F1. In our case, the means of the marginal cost distributions and incumbent advantages come from Buchak et al. (2024a) and industry reports,[51], while price sensitivity comes from Di Maggio et al. (2022b) and Buchak et al. (2024a) for the respective applications. The other 9 parameters (the hedonic value of privacy, the value of

[50] This is a common distributional assumption in models of discrete choice and yields highly tractable market share and pricing equations. See, e.g., in the finance context, Buchak et al. (2024a).

[51] For advice marginal costs, with $mc_{bank} = 1.5\%$ and $mc_{fintech} = 0.35\%$, we use reported fees on JPMorgan's website for automated versus particularized financial advice, respectively.

customization for financial advice, the unobserved marginal cost variance for mortgages, the preference for service from an incumbent for both applications, the outside option utility for both applications, and the entry cost for both applications) are calibrated through our SMM procedure.

We use 10 moments to discipline our overidentified SMM procedure. As a starting point, we assume a market has 30 pre-OB firms, which reflects the typical mortgage market in the US, Buchak et al. (2024a), and that the same number of firms provide advice. We assume that markets for financial advice share common overlap. Next, assuming a pre-OB steady-state number of firms, from our summary statistics and event studies, we can infer the change in the number of firms following OB introduction. Incumbent shares come from the respective financial advice and mortgage papers. Quantities come from industry reports in the case of financial advice,[52] and facts on aggregate outstanding mortgage debt for credit underwriting. Finally, we use data from the UK FLS 2020 consumer survey to measure OB takeup rates. Table F2 shows the targeted moments and their values.

Our SMM approach searches for 9 parameters to match these 10 moments as closely as possible. While all parameters are determined simultaneously, it is instructive to detail the connection between the parameters and the key moments that discipline them. First, hedonic preference for privacy is closely tied to the OB take-up rate. As the preference for privacy becomes smaller, fewer people opt in to data sharing. Second, the value of customization in the financial advice case most directly determines the amount of new firm entry. When the advice is more valuable, more firms enter. Third, the unobserved MC variance in the credit underwriting case jointly determines both the amount of new entry post-OB as well as the overall number of firms. Other things equal, more unobserved MC variance reduces the number of firms pre-OB, and also impacts firm entry post-OB. Fourth and fifth, across both cases, the preference for the incumbent/relationship lender most directly drives the incumbent market share: as this preference increases, incumbents gain more market share. Sixth and seventh, across both applications, the outside option utility most directly drives overall quantities: as the outside option utility increases, quantities decrease. Finally, eighth and ninth, the entry cost most directly drives the number of firms operating in the market.

[52] See here.

Table F1: Calibrated model parameters

Note: This table shows the calibrated parameters for the open banking (OB) model described in Section 4. It provides the parameter, its description, the calibrated value, and how it was calibrated. We cite the relevant industry reports in footnotes. SMM refers to the simulated method of moments, targeting those moments described in Table F2. The relevant industry reports used for average marginal cost in financial advice OB can be found here. The relevant industry reports used for Incumbent MC advantage in financial advice OB can be found here.

Parameter	Description	Calibrated value	Source
Common parameters			
ϕ	Value of privacy	0.75	SMM
Financial advice			
λ^a	Value of customization	0.98	SMM
σ_a^{MC}	Unobserved MC variance	0.00	Assumption
θ^a	Preference for incumbent	0.37	SMM
u_0^a	Outside option utility	2.39	SMM
c^a	Entry cost	0.91	SMM
μ^{MC}	Average marginal cost	0.35	Industry reports
μ_r^{MC}	Incumbent MC advantage	-1.15	Industry reports
α^u	Rate sensitivity	1.38	Di Maggio et al. (2022b)
Mortgage origination			
λ^u	Value of customization	0.00	Assumption
σ_u^{MC}	Unobserved MC variance	0.73	SMM
θ^u	Preference for incumbent	2.44	SMM
u_0^u	Outside option utility	1.17	SMM
c^u	Entry cost	0.60	SMM
μ^{MC}	Average marginal cost	1.62	Buchak et al. (2024a)
μ_r^{MC}	Incumbent MC advantage	0.00	Buchak et al. (2024a)
α^u	Rate sensitivity	1.14	Buchak et al. (2024a)

Table F2: Target Model Moments

Note: This table details the moments used for calibration of the open banking (OB) model described in Section 4. It provides the description of the target, the target moment, the moment from the calibrated model, and the data source for the target. Event study refers to the reduced-form analysis on fintech entry in this paper from Table 5, FLS refers to the Financial Conduct Authority's 2020 Financial Lives Survey and represents our results on consumer update of OB products described in Section 3.1. The relevant industry reports used for quantities in financial advice OB can be found here. Pre-OB number of firms assumes that lenders (e.g., incumbent banks) also provide financial advice.

Moment	Target	Model	Data source
Financial advice			
Δ firms	0.13	0.13	Event study
Incumbent share	0.01	0.01	Di Maggio et al. (2022b)
Quantities	0.35	0.39	Industry reports
Pre-OB number of firms	29.95	30.00	Buchak et al. (2024a)
OB take-up share	0.086	0.081	FLS
Mortgage origination			
Δ firms	0.15	0.14	Event study
Incumbent share	0.12	0.13	Buchak et al. (2024a)
Quantities	0.40	0.33	US outstanding mortgage debt
Pre-OB number of firms	29.89	30.00	Buchak et al. (2024a)
OB take-up share	0.055	0.057	FLS

F.3 Comparative Statics on the Informativeness of Data

An important model comparative static is the informativeness of borrower information. In the case of credit, the main model parameter governing the value of information is the variance of the unobserved marginal cost. This corresponds to the informativeness of borrower information because when the unobserved variance is high, revealing the information eliminates more variance; when the informativeness of borrower information is low, revealing that information does not. One interpretation of this is that a low variation corresponds to an information environment where a credit registry has already revealed most of the useful information on borrower creditworthiness.

In the case of financial advice, the main model parameter governing the value of information is the value of customization, λ. This corresponds to the value of information because it governs the size of the effective product improvement for service providers with access to customer data. Similar to the above, one interpretation of a high λ is a regime where advice customization has a large impact on customer outcomes and OB data is very useful in customization.

Figure F1 Panels (a) and (b) show how several model outcomes vary as a percent change relative to the status quo relationship regime. Panel (a) corresponds to altering the variance of the unobserved marginal cost for credit, and Panel (b) corresponds to altering the value of customization for financial advice. In both panels, the x-axis corresponds to the scale applied to the baseline, i.e., 0.85 in Panel (a) means the variance of unobserved marginal cost is set to 0.85 times its calibrated value. Moving left-to-right along the x-axis corresponds to information being more revealing. In each figure, the black line shows the fraction of the population opting into data sharing, the red line shows the percentage increase in the number of operating firms, the blue line shows the percentage change in relationship bank profits, and the green line shows the percentage change in service provision. The comparison is done at each point on the x-axis between the status quo world with that parameter value and the OB world with that parameter. For example, at an x-value of 0.85, we are looking at how entry changes in going from a world with 0.85 of the MC variance with no OB to a world with 0.85 of the MC variance with OB.

Beginning with Panel (a), we find that customer take-up into data sharing is *decreasing* with the variance of borrower marginal cost. While this is initially counterintuitive, it is driven by the fact that increased MC dispersion reduces, in an absolute sense, the number of outside lenders issuing loans because they are more severely affected by adverse selection. This is still true—and self-reinforcing—in the OB regime because of the incomplete take-up of data sharing. When there are fewer outside lenders, it is less beneficial for borrowers to share their information with them, and thus fewer borrowers share their data.

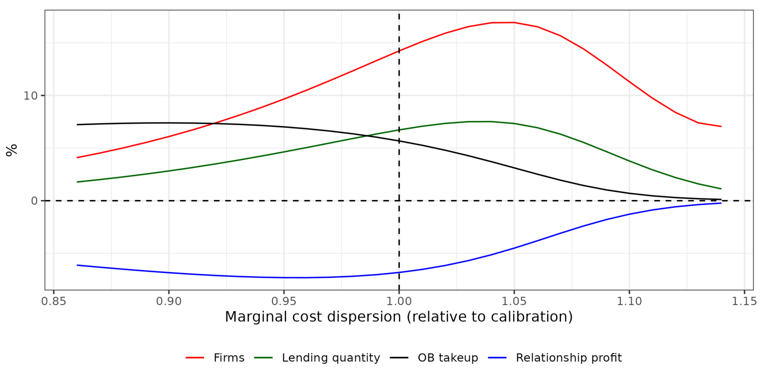
We find an inverse-U-shaped pattern in the percent increase in outside lenders, shown in red. For low marginal cost dispersion, while more borrowers opt in to OB, the informational content of the data is lower, and hence there is relatively modest entry. As marginal cost dispersion increases, there are two opposing forces: on one hand, data becomes more revealing, and so OB has a larger impact on firm entry. On the other hand, data sharing take-up declines, and so the number of potential OB-enabled consumers declines. The former force dominates at first but is ultimately swamped by the latter. The increase in lending quantities tracks new firm entry, and relationship bank profit has the inverse effect, following the same logic.

The effect of borrower information is more straightforward in the case of financial advice, and the relationships are all monotonic, as shown in Panel (b). As the value of customized advice increases from left to right, data sharing take-up increases. This occurs due to the direct effect of it being more beneficial to share data when it allows firms to offer better products, and additionally due to a compounding effect of new firm entry. As data becomes more useful in customizing advice, more outsider providers enter because they can offer (and charge for) an increasingly superior product. This produces a beneficial feedback loop where more firms offering services draw more customers into data sharing, and more customers sharing their data draws more firms in to serve them. The quantity of advice provided increases following the same logic, while new entrants steal an increasing share of customers from the relationship advisor, reducing their profits.

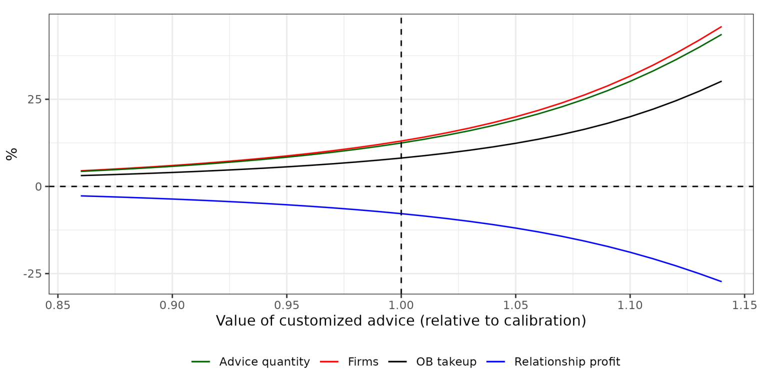
These counterfactuals illustrate the stark economic differences arising from how data is used across OB applications. Incentives around data used for product improvements are straightforward. More revealing data means firms with access provide better products, thus inducing more data sharing and firm entry in a virtuous cycle. In the credit application, these two forces sometimes operate in opposition. When data is more useful, uninformed outsiders face greater adverse selection and the quantity of outsider firms shrinks. With few outsiders and optional data sharing, the benefits of sharing data are small, so few consumers opt in, meaning new entry opportunities for firms are limited. The mediator in this vicious cycle is customers' endogenous opt-in choice, and so policymakers designing OB policies need to consider consumer incentives to share data, particularly when the data may be used against them.

Figure F1: COMPARATIVE STATICS ON DATA INFORMATIVENESS

Note: This figure shows comparative statics on the informativeness of consumer data for the open banking (OB) model described in Section 4. The plots show, compared to the no-OB status quo, the number of service providers (red), relationship bank profit (blue), service quantity (green), and OB take-up rate (black). Panel (a) shows results for the mortgage underwriting case and varies the dispersion of unobserved marginal cost. The x-axis shows the marginal dispersion relative to the baseline calibration. Panel (b) shows the results for the financial advice case and varies the value of customized advice, with the x-axis showing the value of customization relative to the baseline calibration.



(a) Credit



(b) Advice