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Thesis Abstract

This thesis comprises three papers that bridge macroeconomics, finance, and the physical foundations of production in relation to environment.

The first paper, *Supply Chain Uncertainty: Pricing, Growth, and Blockchains*, identifies supply chain disruptions as priced macroeconomic risks in the cross-section of US equities. It develops a structural endogenous growth model in which logistic and financial frictions jointly affect innovation, investment, and long-run growth. Counterfactual analysis shows that decentralized blockchain-based coordination of supply networks can mitigate these frictions, raising welfare and stabilizing growth.

The second paper, *The First Law of Macroeconomics: Implications of Energy Balance Equations*, reinterprets the production side of the economy through the lens of Energy Conservation Law. It introduces the concept of *Energy Differential* - net useful energy after extraction and conversion losses - as a measurable state variable driving output, productivity, and asset prices. Empirical analysis shows that energy availability explains over 94% of Total Factor Productivity variation and shapes long-run growth, long-run productivity and business-cycle dynamics – all of which affects asset prices. This chapter extends macroeconomics of production towards a physics-coherent unified theory of growth and sustainability.

The third paper, *Biodiversity and Financial Crises: Global Evidence*, examines the bidirectional link between ecological resilience and financial stability. Using global panel data from 1970–2018, it finds that banking and triple crises significantly deplete biodiversity, while biodiversity decline, in turn, raises systemic financial risk. The study highlights the complementarity between macroprudential and environmental policies in achieving sustainable global stability.

Together, these three chapters advance novel empirical facts and theoretical results on production processes and their relationship to broader environment.

Supply Chain Uncertainty:
Pricing, Growth & Blockchains

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Abstract

Supply chain shocks are priced in the cross section of US equity returns and their magnitude is significant. R&D-intensive stocks are more exposed to these shocks and hence they bear a higher risk premium. We propose a novel innovation-driven endogenous growth model that reproduces these key features of the data and that predicts a severe disruptive effect of supply chain shocks on long-term growth. In a counterfactual exercise, we show that blockchains for supply management are very valuable assets as they promote innovation and growth by relaxing working capital constraints and increasing production efficiency thanks to near real-time operation information flows.

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1 Introduction

Supply chain shocks have attracted a lot of attention in recent years because of their relevance in the aftermath of geopolitical tensions, trade policy conflicts, and COVID-related disruptions. The literature thus far has focused primarily on their implications for inflation, business cycle fluctuations, and international trade and financing. In this paper, we study the interplay of supply chain shocks, innovation, and long-term growth.

Both in the data and in a our novel endogenous growth model with supply chain shocks, we find that R&D-intensive firms are more exposed to these shocks than other firms. As a result, supply chain shocks affect the value of innovation and long-term growth. Through the lens of this model, we find that FinTech could be a valuable tool. Specifically, supply chain blockchains have the potential to alleviate key frictions at play in our model and hence provide a more resilient growth. We take our approach as a relevant contribution to a novel perspective that we call 'MacroFinTech'.

Specifically, we use the innovations to the Benigno, di Giovanni, Groen, and Noble (2022)'s global supply chain pressure index as a macroeconomic factor and test to see whether it is a priced risk factor in the cross section of US equity returns. After controlling for the six Fama and French (2018) factors (henceforth, FF6), we find that this factor has a significant and negative market price of risk. Equivalently, when the Benigno, di Giovanni, Groen, and Noble (2022) index increases, i.e., it detects supply chain tightness, markets are in a bad state of the world.

In the cross section of R&D-sorted stocks, we see that the exposure to these shocks is negative and increasingly so with R&D intensity. By no arbitrage, this means that innovation intensive stocks bear a higher risk premium. The fact that these macroeconomic shocks are priced after accounting for a wide set of financial factors is both novel and surprising. Indeed, macroeconomic factors are well-known to be less effective at pricing equities than financial factors. This is especially true for the return spread between the high R&D-intensive firms and the low R&D-instensive ones (henceforth HML-R&D). In addition, we confirm these results using an aggregate time-series approach. Specifically, we show that supply chain shocks forecast lower innovation-oriented investments, lower new granted patents, and long-lasting growth decline in output. For this exercise, we use a new shortage index developed by Caldara, Iacoviello, and Yu (2024) that spans a longer time horizon. Differently from what done for GSCPI, the authors perform a text analysis on a sample of 25 million newspaper articles to produce a monthly shortage index for the United States from the year 1900.

Inspired by these results, we propose a novel and 'handy' endogenous growth model that features two distinct sources of shocks. The first one refers to regular productivity shocks that drive business cycle dynamics, and the second refers to supply chain shocks that affect a time-varying share of manufactures.

As in Romer (1990), the production process involves three sectors. The final consumption good is produced in a competitive way using physical capital, labor, and intermediate goods. Stationary shocks drive stochastic fluctuations in the production of the final consumption good. Intermediate goods are produced by manufactures who have monopoly power over their variety but must pay a per-period royalty to the respective innovator. New patents are created by means of innovation through R&D in the innovation sector, which determine the speed of growth.

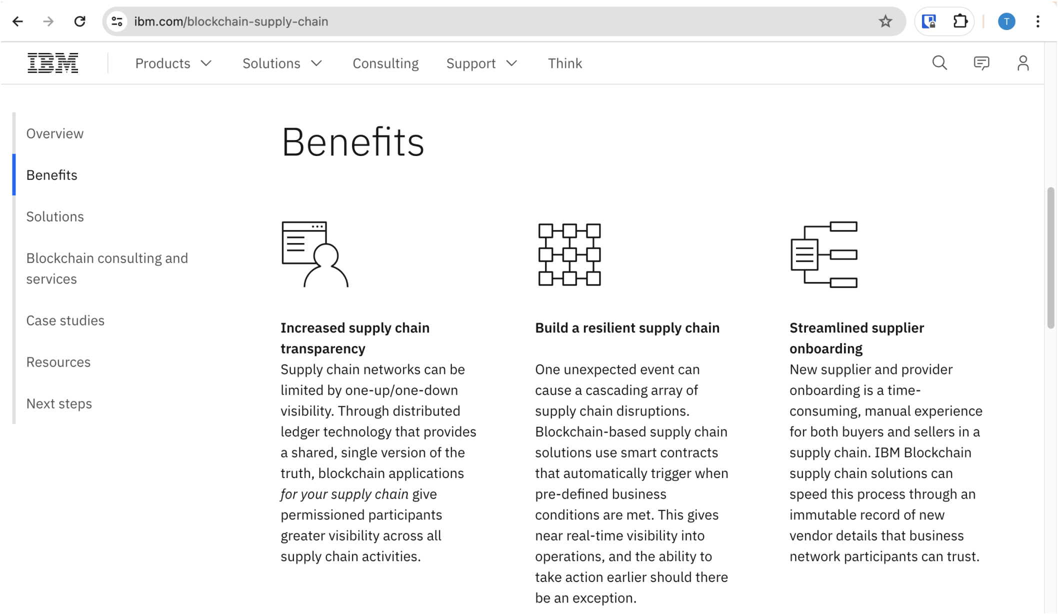
As in Kung and Schmid (2015), the representative agents has recursive preferences and prices growth news shocks. We depart from Kung and Schmid (2015) in two dimensions. First, we assume that in each period there is a time-varying share (or, equivalently, probability) of monopolistic intermediate good producers that are subject to supply shocks (see, for example, Barrot and Sauvagnat 2016; and Carvalho, Nirei, Saito, and Tahbaz-Salehi 2020). This time-varying probability represents a distinct source of risk in addition to time-varying productivity.

Second, we assume that the innovators require the manufacturers to pay a fraction of their per-period royalty at the beginning of the period, that is, before the realization of the supply shock. By doing so, the innovators hedge their cash-flow risk related to supply chain shocks. Manufacturers provide this down payment by borrowing from the household via uncollateralized intra-period loans. These loans are expensive because lenders anticipate default by the manufactures that are ex-post affected by supply chain shocks. Most importantly, at the equilibrium, financing costs increase with the ex-ante probability of supply chain shocks and amplify the resulting economic disruption. The interplay of working capital financial frictions and supply chain shocks depresses the market value of patents and hence R&D investments. At the equilibrium, R&D-capital is more exposed to supply chain shocks than tangible capital.

When focusing on our counterfactual scenario with supply chain blockchains, both payment transfers and the production flows are monitored in real time and an immediate reallocation of resources takes place if supply chain shocks materialize. As a result, there is no need for uncollaterilzed debt and full information is restored. In this setting, innovators pay a convex cost of production reallocation toward productive manufactures. According to our model, the welfare benefits in this setting could be as high as 95% of life-time consumption. In terms of 2023 US consumption, this welfare figure translates to a *total gross* gain of about 17.5 trillions over the long-run. Even though this gain is gross of the cost that corporations should face in order to upgrade their information systems, the potential benefit is remarkable.

More broadly, we think of supply chain blockchains as tools to improve allocation efficiency in real-time. For a motivational example, see figure 1. Our production economy with endogenous growth suggests that the efficiency gains could be substantial due to the resulting real-time information flows that reduces financial frictions and thereby lowers long-run growth risk. When agents value early resolution of uncertainty, this reduction in long-run growth risk results in significant welfare benefits.

The adoption of this technology is currently slow, however, as many firms are concerned about sharing their supply chain data with a few big service providers. Hence, we consider a broader interpretation of our convex cost which embodies also concerns about leakage



Benefits

Increased supply chain transparency
Supply chain networks can be limited by one-up/one-down visibility. Through distributed ledger technology that provides a shared, single version of the truth, blockchain applications *for your supply chain* give permissioned participants greater visibility across all supply chain activities.

Build a resilient supply chain

One unexpected event can cause a cascading array of supply chain disruptions. Blockchain-based supply chain solutions use smart contracts that automatically trigger when pre-defined business conditions are met. This gives near real-time visibility into operations, and the ability to take action earlier should there be an exception.

Streamlined supplier onboarding
New supplier and provider onboarding is a time-consuming, manual experience for both buyers and sellers in a supply chain. IBM Blockchain supply chain solutions can speed this process through an immutable record of new vendor details that business network participants can trust.

Fig. 1: Supply Chain Blockchains: Key Features

Notes – Description of the supply chain blockchain service offered by IBM.

of information and anti-competition practices. Specifically, our reallocation cost comprises all incentives that must be provided in order to sustain a large participation of businesses to the blockchain. In the second part of our counterfactual analysis, we ask the following question: how large should the average reallocation cost be in order to make welfare under the blockchain setting weakly smaller than that obtained in our setting with frictions? We find that an average cost of about 1.6% of GDP equalizes welfare under the two scenarios. This is a relatively tight threshold which suggests the existence of a strong trade-off between the reallocation cost and the willingness to acquire greater resilience against supply shocks. Even a small degree of reduction of the reallocation cost could make the setting with supply chain blockchains superior, and it could trigger major resilience gains. Given our welfare analysis, any policy aimed at mitigating this concerns could produce substantial benefits.

Related literature. There are now multiple ways to measure supply chain tightness. Ersahin, Giannetti, and Huang (2022) use textual analysis of earnings conference calls to identify exposure to supply chain shocks. Bai, Fernández-Villaverde, Li, and Zanetti (2023) use custom data as well as advanced satellite data to measure shipping disruption. We mostly use the Benigno, di Giovanni, Groen, and Noble (2022) index for three reasons: (i) it gives us a longer sample time; (ii) it is measured at high frequency, and hence it gives us more observations; and (iii) it is correlated with the other indices, and hence it comprises a large share of common information.

Many studies focus on the relevance of supply chain shocks for macroeconomic dynamics, inflation, and more broadly, firm-level decisions (see, among others, Acemoglu and Tahbaz-Salehi 2020; di Giovanni, Kalemli-Özcan, Silva, and Yildirim 2023; Franzoni, Giannetti, and Tubaldi 2023; and Acharya, Crosignani, Eisert, and Eufinger 2023). We differ from these study in several dimension. First, we price supply chain shocks in the cross section of equity returns. In contrast to Smirnyagin and Tsyvinski 2022, we do not focus on a model with heterogenous firms, rather we provide a micro-founded model with a useful aggregation result. We estimate a formal linear no-arbitrage model that informs us on the market price of supply chain risk. Smirnyagin and Tsyvinski (2022) complements our results by studying the predictability of returns. Second, we link supply chain shocks to innovation and long-term growth both empirically and in a novel DSGE model with endogenous growth. Third, we explore the potential of supply chain blockchains in mitigating this source of risk. We do so by abstracting away from the analysis of digital money supply in Jermann (2023) and conducting our analysis at a broader level, in the spirit of Townsend and Zhang (2023).

The literature has highlighted the relevance of both logistic and financial frictions in supply chains (see, for example, Alfaro, Brussevich, Minoiu, and Presbitero 2025; Chen, Gui, von Thadden, and Zhao 2024; Alfaro, García-Santana, and Moral-Benito 2021; Ersahin, Giannetti, and Huang 2024; and Gornall and Strebulaev 2013). We take these frictions seriously and nest them in a full-fledged endogenous growth model in a parsimonious way. Dou, Ji, Tian, and Wang (2025) focuses on financial frictions with heterogeneous firms to endogenously generate misallocation in a model with endogenous innovation. Our focus is very different since our model enables us to analyze a counterfactual experiment in which supply chain blockchains could mitigate these frictions and enhance the resilience of the economy in terms of long-run growth (see, among others, Capponi, Du, and Stiglitz 2024; Baldwin, Freeman, and Theodorakopoulos 2023; Grossman, Helpman, and Sabal 2023; Elliott and Golub 2019 and Brunnermeier 2022).

Our empirical analysis relates to the empirical asset pricing literature (among others, see Hou, Xue, and Zhang 2015a, b; Fama and French 2015, Belo, Bazdresch, and Lin 2014 and Lin 2012). We contribute to this literature by taking supply chain shocks as a first-order concern for the cross section of equities. Similarly, our theoretical work builds on recent papers by Comin and Gertler (2006); Comin, Gertler, and Santacreu (2009); Kung and Schmid (2015); Corhay, Kung, and Schmid (2015); and Gavazzoni and Santacreu (2015). Following on the seminal work of Romer (1990) and Grossman and Helpman (1991), these papers integrate innovation-based endogenous growth models into the workhorse real business cycle model of macroeconomics. We provide a novel and 'handy' DSGE model in which supply chain frictions and financing frictions impact long-term growth.

Our work is related to the macrofinance literature (see, among others, Jermann 1998, 2010; Kogan and Papanikolaou 2009; Kogan, Papanikolaou, Seru, and Stoffman 2012; Kogan, Papanikolaou, and Stoffman 2013; Belo, Bazdresch, and Lin 2014; Belo, Lin, and Yang 2018; Belo, Gala, Salomao, and Vitorino 2022 and more recently Diercks, Hsu, and Tamoni 2024 and Ramírez 2024). We adopt recursive preferences since we explore the relevance of priced endogenous consumption news shocks (see, for example, Tallarini 2000; Bansal and Yaron 2004; Campanale, Castro, and Clementi 2010; Kuehn (2008, 2009); Kaltenbrunner and Lochstoer (2010), and Croce (2014)). In the spirit of Gourio (2012, 2013), we think of supply chain shocks as featuring skewness, i.e., they belong to the broad category of disaster shocks and they convey news about long-run growth. We differ from these paper for our attention to supply chain shocks and for our attention to new blockchain technologies (see, Brunnermeier and Payne 2023). We see our paper as belonging to a new field that we call 'MacroFinTech'.

Table 1: Portfolio summary statistics

	Low	High	*HML-R&D*
	Portfolio excess returns (%)		
Mean	13.62	21.03	7.39
Standard deviation	30.54	59.91	44.76
	Portfolio characteristics		
Average number of firms	430	426	
R&D/Assets (%)	0.07	22.48	22.41***
			(0.01)
Leverage (%)	41.83	26.07	−15.76***
			(2.06)
Cash/Assets (%)	5.17	24.50	19.33***
			(1.35)

Notes: This table shows summary statistics for two R&D-sorted portfolios and the implied *HML-R&D* portfolio. Our two extreme portfolios represent the top- and bottom-quintile of firms and cover at least 10% of market capitalization. Excess returns are equally-weighted, annual, and in percentages. R&D/Assets is defined as annual research & development expenses divided by total assets and is used as our benchmark measure of R&D intensity. Leverage is defined as the ratio of book debt to the total of book debt and book equity. Our quarterly sample starts in 1998:Q1 and ends in 2023:Q4. HAC-adjusted standard errors are in parentheses.

2 Empirical Results

In this section, we provide novel empirical evidence on the link between supply chain shocks, R&D-sorted stock returns, and growth. We begin by describing our data sources, and then discuss the results from our empirical asset-pricing tests.

Return data. Our empirical analysis links macroeconomic data with information on stock returns and firm-level fundamental accounting data. We use stock return data from CRSP and fundamental accounting data from COMPUSTAT to construct a combined panel at a quarterly frequency starting in 1975:Q1. Our sample choice reflects the introduction of new accounting standards regarding the expensing of R&D costs by the Financial Accounting Standards Board (FASB) in 1975. For each calendar year, we construct stock return portfolios by sorting firms based on their R&D intensity. Our benchmark measure of intensity is the ratio of R&D expenses to total assets, as reported in COMPUSTAT. Our results also obtain when we measure intensity as the ratio of R&D to capital expenditures (CAPEX), as in Lin (2012).

We group firms into quintile portfolios. In our baseline case, our extreme quintile portfolios constitute at least 10% of the total market capitalization, implying that our results are not driven by a few illiquid assets. The intermediate range of stocks is either evenly distributed across the remaining portfolios, or consolidated in a portfolio that we denote as "Middle". Summary statistics of our extreme portfolios are reported in table 1. Consistent with prior findings, our R&D-intensive firms feature higher average excess returns and cash holdings, but lower leverage. Combined together, in both our empirical investigation and model, we think of R&D-oriented firms as more exposed to financing frictions (see, among others, Li 2011).

The market price of supply chain shocks. We focus our attention on the Global Supply Chain Pressure Index provided by the NY FED (Benigno, di Giovanni, Groen, and Noble 2022) and reported in figure 2. We extract the innovations in GSCPI index via an AR(1) process and think of them as the realization of a non-financial risk factor. Because of short time-series sample (this index starts in 1998), we identify the market price of risk of this factor by using a broad cross section of assets. Namely, we use our cross section of R&D-sorted portfolios and we augment it with portfolios formed according to both (i) operating profits-to-book and change in total assets; and (ii) 49 industry portfolios. In our analysis, we use returns from Kenneth French's website for both our financial factors and the additional abovementioned test assets.

Table 2 reports our estimates for both the market price of risk and the stochastic discount factor loadings associated to our seven factors. We find it impressive that innovations to the GDCPI index are independently priced after controlling for the FF6 factors. The implied market price of risk is negative and statistically significant. Importantly, our estimates remain stable if we exclude the Covid period by ending our sample at the end of 2019. Our

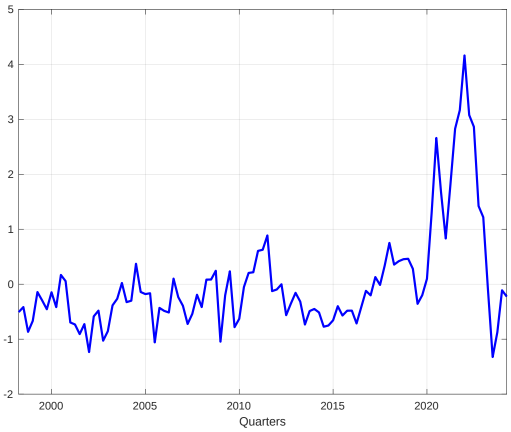


Fig. 2: Global Supply Chain Pressure Index

Notes – Our benchmark measure of supply chain risk from Benigno, di Giovanni, Groen, and Noble (2022). Source: the Federal Reserve Bank of New York.

point estimate of the market price of risk of supply shocks in this shorter sample becomes -1.003 with a standard error of 0.067. This observation is important because it proves that our results are not identified solely by the COVID shock.

Lastly, we note that our short time-series prevents us from running a conditional estimation of the market price of risk. Through the lens of our equilibrium model, this empirical approach is appropriate as the stochastic discount factor loadings (the bs) with respect to the supply disruption shock is nearly constant. Equivalently, the log stochastic discount factor is very close to be linear with respect to these shocks.

Heterogeneous exposures. In order to understand whether these shocks have a relevant impact on our cross section of R&D-sorted firms, we focus on two dimensions. Specifically, we study whether both equity excess returns and investment flows have heterogeneous exposure to supply shocks across portfolios. We start with equity returns by estimating the following regression:

$$R^{ex,i}_{rnd,t} = \left(\sum_{f} \left(\beta_0^f + \beta_{rnd}^f \frac{\overline{R\&D}}{Assets} i \right) \cdot F_{f,t} \right) + e_{i,t} \tag{1}$$

Table 2: Estimation Results for MPRs(λ) and SDF Loadings (b)

$$E\left[m_{t+1}\cdot R^{e}_{i,t+1}\right]=0, \qquad m_{t+1}:=1-b'\cdot F_{t+1}$$

GMM bs							Implied MPR
Mkt-Rf	SMB	HML	RMW	CMA	Mom	GSCPI	GSCPI
0.011^{***}	-0.001^{***}	-0.007^{***}	0.004^{***}	0.020^{***}	0.007^{***}	-0.069^{***}	-1.171^{***}
(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.099)

Notes: Our cross section of test assets comprises (i) 25 portfolios sorted on operating profits-to-book and changes in total assets; (ii) 49 industry portfolios; and (iii) 5 equally-weighted portfolios sorted on R&D intensity, defined as $\overline{\frac{R\&D}{Assets}}i$. Data are from Kenneth-French website. Our monthly data starts in 1998:01 and end in 2023:12. Returns and factors are annualized. Returns are financial factors are multiplied by 100. Numbers in parentheses are GMM HAC-adjusted standard errors. The GSCPI column reports sensitivity to innovations in GSCPI index extracted via an AR(1) process. We test $H_0 : \lambda_{GSCPI} \geq 0$ and $H_0 : b_{GSCPI} \geq 0$ and denote a significance level of 1%, 5%, and 10% with ***, **, *, respectively.

where i denotes a specific R&D-sorted portfolio with average R&D intensity $\overline{\frac{R\&D}{Assets}}i$, and f refers to one of our factors. It is our convention to include as first factor a constant, that is, $F_{1,t} = 1 \quad \forall t$. In particular, we are interested in β^{GSCPI}_{rnd} which measures the cross sectional variation of exposure to supply chain shocks with respect to different levels of R&D intensity. We report our estimates for β^{GSCPI}_{rnd} results in the top panel of table 3.[1]

We find a negative and significant coefficient β^{GSCPI}_{rnd} across different sets of risk factors. FF6 controls for the 6 Fama-French factors. We also explore settings in which we control just for macroeconomic factors. Specifically, we control for news to industrial production and news to both industrial production and the VIX. These factors are relevant because industrial production innovations capture other shocks to the level of economic activity, and innovations to the VIX reflect changes in uncertainty in the economy. Across different sets of factors, our point estimates are close to each other and range from -0.096 to -0.125. If we take an intermediate value of -0.11 and account for the fact that the spread in average R&D intensity is 22.41, we find that the spread in exposure of the returns across R&D sorted portfolios is $-0.11 \times 22.41 = -2.46$. Thus, high R&D firms are significantly more exposed to supply chain shocks than low R&D firms and the implied annualized risk premium differential is 2.46×1.17 that is about 2.9%.

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[1] For parsimony, we remove all of the interaction terms for which the associated coefficient β^{f}_{rnd} is statistically indistinguishable from zero. For each group of factors, we report the results of the associated parsimonious regression.

Table 3: Heterogeneous Exposure across R&D-sorted Portfolios

Panel A: Differential Returns Exposure (β_{rnd}^{GSCPI} in equation (1))

	6FF	Ind. Prod. News	Ind Prod. & VIX News
β_{rnd}^{GSCPI}	-0.096**	-0.125***	-0.118***
	(0.057)	(0.048)	(0.048)

Panel B: Differential Expected Investment Growth Exposure (β_{rnd}^{h} in equation (2))

	1-Year	2-Year	3-Year
$\Delta I_{t \to t+h}$	-0.408***	-0.125	0.056
	(0.110)	(0.113)	(0.096)
$\Delta \frac{R\&D}{Assets}\ _{t \to t+h}$	0.013	-0.096***	-0.367***
	(0.023)	(0.025)	(0.068)

Notes: Our data sample starts in 1998. Both returns and factors are annualized. On the right hand side, R&D intensity, $\overline{\frac{R\&D}{Assets}}i$, is averaged over the sample. All estimates are obtained via GMM. Standard errors in parentheses are HAC-adjusted. We test $H_0 : \beta_{rnd}^{GSCPI} \geq 0$ and denote a significance level of 1%, 5%, and 10% with ***, **, *, respectively. The top panel refers to the contemporaneous response of equity returns to GSCPI shocks (1). The bottom panel refers to the panel forecasting regressions described in equation (2).

In panel B of the same table, we turn our attention to heterogeneous exposure of investment flows. Specifically, we consider the following predictive regression:

$$\Delta[\cdot]_{i,t \to t+h} = \alpha_i^h + \alpha_t^h + \beta_{rnd}^h \cdot \overline{\frac{R\&D}{Assets}}i \times GSCPI_t + cntrl_{i,t} \qquad i = 1, \ldots, 5 \tag{2}$$

where the left hand side refers to the h-periods ahead future growth of either log investment or R&D-intensity. On the right-hand side, we include a portfolio-specific fixed effect, a time-fixed effect to control for all possible aggregate shocks as well as additional portfolio-level control variables, $cntrl_t^i$. Importantly, we test whether the predicted adjustment in future investment activity is related to predetermined R&D intensity by including the interaction term $\overline{\frac{R\&D}{Assets}}i \times GSCPI_t$.

We note that our R&D intensity measure cannot be negative and hence the composite parameter $\beta_i^h := \beta_{rnd}^h \cdot \overline{\frac{R\&D}{Assets}}i \leq 0$ as long as $\beta_{rnd}^h \leq 0$. Equivalently, in relative terms, innovative firms are more sensitive to supply chain shocks as long as $\beta_{rnd}^h < 0$.

Across different horizons, our novel empirical results confirm that high-R&D intensity firms reduce more significantly both total investment and R&D intensity in the aftermath of an adverse volatility shock.[2] This effect is visible over a one-year horizon when we focus on total investment. The disruptive effects of supply chain shocks on R&D intensity is even more long-lasting, as the implied β^h_{rnd} is statistically negative also over a three-year horizon. In order to interpret these effects, one can multiply the estimated coefficient by the difference in the R&D intensity across the extreme portfolios (i.e., about 22%) and a one standard deviation of the GSCPI (i.e., 1.08%). Hence, a one-standard deviation increase in the GSCPI implies a relative decline in R&D intensity across High- and Low-R&D intensity firms of about 8.7% over a three-year horizon.

Robustness. The literature has recently developed additional indices to capture supply chain disruptions. In what follows, we show that our results are robust to alternative measures. Specifically, we consider the Shortage Index All index by Caldara, Iacoviello, and Yu (2024), the Beige Book Supply Chain Disruption Index (BBSCDI) index by Kliesen and Werner (2022), and the Supply Chain Bottleneck Sentiment (SCB Sentiment) index by Soto (2023). All of these indices are based on text analysis methods as opposed to the GSCPI which is based on a large set of quantitative indicators and surveys.

As shown in figure 3, all of these indexes are highly correlated, suggesting that they capture similar information and that they share a strong common component. In order to reduce pure measurement noise coming from text analysis, we extract this common component by averaging the BBSCDI, SCB Sentiment and the log of the Shortage Index All. This composite index is highly correlated with the GSCPI.

Importantly, the results reported in Table 4 are very similar to the ones obtained using the GSCPI (see Table 2 and 3). Specifically, the average index has both a significant negative loading in the stochastic discount factor and market price of risk. The magnitude of the coefficients is slightly larger than those obtained using the GSCPI alone. In addition, our

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[2] These results hold also if we use variation in total assets as opposed to CAPEX to capture tangible investment.

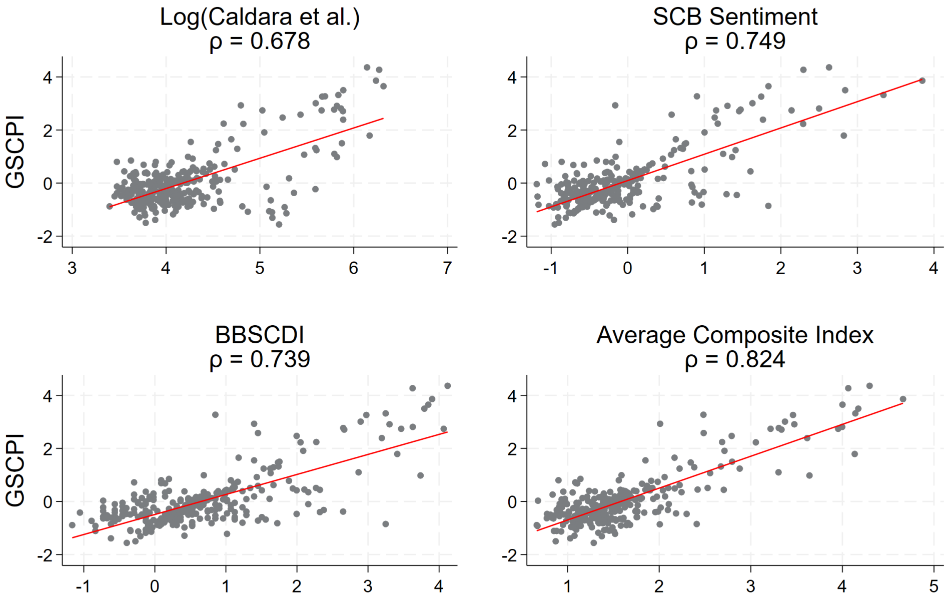

Fig. 3: Correlation between Supply Chain Indexes

Notes – This figure depicts the scatter plot and the implied correlation between GSCPI (horizontal axis) and several supply chain indices (vertical axis). GSCPI refers to the Global Supply Chain Pressure Index (GSCPI) from Benigno, di Giovanni, Groen, and Noble (2022). The other indices are: the Supply Chain Bottleneck Sentiment (SCB Sentiment) index from Soto (2023), the Beige Book Supply Chain Disruption Index (BBSCDI) index from Kliesen and Werner (2022), and the Shortage Index All index from Caldara, Iacoviello, and Yu (2024) in log units. The sample period is 1998M1-2023M4.

cross-sectional beta and growth regressions preserve the patterns in Table 3.

An aggregate perspective. Finally, we study the aggregate impact of supply chain shocks on aggregate investments on Intellectual Property Products (IPP), new patents granted, and GDP utilizing a long-sample perspective. For this exercise, we use a new shortage index developed by Caldara, Iacoviello, and Yu (2024). Differently from what done for GSCPI, the authors perform a text analysis on a sample of 25 million newspaper articles to produce a monthly shortage index for the United States from the year 1900. Specifically, the index measures the intensity of shortages of labor, materials, goods, and energy by calculating the proportion of articles discussing shortages each month. While this measure is potentially less precise, it is overall strongly positively correlated with the GSCPI (see figure 3) and the only one that enables us to use a long time series span. This dimension is crucial

Table 4: Robustness Analysis – Composite Index

Panel A: Estimation Results for MPRs(λ) and SDF Loadings (b)

$$E\left[m_{t+1}\cdot R^e_{i,t+1}\right]=0,\qquad m_{t+1}:=1-b'\cdot F_{t+1}$$

GMM							Implied MPR
Mkt-Rf	SMB	HML	RMW	CMA	Mom	Average CSI	Average CSI
0.010^{***}	-0.003^{***}	-0.004^{***}	0.002^{***}	0.015^{***}	0.008^{***}	-0.089^{***}	-1.733^{***}
(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.005)	(0.091)

Panel B: Differential Returns Exposure ($\beta^{AverageCSI}_{rnd}$ in equation (1))

	6FF	Ind. Prod. News	Ind Prod. & VIX News
$\beta^{AverageCSI}_{rnd}$	-0.028	-0.395^{***}	-0.424^{***}
	(0.036)	(0.038)	(0.034)

Panel C: Differential Expected Investment Growth Exposure (β^h_{rnd} in equation (2))

	1-Year	2-Year	3-Year
$\Delta I_{t\to t+h}$	-0.425^{***}	0.119	0.039
	(0.174)	(0.157)	(0.104)
$\Delta \frac{R\&D}{Assets}\ _{t\to t+h}$	-0.090^{**}	-0.321^{***}	-0.728^{***}
	(0.047)	(0.074)	(0.076)
$\Delta \frac{Patents}{R\&D}\ _{t\to t+h}$	0.225	1.012^{**}	-1.090^{*}
	(1.004)	(0.571)	(0.736)

Notes: Panel A (B and C) mimics Table 2 (Table 3). In this analysis, we adopt a composite supply chain index obtained by averaging the Supply Chain Bottleneck Sentiment (SCB Sentiment) index from Soto (2023), the Beige Book Supply Chain Disruption Index (BBSCDI) index from Kliesen and Werner (2022), and the Shortage Index All index from Caldara, Iacoviello, and Yu (2024) in log units. The sample period is 1998M1-2023M4.

when looking at aggregate US data, i.e., in the absence of a rich cross section.

Specifically, we estimate the following forecasting regressions using US quarterly data from 1972:Q1 to 2023:Q4:

$$\Delta[\cdot]_{t\to t+h}=\alpha^h+\beta^h\cdot\log(\text{shortage index})_{t-1}+\gamma^h_1\ Cycle(TFP)_{t-1}+\gamma^h_2 BAA_{t-1}+e^h_t, \tag{3}$$

where the left hand side refers to the h-periods ahead future real growth of either fixed investments in IPP, aggregate GDP, or new patents granted.[3] On the right hand side, we

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[3] Data on US nominal fixed investment in IPP and GDP are obtained from the NIPA tables. Nominal values are transformed in real growth rate using the GDP deflator. New patent granted is obtained from PatentsView.

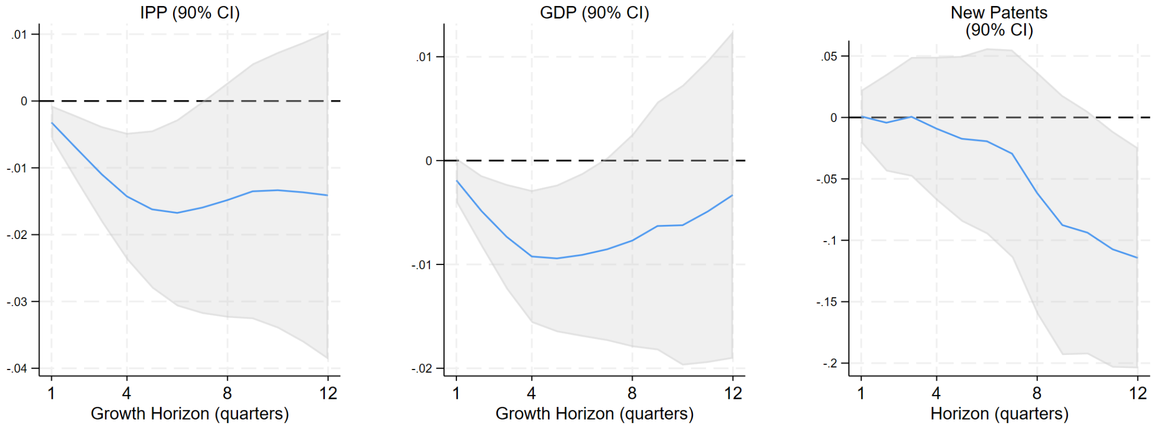

Fig. 4: US IPP, GDP, and Patents Response to Shortage Shock

Notes – This figure depict the estimate of β^h according to the following regression:

$$\Delta[\cdot]_{t\to t+h} = \alpha^h + \beta^h \cdot \log(\text{shortage index})_{t-1} + \gamma_1^h\ Cycle(TFP)_{t-1} + \gamma_2^h BAA_{t-1} + e_t^h$$

The left hand side refers to the h-periods ahead future real growth of either fixed investments in IPP, aggregate GDP, or new patents granted. On the right hand side, we use the lagged log value of overall shortage index (inclusive of labor, materials, goods, and energy) by Caldara, Iacoviello, and Yu (2024). We control for both general economic activity shocks (via lagged TFP) and financial conditions (via lagged Baa corporate spread). To ensure stationarity, the Hodrick-Prescott filter is applied to the TFP to extract its cyclical component.

use the lagged log value of overall shortage index (inclusive of labor, materials, goods, and energy), and we control for both general economic activity shocks (via lagged HP-filtered TFP) and financial conditions (via lagged Baa corporate spread).

We depict the estimates of β^h in Figure 4 in blue. Adverse shortage shocks generate a negative impact on IPP investments significant over several quarters. Importantly, the impact on output growth is both significant and negative over a longer horizon, implying that shortage shocks can affect economic activity growth in the medium-run consistent with results documented by Caldara, Iacoviello, and Yu (2024). In addition, when we focus on the output of innovation activities as measured by the growth of patents granted, we see a persistent decline which becomes statistically significant after approximately 9 quarters. This result supports further our attention toward the negative link between supply shocks and innovation.

In the next section, we propose a novel model in which the interplay of supply chain shocks and financial frictions affects growth in the long-run. Furthermore, we put forth a new counterfactual analysis in which we allow firms to access information on a supply chain blockchain in order to reallocate their activities in real time. We find that this technology may be extremely valuable with large social benefits.

3 The Model

As in Romer (1990), the production process involves three sectors. The final consumption good is produced in a competitive way using physical capital, labor, and intermediate goods. Stationary shocks drive stochastic fluctuations in the production of the final consumption good. Intermediate goods are produced by manufactures who have monopoly power over their variety but must pay a per-period royalty to the respective innovator. New patents are created by means of innovation through R&D in the innovation sector, which determine the speed of growth.

As in Kung and Schmid (2015), the representative agents has recursive preferences and prices growth news shocks. We depart from Kung and Schmid (2015) in two dimensions. First, we assume that in each period there is a time-varying share (or, equivalently, probability) of monopolistic intermediate good producers that are subject to supply shocks. This time-varying probability represents a distinct source of risk in addition to time-varying productivity.

Second, supply chains are linked to relevant financial frictions (among others, see Ersahin, Giannetti, and Huang (2024) for a US-based study and Alfaro, Brussevich, Minoiu, and Presbitero (2025) for an international perspective). We introduce financial frictions in a parsomonious way by assuming that the innovators require the manufacturers to pay a fraction of their per-period royalty at the begging of the period, that is, before the realization of the supply shock. Manufactures face a financing friction on their working capital since they provide this down payment by borrowing resources from the household via uncollateralized intra-period loans. These loans are expensive because the lenders anticipate default by the manufactures that are ex-post affected by production shocks. The interplay of working capital financial frictions and supply chain shocks depresses the market value of patents and hence R&D investments. At the equilibrium, R&D-capital is more exposed to supply chain shocks than tangible capital.

When focusing on our counterfactual scenario with supply chain blockchains, both all payment transfers and the goods produced are monitored in real time and an immediate reallocation of resources takes place. As a result, there is no need for uncollaterilzed debt and full information is restored. In this setting, innovators pay a convex cost of production reallocation toward productive manufactures.

3.1 The supply chain

The final good producer needs a bundle of intermediate goods denoted by Γ_t and defined as

$$\Gamma_t \equiv \left[\int_0^{N_t} (\mathbb{1}_{i,t+} \cdot X_{i,t})^{\nu} \, di \right]^{\frac{1}{\nu}}, \tag{4}$$

in which $\nu < 1$ determines the elasticity of substitution between variaties $(\frac{1}{1-\nu})$; $X_{i,t}$ is the quantity of intermediate good $i \in [0, N_t]$ ordered at the beginning of the period, whereas $(\mathbb{1}_{i,t+} \cdot X_{i,t})$ is the amount effectively produced after the realization of the supply shocks. N_t is the measure of intermediate goods in use at date t and we interpret it as the stock of R&D-intensive capital.

In contrast to Romer (1990) and Kung and Schmid (2015), we assume that producers are identical only ex-ante. Each one of them is subject to a disruption shock that materializes with probability $1 - \lambda_t$ in the middle of each period. This shock is assumed to be serially uncorrelated, meaning that in each period a random mass $(1 - \lambda_t)N_t$ is subject to it. If there is a supply chain shock, the firm will ex-post produce a fraction of the pre-ordered amount, $\theta X_{i,t}$, with $0 < \theta \leq 1$. In order to keep our model as close as possible to the original Romer's economy, we keep the size of the disruption, θ, constant. This assumption produces no loss of generality as λ_t determines how perversive the shock is. Given these assumptions, the indicator $\mathbb{1}_{i,t+}$ can be defined as follows:

$$\mathbb{1}_{i,t+} = \begin{cases} 1 & \text{with prob. } \lambda_t \\ \theta & \text{with prob. } 1-\lambda_t \end{cases}, \tag{5}$$

By law of large numbers and symmetry, Γ_t can be represented as:

$$\begin{aligned} \Gamma_t &= \left[\int_0^{\lambda_t \cdot N_t} X_{i,t}^{\nu} di + \int_{\lambda_t \cdot N_t}^{N_t} (\theta X_{i,t})^{\nu} di\right]^{\frac{1}{\nu}} & (6) \\ &= \{\underbrace{(\lambda_t + (1-\lambda_t)\theta^{\nu})}_{\omega_t} N_t\}^{\frac{1}{\nu}} X_t & (7) \end{aligned}$$

where $\omega_t := \lambda_t + (1-\lambda_t)\theta^{\nu} \in (0,1)$ captures the expected fraction of successful production, and $X_t = X_{i,t} \quad \forall i$ is the equilibrium amount of each good demanded before knowing the supply shocks. When either $\lambda_t = 1$ (no supply chain risk) or $\theta = 1$ (no disruption), we obtain the same result featured in Romer (1990).

3.2 The final good producer

There is a representative firm that uses tangible capital K_t, labor L_t, and a composite of patents Γ_t to produce the final good according to the following production technology,

$$Y_t = (K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi}\Gamma_t^{\xi}, \tag{8}$$

in which the parameter α (ξ) is the physical (intangible) capital share.

We introduce uncertainty into the model by means of an exogenous stochastic process Ω_t affecting the level of output. Importantly, we assume that Ω_t follows a stationary Markov process by specifying that $\Omega_t = e^{a_t}$, and $a_t = \rho a_{t-1} + \epsilon_t$, with $\epsilon_t \sim N(0, \sigma^2)$ and $\rho < 1$. Because the forcing process is stationary, sustained growth arises endogenously from the development of new patents. We describe how new patents are developed by means of innovation below.

The firm's objective is to maximize shareholder value. This can be formally stated as

$$\max_{\{I_t, L_t, K_{t+1}, X_{i,t}\}_{t\geq 0, i\in[0,N_t]}} \mathbb{E}_0 \left[\sum_{t=0}^{\infty} M_t D_t \right],$$

where the firm's dividends are

$$D_t = \left[Y_t - \int_0^{N_t} P_{i,t} \cdot (\mathbb{1}_{i,t+} \cdot X_{i,t})\, di \right] - W_t L_t - I_t. \tag{9}$$

Here, M_t is the stochastic discount factor, I_t is investment in physical capital, W_t is the wage rate, and $P_{i,t}$ is the price per unit of pre-ordered intermediate good i at time t. Prices $P_{i,t}$ are set by manufacturers in the intermediate good sector, while the stochastic discount factor and the wage rate are determined in the general equilibrium and are all taken as given by the final goods firm.

In line with the literature on production-based asset pricing, we assume that investment is subject to convex capital adjustment costs, so the physical capital stock evolves as

$$K_{t+1} = (1-\delta)K_t + \Lambda\left(\frac{I_t}{K_t}\right) K_t. \tag{10}$$

Here, δ is the depreciation rate of physical capital and $\Lambda(\cdot)$ the capital adjustment cost function. We specify $\Lambda(\cdot)$ as in Jermann (1998), $\Lambda\left(\frac{I_t}{K_t}\right) \equiv \frac{\alpha_1}{\zeta}\left(\frac{I_t}{K_t}\right)^{\zeta} + \alpha_2$, where $\frac{1}{1-\zeta}$ represents the elasticity of the investment rate with respect to Tobin's Q. The parameters α_1 and α_2 are set so that there are no adjustment costs in the deterministic steady state.

Intraperiod problem. We note that the final producer must order intermediate goods at the beginning of the period, that is, prior to observing the manufactures that are ex-post affected by production disruption. As a result, after having observed the current productivity level in the final sector, this firm demand intermediate goods by solving the following problem:

$$\max_{\{X_{i,t}\}_{t\geq 0, i\in[0,N_t]}} \mathbb{E}_t \left[(K_t^{\alpha}(\Omega_t L_t)^{1-\alpha})^{1-\xi} \left[\int_0^{N_t} (\mathbb{1}_{i,t+} \cdot X_{i,t})^{\nu} \, di \right]^{\frac{\xi}{\nu}} - \int_0^{N_t} P_{i,t} \cdot (\mathbb{1}_{i,t+} \cdot X_{i,t}) \, di \right],$$

Since all manufactures are ex-ante identical, the optimal demand of variety i is:

$$P_{i,t} = P_t = \xi \frac{Y_t}{\Gamma_t^{\nu}} \cdot \frac{\omega_t}{\omega_t^A} \cdot X_{i,t}^{\nu-1} \quad \forall i, \tag{11}$$

where $\omega_t^A := \lambda_t + (1-\lambda_t)\theta \in (0,1)$. Specifically, ω_t accounts for the expected productivity of a pre-ordered marginal unit of good $X_{i,t}$, whereas $P_{i,t}\omega_t^A$ is the expected price of an ex-post delivered marginal unit. In the absence of supply chain shocks ($\omega_t = \omega_t^A = 1$), this demand function is identical to the one in Romer (1990).

3.3 Intermediate goods sector

Supply chains are linked to relevant financial frictions that apply to working capital (among others, see Ersahin, Giannetti, and Huang (2024) for a US-based study and Alfaro, Brussevich, Minoiu, and Presbitero (2025) for an international perspective). We introduce working capital financing needs in a parsimonious way that we detail below.

Intermediate producers must pay a per-period royalty, $\mathcal{R}_i$, in order to produce good i under monopoly power. The agreement manufacturer-innovator happens at the beginning of the period, but the payment of the royalty takes place at the end of the period after production is realized. Since innovators are aware of the potential loss that they may incur because of the supply chain shock, they require collateral from the manufacturer, i.e., an initial downpayment. As in Romer (1990), the marginal cost of production is assumed to be equal to one and the sale price is denoted as $P_{i,t}$. The price is set at the beginning of the period and is not renegotiated.[4] Thus, each patent owner, i.e., each innovator, requires the following collateral

$$Cl_{i,t} = (1-\theta) \cdot (P_{i,t} - 1) \cdot X_{i,t} \tag{12}$$

which each producer must borrow from the households at rate r_t^c. In case of disruption, the collateral is retained by the innovator and the loss is suffered by the households.

We note that an alternative interpretation of equation (12) prescribes that at the beginning of the period the manufacturer needs funds in order to buy the inputs of production. The fraction of funds required to buy one unit of input is $(1-\theta) \cdot (P_{i,t} - 1)$ and $X_{i,t}$ measures the mass of inputs required.

The problem of the producer at the beginning of the period can be stated as follows:

$$\max_{X_{i,t}} \mathbb{E}_t \left[\mathbb{1}_{i,t+} \Pi_{i,t} \right] = \omega_t^A \cdot (P_{i,t} - 1) X_{i,t} - r_t^c (1-\theta) \cdot (P_{i,t} - 1) X_{i,t} - \mathcal{R}_{i,t}, \tag{13}$$

where the royalty $\mathcal{R}_{i,t}$ is taken as given since it is set by the innovator, and the process ω_t^A accounts for the expected disruption. Given this formulation of the problem, at the optimum,

$$\left[X_{i,t} + \frac{\partial X_{i,t}}{\partial P_{i,t}} \cdot (P_{i,t} - 1) \right] = 0 \quad \forall i,$$

as in a standard Romer's economy. As a result,

$$P_{i,t} = P_t = 1/\nu > 1 \quad \forall i. \tag{14}$$

By symmetry, equations (11) and (14) imply:

$$X_{i,t} = X_t = \left[\xi \nu \left(K_t^{\alpha} \left(\Omega_t L_t \right)^{1-\alpha} \right)^{1-\xi} \left[\omega_t N_t \right]^{\frac{\xi}{\nu} - 1} \frac{\omega_t}{\omega_t^A} \right]^{\frac{1}{1-\xi}} \quad \forall i \tag{15}$$

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[4] The buyer has no incentive to pay a higher price in case of supply disruption. She appeals to the contract and gets the residual quantity at the predetermined contract.

At the equilibrium, the ex-post realized dividends for the final good producer (equation (9)) are:

$$D_t = Y_t - W_t L_t - \frac{1}{\nu}\omega_t^A X_t N_t - I_t.$$

3.4 Innovation sector

Innovators develop new patents necessary to produce intermediate goods used in the production of final output. They do so by conducting research and development, using the final good as input at unit cost. Once a patent is produced, innovators receive royalties from the intermediate good producers. Each patent owner sets the royalty to extract the whole surplus from production. After accounting for both the expected produciton disruption and the costly collateral, the rent is:

$$\mathcal{R}_{i,t} = \left(\omega_t^A - r_t^c(1-\theta)\right)\left(\frac{1}{\nu} - 1\right) X_{i,t}.$$

A patent has a probability ϕ to become obsolete. Hence the market value of patent i is:

$$V_{i,t} = \mathcal{R}_{i,t} + (1-\phi)\,\mathbb{E}_t(M_{t+1}V_{i,t+1}), \tag{16}$$

where M denotes the stochastic discount factor in the economy. This present value pins down the benefit of innovation.

In order to determine the cost of innovation, we link the evolution of the intangible capital stock N_t, to innovation as follows:

$$N_{t+1} = \vartheta_t S_t + (1-\phi)N_t, \tag{17}$$

where S_t denotes R&D expenditures (in terms of the final good), and ϑ_t represents the productivity of the R&D sector. This process is taken as exogenous by the R&D sector and, as a result, ϑ_t^{-1} is perceived as the cost of innovating at the margin.

In the spirit of Comin and Gertler (2006), we assume that this technology coefficient involves a congestion externality effect

$$\vartheta_t = \frac{\chi \cdot N_t}{S_t^{1-\eta} N_t^{\eta}}, \tag{18}$$

where $\chi > 0$ is a scale parameter, and $\eta \in [0, 1]$ is the elasticity of new patents with respect to R&D. This specification captures the notion that concepts already discovered make it easier to come up with new ideas, $\partial\vartheta/\partial N > 0$, and that R&D investment has decreasing marginal returns, $\partial\vartheta/\partial S < 0$.[5]

We assume free-entry in the innovation sector and obtain the following market clearing condition:

$$\mathbb{E}_t[M_{t+1} V_{i,t+1}] = \frac{1}{\vartheta_t}, \tag{19}$$

This condition is crucial in this model, as it sets the equilibrium amount of R&D investment and ultimately determines the equilibrium growth rate of the economy. Importantly, R&D investment inherits the riskiness of profits.

3.5 Household

The household sector is standard. The representative household has Epstein-Zin preferences defined over consumption:

$$U_t = \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta (\mathbb{E}_t[U_{t+1}^{1-\gamma}])^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}}, \tag{20}$$

where γ is the coefficient of relative risk aversion, and ψ is the intertemporal elasticity of substitution. When $\psi \neq \frac{1}{\gamma}$, the agent cares about news regarding long-run growth prospects.

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[5] Similarly, this congestion externality can be thought of as giving rise to adjustment costs to investment in intangible capital, that is, R&D. We will later see that the optimality condition for R&D is $\frac{1}{\vartheta_t} = \mathbb{E}_t[M_{t+1} V_{t+1}]$. Absent the congestion externality, this becomes $1 = \mathbb{E}_t[M_{t+1} V_{t+1}]$, a result analogous to q-theory, in which case the absence of adjustment cost fixes marginal Q at unity.

We assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty and dislikes shocks to long-run expected growth rates.

The household maximizes utility by participating in financial markets and by supplying labor. Specifically, the household can take positions $\mathcal{Z}_t$ in the stock market, which pays an aggregate dividend $\mathcal{D}_t$, and positions B_t in the credit market.

The stock market is a claim to total cash flows generated by both the final goods producer and the innovators. Accordingly, we define the aggregate dividend as the net payout from all production sectors:

$$\mathcal{D}_t = D_t + N_t \cdot \mathcal{R}_t - S_t. \tag{21}$$

In addition, the credit market has to clear,

$$B_t = (1 - \theta)X_t \cdot (1/\nu - 1)N_t,$$

meaning that household must provide the intra-period financing required by the manufacturers. Since the bondholder gets nothing in case of default, by no arbitrage,

$$1 = (1 + r_{c,t})\lambda_t,$$

and hence at the equilibrium,

$$1 + r_{c,t} = \frac{1}{\lambda_t}.$$

Thus the household requires a default premium that perfectly offsets the default loss and her diversified loan portfolio pays B_t, i.e., the amount provided at the beginning of the period. Accordingly, the budget constraint of the household simplifies to

$$C_t + \mathcal{Q}_t \mathcal{Z}_{t+1} = W_t L_t + (\mathcal{Q}_t + \mathcal{D}_t)\mathcal{Z}_t,$$

where $\mathcal{Q}_t$ is the stock price, W_t is the wage, L_t denotes hours worked, and $\mathcal{Z}_t$ is the share of stock market equity held.

3.6 Aggregate Conditions and Supply Shocks

It can be shown that under the parameteric restriction $1-\alpha = \frac{\frac{\xi}{\nu}-\xi}{1-\xi}$, which we impose in the remaining of the paper, the model is equivalent to a real business cycle model with a standard neoclassical production function of the form $Y_t = Z_t K_t^{\alpha} L_t^{1-\alpha}$, where

$$Z_t \equiv \overline{A}(\Omega_t \omega_t N_t)^{1-\alpha} \left(\frac{\omega_t}{\omega_t^A}\right)^{\frac{\xi}{1-\xi}}, \tag{22}$$

is an endogenous productivity process, with $\overline{A} \equiv (\xi\nu)^{\frac{\xi}{(1-\xi)}} > 0$. In other words, our model can be seen as a real business cycle model in which productivity is endogenously driven by the accumulation of intangible capital via innovation. Supply chain shocks affect productivity both directly (through the ω_t process) and indirectly through its effect on the demand for intangible capital.

Given our assumptions, the aggregate resource constraint is:

$$Y_t = C_t + S_t + I_t + \omega_t^A X_t N_t,$$

and it accounts for production disruption. Consistently, measured GDP is

$$GDP_t = Y_t - \omega_t^A X_t N_t,$$

where the last term captures the network effect of production disruption.

We assume that the following holds:

$$\lambda_t = \frac{1}{1+\exp(-e_t)},$$

where

$$e_t = \overline{e}(1-\rho_e) + \rho_e e_{t-1} - J_t.$$

is a persistent process subject to a skewed shock J. For computational reasons, we mimic an infrequent 'jump' shock with the following continuous function:

$$J_t = \phi_0 \cdot \exp(u_t),$$

where (i) u_t is distributed as an *i.i.d.* $\mathcal{N}(0,1)$ shock, and (ii) we set ϕ_0 to be a small positive number. This formulation enables us to efficiently solve our model using the perturbation method.

3.7 An alternative setting with a supply chain blockchain

In our counterfactual setting, all the firms producing intermediate goods onboard into the 'blockchain', i.e., they belong to a peer-to-peer business network sharing information through a ledger which is updated using a cryptographically-enforced consensus rule (also denoted as Web 3.0 platform). By doing so, manufacturers can providing near real-time information about their production flows to the innovators. As a result, innovators subject to supply chain shocks have time to reallocate production and avoid production losses. Hence improved operational efficiency and resilience are a direct benefit of the blockchain adoption.

An indirect benefit of the blockchain is that it mitigates financial frictions. A ledger on a Web 3.0 platform can be programmed to execute smart contracts granting that invoices are automatically paid conditioned on a successful production outcome. In this case, the blockchain platform act as 'a decentralized issuer of supply-chain credit and payment solutions'.[6] Thanks to this functionality, in this setting we assume that the initial down payment

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[6] An application of this concept was announced by NTT Digital at the Singapore Fintech Festival 2024. NTT Digital is partnering with Amazon and StraitsX to provide tokenized accounts payable using their "scramberry WALLET SUITE". This application allows SMEs to receive payable tokens and trade them for XSGD tokens (a stablecoin), potentially enabling faster payment processing compared to traditional 7-90 day terms. See `https://nttdigital.io/pdf/20241105_nttdigital_press-release.pdf`.

is no longer required, and hence there is no longer a working capital financing constraint.

The reallocation, however, is not completely costless. Specifically, we assume that the reallocation is both costly and increasing in the extent of the supply chain shock. We denote this cost by $\tau(\lambda_t)$ and define it as follows:

$$\tau(\lambda_t) = \phi_0^\tau \cdot \exp(1 - \lambda_t).$$

The idea is that when the fraction of disrupted manufactures is high, it is more costly for the other producers to accommodate additional production. This statement must be interpreted broadly, as our function τ captures several margins of supply chain management, including, for example, shipping and inventory management (Ersahin, Giannetti, and Huang 2022). In addition, $\tau(\lambda_t)$ captures the cost of (i) running the platform, (ii) providing short-term financing through smart contracts, as well as the gas fees paid to the decentralized validators.

As a result of these assumptions, we need to modify our model in a few dimensions. First of all, we impose $\theta = 1$ in order to account for the fact that ordered and delivered intermediate goods coincide in every period. Since there is no longer need for collateral, $B_t = 0\ \forall t$. As a result, total rents become:

$$\int_0^{N_t} \mathcal{R}_{i,t} di = N_t \cdot \left[\left(\frac{1}{\nu} - 1 \right) X_{i,t} - (1 - \lambda_t) \cdot \tau(\lambda_t) \right],$$

where by law of large numbers $(1 - \lambda_t) \cdot \tau(\lambda_t) \cdot N_t$ is both the expected total reallocation cost at the beginning of the period and the ex-post realized cost. Finally, the aggregate resource constraint is:

$$Y_t = C_t + S_t + I_t + X_t N_t + (1 - \lambda_t) \cdot \tau(\lambda_t) \cdot N_t.$$

Why a blockchain? The reader satisfied with our model description can skip this paragraph and go to the next section. The reader curious about our choice to discuss a setting with a decentralized blockchain technology, instead, should to focus on what follows.

In our model, we assume that all firms participate to the web platform. In reality, unless mandatory by regulation, participation is an individual decision that depends on benefits and costs. One important dimension relates to the governance of the platform and the implied market power of its owner. Web 3.0 platforms have a decentralized ownership and hence they minimize the risk that one or few entities can take control of the platform and develop monopoly power. Hence the key difference between any other digital technology and 'the blockchain' is that a Web 3.0 platform may coordinate a group of firms without requiring their vertical integration and without altering their corporate structure. In a centralized platform (denoted as Web 2.0), the owner of the platform could act as a financial intermediary that monitors the suppliers and extracts a rent, in turn increasing the reallocation cost $\tau(\lambda_t)$.

Summarizing, our model characterizes a maximally efficient form of decentralized both (i) securitization of accounting receivables, and (ii) sharing of production flow information. The costs associated to this decentralized setting are determined by the parameter ϕ_0^τ, for which we provide sensitivity analysis in the next section.

3.8 Equilibrium and Asset Prices

An equilibrium is a set of sequences of prices and quantities such that (i) quantities solve producers' and the household's optimization problems, and (ii) prices are such that the markets clear. We focus on a symmetric equilibrium in which all patent producers are identical. In the following, we describe the most important equilibrium conditions.

The return to tangible capital. The final-good firm's optimality conditions are mostly standard. Denoting by $q_t = 1/\Lambda_t'$ the shadow value of physical capital, the first-order condition for investment in physical capital implies

$$\begin{aligned} R_{k,t+1} &:= \frac{1}{q_t}\left(\alpha(1-\xi)\frac{Y_{t+1}}{K_{t+1}} + q_{t+1}(1-\delta) - \frac{I_{t+1}}{K_{t+1}} + q_{t+1}\Lambda_{t+1}\right), \qquad (23) \\ 1 &= \mathbb{E}_t\left[M_{t+1}R_{k,t+1}\right]. \end{aligned}$$

The return to intangible capital. In the model, the return of intangible capital is

$$R_t^{rd} = \frac{V_t}{V_{t-1} - \mathcal{R}_{t-1}}.$$

The existence of two capital stocks, namely those of physical and intangible capital, gives rise to a cross section of stock returns in our model. For empirical purposes, we associate the return on tangible (intangible) capital, with the empirical returns of Low-R&D (High-R&D) firms. While clearly not unique, we view this mapping as natural and economically meaningful.

The return to the market. Optimality implies the following asset pricing condition:

$$\begin{aligned} R_{mkt,t+1} &= \frac{\mathcal{Q}_{t+1} + \mathcal{D}_{t+1}}{\mathcal{Q}_t} \\ 1 &= \mathbb{E}_t[M_{t+1} R_{mkt,t+1}]. \end{aligned} \tag{24}$$

Equivalently, the return to the market can be derived as the value-weighted average of the returns of tangible and intangible capital.

The stochastic discount factor in the economy is given by

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{\theta - 1} \left(\frac{U_{t+1}}{\mathbb{E}_t(U_{t+1}^{1-\gamma})^{\frac{1}{1-\gamma}}} \right)^{1-\gamma-\theta}, \tag{25}$$

where the second term involves continuation utilities and captures concerns about long-run growth prospects, and the risk-free rate is defined as usual

$$R_{f,t} = 1/\,\mathbb{E}_t[M_{t+1}].$$

In equilibrium, the representative agent holds the entire supply of both bonds and equities. The latter is normalized to be one, that is, $\mathcal{Z}_t = 1 \; \forall t$.

Table 5: Benchmark calibration

Parameter	Symbol	Value
Subjective discount factor	β	0.996
Risk aversion	γ	10
Intertemporal elasticity of substitution	ψ	1.2
Capital share	α	0.35
Intangible capital congestion, scale parameter	χ	0.37
Intangible capital congestion, elasticity	η	0.83
Physical capital adjustment costs, elasticity	$1/(1-\zeta)$	5
Elasticity of substitution across goods	$1/\nu$	1.65
Intangible capital share	ξ	0.5
Probability of patent obsoletes	ϕ	0.0375
Depreciation rate of capital	δ	0.02
Persistence of productivity shock	ρ	0.9925
Share of un-disrupted production	θ	0.4
Persistence of disruption shock	ρ_e	0.6
Mean of disruption	$\bar{e}$	3.5
Parameter of the jump process	ϕ_0	0.35
Parameter of the relocation cost function	ϕ_0^τ	0.003

Empirical estimates of the likelihood of non-disruption shock λ_t

	Model	Estimate	Standard Error
Mean	0.872	0.757	0.017
Standard deviation	0.114	0.176	0.022
Autocorrelation	0.597	0.587	0.095
Skewness	-3.408	-2.076	0.942

Notes – The top panel of table reports our benchmark quarterly calibration. See section 4.1 for a detailed discussion. The bottom panel reports summary statistics for our measure of λ_t^{Data}, defined in equation (26). When estimating the persistence, we end the sample in 2019:Q4 to avoid bias due to the large skewness of the shocks during the COVID years. The entries from the model are based on repetitions of small samples.

4 Quantitative results

In this section, we calibrate our model and explore its predictions on the effects of supply chain disruption risk on asset prices, R&D investment, and growth. We show that supply chain risk is of first-order effect. We will first discuss our calibration in the next section, and then present our quantitative findings.

4.1 Calibration

We report our benchmark quarterly calibration in table 5. The household's subjective discount factor (β) is set to 0.996, and the risk aversion (γ) is set to 10 in line with reasonable upper bounds (Mehra and Prescott 1985). The intertemporal elasticity of substitution (IES, ψ) is set it to 1.2, consistent with results in the long-run risk literature. The household's subjective discount rate is chosen to target the average historical level of the risk-free rate.

In the R&D sector, we set the quarterly survival rate $1-\phi$ of a patent to 0.96, consistent with the BEA annual depreciation rate for R&D capital of about 16%. The elasticity of new intermediate goods with respect to R&D (η) is set to the value reported in Croce, Nguyen, and Schmid (2012). Furthermore, our choice of η is within the range of panel and cross-sectional estimates from Griliches (1990). χ is a scale parameter that is set to match an average annual consumption growth of about 2.0%.

In the data, low-R&D firms command a lower risk premium than R&D-intensive firms. To reproduce this fact, we set the elasticity of the adjustment cost function $1/(1-\zeta)$ to 5. The elasticity of substitution between intermediate goods (ν) is set to capture the fact that the level of productivity in the final goods sector is increasing. Given ν and ξ, the parameter α—which determines the average income share of physical capital—is pinned down from the balanced growth restriction. The annualized depreciation rate of physical capital (δ) is set to a standard value of 8%.

Turning to parameters that determine the prevalence of supply chain shocks, we use the Global Supply Chain Pressure Index (GSCPI) from the Federal Reserve Bank of New York to discipline them. This measure is available at the monthly frequency, and we aggregate it up to quarterly frequency by taking the average of the monthly observations. As seen in figure 2, firms are under extreme supply chain pressures during the COVID years. We normalized the GSCPI to be between 0 and 1 and use it to proxy for the fluctuations of

$1 - \lambda_t$ in our model. Specifically, at quarter t, we define

$$\lambda_t^{Data} = 1 - \frac{GSCPI_t - \min(GSCPI_t)}{\max(GSCPI_t) - \min(GSCPI_t)}. \tag{26}$$

This normalization assumes that when the GSCPI index reaches its highest (lowest) level in the current sample, all (none) of the intermediate good producers are affected by disruption.

We report four key empirical moments of this measure in table 5, and we pick $\overline{e}$, ρ_e, and ϕ_0 to broadly match these four empirical moments, i.e., to make sure that the model-simulated moments are in our empirical confidence intervals. We acknowledge that our average λ is higher than in the data, but this implies that in the model the average frequency of our disruption shocks is conservative.

Given the implied supply chain risk governed by these parameters, we choose θ to match the average supply chain disruption costs in the spirit of empirical estimates by Barrot and Sauvagnat (2016), Carvalho, Nirei, Saito, and Tahbaz-Salehi (2020), and Alfaro, Minoiu, Brussevich, and Presbitero (2024).

The calibration of ϕ_0^τ is rather difficult, as it refers to a setting in which the reallocation costs are mitigated by the fact that all firms adopt the blockchain technology. This is clearly a counterfactual scenario for which we have no direct empirical counterpart. We calibrate this parameter so that the supply management costs are lower than those observed in Ersahin, Giannetti, and Huang (2022) and run sensitivity analysis about it. When we choose $\phi_0^\tau = 0.003$, the average cost is 0.07% of GDP, i.e., a relatively small amount.

4.2 Results

In table 6, we report simulated moments from our model both with and without blockchain technology. We refer to these two scenarios as “Platform model” and “Disruption model”, respectively. The “Disruption model” is the one that reflects our current data. Our model matches key macroeconomic dynamics. In addition, our model is able to produce a sizeable average HML-R&D, i.e., innovation capital is riskier than regular capital as in the data.

Table 6: Model summary statistics

	Data		Model	
	Point Est.	St.Err.	Disruption	Platform
$E[\Delta C]$	2.09	0.25	2.21	3.16
$\sigma(\Delta C)$	2.16	0.48	1.67	1.61
$\sigma(\Delta C)/\sigma(\Delta GDP)$	0.79	0.09	0.52	0.59
$\sigma(\Delta S)/\sigma(\Delta GDP)$	1.52	0.25	1.99	1.40
$E[R_f]$	1.25	0.21	2.35	3.25
$E[R_c]$	3.57	1.16	3.50	4.24
$E[R_{R\&D}^{HML}]$	7.39	5.52	2.94	0.66
$\log(U_t/N_t)$			-0.58	0.38
$\log(U_t/C_t)$			1.30	2.35
$\log(V_{c,t}/C_t)$			5.74	5.92

Notes – Statistics are obtained from averages of 100 short-sample simulations. GDP, C, I and S denote gross domestic product, consumption, tangible investment, and R&D investment, respectively. U/N is the utility-to-stock of patent ratio, and V_c/C is the price-dividend ratio for the asset that pays dividend equals to consumption every period. R_c is the return to the asset that pays aggregate consumption. Its data counterpart comes from Lustig, Van Nieuwerburgh, and Verdelhan (2013). R_f denotes the risk-free rate; $R_{R\&D}^{MHL}$ is the difference between the levered log return of intangible and tangible capital. Means and standard deviations are annualized and expressed in percent.

Our study of the environment with supply chain blockchain is novel to the literature. Our model implies that this tool could be very valuable across many dimensions. First, long-run growth is predicted to increase by 0.95% every year. This substantial improvement is due to both less production disruptions and less concerning financial frictions.

Second, we can compare the welfare of out two economies with and without blockchain, assuming that they both start with the same amount of intangible capital. Equivalently, we can compare welfare gains by looking at the U/N ratios. Since our utility is homogeneous of degree one, we can conclude that moving to a setting with a supply chain blockchain could produce welfare gains equal to 96% of time-0 consumption in the economy with disruptions.[7]

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[7] Assuming a common level of time-0 intangible capital, N_0, one can compute the welfare gains, $1+g$, using the following equation:

$$\frac{U\left(C^D(1+g)\right)}{N}N_0 = \frac{U\left(C^P\right)}{N}N_0,$$

where D and P denote the consumption stream under the 'disruption' and the 'platform' settings. Because of the homogeneity of U, the log gain is

$$\log(1+g) = \log\frac{U^D}{N} - \log\frac{U^P}{N}.$$

This sizable gain can be decomposed in two parts. The first component is determined by differences in the time-0 level of consumption per unit of capital, $\frac{C_0}{N_0}$, across the two economies. The second part is driven by the utility gains per unit of consumption, U/C. The second components is what Lucas (1987) computes an in endowment economy in which capital accumulation is not considered. In our experiment, the economy with the platform produces a utility-consumption ratio that is 105% higher than that of the economy with disruption. A higher gain in the utility-consumption ratio compared to the welfare figure reflects the fact that in the economy with the platform the consumption-to-intangible capital ratio is lower than in the economy with disruption. This result is driven by the fact that in this alternative setting production is less risky and there is an incentive to accumulate more capital than in the economy with disruption. Hence, at the steady state, the consumption-intangible capital ratio is lower than in the economy without platform. Simultaneously, we observe an improvement in the wealth-consumption ratio of 18%. Both of these figures are driven mainly by the improved dynamic properties of the consumption profile in the economy with the platform. Equivalently, the economy with the platform setting features a lower amount of consumption risk. Indeed under the platform model all risk premia decline substantially implying more investment. To the extent that R&D investment also increases, growth improves as well.

In what follows, we study the change in risk by inspecting the impulse response functions produced by our model. In figure 5, we depict the responses of key macro variables to both productivity (left panels) and supply chain shocks (right panels).

The responses with respect to productivity are standard and consistent with Kung and Schmid (2015). We find it more informative to discuss the responses upon the realization of an adverse supply chain shock. Under the setting without blockchain, this type of shock is as contractionary as a negative productivity shock. In addition, it has a persistent negative effect on both consumption and intangible investment growth. These adverse effects are substantially mitigated in the setting with the blockchain platform, and as a result, the

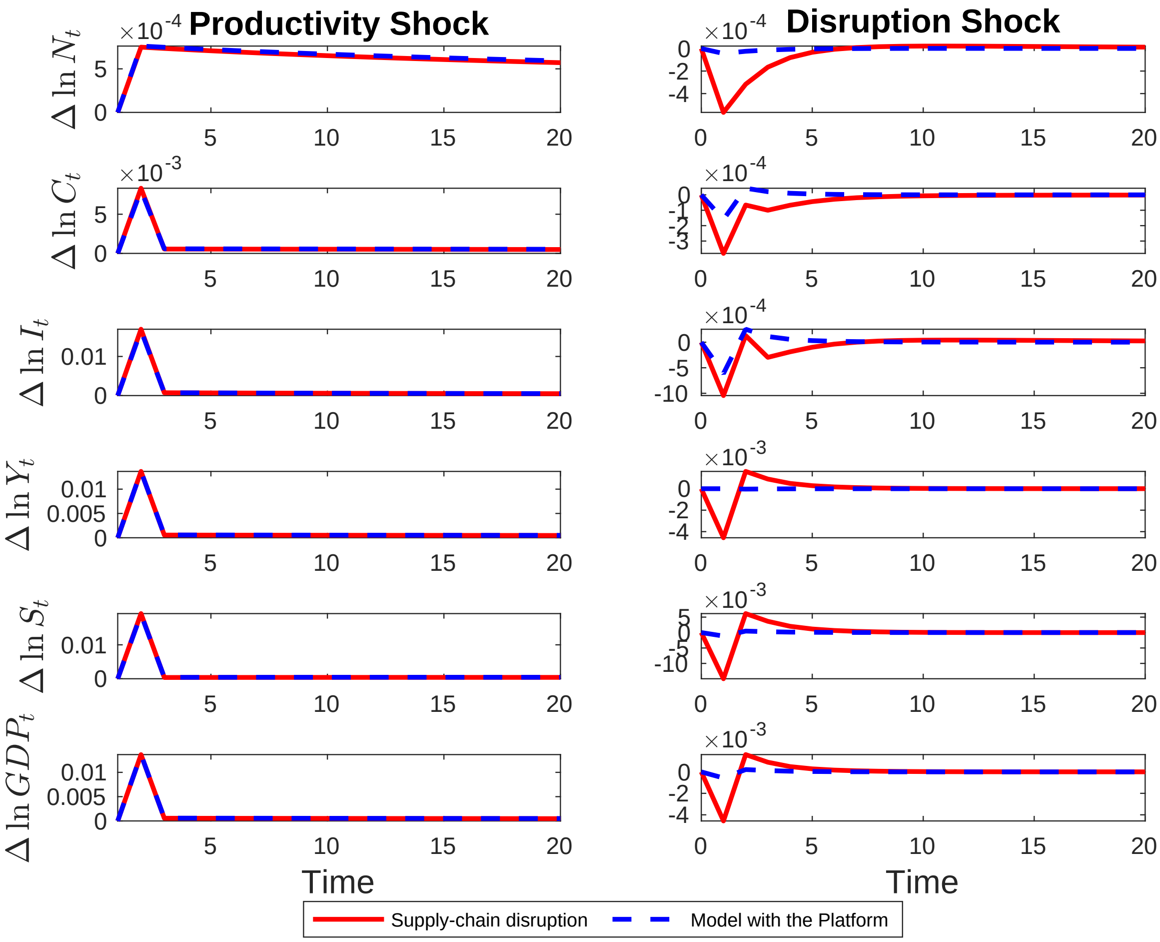


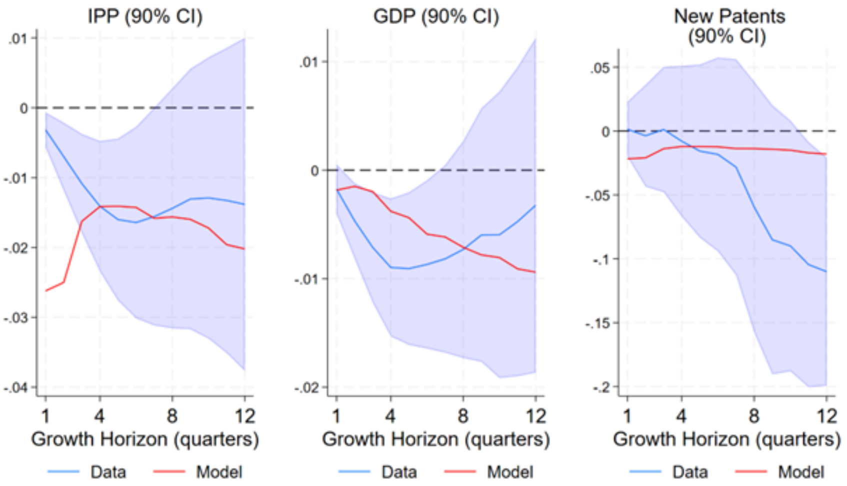
Fig. 5: Impulse responses to structural shocks

Notes – Impulse responses to one-standard-deviation shocks to technology and supply chain. All parameters are calibrated as in table 5. A positive productivity shock is expansionary. A positive disruption shock corresponds to a higher supply chain disruption and it is contractionary.

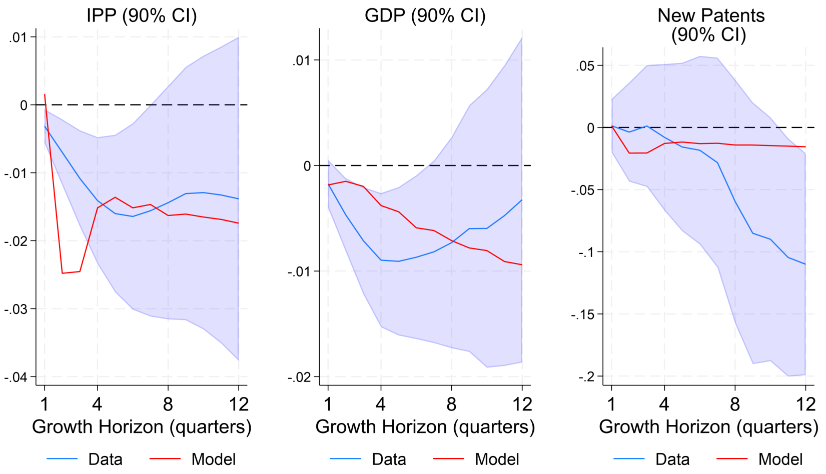
disruption to GDP is almost null.

We find it important to compare the responses in our model to those reported in figure 4. We do so by running our local projections regressions on simulated data and we depict the results in figure 6. In the model, investment is adjusted simultaneously with the disruption shock. In reality, investment decisions may be pre-committed by multiple quarters (Kuehn, 2007). This means that the decided adjustment of corporate investment would show up with delay in national accounting.

In order to account for this consideration, we ask what the local projections would look



(a) Benchmark



(b) One additional quarter of delay

Fig. 6: US IPP, GDP, and Patents Response to Shortage Shock (II)

Notes – This figure depicts the data estimate of β^h obtained as described in figure 4. The red line is obtained by running the same regressions on simulated data. In the model, the shortage index counterpart is $-e_t$, and we control for a_{t-1}, k_{t-1}, $\log(N_t/N_{t-1})$, and the cyclical component of Z_t from a HP filter. IPP and new patents are $\log(S_t)$ and $\log(\vartheta_t \cdot S_t)$, respectively. We depict the median of the estimated coefficients across 100 repetitions of small samples. In panel (b), we consider the case in which investment decisions are lagged by two quarters, as opposed to one quarter as in the model. Equivalently, the econometrician receives simulated investment data with a total delay of two quarters.

like if the econometrician would receive simulated investment and patent data with an additional delay of one quarter. The answer is depicted in the bottom portion of figure 6. The initial estimated reaction is mechanically null. The decline of both IPP and new patents

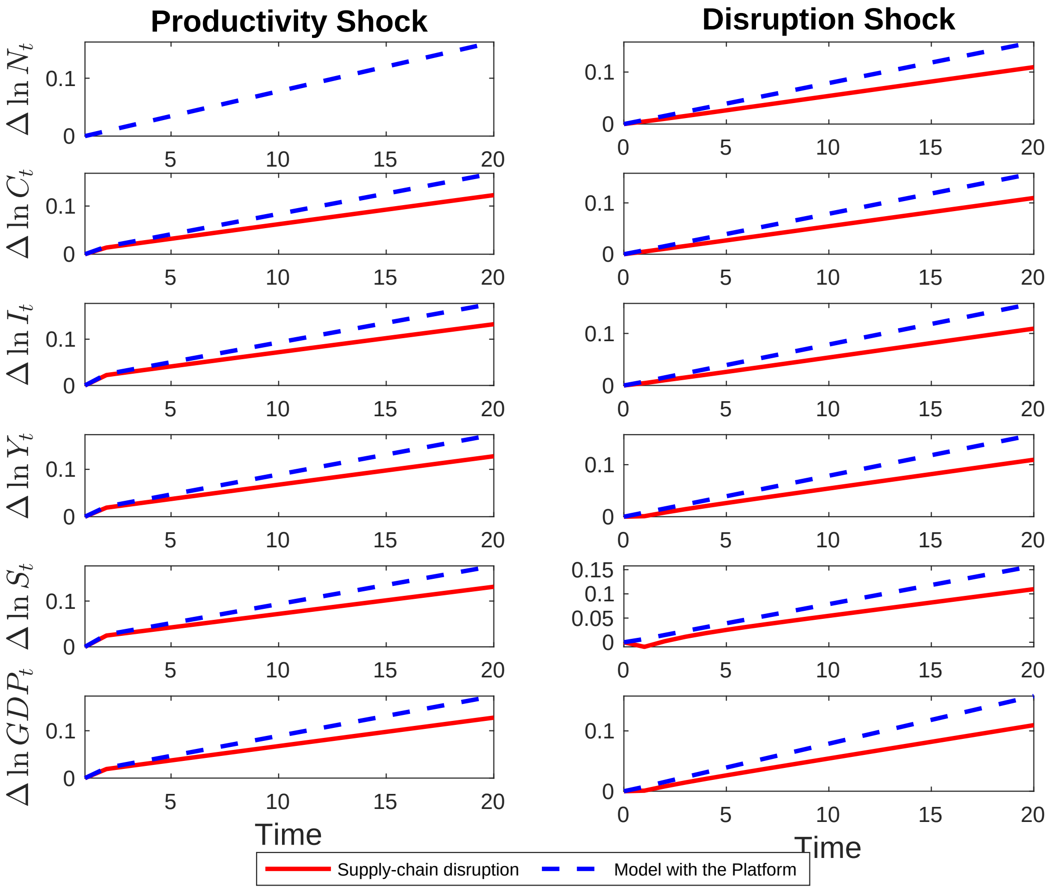


Fig. 7: Cumulative impulse responses to structural shocks

Notes – Cumulative impulse responses to one-standard-deviation shocks to technology and supply chain disruption. All parameters are calibrated as in table 5.

would be estimated to be gradual over time. Across different lags, our model captures a plausible contraction in both aggregate IPP and GDP.

In order to better assess the long-run implications of these shocks, in figure 7 we depict cumulative impulse response functions, meaning that we accumulate the per-period growth adjustments. This figure clearly shows that the economy with the blockchain platform is more resilient across all shocks. In particular, supply chain shocks have a modest short-run effect in this setting, and the long-run path of the economy grows at a much faster pace.

In figure 8, we turn our attention to asset prices. As in the data, our model predicts that innovation-oriented capital is more exposed to supply chain shocks than regular capital (right panel). In addition, as seen in the left panel, the implied market price of risk is negative,

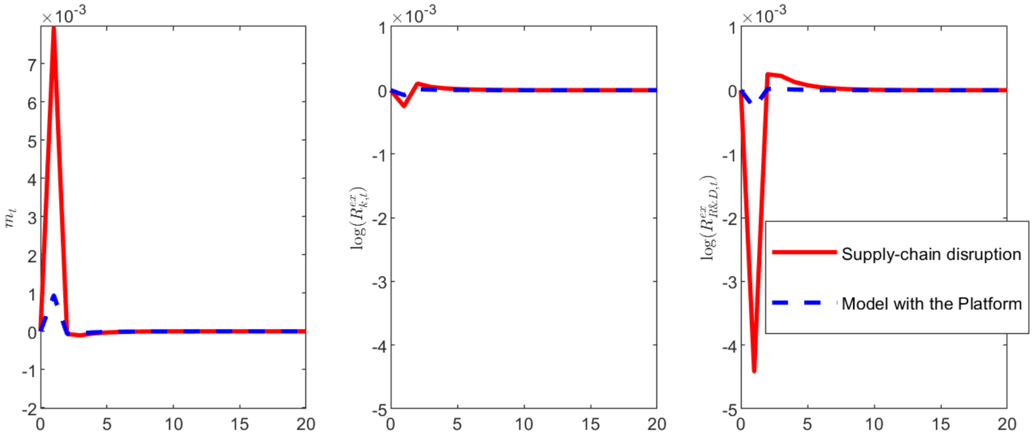


Fig. 8: Impulse responses to a one-standard-deviation disruption shock

Notes – Impulse responses to a one-standard-deviation disruption shock. All parameters are calibrated as in table 5.

meaning that positive shocks correspond to high-marginal utility states (high stochastic discount factor). By no-arbitrage, R&D capital is riskier than tangible capital, consistent with our empirical results discussed previously.

Importantly, these effects are mitigated when we look at a setting with a blockchain platform. This explains why in this setting risk premia declines together with substantial improvement in welfare.

Sensitivity analysis. In the last part of our couterfactual exercise, we study welfare and wealth in the economy with the supply chain blockchain platform as we vary the average level of the reallocation cost. We do so by varying the ϕ_0^τ so that the average reallocation costs ranges from nearly 0% to 2% of GDP. As seen in figure 9, the economy where a blockchain-based platform is used to manage supply chain shocks features a welfare level that is superior to that without a platform as long as the reallocation costs are below 1.6% of GDP, that is, $\phi_0^\tau \leq 0.07$. We interpret this threshold as suggesting that there is a very strong trade-off between the reallocation cost and the willingness to acquire greater resilience against supply shocks, meaning that even a small degree of reduction of the reallocation cost can trigger major resilience gains.

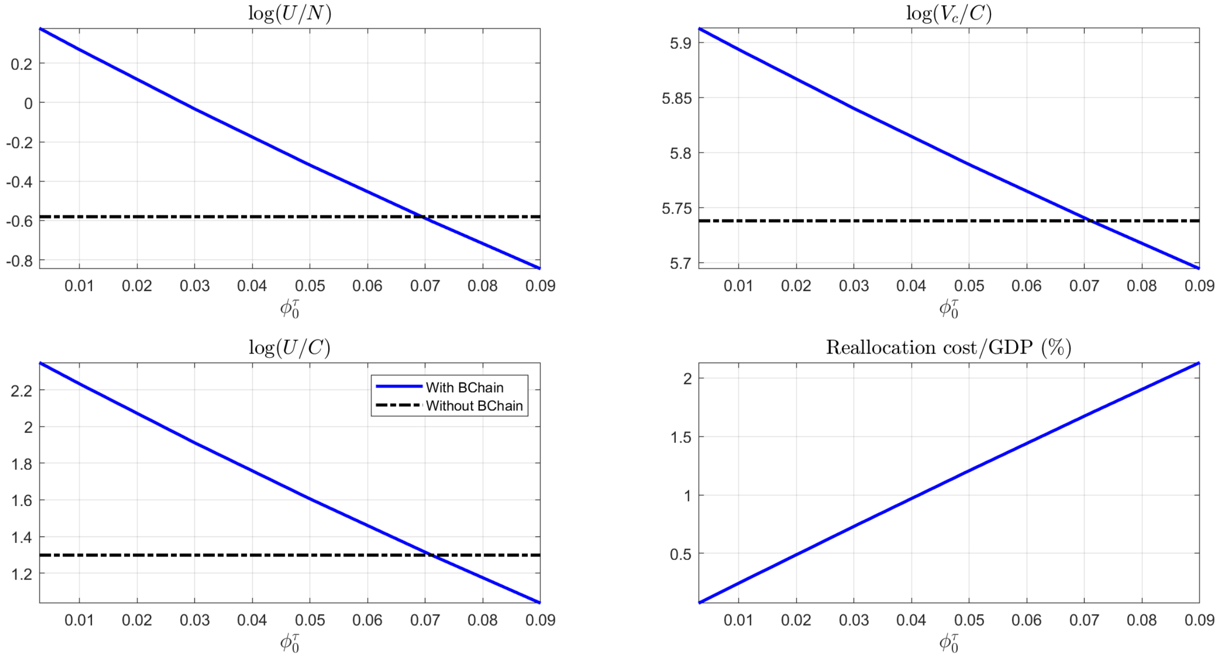


Fig. 9: The Role of Supply Chain Blockchain Efficiency

Notes – This figure depicts quarterly steady state values as we vary the average reallocation cost associated to the model with the supply chain blockchain platform.

Interpreting this result more broadly, one can think of the reallocation convex cost as capturing many margins, including concerns about data leakage. This aspect is important because the adoption of this technology is currently slow, as many firms are concerned about sharing their supply chain data with a few big service providers. Hence, we can think of our convex cost as embodying also concerns about leakage of information and anti-competition practices. Given our welfare analysis, any policy aimed at mitigating this concerns could produce substantial benefits.

5 Conclusions

Supply chain shocks are pervasive with significant consequences. In the data, we show that R&D-intensive firms are more exposed to these shocks, making their cost of equity higher. In the cross section of R&D-sorted stocks, the exposure to supply chain shocks is negative and increasingly so with R&D intensity. Thus, innovation intensive stocks bear a higher risk premium. As investments and innovations by these R&D firms are the engine to growth, the higher cost of equity hinders long-term economic outcomes and can have large consequences from a social perspective.

We interpret our empirical results in the context of a 'MacroFinTech' general equilibrium production economy in which endogenous innovation drives long-term growth and firms are exposed to supply chain risk. We find that supply chain shocks are as important as productivity shocks in driving innovations and hence growth. Moreover, we show that FinTech, such as supply chain blockchains—which provide near real-time information that allows innovators to reallocate production and avoid losses—can bring us close to the first best with substantial welfare gains. We believe our paper makes a relevant contribution to a new perspective within the emerging strand of 'MacroFinTech' literature.

References

Acemoglu, Daron, and Alireza Tahbaz-Salehi, 2020, Firms, Failures, and Fluctuations: The Macroeconomics of Supply Chain Disruptions, Discussion Paper 15074 CEPR Press Paris & London.

Acharya, Viral V, Matteo Crosignani, Tim Eisert, and Christian Eufinger, 2023, How Do Supply Shocks to Inflation Generalize? Evidence from the Pandemic Era in Europe, Working Paper 31790 National Bureau of Economic Research.

Alfaro, Laura, Mariya Brussevich, Camelia Minoiu, and Andrea Presbitero, 2025, Bank Financing of Global Supply Chains, NBER Working Paper 33754 National Bureau of Economic Research.

Alfaro, Laura, Manuel García-Santana, and Enrique Moral-Benito, 2021, On the direct and indirect real effects of credit supply shocks, *Journal of Financial Economics* 139, 895–921.

Alfaro, Laura, Camelia Minoiu, Mariya Brussevich, and Andrea Presbitero, 2024, Bank Financing of Global Supply Chains, *HBS Working paper*.

Bai, Xiwen, Jesús Fernández-Villaverde, Yiliang Li, and Francesco Zanetti, 2023, The Causal Effects of Global Supply Chain Disruptions on Macroeconomic Outcomes: Evidence and Theory, University of Oxford.

Baldwin, R., R. Freeman, and A. Theodorakopoulos, 2023, Hidden Exposure: Measuring US Supply Chain Reliance, Discussion Paper 18555 CEPR Press Paris & London.

Bansal, Ravi, and Amir Yaron, 2004, Risk for the Long Run: A Potential Resolution of Asset Pricing Puzzles, *The Journal of Finance* 59, 1481–1509.

Barrot, Jean-Noël, and Julien Sauvagnat, 2016, Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks, *The Quarterly Journal of Economics* 131, 1543–1592.

Belo, Frederico, Santiago Bazdresch, and Xiaoji Lin, 2014, Labor Hiring, Investment, and Stock Return Predictability in the Cross Section, *Journal of Political Economy* 122, 129–177.

Belo, Frederico, Vito Gala, Juliana Salomao, and Maria Ana Vitorino, 2022, Decomposing Firm Value, *Journal of Financial Economics* 143, 619–639 Lead Article, Editor's choice.

Belo, Frederico, Xiaoji Lin, and Fan Yang, 2018, External Equity Financing Shocks, Financial Flows, and Asset Prices, *Review of Financial Studies* 32, 3500–3543.

Benigno, Gianluca, Julian di Giovanni, Jan J. Groen, and Adam I. Noble, 2022, The GSCPI: A New Barometer of Global Supply Chain Pressures, Staff Report 1017 FRB of New York.

Brunnermeier, M., 2022, *The Resilient Society: Economics After Covid.* (HarperBusiness).

Brunnermeier, Markus K., and Jonathan Payne, 2023, FinTech Lending, Banking, and Information Portability, Working paper Princeton University.

Caldara, D., M Iacoviello, and D Yu, 2024, Measuring Shortages Since 1900, *Working paper.*

Campanale, Claudio, Rui Castro, and Gian Luca Clementi, 2010, Asset pricing in a production economy with Chew–Dekel preferences, *Review of Economic Dynamics* 13, 379–402.

Capponi, Agostino, Chuan Du, and Joseph E. Stiglitz, 2024, Are supply networks efficiently resilient?, Available at SSRN: https://ssrn.com/abstract=4741174 or http://dx.doi.org/10.2139/ssrn.4741174.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi, 2020, Supply Chain Disruptions: Evidence from the Great East Japan Earthquake, *The Quarterly Journal of Economics* 136, 1255–1321.

Chen, Y., Z. Gui, E. von Thadden, and X. Zhao, 2024, Supply Chain Frictions, Discussion Paper 19013 CEPR Press Paris & London.

Comin, Diego, and Mark Gertler, 2006, Medium-Term Business Cycles, *American Economic Review* 96, 523–551.

Comin, Diego A, Mark Gertler, and Ana Maria Santacreu, 2009, Technology innovation and diffusion as sources of output and asset price fluctuations, npublished working paper. National Bureau of Economic Research.

Corhay, Alexandre, Howard Kung, and Lukas Schmid, 2015, Competition, Markups and Predictable Returns., Unpublished working paper. Duke University.

Croce, Max, 2014, Long-run productivity risk: A new hope for production-based asset pricing?, *Journal of Monetary Economics* 66, 13–31.

Croce, Max, Thien T. Nguyen, and Lukas Schmid, 2012, The Market Price of Fiscal Uncertainty, *Journal of Monetary Economics* 59, 401–416.

di Giovanni, Julian, Sebnem Kalemli-Özcan, Alvaro Silva, and Muhammed A. Yildirim, 2023, Pandemic-era Inflation Drivers and Global Spillovers, Faculty Working Paper 440 Center for International Development (CID), Harvard University.

Diercks, Anthony M., Alex Hsu, and Andrea Tamoni, 2024, When It Rains It Pours: Cascading Uncertainty Shocks, *Journal of Political Economy* 132, 694–720.

Dou, Winston Wei, Yan Ji, Di Tian, and Pengfei Wang, 2025, Misallocation and Asset Prices, .

Elliott, Matthew, and Benjamin Golub, 2019, Networks and Economic Fragility, *Annual Review of Economics* 11, 465–488.

Ersahin, N., M. Giannetti, and R. Huang, 2022, Supply Chain Risk: Changes in Supplier Composition and Vertical Integration, Discussion Paper 17208 CEPR Press Paris & London.

Ersahin, Nuri, Mariassunta Giannetti, and Ruidi Huang, 2024, Trade credit and the stability of supply chains, *Journal of Financial Economics* 155.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F., and Kenneth R. French, 2018, Choosing factors, *Journal of Financial Economics* 128, 234–252.

Franzoni, F., M. Giannetti, and R. Tubaldi, 2023, Supply Chain Shortages, Large Firms' Market Power, and Inflation, Discussion Paper 18574 CEPR Press Paris & London.

Gavazzoni, Federico, and Ana Maria Santacreu, 2015, International R&D Spillovers and Asset Prices., Unpublished working paper. INSEAD.

Gornall, William, and Ilya A Strebulaev, 2013, Financing as a Supply Chain: The Capital Structure of Banks and Borrowers, Working Paper 19633 National Bureau of Economic Research.

Gourio, Francois, 2012, Disaster Risk and Business Cycles, *American Economic Review* 102, 2734–2766.

Gourio, Francois, 2013, Credit Risk and Disaster Risk, *American Economic Journal: Macroeconomics* 5, 1–34.

Griliches, Zvi, 1990, Patent Statistics as Economic Indicators: A Survey, *Journal of Economic Literature* 28, 1661–1707.

Grossman, G., E. Helpman, and A. Sabal, 2023, Resilience in Vertical Supply Chains, Discussion Paper 18491 CEPR Press Paris & London.

Grossman, Gene M, and Elhanan Helpman, 1991, Quality ladders in the theory of growth, *The Review of Economic Studies* 58, 43–61.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015a, A Comparison of New Factor Models., Unpublished working paper. Ohio State University.

Hou, Kewei, Chen Xue, and Lu Zhang, 2015b, Digesting Anomalies: an Investment Approach, *Review of Financial Studies* 28, 650–705.

Jermann, Urban Joseph, 1998, Asset Pricing in Production Economies, *Journal of Monetary Economics* 41, 257–275.

Jermann, Urban Joseph, 2010, The Equity Premium Implied by Production, *Journal of Financial Economics* 98.

Jermann, Urban J., 2023, A Macro Finance Model for Proof-of-Stake Ethereum, *Working Paper* Available at SSRN: https://ssrn.com/abstract=4335835 or http://dx.doi.org/10.2139/ssrn.4335835.

Kaltenbrunner, Georg, and Lars A. Lochstoer, 2010, Long-Run Risk through Consumption Smoothing, *Review of Financial Studies* 23, 3190–3224.

Kliesen, Kevin L, and Devin Werner, 2022, Using Beige Book text analysis to measure supply chain disruptions, *Economic Synopses*.

Kogan, Leonid, and Dimitris Papanikolaou, 2009, Growth Opportunities and Technology Shocks, .

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2012, Technological Innovation, Resource Allocation and Growth, *Working Paper, MIT*.

Kogan, Leonid, Dimitris Papanikolaou, and Noah Stoffman, 2013, Technologial Innovation: Winners and Losers, *Working Paper, MIT*.

Kuehn, Lars-Alexander, 2007, Disentangling Investment Returns and Stock Returns: The Importance of Time-to-Build, .

Kuehn, Lars Alexander, 2008, Asset Pricing and Real Investment Commitment., Unpublished working paper. Carnegie Mellon University.

Kuehn, Lars Alexander, 2009, Disentangling Investment Returns and Stock Returns: the Importance of Time-to-Build., Unpublished working paper. Carnegie Mellon University.

Kung, Howard, and Lukas Schmid, 2015, Innovation, Growth, and Asset Prices, *Journal of Finance* 70, 1001–1037.

Li, Dongmei, 2011, Financial Constraints, R&D Investment, and Stock Returns, *The Review of Financial Studies* 24.

Lin, Xiaoji, 2012, Endogenous technological progress and the cross-section of stock returns, *Journal of Financial Economics* 103, 411–427.

Lucas, Robert E., 1987, *Models of Business Cycles.* (Oxford: Basil Blackwell).

Lustig, Hanno, Stijn Van Nieuwerburgh, and Adrien Verdelhan, 2013, The Wealth-Consumption Ratio, *Review of Asset Pricing Studies* 3, 38–94.

Mehra, Rajnish, and Edward C. Prescott, 1985, The Equity Premium: a Puzzle, *Journal of Monetary Economics* 15, 145–161.

Ramírez, Carlos A., 2024, Firm Networks and Asset Returns, *Review of Financial Studies* 37.

Romer, Paul M, 1990, Endogenous technological change, *Journal of Political Economy* 98, 71–102.

Smirnyagin, Vladimir, and Aleh Tsyvinski, 2022, Macroeconomic and Asset Pricing Effects of Supply Chain Disasters, Working Paper 30503 National Bureau of Economic Research.

Soto, Paul E, 2023, Measurement and effects of supply chain bottlenecks using natural language processing, Working paper, FEDS Notes.

Tallarini, Thomas D., 2000, Risk Sensitive Real Business Cycles, *Journal of Monetary Economics* 45, 507–532.

Townsend, Robert M., and Nicolas X. Zhang, 2023, Technologies That Replace a "Central Planner", *AEA Papers and Proceedings* 113, 257–62.

A Additional Derivations

In what follows, we report derivations of first order conditions that characterize allocations of our macro-finance model and the parametric restriction required to have a well-behaved production function and balanced growth.

A.1 Final Goods Sector

The Lagrangian for the firm's problem is

$$\mathcal{L} = E_0 \left[\sum_{t=0}^{\infty} M_t \left\{ Y_t - I_t - W_t L_t - \int_0^{N_t} P_{i,t}(\mathbb{1}_{i,t+} \cdot X_{i,t}) di + q_t \left((1-\delta)K_t + \Lambda \left(\frac{I_t}{K_t} \right) K_t - K_{t+1} \right) \right\} \right]$$

The corresponding first order conditions are

$$\begin{aligned}
[I_t] &: -1 + q_t \cdot \Lambda' \left(\frac{I_t}{K_t} \right) = 0 \\
[L_t] &: (1-\alpha)(1-\xi) \frac{Y_t}{L_t} - W_t = 0 \\
[K_{t+1}] &: q_t = E_t \left[M_{t+1} \left\{ \alpha(1-\xi) \frac{Y_{t+1}}{K_{t+1}} + q_{t+1} \left((1-\delta) - \Lambda' \left(\frac{I_{t+1}}{K_{t+1}} \right) \cdot \left(\frac{I_{t+1}}{K_{t+1}} \right) + \Lambda \left(\frac{I_{t+1}}{K_{t+1}} \right) \right) \right\} \right] \\
[X_{i,t}] &: \left(K_t^{\alpha} \left(\Omega_t L_t \right)^{1-\alpha} \right)^{1-\xi} \frac{\xi}{\nu} \left[\int_0^{N_t} (\mathbb{1}_{i,t+} \cdot X_{i,t})^{\nu} \, di \right]^{\frac{\xi}{\nu}-1} \times \\
&\quad \nu(\lambda_t + (1-\lambda_t)\theta^{\nu}) \cdot X_{i,t}^{\nu-1} - (\lambda_t + (1-\lambda_t)\theta) P_{i,t} = 0.
\end{aligned}$$

These conditions together with equation (15) characterize allocations in the model.

A.2 Balanced Growth Path Condition

Plugging X_t from equation (15) into the production function and after some algebra, we obtain

$$Y_t = \left[\xi \nu \frac{\omega_t}{\omega_t^A} \right]^{\frac{\xi}{1-\xi}} K_t^{\alpha} (\Omega_t L_t)^{1-\alpha} \left[\omega_t N_t \right]^{\frac{\xi(1-\nu)}{\nu(1-\xi)}} .$$

Thus, for the existence of a balanced growth path in the model, we require the parametric restriction

$$\alpha + \frac{\xi(1-\nu)}{\nu(1-\xi)} = 1.$$

First Law of Macroeconomics
Implications of Energy Balance Equations

Daniil Parfenov*

Abstract

This paper introduces energy conservation - a fundamental symmetry in physical transformations - as a foundational element of production in macroeconomic models. A novel variable, Energy Differential, measures net useful energy after extraction and conversion losses. Energy balances are embedded in an endogenous-growth setting linking exogenous energy flows to technological dynamics. Net useful energy emerges as the core state variable driving output, capital formation, and innovation, endogenously giving rise to Total Factor Productivity. Energy flows shape long-run growth and business-cycle dynamics, cascading into asset prices. Empirical evidence confirms that Energy Differential is a robust driver of TFP, growth, and asset prices.

JEL classification: O44, Q43, E32, G12, O41.
Keywords: Macroeconomics, Energy, Total Factor Productivity (TFP), Business Cycles, Endogenous Growth, Long Run Risks
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1 Introduction

Economic growth stems from capacity to expand output - by mobilizing more resources or transforming them with greater efficiency. Energy is the most fundamental resource enabling this process. It enters the macroeconomy from outside as a primary exogenous flow that makes all production possible; raw materials, labor, capital, and even knowledge - are all subsequent to it.

Throughout history, each surge in economic growth and productivity - from manual labor and mechanical energy, to steam power and electricity, up to today's energy-intensive Artificial Intelligence - has relied on an expansion in available energy surplus (Figure 1).

It takes energy to build the hardware, train large models, and operate the digital infrastructure. Yet all productive actions obey a universal physical law - energy conservation, the fundamental symmetry underlying all change. In the end, even most intangible leaps in productivity must obey the laws of energy transformation.

This paper formalizes the relationship between energy - the most fundamental input - and all forms of productivity, and explores implications of grounding economic dynamics in physical laws.

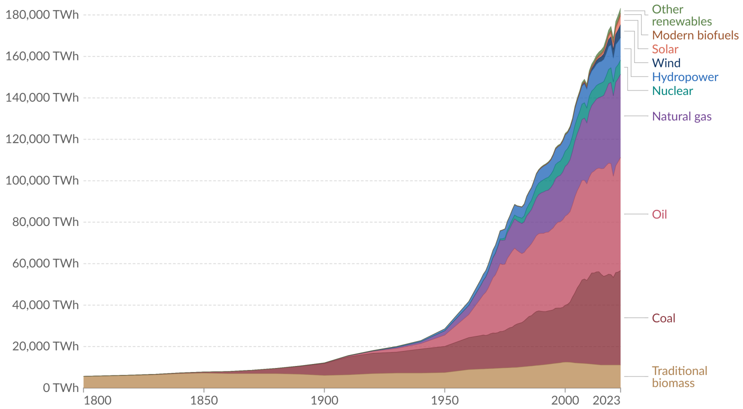

Fig. 1: World energy balance decomposition over time

Notes - Picture taken from Energy Institute - Statistical Review of World Energy (2024) - vertical axis depicts decomposition of raw energy sources in energy generation across the world, as measured in TerraWatt-hours.

This paper grounds macroeconomic production in fundamentals of thermodynamcs relying on two tenets. First, energy is conserved in all physical transformations: it can neither be created nor destroyed, only transformed - a restatement of the First Law of Thermodynamics. Every economic action therefore requires energy, making it both the enabling and limiting factor of production. Second, the macroeconomy functions as an open thermodynamic system that exchanges energy and matter with its environment. Output production and energy extraction both consume energy; only the latter supplies a new inflow from environment. Measure of useful energy, net of extraction and conversion losses - the Energy Differential - determines productive capacity of macro-economy as a whole.

Result of the approach yields convenient energy balance equations that can enter any production based model. Application of energy balances to certain processes per se yields testable predictions for economic theory and allows to filter out assumptions that are not coherent with physical reality. Capital, labour, productivity and wealth are all subsequent to energy - and can be represented as forms of accumulated energy. This allows to map every unit of production and consumption to an objective and measurable energy cost - which hints at emergent Energy Value Theory to complement subjective Utility-based valuations. In fact, many economic notions - utility functions, stochastic discount factors - all can be given theoretical foundation through the lens of energy flows. Later paper shows an example of how augmentation with energy balances can improve predictive performance and fit existing production-based models closer to data.

Macroeconomics has long been relying on different forms of symmetry assumptions, e.g. representative agents (see, for example, Backus, Chernov, and Zin (2014)) model are introducing behavioural symmetry with respect to optimal decision. Energy conservation, long recognized in the natural sciences as a fundamental symmetry, can thus be viewed as the missing structural symmetry in macroeconomics - that restores internal coherence between economic theory and natural sciences. Incorporating energy symmetry defines a consistent unifying dimension linking the scale of the economic system to environmental energy flows and provides a benchmark for distinguishing feasible from non-physical growth trajectories. Latter naturally shifts perception of energy from *yet another input*, introduced with assumptions (see Atkeson and Kehoe (1999), Stern and Kander (2012), Apostolakis (1990), Hassler, Krusell, and Olovsson (2021), Komatsu (2024)) - to necessary, universal factor, which should be modelled relying on **laws**, governing its transitions.

Models that describe production while omitting the primary source of productive activity - or abstracting from the physical laws governing energy transformation - inevitably rely on assumptions inconsistent with material reality. Such abstraction (i) excludes the source and principle component of the productive process, (ii) breaks the symmetry inherent in all physical transformations, (iii) misattributes the source of growth to derivative concepts, (iv) introduces theoretical constructs not consistent with nature, (v) yields interpretations and policy implications misaligned with the real structure of the economy, and (vi) produces imprecise or even infeasible predictions about the trajectory of growth and production.

It may appear unconventional to couple macroeconomic reasoning with thermodynamics, yet this connection is both natural and empirically grounded. Contemporary climate economics relies on models for thermodynamic balance of the atmosphere to project temperature changes on the surface of the planet and estimat their economic impacts (Bansal, Kiku, and Ochoa (2016) , Schlenker and Taylor (2021),Bilal and Känzig (2024), Nath, Ramey, and Klenow (2024)). Current approaches typically connect physical and economic domains through arbitrarily parametrized indirect functional assumptions (e.g. kg of CO_2 emissions per dollar of real GDP), rather than through tightly-connected physical processes that share a common unit of measurement. Extending the concept of thermodynamic balance to the macroeconomy as a whole (and not only atmosphere) offers a coherent, law-based framework in which economic and ecological processes are linked through directly connected and measurable energy flows.

Complete thermodynamic balance of the macro-economy offers a framework to think about environmental damage not only through the lens of CO2 (Bolton and Kacperczyk

(2021)) or particular pollution agents (Hsu, Li, and Tsou (2023)), but taking into account all forms of environmental damage via measuring entropy (measure of disorder) gradients, that are directly linked to energy flows. Entropy-Energy dimension analysis of technological landscape calls into question whether "green" production is a valid concept. Even if certain polluting agents are taken care of - due to inefficiencies and irreversible processes in production chain - entropy, broader measure of environmental damage is created inevitably, and can be offset only with abundant source of energy.

To examine *quantitatively* the role these principles in shaping macro-outcomes - a model is needed that embeds exogenous energy flow into internal production dynamics. Economic growth can be thought of as an interplay between the energy supply and system's capacity to transform it into ordered output. The latter - productive complexity and innovation dynamics - is well captured by the endogenous growth literature, placing these models as a natural starting point for augmentation. Embedding energy balances into endogenous growth setting reveals a new structure - where productivity, business-cycles, and asset valuations emerge as endogenous adjustments to stochastic energy flows.

Within the model, Energy Differential determines the feasible output across all productive sectors. Total Factor Productivity (TFP) no longer materializes as an abstract and unexplained residual, but emerges endogenously through energy-constrained optimization of intermediate goods production. This also alleviates concerns associated with intepretation of downward TFP swings. Overall, Macro-economy is dependent on the aggregate energy yield - captured by the Energy Return on Investment (EROI), aggregate energy flow and conversion efficiencies. As the net energy yield rises, so does the range of productive configurations available to the macro-economy. When the relative price of energy rises, it directly reduces the optimal production of intermediate goods, lowering measured TFP in equilibrium. The model quantifies the economic implications of transitioning to renewable energy sources, whose documented lower energy yields constrain growth potential.

Innovation dynamics also respond to these fluctuations. Both the incentives and the capacity to invest in R&D - as well as the resulting steady-state rate of innovation - are tied to the energy density of the environment. Thermodynamic constraints cascade into financial markets, where royalties, capital returns, and asset prices adjust endogenously to evolving energy availability. This framework reinterprets long-run growth, business cycles and financial dynamics as emergent consequences of energy transformation.

Empirical evidence supports the theoretical implications and model's mechanisms. A data-constructed measure of useful energy - net of extraction and transformation losses - explains over 94% of the observed variation in TFP, while causal direction is inherent in physics of production (Granger causality tests support causal direction). The Energy Differential consistently outperforms TFP in tracking business-cycle dynamics and subsumes its role in predicting the long-run growth potential. Consequently, energy trend emerges as the principal component of long-run productivity risk. Model-based and SVAR impulse-response analysis reveals that earlier endogenous-growth models systematically overstate the economy's response to exogenous productivity shocks, falling well outside of empirical bounds. In contrast, both the model and the data show that shocks transmitted through the energy-productivity channel generate stronger yet empirically-consistent responses in GDP and consumption, compared to pure TFP shocks cleaned of energy component. Incorporating energy dynamics anchors fluctuations of other macroeconomic variables closer to data.

These considerations suggest that energy is the enabling factor of innovative activity, main source of long-run economic growth, fluctuations in aggregate productivity and asset-prices.

Related Literature: The introduced framework is relevant for augmenting several strands of literature:

(i) Standard endogenous growth models - e.g., Romer (1990), Aghion and Howitt (1992), Grossman and Helpman (1991), Comin and Gertler (2006); Comin, Gertler, and Santacreu (2009); Corhay, Kung, and Schmid (2015); and Gavazzoni and Santacreu (2015), Kung and

Schmid (2015) - raise output through innovation, yet typically treat energy as an unlimited input, assuming growth can proceed unconstrained by physical limits. Ecological economists and phycisists, notably Georgescu-Roegen (1971), Prigogine (1979), Prigogine and Stengers (1984), Ayres and Warr (2005), and Smil (2017), have long emphasized that sustained complexity in open systems necessitates continuous inflows of high-grade energy. This paper bridges these traditions.

Where prior studies appended gross energy or exergy terms (e.g. Ayres, Ayres, and Warr (2003), Kummel (2011), Hassler, Krusell, and Olovsson (2021)), often with arbitrary elasticity assumptions, this framework derives energy constraints from the first law of thermodynamics, treating them as symmetry conditions that must hold. Additionally, main focus of the paper is on novel emergent varible - Energy Differential - *net useful energy* after extraction and conversion losses. The Energy Differential governs the frontier of productive potential and places the abstract technology frontier within measurable physical bounds. The structure of Kung and Schmid (2015) is taken as a baseline to analyze how shifts in energy composition - e.g., transitions to low-EROI or "green" technologies - alter innovation rates, business cycles, and asset valuations.

(ii) Following Kydland and Prescott (1982), RBC models typically assign macroeconomic fluctuations to exogenous TFP shocks -residuals often interpreted as abstract "technology" movements (see also Lucas (1987), Barlevy (2004), Bianchi, Ilut, and Schneider (2012)). Meanwhile, a strand of literature studied oil and energy shocks, including Kim and Loungani (1992), Rotemberg and Woodford (1996), Finn (2000), Kilian (2008) concluding that inclusion of energy prices improves model performance (see also Jo, Karnizova, and Reza (2019), Gao, Hitzemann, Shaliastovich, and Xu (2022)). However, Barsky and Kilian (2004) argued that energy inputs are too small to matter significantly for aggregate output.

A production-based counterargument is offered: TFP is redefined as a transformation of usable energy, with quantity rather than price being the relevant variable. Empirically, Energy Differential explains most cyclical variation in TFP, outperforms TFP in tracking cyclical variation, ED subsumes the role of TFP in predicting long-run growth prospects.

(iii) Paper is relevant for asset-pricing and macro-finance literature, placing useful energy as main driver of asset valuations (see, among others, Jermann 1998, 2010; Kogan and Papanikolaou 2009; Kogan, Papanikolaou, Seru, and Stoffman 2012; Kogan, Papanikolaou, and Stoffman 2013; Belo, Bazdresch, and Lin 2014; Belo, Lin, and Yang 2018; Belo, Gala, Salomao, and Vitorino 2022 and more recently Diercks, Hsu, and Tamoni 2024). Recursive preferences are adopted since relevance of priced shocks is explored (see, for example, Tallarini 2000; Bansal and Yaron 2004; Campanale, Castro, and Clementi 2010; Kuehn (2008, 2009); Kaltenbrunner and Lochstoer (2010), and Croce (2014)). Since energy availability underlies the long-run trajectory of the economy, the agricultural and other sub-components of energy supply may also influence demographic dynamics - an important channel previously shown to affect asset prices (Favero, Gozluklu, and Tamoni, 2011; Favero, Gozluklu, and Yang, 2016). Paper is also relevant for long-run risk models, such as Bansal and Yaron (2004), Bansal and Ochoa (2011), Bansal, Kiku, and Yaron (2016) that explain asset prices through persistent shocks in consumption and productivity growth. Empirically energy trend explains most of persistent long-run components in productivity growth.

This framework also aligns with recent asset-pricing literature on environmental risks (e.g., Bansal, Kiku, and Ochoa (2016),Engle, Giglio, Kelly, Lee, and Stroebel (2020),Bolton and Kacperczyk (2021), Giglio, Maggiori, Rao, Stroebel, and Weber (2021), Schlenker and Taylor (2021)), offering a coherent framework to measure and tie together various forms of environmental risks. Clean technologies, while critical, still obey laws of thermodynamics - requiring energy and creating entropy (Heal (2009), Holechek, Geli, Sawalhah, and Valdez (2022), Arkolakis and Walsh (2023)). This raises concerns about the feasibility and macro-outcomes of “green” transition.

2 Theoretical Framework

Main philosophical approach of this paper consists in the holistic and materialistic outlook on the economy and its environment. This paper also relies on insights of Ilya Prigogine (1979) on the phenomenon of self-organisation in open thermodynamic systems.

Thermodynamics provides a framework for understanding how energy is transferred, transformed, and conserved across physical systems. Macro-economy has to obey the laws governing energy transitions in physical systems. Thermodynamic systems can be classified into three types:

(i) **isolated** systems, which do not exchange energy or matter with their surroundings;
(ii) **closed** systems, which exchange energy but not matter;
(iii) **open** systems, which exchange both energy and matter.

This paper treats the economy exactly as physics treats any living organism: an open thermodynamic system that must import high-grade energy and export degraded energy / wastes to maintain its internal order (low entropy state). Every good or service is, at bottom, an ordered configuration of matter, and organizing matter always costs energy. Schrödinger (1944) described consumption of energy inputs for living organisms as consumption "negative entropy"; this paper generalizes that insight to all economic output. Through this lens, production of consumable items - can be thought of as entropy reduction/complexity increase operation, that requires positive energy input.

Prigogine's theory of dissipative structures (energy-exchanging open systems) formalizes the conditions for local entropy-reduction in open thermodynamic systems:

$$\partial_t S_i + \partial_t S_e = \partial_t S_{system} \leq 0 \quad \Leftrightarrow \quad \partial_t E_{ext} \geq 0 \tag{1}$$

where $\partial_t S_i$ is internal entropy - overall measure of internal physical degradation (loss of order) - produced within the system, $\partial_t S_e$ - entropy flow exchange with the environment, $\partial_t E_{ext}$ - energy flow from external environment. Second Law of Thermodynamics states that in a closed system - entropy can never decrease. In other words, physical systems tend to degrade and lose energy due to physical forces in place - not all energy flows can be directed to perform useful work. Most of the processes studied in economics - production, consumption, allocations - are all are energy-consuming, most are irreversible and entropy-increasing. However, open systems have capacity to discard internally accumulated entropy into outer environment. Equation (1) states that open system's total entropy can decrease only in presence of positive energy flow. Local self-organization - life, technology, capital formation and innovation - can persist only when incoming energy is large enough to offset internally generated disorder, so that the inequality is (weakly) negative. A positive energy inflow therefore underwrites every increase in complexity, from a biological cell to modern economy.

Economic growth is the macro-level manifestation of the same principle: we continually convert external energy gradients - solar flux, metabolic calories, and fossil fuels - into lower-entropy structures such as infrastructure, technology, knowledge, and even human body itself (energy dynamics, especially in food and heat equivalents, also shape the trajectory of population growth).

Energy preceeds, enables and limits any productive action within economy. Since each operation has to obey energy conservation principle - we can formalize simple balance equation for a single production operation and then aggregate those balances within a period for a given macro-economy. The result is a compact set of energy-flow identities - a thermodynamic symmetry that any macro-economy, however complex, has to obey.

Energy decomposition of any production operation: Any production operation (Y) requires energy first for its completion, and therefore can be split in two steps:
(i) Energy is spent ($\Delta_t E_{Y_E}$) on securing a positive flow of energy from external source ($\Delta_t E_{ext}$); (ii) Energy is spent on producing output itself ($\Delta_t E_Y$).
Any production operation - as any physical transformation of matter - must obey energy

conservation principle:

$$\Delta_t E_{ext} - \Delta_t E_{Y_E} = \Delta_t E_Y + \Delta_t E^{total}_{waste} \tag{2}$$

where $\Delta_t E^{total}_{waste}$ captures total losses from friction, heat dissipation, and other irreversibilities physical forces. Wastes can also be decomposed into two-types: (i) wastes in energy generation and conversion; (ii) wastes in output production.

Only a fraction of raw external energy is available for production of useful output, as captured with the notion of thermodynamic efficiency $\eta^e_t \in (0,1)$ of (technology-specific) energy-generation:

$$\Delta_t E_{ext} \cdot \eta^e_t - \Delta_t E_{Y_E} \equiv ED_t \tag{3}$$

where ED_t is the **Energy Differential** - flow of useful energy available to the economy in a given period after accounting for (i) efficiency of converting gross energy into useful form, (ii) dynamic energy costs associated with energy-extraction. Interplay of the external flow, energy-extraction costs and conversion efficiency - determines the system's potential to perform productive work. In other words, it can be thought of as *realized Exergy* measure.

Physical energy-efficiency in productive operations outside of energy-generating sector can be formalized as $\eta^p_t \in (0,1)$, to describe the efficiency of energy flow towards energy-value of final output:

$$(\Delta_t E_{ext} \cdot \eta^e_t - \Delta_t E_{Y_E}) \cdot \eta^p_t = \Delta_t E_Y \tag{4}$$

Energy decomposition for macro-economy: Modern day macro-economy is ultimately fueled by a variety of energy sources (es), each with its own thermodynamic efficiency and dynamic energy extraction costs, associated with technology in place. To compare energy-generating technologies, engineering literature at times relies on notion of Energy Return on

Investment, defined as gross energy output per energy costs: $EROI \equiv \frac{\Delta_t E_{ext}}{\Delta_t E_{Y_E}}$. Aggregate Energy Differential is the sum of useful flows across sources:

$$\sum_{es=1}^{ES_n} [\Delta_t E_{ext}^{es} \cdot \eta_t^{e,es} - \Delta_t E_{Y_E}^{es}] := ED_t \tag{5}$$

$$\sum_{es=1}^{ES_n} \Delta_t E_{ext}^{es} \cdot [\eta_t^{e,es} - \frac{1}{EROI_t^{es}}] = \sum_{es=1}^{ES_n} \Delta_t E_{ext}^{es} \cdot F_{ED,t} := ED_t \tag{6}$$

where $F_{ED,t}$ is the **Energy Differential Factor** that takes into account conversion efficiency and relative energy costs of certain technology.

Energy-Entropy and Environment: Within the macro-economy, the flow of useful energy is distributed across industries (I) and physical technological operations (T) within each industry. Each operation consumes energy to produce output and, as a byproduct, generates entropy - physical disorder - manifested in various forms, e.g. such as pollutant emissions, material dissipation, or electromagnetic pollution. The energy costs of extraction are decomposed identically: they require organized output from other sectors to access energy sources. The complete thermodynamic balance therefore integrates all inflows adjusted for efficiencies with all operational and waste expenditures:

$$\sum_{es=1}^{ES_n} [\Delta_t E_{ext}^{es} \cdot \eta_t^{e,es} - \underbrace{\sum_{I=1}^{I_n^{en}} \sum_{T=1}^{T_n} [\Delta_t E_{operation} + \Delta_t E_{waste}]]}_{\Delta_t E_{Y_E}^{es}} = \sum_{I=1}^{I_n} \sum_{T=1}^{T_n} [\Delta_t E_{operation} + \Delta_t E_{waste}] \tag{7}$$

Complete thermodynamic balance appears as a tool to integrate all forms of environmental entropic damages and production processes into a unified framework.

In particular, each energy gradient within certain technological operation in Equation (7) is spent along certain physical force (J) - therefore creating respective entropy flow:

$$\sum_{ES=1}^{ES_n} [\Delta_t S_{ext} - \sum_{I=1}^{I_n} \sum_{J=1}^{J_n} [\Delta_t S_{operation} + \Delta_t S_{waste}]] <> \sum_{I=1}^{I_n} \sum_{J=1}^{J_n} [\Delta_t S_{operation} + \Delta_t S_{waste}] \tag{8}$$

The transition toward a “green” economy is often framed as a directed technological change towards environment-friendly or "greener” technological processes and renewable energy sources (see Acemoglu, Aghion, Bursztyn, and Hemous (2012), Popp (2002)). Yet even carbon-neutral renewables and alternative production technologies entail environmental damages inherent in physical inefficiencies of production and infrastructure development. What is a green technology - if all technological processes create entropy?

First, energy expenditures entail entropy flows - that reflects on presence of 2nd Law of Thermodynamics in production structure. This entropy incease can potentially be discarded by a large enough flow of high-grade energy, consistent with Prigogine’s principles of self-organization in open systems.

Second, "green" energy sources are documented to have lower Energy Return on Investment (EROI), meaning more energy must be spent (and more damage entailed) to obtain a unit of usable energy, thus squeezing Energy Differential.

Third, the environmental impact of renewables (or alternative ”greener” technological processes) is frequently assessed locally - focusing on carbon at the point of use - while upstream broader entropic damages (including carbon emissions as a subset of broader damage) along the entire supply-chain are overlooked.

These factors form a "transition trap" and challenge whether concept of directed technical change to "greener" production structure is even feasible from standpoint of natural science. In thermodynamic terms, the success of a sustainable entropy-minimising economy depends not only on the sources of energy, but also on the net energy gain and the system’s capacity to offset growing entropy with sufficient usable inflows.

A shift toward lower-EROI energy sources, whether by directed change or by depletion of high-grade energy sources, reduces the net pool of usable energy available for productive activity. This poses a direct threat to the stability and resilience of the production system and its capacity to discharge entropy outwards.

Rest of the paper seeks to understand quantitatively how the rest of macro-variables (so far abstracting away from entropic considerations) - from productivity to asset-prices - might respond to the narrowing energy gap.

Economic Growth as an Energy Chain: Each production operation is an energy transformation that obeys the law of energy conservation. All goods and services we produce and consume require a positive energy inflow and can therefore be viewed as bundles of ordered matter. Macroeconomic growth is thus not a purely technological or innovation-driven phenomenon; rather, the very capacity for technological advancement depends on the energy density of the environment.

The history of economic growth can be reinterpreted as a continuous process of accumulating organized energy in the form of ordered matter - embodied in goods, capital stock, infrastructure, and knowledge. The resulting chain of energy transformations is bounded by the technological frontier and determines the objective, physical cost that society must pay to achieve a given outcome. Let $\Delta_t E_Y$ denote the energy-equivalent of production in a given period and W_t is the energy-equivalent of accumulated wealth, objective energy cost society paid to accumulate the current level of wealth. Then:

$$[\sum_{es=1}^{ES_n} (\Delta_t E_{ext} \cdot \eta_t^e - \Delta_t E_{Y_E})] \cdot \eta_t^p = \Delta_t E_Y$$

$$W_{t+1} = W_t + \underbrace{\theta \cdot \Delta_t E_Y}_{\textit{fraction is consumed, } \theta \in [0,1)} - \underbrace{\delta \cdot W_t}_{\textit{degradation, 2nd Law}}$$

where θ - represents the share of accumulated, not consumed energy-wealth; and δ - is the natural erosion of ordered matter in the stock of currently accumulated wealth due to entropy. This approach to describe production holds true across all technological stages of societal development - where Cobb-Douglas production representations may not hold true - from primal-gathering society to space exploration economy.

Energy conservation principle naturally postulates existence of **Energy Value Theory** - an objective physical measure of societal costs. Preferences based theories of utility naturally complement it, since they appear as a study of choice between various forms of energy input.

Preferences describe which bundles we choose; Energy Value describes objecitve physical costs underlying those choices.

Productivity in Energy Equivalents: Labor and capital are both subsequent to energy: stock of both is the result of accumulating energy in previous periods, each requires a continuous energy input to remain functional in any given period. This per se implies that energy must be a foundational component of production function. In standard production theory, capital - from steam engines to AI systems - enhances the productive capacity of labor, yet labor itself embodies energy. In fact, both cognitive and physical labour output average to 2500 kcal output a day.

When the principle of energy conservation is ignored, Total Factor Productivity (TFP) appears as a residual that balances output against the measured use of capital and labor. In an energy-conserving framework, productivity can be defined as the amplification of labor's energy-content through the energy supplied by external sources and technology in place.

$$V_{L,t} \cdot \underbrace{A_t}_{\textit{Productivity}} = V_{Y,t} \qquad [\text{ Labor Value Theory }]$$

$$[\underbrace{\Delta_t E_{ext}}_{\textit{source}} \cdot \eta_t^e - \Delta_t E_{Y_E}] \cdot \eta_t^p = \underbrace{\Delta_t E_{L,t} \cdot A_t}_{\textit{pass-through}} = \Delta_t E_Y \qquad [\text{ Energy Value Theory }] \qquad (9)$$

The first equation above represents the main tenet of classic labor value theories - intrinsic value of human labour augmented by productivity of capital in place determines inherent value (not exchange value) of output in given period. Second equation above establishes the symmetry inherent in physics of production - all of energy needed to produced output in current period has to come from outer environment.

Energy output of labor in certain period is a derivative to that inflow - it is a portion of energy tranformed by workers from energy harvested in agricultural products into cognitive and physical labor. When measured in energy equivalents, aggregate productivity of technological chain (A_t) quantifies the energy value of produced output relative to the energy output of human labor.

It is of interest to note that second equation mirrors the intuition of labor value theories - yet has to be satisfied as most fundamental symmetry in physics of production.

Two examples illustrate this relationship. During the Industrial Revolution, steam engines magnified mechanical labor by channeling human effort through machines - at the cost of a continuous inflow of high-grade energy from coal and other fossil fuels. If there is not enough coal - more of mechanical work has to be done by humans, less of output is produced, and energy-measured productivity falls.

Today, a similar pattern unfolds with cognitive labor: AI systems save up energy spent on cognitive labor but depend on vast computational infrastructure that requires constant energy input. In both cases, productivity gains are inseparable from the energy flows that sustain them. A collapse in available energy would eliminate AI-driven productivity as surely as the steam engine's rise would have stalled without coal.

One could imagine economy where everything is automated - and human presence is not required - objective energy cost of production chain will remain, the middle pass-through mechanism within equation (9) can be replaced with energy spent by human-replacing machines.

This framework provides a unified method for evaluating the energy efficiency of human, mechanical, and automated labor. It clarifies how productivity depends on the balance between available useful energy and capital amplification, and it offers a basis for assessing the trade-offs between energy transitions, technological choice and aggregate productivity.

Further theoretical implications of energy-conservation are discussed in the Appendix, while the main text proceeds to test presented predictions empirically and to embed energy flows within the model to generate quantitative results.

3 Empirical Results

This section provides empirical evidence on the link between the novel macro-variable - *Energy Differential* - and the rest of the macro-economy. Description of data sources and measure construction goes first, with references to relevant reviews, and then regressions on trend and cyclical behaviour, growth rate predictions and other exercises are reported.

Energy Data. To empirically *approximate* the Energy Differential, this paper adopts a static-technology formulation:

$$ED_t = \sum_{ES=1}^{ES_n} \Delta_t E_{ext}^{es} \cdot \left[\eta^{E,es} - \frac{1}{EROI^{es}} \right], \tag{10}$$

where gross energy inflow from each source is adjusted by its respective conversion efficiency and energy return on investment (EROI). The implementation follows these steps:

(i) Harmonized EROI values are used for each energy source, measured at the point-of-use.

(ii) Averaged conversion efficiency $\eta^{E,es}$ is applied to each source. For example, BEA data indicates only a 10% efficiency gain for natural gas since the 1970s, reflecting both slow technological advancement and intertia of factories in place.

(iii) Gross energy generation data for the U.S., disaggregated by source ($\Delta_t E_{ext}^{es}$), is taken from BEA.

(iv) The measure naturally excludes energy embodied in raw agricultural goods. This does not present a major problem - (i) since energy-value of human labour output serves as a convenient proxy, (ii) share of energy embodied in agricultural products is eminently modest in comparsion to other energy-sources.

(v) This formulation allows for analysis of shifts in "useful energy" availability driven by compositional changes in the energy supply.

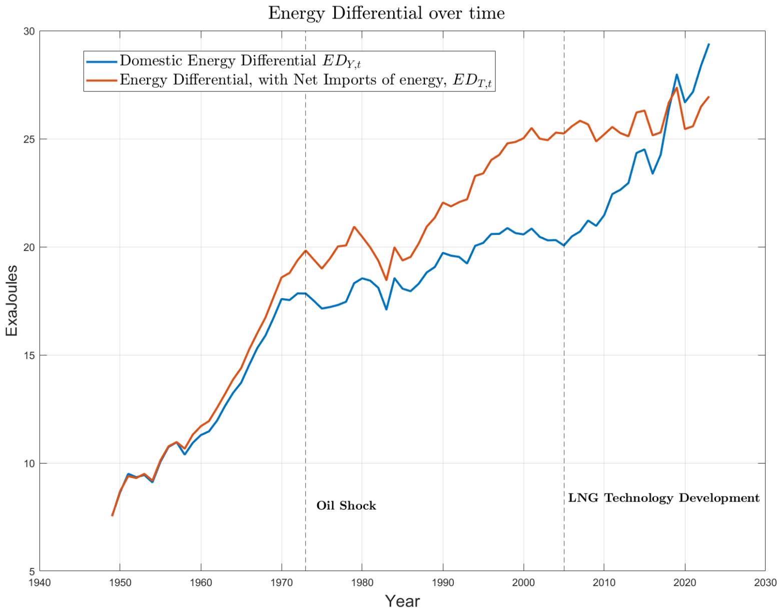

Fig. 2: Energy Differential in the U.S. Economy

Notes – The figure shows the level of Energy Differential (ED_t) in the U.S., measured in ExaJoules. The series captures the quantity of useful energy net of extraction and conversion losses. Data is annual and spans 1949–2023.

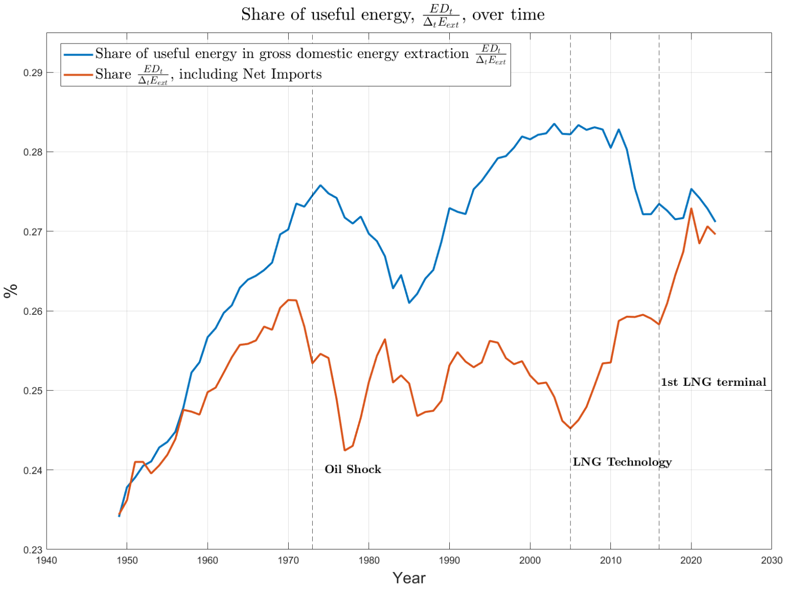

Fig. 3: Share of useful energy in the U.S. Economy

Notes – The figure shows share of useful energy relative to raw energy flow. Blue line represents the share for production within the US, orange line shows the same metric taking into account Net Imports. Data is yearly and spans 1949-2023

The dataset primarily comprises energy-related variables obtained from the U.S. Energy Information Administration (EIA), the main American agency responsible for collecting, analyzing, and disseminating energy information[1] Estimates for harmonized Energy Return on Investment (EROI), shown in Table 1, are compiled from a range of studies such as Hall et al. (2014) and Murphy and Hall (2010), which assess the energy efficiency and sustainability of various resources. EROI - defined as the ratio of energy output to energy input - captures technological, geographic, and operational variability across fossil fuels, renewables, and nuclear sources.

Table 1: Harmonized estimates for Energy Return on Investment (EROI) by Source

	EROI		
	Min	Median	Max
Coal	8.8	9.4	10
Natural Gas	5.2	8.6	12
Crude Oil	4.2	4.5	8.7
NGPL	5.2	6.5	12
Nuclear	20	30	60
Hydro	50	80	100
Geothermal	8	10	25
Solar	5	12	20
Wind	12	20	40
Biomass	3.2	6.5	16
Renewables Weighted by Share	13	21	34
BECCS	1.2	3	5

Notes – EROI refers to Energy Return on Investment. Min, Median, and Max represent minimum, Median, and maximum estimates. BECCS refers to Bioenergy with Carbon Capture and Storage, a renewable energy technology that combines biomass-based energy production with carbon sequestration. Harmonized EROI estimates are collected from Murphy et al. (2022): *Energy Return on Investment of Major Energy Carriers: Review and Harmonization.*

Conversion efficiency values (Table 2) are based on engineering assessments from sources such as Smil (2017) and the International Energy Agency (IEA), accounting for energy conversion efficiency of heat engines. These metrics are usually inertial and point to a

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[1] The energy variables include detailed information on production, consumption, energy prices, and other metrics relevant to understanding the U.S. energy sector.

certain range of estimates for each technology.

Table 2: Efficiency (η_e) of Energy Conversion by Source

	η_e		
	Min	Mean	Max
Coal	0.33	0.365	0.4
Natural Gas	0.45	0.525	0.6
Crude Oil	0.3	0.35	0.4
NGPL	0.3	0.375	0.45
Nuclear	0.33	0.35	0.42
Hydro	0.85	0.875	0.9
Geothermal	0.1	0.15	0.2
Solar	0.15	0.185	0.22
Wind	0.4	0.45	0.5
Biomass	0.12	0.2	0.3
Renewables Weighted by Share	0.279	0.344	0.422
BECCS	0.324	0.372	0.424

Notes – η_e represents the efficiency of energy conversion for various sources. Min, Median, and Max refer to minimum, median, and maximum efficiency estimates respectively. BECCS refers to Bioenergy with Carbon Capture and Storage, a renewable energy technology that combines biomass-based energy production with carbon sequestration. *Renewables Weighted by Share* aggregates renewable η_e values based on proportional contributions to energy production.

Table 3 reports the Energy Differential conversion factor, $\left[\eta_t^{e,es} - \frac{1}{EROI^{es}}\right]$, which adjusts gross energy generation to reflect net useful energy. If value for a given technology is negative - it reads as energy expenditures to extract are larger than the flow of useful energy. While statistical models often yield significant results using raw gross energy data, accounting for source-specific energy differentials improves explanatory power by filtering out non-informative variance.

Macroeconomic variables are sourced from the Federal Reserve Bank of St. Louis' FRED (Federal Reserve Economic Data) database, available in both quarterly and annual frequency. Utilization-adjusted Total Factor Productivity series is used as becnhmark measure of TFP.[2] Financial factors are obtained from the Kenneth R. French Data Library, and R&D-sorted

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[2] Fernald, J. (2014). "A Quarterly, Utilization-Adjusted Series on Total Factor Productivity." *Federal Reserve Bank of San Francisco Working Paper 2012-19.*

Table 3: Energy Differential Factors by Energy Source

	ED Conversion Factor		
	Min	Median	Max
Coal	0.216	0.259	0.300
Natural Gas	0.258	0.409	0.517
Crude Oil	0.062	0.128	0.285
NGPL	0.108	0.221	0.367
Nuclear	0.280	0.317	0.403
Hydro	0.830	0.863	0.890
Geothermal	-0.025	0.050	0.160
Solar	-0.050	0.102	0.170
Wind	0.317	0.400	0.475
Biomass	-0.193	0.046	0.238
Renewables Weighted by Share	0.048	0.229	0.373
BECCS	-0.509	0.039	0.224

Notes – ED Factor refers to Energy Differential Factors. Min, Median, and Max represent minimum, median, and maximum estimates. BECCS refers to Bioenergy with Carbon Capture and Storage, a renewable energy technology that combines biomass-based energy production with carbon sequestration. Renewables Weighted by Share aggregates factors for renewable sources based on their proportional contributions to the US energy balance. Harmonized EROI estimates are collected from Murphy et al. (2022).

equity portfolios are constructed using CRSP (Center for Research in Security Prices) data.

Useful Energy is the Trend Carrier. Main intuition for the empirical investigation comes from the energy-chain balances and productivity measured in energy equivalents:

$$\textit{Conservation Law:} \quad ED_t \cdot \eta_t^p = \Delta_t E_L \cdot A_t^{en} = \Delta_t E_Y \tag{11}$$

$$\textit{In levels:} \quad \log(A_T) = \alpha + \beta^L \cdot g(ED_T, \eta_t^P \cdot \varpi_t) + \epsilon_t^L \tag{12}$$

$$\textit{In growth rates:} \quad \Delta \log(A_T) = \beta \cdot \Delta \log(ED_T) + \epsilon_t \tag{13}$$

Ultimately, Energy Conservation postulates a mapping between realized production in current period and amount of useful energy supplied to the system. Equation (11) clearly defines the productivity of human labour in energy-equivalent to be solely driven by the inflow of energy from the outside environment given current technological energy-transformation chain.

One unit of useful energy supplied from energy-producing sectors ED_t is supplied to production chain, where it gets embodies in the final good with certain inefficiency, described by $\eta_t^p \in [0, 1)$. One unit of energy gets converted into the monetary value of final output with different conversion efficiency, later defined as ϖ_t, based on the identity $\eta_t^p \cdot \varpi_t = \frac{Y_t}{ED_t}$, where Y_t is the real GDP measured in monetry units. $\eta_t^P \cdot \varpi_t$ represents energy-efficiency usage in production chain and is measured non-parametrically as ratio in the data.

$\eta_t^P \cdot \varpi_t$ is driven by the research effort directed at increasing energy usage efficiency and increasing output per unit of energy. However, innovation, as the rest of economic activity, is subsequent to the realized energy supply. In the mathematical limit, at the boundary of the macroeconomy with its environment, this process is driven by the transmission of past energy flows through the system: over time, energy surpluses are embodied in improvements to the technological energy chain (intermediate dynamics, of course, are more complex and are the main scope of endogenous-growth models). If the growth-rate process for TFP is assumed to contain its own trend component, this is equivalent to attributing the effects of rising $\eta_t^P \cdot \varpi_t$ to the TFP term - though the latter ultimately remains driven by energy availability in the limit. In other words, the trend effect of intermediate transmission dynamics depends on the flow of the primary input - useful energy. This argument justifies the specification for Equations 12 and 13, where the trend of productivity is ultimately shaped by the inflow of useful energy.

Figure 4 shows the subsequent reconstruction of TFP dynamics, outside of energy component, assuming that all of the trend in growth rate of TFP is coming from useful energy growth rate (as in Equation 13). In other words, it takes away co-integrating component from TFP growth rate series that is related to energy input. This pre-cleaning procedure is used to construct empirical Impulse Response Functions in the Quantitative Results section. It is worth noting that TFP defined in this manner - appears almost unaltered relative to the start of the measurement date.

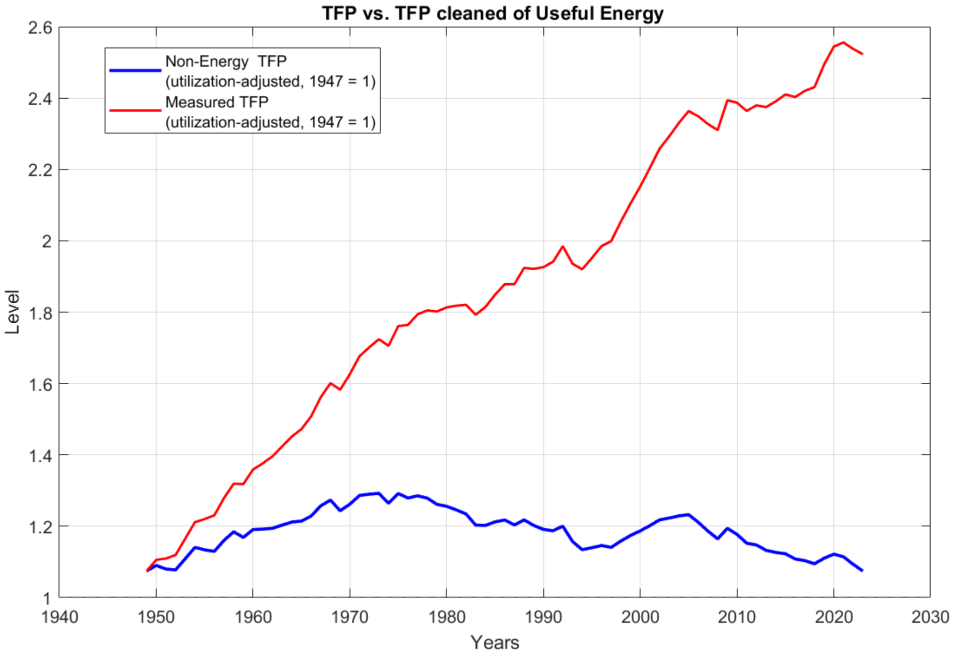


Fig. 4: Measured TFP vs. TFP cleared of Energy Trend

Notes – The figure shows the utilization-adjusted TFP and the re-constructed level of TFP, that assumes in the limit that trend behaviour of production is specified to be driven by energy. Data is yearly and spans 1949-2023

Application of that energy-chain within endogenous growth setting also informs the direction of empirical investigation. Energy Integration in the setting yields production function of the form:

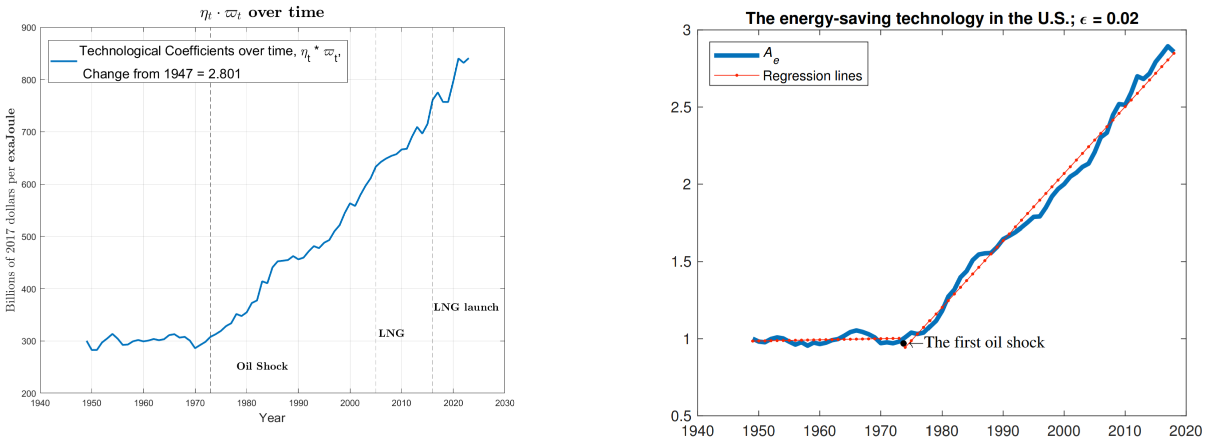
$$Y_t = \underbrace{\left(\frac{\xi\,\nu}{1 + \frac{P_{en,t}}{\eta_t^p\,\varpi_t}} \right)^{\frac{\xi}{1-\xi}} \frac{ED_t}{\varepsilon_t^{pv}}^{\frac{\xi\,(1-\nu)}{\nu\,(1-\xi)}}}_{\equiv A_t \approx f(\sum_{t=0}^{T} ED_t)} K_t^{\alpha}\, L_t^{1-\alpha} \tag{14}$$

TFP arises within the model (featuring single exogenous shock - energy) as a function of energy surpluses accumulated in forms of research in previous periods. This structural result further informs the measurement of trend behaviour behind productivity dynamics.

Figure 5 compares non-parametric estimates of conversion coefficients out of theoretical framework presented here with parametric estimate of energy-saving technology in the US from Hassler, Krusell, and Olovsson (2021), where production function assumes following specification:

$$y_t = \left[(1-\gamma) \left(A_t k_t^{\alpha} h_t^{1-\alpha} \right)^{\frac{\varepsilon-1}{\varepsilon}} + \gamma \left(A_{et} e_t \right)^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}} \tag{15}$$

This specification allows to produce output even when energy input equals zero - an abstraction that breaks the physical symmetry inherent in all matter transformations. It is worth noting, that estimates of energy-efficiency in production chain remain similar between the two studies. In contrast, presented framework allows to treat energy as necessary factor enabling input, since both capital and labor require energy to operate.



(a) Conversion Coefficients (b) Energy Productivity

Fig. 5: Non-parametric vs. parametric estimates from the literature

Notes - Left panel shows the dynamics of $\eta_t^p \cdot \varpi_t = \dfrac{Y_t}{ED_t}$ - an energy-conversion formulation of production. Right panel shows parametric estimates of energy productivity from Hassler, Krusell, and Olovsson (2021), with production function specified in equation 15.

The hypothesis that productivity A_t is a function of energy availability and production efficiency is tested using a linear factor model:

$$A_t = \alpha + \beta \cdot F_t + \varepsilon_t, \tag{16}$$

$$where \quad F_t \in [ED_t] \, or \in \left[ED_t; \varpi_t \hat{\cdot}\, \eta_t^p\right]$$

Left panel of Figure 6 reports the results of predicting TFP from Useful Energy, abstracting from the relative change in conversion efficiencies - results yield R^2_{adj} of 0.937. Introducing an instrument for $\eta_t^p \cdot \varpi_t$, based on the identity $\eta_t^p \cdot \varpi_t = \frac{Y_t}{ED_t}$, raises the explanatory power of Factor-model *marginally* to 0.986, with associated t-statistics exceeding 25 for ED_t and 15 for ϖ_t. Addition of previous energy realizations to the factor model is expected to naturally improve the quality of prediction given structure of Equation 14. Remaining variance appears attributable to disruptions in material inputs or other supply-chain disruptions. Additionally, while the physical structure of reality already implies a directional causality within each period - energy must precede production - Granger causality tests empirically

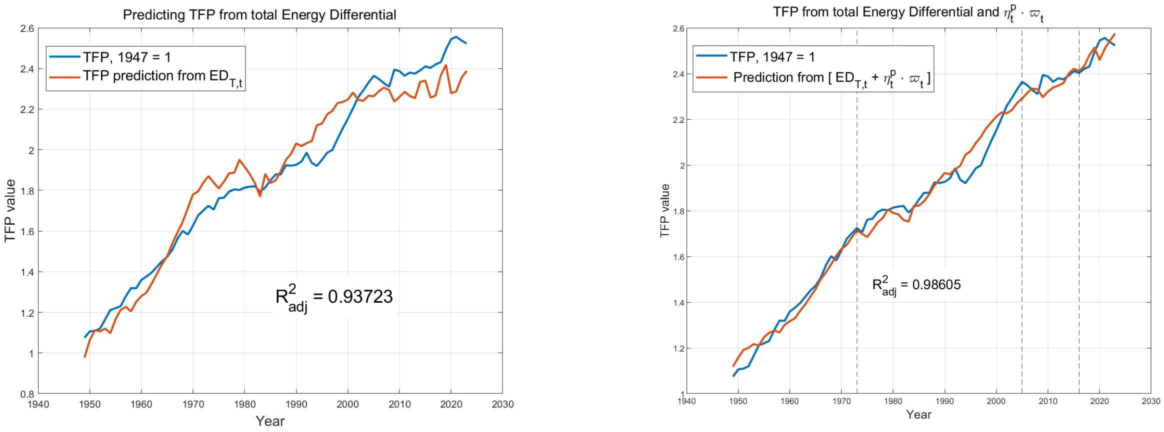


Fig. 6: Factor-models in application to TFP measurement

Notes - Left panel shows non-parametric estimate of Energy-Productivity in the US in non-energy-extracting sectors. Right panel reports TFP predictive performance of a two-factor linear model consisting of Energy Differential and Energy-Productivity.

confirm that energy availability systematically predicts TFP realization over time.

If *Net Useful Energy* drives the bulk of productivity level, several implications follow:

(i) not only a factor model linking TFP to the Energy Differential should exhibit high explanatory power, but also;

(ii) in a real business cycle (RBC) framework, where macroeconomic fluctuations are largely driven by TFP, variation in the Energy Differential should closely track business cycle dynamics;

(iii) in joint specifications, the long-run growth effect of TFP on macro variables should be largely subsumed by the contribution of Energy Differential;

(iv) most of the Long-Run Productivity fluctuations should be driven by the trend component of Energy Differential;

(v) Impulse Response Functions of macroeconomic variables to TFP and Energy Differential shocks should appear similar - both in empirical data and within the model.

Point (v) is presented in the section Quantitative Results. While the remainder of the section tests (ii)-(iv), and concludes by discussing how decomposing TFP in this way enhances our understanding of Long-Run Risk (LRR) models - an influential asset pricing framework that links macroeconomic uncertainty with expected returns.

Business-Cycle fluctuations. Energy Differential, TFP, and macroeconomic aggregates are decomposed into trend and cyclical components using three alternative filters: the Hamilton filter, the Christiano–Fitzgerald (CF) filter, and the Henderson filter.[3] Each resulting component is then used in a factor model to assess its explanatory power, based on the following regression specification:

$$[\cdot]_t^{comp} = \alpha^{comp} + \beta_x^{comp} \cdot [X^{comp}]_t + \varepsilon_t^{comp} \tag{17}$$

$$\text{where } comp \in \{Trend, Cyclical\}, X \in \{TFP_{util-adj,t}, ED_{T,t}\}$$

$[\cdot]_t^{\mathrm{comp}}$ denotes either the trend or cyclical component of a variable (e.g., GDP, consumption, investment), while X_t^{comp} corresponds to the filtered component of either the utilization-adjusted TFP or the Energy Differential. This setup allows us to evaluate which factor - TFP or energy - is more closely aligned with macroeconomic dynamics across both long-term trends and short-run fluctuations.

Table 4 presents the results of factor regressions comparing the explanatory power of utility-adjusted Total Factor Productivity (TFP) and the Energy Differential (ED) in capturing macroeconomic business-cycle fluctuations.

Across all variables and filtering methods, the Energy Differential consistently exhibits a stronger relationship with cyclical fluctuations than TFP. This is especially evident in the cycle regressions, where ED's β coefficients are not only economically meaningful but also statistically significant, with high t-statistics and R^2_{adj} values indicating substantial explanatory power. By contrast, TFP-based cyclical regressions often yield insignificant or even negative coefficients, with poor fit indications.

While utility-adjusted TFP is constructed to better reflect economic reality than raw Solow residuals, its quarterly behavior may still embed artifacts from complex estimation

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[3] In the case of the Henderson filter, the "cycle" refers to the comparison of extracted irregular components.

Table 4: Connection Across Business-Cycle

Component	**TFP**			**Energy Differential (ED)**		
	β^{comp}_{TFP}	**t-stat**	R^2_{adj}	β^{comp}_{ED}	**t-stat**	R^2_{adj}
GDP						
Hamilton: trend	0.985	[**77.996**]	0.970	0.954	[**43.763**]	0.910
CF: trend	0.989	[**96.802**]	0.979	0.952	[**44.507**]	0.906
Henderson: trend	0.993	[**116.748**]	0.985	0.965	[**52.433**]	0.931
Hamilton: cycle	0.019	[0.268]	-0.005	0.469	[**7.305**]	0.216
CF: cycle	-0.326	[**-4.923**]	0.102	0.560	[**9.656**]	0.310
Henderson: cycle	-0.079	[-1.132]	0.001	0.491	[**8.058**]	0.238
Consumption						
Hamilton: trend	0.986	[**80.685**]	0.972	0.946	[**40.107**]	0.894
CF: trend	0.990	[**99.619**]	0.980	0.944	[**40.915**]	0.891
Henderson: trend	0.993	[**121.036**]	0.986	0.958	[**47.577**]	0.917
Hamilton: cycle	-0.002	[-0.026]	-0.005	0.348	[**5.099**]	0.116
CF: cycle	-0.312	[**-4.682**]	0.093	0.497	[**8.181**]	0.243
Henderson: cycle	-0.092	[-1.314]	0.004	0.407	[**6.366**]	0.162
Investment						
Hamilton: trend	0.960	[**47.109**]	0.921	0.929	[**34.545**]	0.863
CF: trend	0.970	[**57.171**]	0.941	0.932	[**36.675**]	0.868
Henderson: trend	0.980	[**70.120**]	0.960	0.947	[**42.293**]	0.897
Hamilton: cycle	-0.084	[-1.158]	0.002	0.332	[**4.845**]	0.106
CF: cycle	-0.286	[**-4.264**]	0.077	0.447	[**7.132**]	0.196
Henderson: cycle	-0.179	[**-2.600**]	0.027	0.434	[**6.873**]	0.184
Employment						
Hamilton: trend	0.950	[**41.637**]	0.901	0.969	[**54.118**]	0.939
CF: trend	0.959	[**48.175**]	0.919	0.970	[**56.886**]	0.940
Henderson: trend	0.966	[**53.742**]	0.934	0.982	[**74.756**]	0.965
Hamilton: cycle	-0.177	[**-2.471**]	0.026	0.590	[**10.037**]	0.344
CF: cycle	-0.495	[**-8.136**]	0.241	0.690	[**13.607**]	0.473
Henderson: cycle	-0.284	[**-4.234**]	0.076	0.578	[**10.104**]	0.330

Notes: Bold t-statistics indicate significance at the 5% level. All values rounded to three decimal places. Data is quarterly and standardized for comparable β estimates.

choices - including capital service imputations, smoothing assumptions, and labor quality adjustments - which can distort its short-run dynamics. This issue is less pronounced in annual data, as shown in the appendix, where TFP behaves more smoothly and its correspondence with macroeconomic variables becomes more interpretable.

The results are robust across all filtering approaches, suggesting that the connection between ED and business-cycle dynamics is not an artifact of trend-cycle decomposition method. Notably, this contrast is particularly stark in employment and investment, where ED outperforms TFP by a wide margin. In summary, the table reinforces the empirical relevance of the Energy Differential as a physically grounded driver of macroeconomic variation, offering stronger and more stable predictive capacity than conventional productivity measures at the quarterly frequency.

Long-Run Growth and the Role of Energy. To explore the drivers of long-run macroeconomic growth, the predictive content of energy and productivity variables is estimated across various horizons. The regression framework forecasts the y-year-ahead growth of a macroeconomic variable using current growth in (i) total factor productivity (TFP), (ii) trend growth rate of Energy Differential, and (iii) growth rate of energy differential above the trend. This approach allows to separate persistent energy availability from short-run fluctuations.

The Energy Differential is decomposed into its long-run trend and short-run deviation components using the Henderson filter, chosen for its ability to produce a smooth trend estimate. The resulting regression specification is:

$$\Delta[\cdot]_{[t\rightarrow t+y]} = \alpha^{y} + \beta^{y}_{ed^{t}} \cdot \Delta ed^{trend}_{t} + \beta^{y}_{ed^{\neg t}} \cdot \underbrace{(\Delta ed_t - \Delta ed^{trend}_{t})}_{growth\ above\ trend} + \beta^{y}_{a} \cdot \Delta a_t + \varepsilon^{y}_{t} \tag{18}$$

Here, Δed^{trend}_{t} represents long-run growth in useful energy availability, while $(\Delta ed_t - \Delta ed^{trend}_{t})$ captures fluctuations above the trend - interpreted as temporary energy abundance or scarcity. TFP growth Δa_t is included to benchmark the relative informativeness of energy vs. raw productivity shocks.

The results presented in Table 5 reveal a structured pattern. Once usesul energy growth is accounted for, TFP loses its predictive power for long-run performance, supporting the hypothesis that TFP may reflect a mismeasured pass-through of energy inflows. Deviations above the energy trend significantly affect only current-period growth, consistent with the model's logic: temporary energy surpluses relax constraints and reduce prices, boosting short-run output without altering the long-run trajectory.

Interestingly, investment responds primarily to transitory energy availability, not the trend. This points to a forward-looking channel that deserves further attention - namely, how expectations about future energy conditions shape current investment behavior. Future research should explore this interaction, particularly the role of energy-sector optimization, capital allocation, and the dynamics of innovation in sustaining growth.

Table 5: Long-Run Growth Predictive Potential

	Δed^{trend}		$\Delta ed - \Delta ed^{\text{trend}}$		Δa_t		R^2_{adj}
	$\beta^y_{ed^t}$	[t-stat]	$\beta^y_{ed^{\neg t}}$	[t-stat]	β^y_a	[t-stat]	
GDP:							
current	0.682	[**2.824**]	0.407	[**6.512**]	-0.002	[-1.069]	0.439
1 year ahead	0.643	[**2.135**]	-0.058	[-0.745]	0.002	[1.223]	0.080
3 year ahead	0.763	[**2.501**]	-0.091	[-1.177]	-0.002	[-1.218]	0.052
4 year ahead	0.806	[**2.632**]	0.020	[0.253]	-0.004	[**-2.011**]	0.077
10 year ahead	0.810	[**2.421**]	-0.029	[-0.353]	-0.003	[-1.432]	0.049
Consumption:							
current	0.608	[**3.301**]	0.169	[**3.540**]	-0.001	[-0.536]	0.266
1 year ahead	0.642	[**3.215**]	-0.080	[-1.560]	0.001	[0.896]	0.155
3 year ahead	0.661	[**3.100**]	0.002	[0.043]	-0.001	[-0.655]	0.094
4 year ahead	0.644	[**3.000**]	0.068	[1.222]	-0.001	[-0.849]	0.116
10 year ahead	0.720	[**2.831**]	-0.007	[-0.118]	-0.002	[-1.455]	0.081
Investment:							
current	0.508	[0.491]	1.621	[**6.055**]	-0.009	[-1.384]	0.349
1 year ahead	0.375	[0.329]	-0.730	[**-2.485**]	0.012	[1.746]	0.096
3 year ahead	1.259	[1.031]	-0.291	[-0.935]	-0.011	[-1.460]	-0.001
4 year ahead	1.568	[1.289]	0.216	[0.686]	-0.017	[**-2.316**]	0.048
10 year ahead	1.179	[0.855]	-0.048	[-0.143]	-0.009	[-1.223]	-0.021
Employment:							
current	0.643	[**3.081**]	0.370	[**6.846**]	-0.004	[**-3.177**]	0.492
1 year ahead	0.567	[1.981]	0.087	[1.184]	-0.001	[-0.543]	0.047
3 year ahead	0.467	[1.650]	-0.093	[-1.296]	0.000	[0.158]	0.018
4 year ahead	0.726	[**2.612**]	-0.017	[-0.230]	-0.004	[**-2.514**]	0.089
10 year ahead	0.711	[**2.270**]	0.013	[0.167]	-0.001	[-0.669]	0.042

Notes: Bold t-statistics indicate significance at the 5% level. All values rounded to three decimal places.

Energy for the Long Run. The framework developed in this paper establishes a direct mapping between consumption bundles and energy inflows, with productivity reframed as a pass-through derived from energy-conversion. Empirically, the trend component of energy availability is a highly persistent driver of long-run consumption growth, subsuming the explanatory power of conventional productivity.

These findings have direct implications for the Long-Run Risk (LRR) asset-pricing framework of Bansal and Yaron (2004), where persistent fluctuations in expected consumption growth and its volatility explain risk premia. Specifically, (i) long-run components extracted from TFP and from the Energy Differential should exhibit similar dynamics and high correlation; and (ii) the trend growth of useful energy should dominate as the main source of long-run risk.

To test these predictions, the following baseline specification extracts LRR components from either productivity or energy data:

$$\begin{aligned} \Delta z_t &= \mu_z + x_t + \sigma_z \epsilon_z, \quad z_t \in \{\Delta a_t,\, \Delta \ln(ED_t)\}, \\ \Delta c_t &= \mu_c + x_t + \sigma_c \epsilon_c, \\ x_t &= \rho_x x_{t-1} + \sigma_x \eta_t. \end{aligned}$$

Here, x_t denotes the persistent growth component interpreted as the LRR process, while ϵ_z and ϵ_c capture short-run shocks; Δa_t is TFP growth and $\Delta \ln(ED_t)$ is the growth of Energy Differential. Estimation via a state-space representation (Kalman filter and GMM) shows that LRR processes extracted from both series are nearly identical and highly correlated.

Results of estimation are presented on Figure 7, and can be summarized as:

(i) Whether the LRR process x_t is extracted from the TFP series (a_t) or from Energy Differential (ED_t), the resulting components are nearly identical (left panel of Figure 7) - indicating the deep structural relationship between energy availability and perceived productivity.

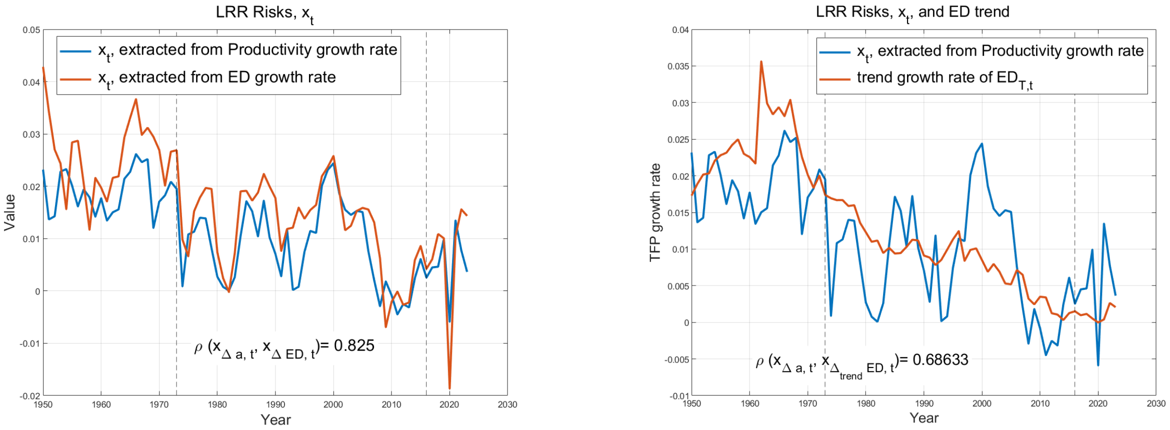

Fig. 7: Connections between Energy and Long-Run Risks (LRR)

Notes - Left panel reports Long-Run Risks extracted from TFP series compared with those derived from the Energy Differential, along with their correlation. Right panel shows the trend growth rate of Energy Differential plotted against LRR extracted from TFP.

(ii) Even when extracted solely from the productivity series, the most persistent component of x_t is ultimately tied to the trend in energy availability (right panel of Figure 7) - a relationship grounded in thermodynamic identities that govern production.

Moreover, when the model is augmented with the trend growth rate of energy availability:

$$x_t = \rho_x x_{t-1} + \beta_{en} \Delta ed_t^{\text{trend}} + \sigma_x \eta_t,$$

$\Delta ed_t^{\text{trend}}$ accounts for most of the persistence observed (estimated ρ_x falls from 0.98 to 0.27 between two specifiations) in long-run risk process, as shown in Figure 8. This reinforces the interpretation of ED_t as a fundamental state variable in macro-finance models - and suggests that asset-pricing applications of LRR can be re-examined through the lens of energy flows.

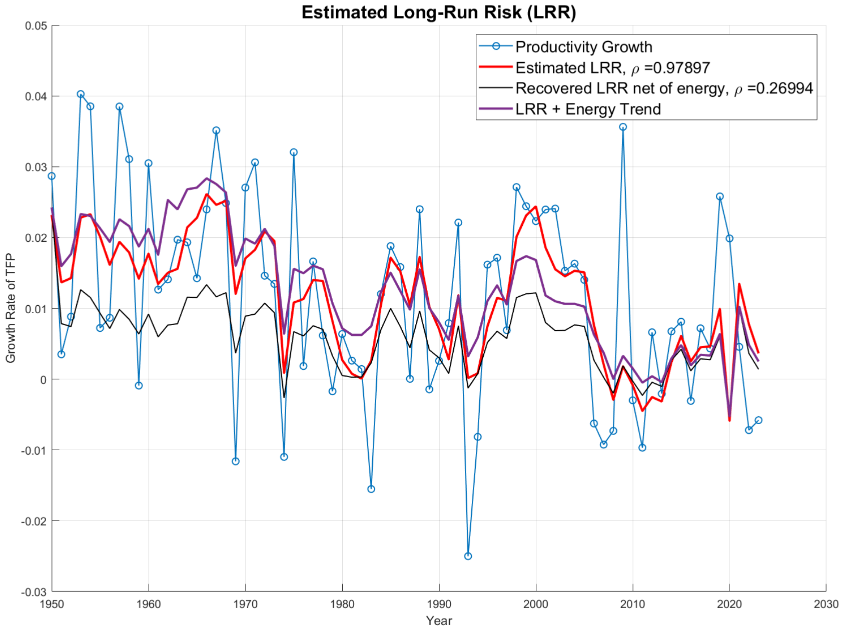

Fig. 8: Long-Run Risks Augmented by Energy

Notes - Blue line shows the utility-adjusted TFP growth rate. Red line represents Long-Run Risks extracted from the TFP series using the Bansal & Yaron (2004) specification. Violet line shows the LRR extracted using a specification augmented with the trend growth of Energy Differential. Black line represents LRR net of the energy component.

4 Energy-Based Endogenous Growth

This paper develops a dynamic stochastic general equilibrium endogenous growth model that integrates energy flows and thermodynamic constraints into production structure. Paper builds on Kung and Schmid (2015) model to investigate the implications of energy fluctuations for asset-markets. Paper departs from their model in three ways: (i) exogenous productivity is taken out of the baseline model; (ii) economy is fueled by exogenous energy source; (iii) production of intermediates has to obey thermodynamic identities.

Therefore, stylized features emerge: (i) The model avoids exponential productivity assumptions, growth is rooted in the trajectory of available energy flows; (ii) Production in intermediate sector requires *useful* energy input; no economic activity can proceed without satisfying the energy constraint. Useful energy becomes main underlying state-variable for the system; (iii) A stylized energy sector supplies energy subject costly extraction, with technological conversion limits (η_t^e) and energy yield (EROI); (iv) The price of energy ($P_{en,t}$) adjusts to balance supply and demand, feeding back into both intermediate good costs, final goods production and innovation incentives. Appendix reports how one could alternatively define energy market clearing as imperfect, and thermodynamic constraint on production occasionally binds (v) The rate of innovation depends on energy density of the environment; (vi) The framework allows for endogenization of conversion parameters (η_t^e, η_t^p and ϖ_t).

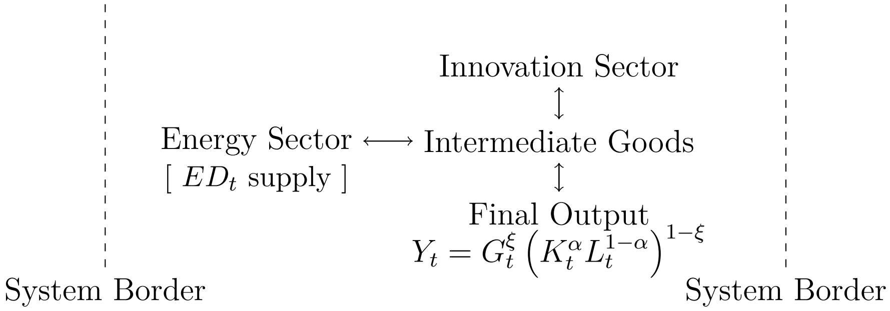

Fig. 9. Structure of the model. Arrows represent flows of energy and energy-related signals.

The model yields closed-form predictions: productivity, growth, and asset prices are jointly determined by energy availability and conversion efficiencies. Business cycle fluctuations in TFP are reinterpreted as fluctuations in ED_t, and the long-run growth rate becomes a function of both R&D effort and the underlying thermodynamic structure of the economy. As energy becomes harder to extract or convert, innovation slows, and real returns on capital decline. The model formalizes a tractable bridge between macroeconomic theory, fundamental physical laws and constraints on growth - and allows to later incorporate broader measures of environmental entropic damage to environment.

4.1 The final good producer

There is a representative firm that uses tangible capital K_t, labor L_t, and a composite of patents Γ_t to produce the final good according to the following production technology,

$$Y_t = (K_t^{\alpha}(L_t)^{1-\alpha})^{1-\xi}\Gamma_t^{\xi} \tag{19}$$

where the parameter α (ξ) is the physical (intangible) capital share. While Γ_t is given by:

$$\Gamma_t \equiv \left[\int_0^{N_t} (X_{i,t})^{\nu}\, di\right]^{\frac{1}{\nu}},$$

where $\nu < 1$ determines the elasticity of substitution between variaties $(\frac{1}{1-\nu})$; $X_{i,t}$ is the quantity of intermediate good $i \in [0, N_t]$. N_t is the measure of intermediate goods in use at date t and can be interpreted as the stock of R&D-intensive capital.

There is no stochastic exogeneity in production function - production technology is deterministic[4] at t, level of production varies depending on availability of intermediate goods (Γ_t), and latter depends on energy inflow. If energy-density of the environment is sufficient, growth arises endogenously with expansion of knowledge frontier.

Firm maximizes shareholder value, which is formally stated as:

$$\max_{\{I_t, L_t, K_{t+1}, X_{i,t}\}_{t\geq 0, i\in[0,N_t]}} \mathbb{E}_0\left[\sum_{t=0}^{\infty} M_t D_t\right],$$

where the firm's dividends are

$$D_t = \left[Y_t - \int_0^{N_t} P_{i,t}\cdot X_{i,t}\, di\right] - W_t L_t - I_t. \tag{20}$$

Here, M_t is the stochastic discount factor, I_t is investment in physical capital, W_t is the wage rate, and $P_{i,t}$ is the price per unit of pre-ordered intermediate good i at time t. Prices $P_{i,t}$

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[4] yet production frontier expands with declining marginal returns as N_t grows, due to changing conversion coefficients

are set by manufacturers in the intermediate good sector and they scale with energy price, affecting optimal production decision of the final goods firm, while the stochastic discount factor and the wage rate are determined in the general equilibrium and are all taken as given by the final goods firm.

Investment is subject to convex capital adjustment costs, so the physical capital stock evolves as

$$K_{t+1} = (1 - \delta)K_t + \Lambda\left(\frac{I_t}{K_t}\right)K_t. \tag{21}$$

Here, δ is the depreciation rate of physical capital and $\Lambda(\cdot)$ the capital adjustment cost function. $\Lambda(\cdot)$ is specified as in Jermann (1998), $\Lambda\left(\frac{I_t}{K_t}\right) \equiv \frac{\alpha_1}{\zeta}\left(\frac{I_t}{K_t}\right)^{\zeta} + \alpha_2$, where $\frac{1}{1-\zeta}$ represents the elasticity of the investment rate with respect to Tobin's Q. The parameters α_1 and α_2 are set so that there are no adjustment costs in the deterministic steady state.

4.2 Intermediate goods sector

The local monopolist must pay a per-period royalty ($\mathcal{R}_i$) in order to produce good i under monopoly power. They produce $X_{i,t}$ using both final good input and unit of **useful** energy ($ED_{i,t}$). In the stylized model, only intermediate goods production requires energy, which reflects on the structure of the GDP - provision of services is reliant on energy-consuming hardware infrastructure in place.

$$\max_{X_{i,t}} \Pi_{i,t} = P_{i,t} \cdot X_{i,t}(P_{i,t}) \cdot [ED_{i,t} \cdot \eta_t^p \cdot \varpi_t] - X_{i,t}(P_{i,t}) - P_{en,t} \cdot ED_{i,t} - \mathcal{R}_{i,t}$$

$$\text{subject to} \quad X_{i,t} = ED_{i,t} \cdot \eta_t^p \cdot \varpi_t$$

where $\eta_t^p \in [0, 1)$ describes the energy-efficiency in production chain, while ϖ_t represents productivity with which unit of energy is converted towards one unit of intermediate good, both grow as sigmoids of knowledge frontier N_t.

As in Romer (1990), Intermediate sector sells variety with a markup $\frac{1}{\nu}$ over its marginal cost. However, infinitely small monopolists are price-takers for energy, and therefore energy price affects the price of intermediates $P_{i,t}$:

$$P_{i,t} = \frac{1}{\nu}\,\mathrm{MC}_{i,t} \;=\; \frac{1}{\nu}\Big(1 + \frac{P_{en,t}}{\eta_t^p\,\varpi_t}\Big). \tag{22}$$

4.3 Energy Sector

The model relies on EROI formulation of energy flow - to capture the dependence of macroeconomy from aggregate energy-yield - be it rising costs of extraction or shift to lower-EROI energy sources.

$$ED_t = \Delta_t E_{ext} \cdot \eta_t^e - \Delta_t E_{Y_E} \approx \Delta_t E_{ext} \cdot \eta_t^e - \Delta_t E_{in} \cdot \frac{1}{EROI}$$

In the model, total useful energy supply ($ED_{S,t}$) is given, and grows with patents, subject to stochasticity of energy flow/extraction costs (θ_t):

$$ED_{S,t} = N_t \cdot \theta_t \cdot \eta_t^e - \underbrace{N_t \cdot \theta_t \cdot \frac{1}{EROI}}_{\approx \Delta_T E_{Y_E}} = N_t \cdot \theta_t \cdot (\eta_t^e - \frac{1}{EROI})$$

The energy inflow scaled by N_t serves as a metaphor for an expanding economic system interacting with its external environment through accumulated knowledge. Within the model, the variable θ_t can thus be interpreted not only as the energy requirement per variety (or per patent), but also as a measure of the effective energy density of the environment. It is possible to parametrize θ_t as an-AR(1) process:

$$\frac{\Delta_t E_{ext}}{N_t} \equiv \theta_t = (1-\rho) \cdot \bar{\theta} + \rho \cdot \theta_{t-1} + \varepsilon_t, \tag{23}$$

where $\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ is a mean-zero innovation term. This formulation captures persistent fluctuations in environmental energy density, driven by factors such as technological discovery, resource access, or shifting extraction efficiency.

This paper focuses on the role of energy flow constraints in shaping macroeconomic equilibrium. At each point in time, energy preceeds real economic activity; while its availability is determined either by current shocks in generation or by forward-looking variables. The model incorporates these stochastic fluctuations through exogenous flow of usable energy, calibrated to match observed data.

The reason for this modeling choice is structural: before embedding endogenous extraction into a general equilibrium framework, further investigation is needed to determine which forward-looking variables most strongly influence extraction decisions - under uncertainty, technological transitions and intertemporal tradeoffs - which makes it a natural extension for future work.

Current formulation allows to achieve several outcomes: (i) compare 1-to-1 exogenous productivity - with exogenous energy flow, (ii) in alternative setting, introduce stochasticity to EROI component - to differentiate between *trend* variability of energy flow, and short-run variability in costs of extraction, (iii) conduct scenario analysis of transition to certain energy source - via direct plug-in of EROI and η^e values for given technology.

4.4 Interplay of Intermediate and Energy sectors

Optimal intermediate goods production depends on energy abundance via its price, and may be directly constrained by the available energy inflow. The logic is simple: if the energy supply - e.g., from fossil or nuclear sources - is disrupted, energy-intensive operations like steelmaking scale down or halt completely, reducing aggregate intermediate output.

Let's denote $X_{i,t}$ as optimal demand for intermediate goods. It now depends on the cost of energy. From Final Goods firm optimization with respect to $X_{i,t}$, and given equation (12), it follows:

$$X_t = \left[\frac{\xi\nu}{(1+\frac{P_{en,t}}{\eta_t^p \varpi_t})}\left(K_t^\alpha L_t^{1-\alpha}\right)^{1-\xi} N_t^{\frac{\xi-\nu}{\nu}}\right]^{\frac{1}{1-\xi}} \tag{24}$$

Aggregate demand for energy is formed by optimal production of intermediates, subject to thermodynamic constraint:

$$ED_{D,t} = \int_0^{N_t} ED_{i,t}\,di = \int_0^{N_t} \frac{X_{i,t}}{\eta_t^p \varpi_t}\,di = N_t \cdot X_t \cdot \frac{1}{\eta_t^p \varpi_t} \tag{25}$$

Energy market clears via the price, hence:

$$P_{en,t} = \left[\frac{\xi\nu \cdot (K_t^\alpha L_t^{1-\alpha})^{1-\xi}}{\left[\theta_t \cdot \left(\eta_t^e - \frac{1}{\text{EROI}}\right) \cdot \eta_t^p \cdot \varpi_t\right]^{1-\xi}} \cdot N_t^{\frac{\xi-\nu}{\nu}} - 1\right] \cdot \eta_t^p \cdot \varpi_t \tag{26}$$

Realized optimal production (X_t) of intermediate goods is then fluctuating to match the supplied amount of energy.

Additionally, assuming symmetry in energy distribution across sectors, we can define *realized* energy-intensity per-variety

$$\varepsilon_t^{pv} := \frac{ED_t}{N_t} \quad or \quad ED_t = \int_0^{N_t} \varepsilon_t^{pv}\,di \tag{27}$$

where $\varepsilon_t^{pv} \propto f(\frac{\varepsilon}{\eta_t^p \varpi_t}) = f(N_t)$ scales over time with knowledge expansion. As knowledge accumulates, driven by past realization of energy abundance, there's more useful production per unit of energy - reflecting on increased efficiency of production chains.

4.5 Innovation sector

Innovators create patents that enable the extraction of energy from the environment, improve conversion efficiencies, and support intermediate goods production. This process requires investment in R&D, with the final good serving as the input.

In equilibrium, each patent holder sets the royalty rate to extract the full surplus from production.

$$\mathcal{R}_t = \left(\frac{1}{\nu} - 1\right) \cdot \left(1 + \frac{P_{en,t}}{\eta_t^p \, \varpi_t}\right) \cdot X_t \tag{28}$$

Royalty revenues respond to energy availability through two channels. As energy prices rise, markups increase and so does the incentive to invest in energy-saving technologies - fostering innovation targeted at efficiency. Yet if available energy becomes too scarce and intermediate production contracts, the royalty stream collapses, revealing that innovation is bounded by the physical capacity of the system to sustain productive activity. Energy-innovation mechanism embedded in the model goes beyond the free-market structure and innovation incentives - even centralized innovation-effort is not feasiable in absence of sufficient energy flow.

A patent has a probability ϕ to become obsolete. Hence the market value of patent i is:

$$V_{i,t} = \mathcal{R}_{i,t} + (1 - \phi)\, \mathbb{E}_t[M_{t+1} V_{i,t+1}]$$

Evolution of the intangible capital stock N_t is given by:

$$N_{t+1} = \vartheta_t S_t + (1 - \phi) N_t$$

where S_t denotes R&D expenditures (in terms of the final good), and ϑ_t represents the productivity of the R&D sector. This process is taken as exogenous by the R&D sector and, as a result, ϑ_t^{-1} is perceived as the cost of innovating at the margin.

In the spirit of Comin and Gertler (2006), there is a technology coefficient that involves a congestion externality effect:

$$\vartheta_t = \frac{\chi \cdot N_t}{S_t^{1-\eta} N_t^{\eta}},$$

where $\chi > 0$ is a scale parameter, and $\eta \in [0, 1]$ is the elasticity of new patents with respect to R&D. This specification captures the notion that concepts already discovered make it easier to come up with new ideas, $\partial\vartheta/\partial N > 0$, and that R&D investment has decreasing marginal returns, $\partial\vartheta/\partial S < 0$. [5]

There is a free-entry in the innovation sector, and therefore a following market-clearing condition:

$$\mathbb{E}_t[M_{t+1}V_{i,t+1}] = \frac{1}{\vartheta_t}$$

This condition sets the equilibrium amount of R&D investment and ultimately determines the equilibrium growth rate of the economy. R&D investment inherits the response of profits to energy fluctuations.

Knowledge-driven Efficiencies: Model allows to endogenize energy-productivity in production chains and conversion efficiencies. Certain shares ($\lambda_p, \lambda_e \in (0,1)$) of created knowledge go into improving energy-efficiency, productivity in production and energy-generation respectively. These channels are captured with bounded sigmoid functions:

$$\begin{aligned} \eta_t^p \cdot \varpi_t &= \eta_{\min} + \frac{\varpi_{\max} - \eta_{\min}}{1 + \exp(-\lambda_p N_t)} && [\text{ Production-chain efficiency and productivity }] \\ \eta_t^e &= \eta_{\min}^e + \frac{1 - \eta_{\min}^e}{1 + \exp(-\lambda_e N_t)} && [\text{ Energy-generation efficiency }] \end{aligned}$$

The sigmoid is a natural functional choice here, as both efficiencies are bounded above due to physical limit. While ϖ_t is bound to reach a horizontal asymptote, otherwise - we would be creating infinite amount of final output given finite amount of energy.

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[5] Similarly, this congestion externality can be thought of as giving rise to adjustment costs to investment in intangible capital, that is, R&D. Optimality condition for R&D is $\frac{1}{\vartheta_t} = \mathbb{E}_t[M_{t+1}V_{t+1}]$. Absent the congestion externality, this becomes $1 = \mathbb{E}_t[M_{t+1}V_{t+1}]$, a result analogous to q-theory, in which case the absence of adjustment cost fixes marginal Q at unity.

4.6 Household

The model features a representative household with Epstein-Zin preferences defined over consumption:

$$U_t = \left\{ (1-\beta) C_t^{1-\frac{1}{\psi}} + \beta (\mathbb{E}_t[U_{t+1}^{1-\gamma}])^{\frac{1-1/\psi}{1-\gamma}} \right\}^{\frac{1}{1-1/\psi}}, \tag{29}$$

where γ is the coefficient of relative risk aversion, and ψ is the intertemporal elasticity of substitution. When $\psi \neq \frac{1}{\gamma}$, the agent cares about news regarding long-run growth prospects. We assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty and dislikes shocks to long-run expected growth rates.

The household maximizes utility by participating in financial markets and by supplying labor. Specifically, the household can take positions $\mathcal{Z}_t$ in the stock market, which pays an aggregate dividend $\mathcal{D}_t$, and positions B_t in the credit market.

The stock market is a claim to total cash flows generated by both the final goods producer and the innovators. Accordingly, the net payout from all production sectors:

$$\mathcal{D}_t = D_t + N_t \cdot \mathcal{R}_t - S_t. \tag{30}$$

Ultimately, exogenous productivity component can be re-introduced in the model to account for supply-chain disruptions, lack of materials and other shocks to aggregate productivity, outside of energy influence.

5 Quantitative Results

Table 6: Benchmark calibration

Parameter	Symbol	Value
Subjective discount factor	β	0.9965
Risk aversion	γ	8.00
Intertemporal elasticity of substitution	ψ	1.60
Capital share	α	0.35
Intangible capital congestion, scale parameter	χ	0.343
Intangible capital congestion, elasticity	η	0.83
Physical capital adjustment costs, elasticity	$1/(1-\zeta)$	0.80
Elasticity of substitution across goods	$1/\nu$	1.65
Intangible capital share	ξ	0.50
Probability of patent obsoletes	ϕ	0.0375
Depreciation rate of capital	δ	0.020
Aggregate Energy Yield	$EROI$	12
Conversion Efficiency	η_t^e	0.40
Efficiency in production chains	$\eta_t^p \varpi_t$	2.80
Additional productivity values:		
Persistence of productivity shock	ρ_a	0.9925
Volatility of productivity shock	σ_a	0.021
Downscale non-energy productivity impact	κ_a	10.00

Empirical estimates of energy-per-variety θ_t

	Model	Estimate	Standard Error
Mean	0.143	0.135	0.012
Standard deviation	0.0055	0.0097	0.0014
Autocorrelation	0.904	0.949	0.012

Notes – The top panel of table reports benchmark quarterly calibration. See section 5 for a detailed discussion. The bottom panel reports summary statistics for measure of θ_t, displayed in Figure 10.

Calibration Benchmark quareterly calibration of the model (presented in 6) is standard and in conservative accordance with most of asset-pricing literature references. As in Kung & Schmid (2015), BLS data on stock of Intangible capital, measured in billions of 2017 dollars, informs the N_t variable, which is used for calibrating the process $\theta_t \equiv \dfrac{\Delta_t E_{ext}}{N_t}$, dynamics of which are presented on Figure 10.

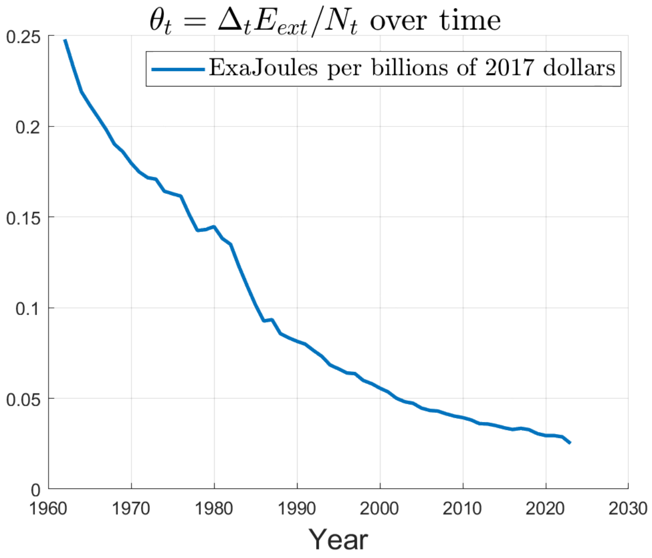

Fig. 10: Share of useful energy in the U.S. Economy

Notes – The figure shows the ration of gross energy inflow into the macro-economy relative to the stock of Intangible capital, figure depicts measure in ExaJoules per billions of 2017 US dollars.

Benchmark calibration measures energy differential factor as an outcome of $EROI = 10$ and $\eta^e = 0.4$, in the model $F_{ED} = 0.3$, while in the data $F_{ED} = \mathbb{E}[\dfrac{ED_t}{\Delta_t E_{ext}}] = 0.245$.

Coefficients that measure energy-efficiency and productivity in production-chain are estimated non-parametrically (1947 level is normalized to be 1) out of Energy Conversion Chain Expression $ED_t \cdot \eta_t^p \cdot \varpi_t = Y_t$. Change from 1947 equals 2.8 - and that value informs calibration.

Results Model that features only exogenous energy shock is illustatative. It can be shown that under the parameteric restriction $\alpha + \frac{\xi(1-\nu)}{\nu(1-\xi)} = 1$, which is introduced throughout the model, the model is equivalent to a real business cycle model with a standard neoclassical production function of the form:

$$Y_t = \underbrace{\left(\frac{\xi\,\nu}{1 + \frac{P_{en,t}}{\eta_t^p\,\varpi_t}} \right)^{\frac{\xi}{1-\xi}} \frac{\Gamma_t}{\varepsilon_t^{pv} \cdot \eta_t^p \cdot \varpi_t}^{\frac{\xi\,(1-\nu)}{(1-\xi)}}}_{\equiv A_t} K_t^{\alpha}\,L_t^{1-\alpha} \tag{31}$$

where A_t represents aggregate Total Factor Productivity (TFP) - and it is fully dependent on current energy level and past trajectory of energy availability. Ceteris Paribus, eneryg shortage or higher energy price causes a cascading suppressing effect on aggregate productivity of the economy. Γ_t adjusts dynamically to current energy-level via optimal production of intermediates X_t. Second component of Γ_t - N_t is the trajectory-driven accumulation of excess energy supplied to macro-economy stored in the form of accumulated intangible capital stock. This highlights the dense connection between knowledge accumulation and energy availability. Energy enables creation of excess output that can be spent on expanding knowledge frontier and increasing long-run productivity. However, short-run positive shocks to energy are as productive as the accumulated knowledge allows. In the long-run, trend component of energy should be cointegrated with knowledge expansion - and that cointegrating relationship should drive productivity growth.

Energy-shock only model is capable of replicating key moments and features of Kung and Schmid (2015). Adding an exogenous productivity component, beyond energy-impact, is redudant - yet helpful in (i) analyzing joint impact of pure energy shock and pure productivity shock on macrodynamics: (ii) delivering asset-pricing moments of the model *marginally* closer to their empirical counterparts. In order to be consistent with empirical bounds from SVAR IRFs, the effective impact of pure productivity shock has to be downscaled with parameter $\kappa_a = 10$.

Table 7 reports the performance of the model including both exogenous energy shock and effective productivity shock. The model is capable of replicating the measure premium on the market, even in absence of pure productivity shock, That illustrated the dependence of stock market fluctuations from underlying energy availability. Column three of Table 7 reports the aggregate energy yield that is closer to current empirical energy yield - including energy extraction from coal, oils, etc. While fourth columns provides simulated moments from an imaginative scenario of transitioning to carbon-sequestrating energy production. In that scenario aggregate Yield is set to 5 joules of output per 1 joule of energy expenditure on extraction (maximum bounds from literature review). Despite optimistic value of EROI, BECCS scenario delivers negative growth rate of consumption, almost negligible market return

Across both EROI scenarios, assuming that they both start with the same amount of intangible capital, one can compare welfare gains by looking at the U/N ratios. Since specified utility is homogeneous of degree one[6], one can conclude that moving to a setting with a carbon-emissions-neutral EROI could produce welfare loss equal to approximately 321% of time-0 consumption compared to modern-day economy fueled by variety of energy sources.

This loss can be decomposed in two parts. The first component is determined by differences in the time-0 level of consumption per unit of capital, $\frac{C_0}{N_0}$, across the two economies. The second part is driven by the utility gains per unit of consumption, U/C. Latter component is what Lucas (1987) computes an in endowment economy in which capital accumulation is not considered. In this experiment, the economy with the BECCS energy-harvesting technology produces a utility-consumption ratio that is 322% lower than that of the economy with a current spectrum of energy sources. In any case, the economy with the current day EROI features a considerably lower amount of consumption risk.

Transition to carbon-neutral energy harvesting implies a serious hit to consumption profile and aggregate macro-dynamics.

IRF comparison. Figure 11 reports in left column the performance of Energy-Driven Endogenous Growth (no productivity shock) with the Kung and Schmid (2015) model (ex-

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[6] Assuming a common level of time-0 intangible capital, N_0, one can compute the welfare gains, $1+g$, using the following equation:

$$\frac{U\left(C^D(1+g)\right)}{N}N_0 = \frac{U\left(C^P\right)}{N}N_0,$$

where D and P denote the consumption stream under the 'Current EROI' and the 'BECCS EROI' settings. Because of the homogeneity of U, the log gain is

$$\log(1+g) = \log\frac{U^D}{N} - \log\frac{U^P}{N}.$$

Table 7: Model summary statistics

	Data		Model	
	Point Est.	St.Err.	Current EROI	BECCS EROI
$E[\Delta C]$	2.09	0.25	2.02	-2.18
$\sigma(\Delta C)$	2.16	0.48	1.96	1.75
$\sigma(\Delta C)/\sigma(\Delta GDP)$	0.79	0.09	0.96	0.91
$\sigma(\Delta S)/\sigma(\Delta GDP)$	1.52	0.25	1.44	1.61
$E[R_f]$	1.25	0.21	2.61	0.00
$E[R_c]$	3.57	1.16	2.67	0.04
$E[R_{mkt}]$	7.39	5.52	7.99	0.12
$\log(U_t/N_t)$			0.17	-3.04
$\log(U_t/C_t)$			2.08	-1.22
$\log(V_{c,t}/C_t)$			6.44	5.20

Notes – Model features energy and non-energy-productivity shock. Statistics are obtained from averages of 120 short-sample simulations. GDP, C, I and S denote gross domestic product, consumption, tangible investment, and R&D investment, respectively. U/N is the utility-to-stock of patent ratio, and V_c/C is the price-dividend ratio for the asset that pays dividend equals to consumption every period. R_c is the return to the asset that pays aggregate consumption. Its data counterpart comes from Lustig, Van Nieuwerburgh, and Verdelhan (2013). R_f denotes the risk-free rate; R_{mkt} is the levered log return on the market. Means and standard deviations are annualized and expressed in percent. BECCS refers to Bioenergy with Carbon Capture and Storage, a renewable energy technology that combines biomass-based energy production with carbon sequestration, in this experiment its EROI is set to 5. Current EROI is set to 12.

ogenous productivity shock), latter model systematically overstates the dynamic response of output and consumption to productivity shocks - by nearly an order of magnitude - falling outside empirical bounds derived from SVARs. SVAR Cholesky scheme assumes the ordering $[TFP/ED] \rightarrow GDP \rightarrow Consumption$. In contrast, the Energy-Driven Endogenous Growth model reproduces data-consistent magnitude and shape of observed responses.

To be consistent with data, in baseline Kung and Schmid model productivity shock has to be effectively downscaled by a factor of ten (Figure 14), yet its timing remains misaligned with data. In case of energy shock, timing mismatch can be explained by the fact energy in real world is distributed with certain lag across productive facilities - easily replicatable with timing convention within the model.

Figure 12 reports the analysis of joint channel transmission - model features two separate exogenous shocks jointly, SVAR uses the following Choletsky decomposition $ED \rightarrow$

$TFP \rightarrow Consumption$. This specification leaves room for the impact of non-energy related productivity shocks, both in the data and in simulation. TFP series is pre-cleaned from cross-correlation with ED (as in Equation 13).

Main results can be summarized as follows:

(i) in the data, the response of GDP and Consumption to shocks in the Energy Differential is 2-5 times stronger than to pure (cleaned of energy) productivity shocks;

(ii) dynamics of traditional endogenous-growth models with exogenous TFP shocks are inconsistent with empirical IRFs and require large ad-hoc downscaling to fit the data;

(iii) energy–productivity channel provides a coherent and empirically stable mechanism - most of the fluctuation in measured productivity is delivered by variations in useful energy, which acts as the natural anchor for dynamics of macro-variables within the model - that allows for dynamic prediction consistent with data.

Growth Rates and Energy Yield. Figure 13 reports the counterfactual simulation - in order to re-construct the dependce of average growth rates and financial returns on aggregate Energy Yield. The resulting relationship is non-linear. Lower energy yields are exerting strong negative pressure on average growth rate of the economy, if not offset with respective improvements in energy-efficiency. Latter measure in the data increased 2.8 times since 1973, in a period of $\approx$ 50 years associated with relatively abundant energy yields. Innovation outcomes within the model depend on energy yields. Declining EROI values present a double threat on the aggregate performance of the economy: (i) by shutting down current production; (ii) by suppressing capacity for innovation.

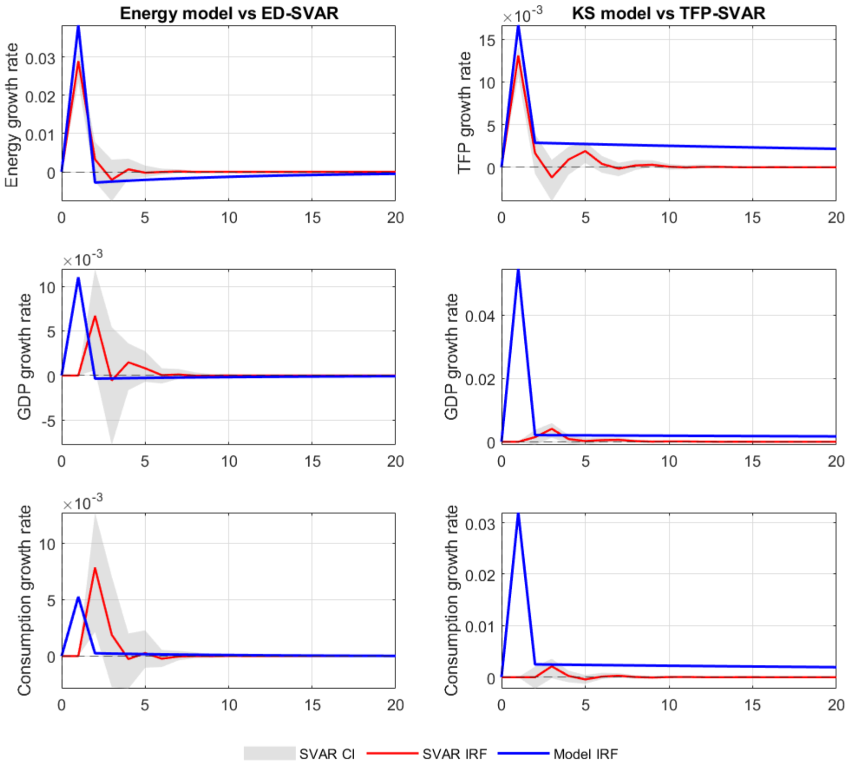

Fig. 11: Impulse Response Functions from KS and Energy models vs. SVARs

Notes - figure displays impulse response functions of real GDP and consumption growth rates to structural shocks in either Energy Differential or TFP (right). Red line is empirical estimate from a Structural-VAR. Cholesky decomposition assumes the ordering $[TFP/ED] \rightarrow GDP \rightarrow Consumption$. KS stands for Kung and Schmid (2015) model, Energy stands for endogenous growth model with energy as single exogenous component. Model simulations replicate the shock ordering in empirical SVARs. The specification is estimated using yearly U.S. data for 1949–2023, to improve signal-to-noise ratio. Confidence intervals are at the 10% significance level constructed with Newey-West adjusted standard errors.

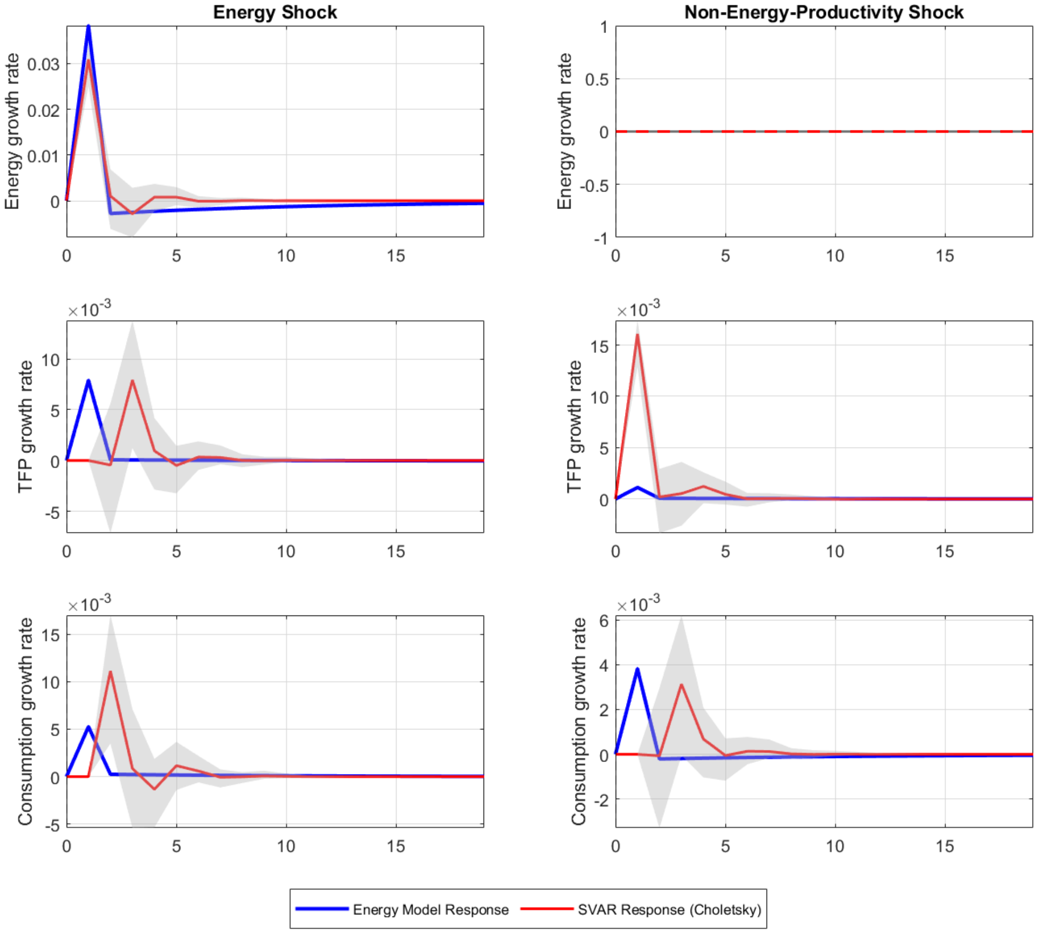

Fig. 12: IRFs from Energy model with productivity shock vs. SVAR

Notes - figure displays impulse response functions of consumption growth rates to structural shock in useful energy or non-energy-productivity, estimated via a Structural-VAR jointly. In the model, both shocks are featured, non-energy productivity shock is introduced effectively with downscale parameter α=10 to be consistent with data bounds, blue line reports effective, downscaled shock. Cholesky decomposition assumes the ordering $ED \rightarrow TFP \rightarrow Consumption$. The specification is estimated using yearly U.S. data for 1949–2023, which improves signal-to-noise ratio. Confidence intervals are at the 10% significance level with Newey-West adjusted standard errors

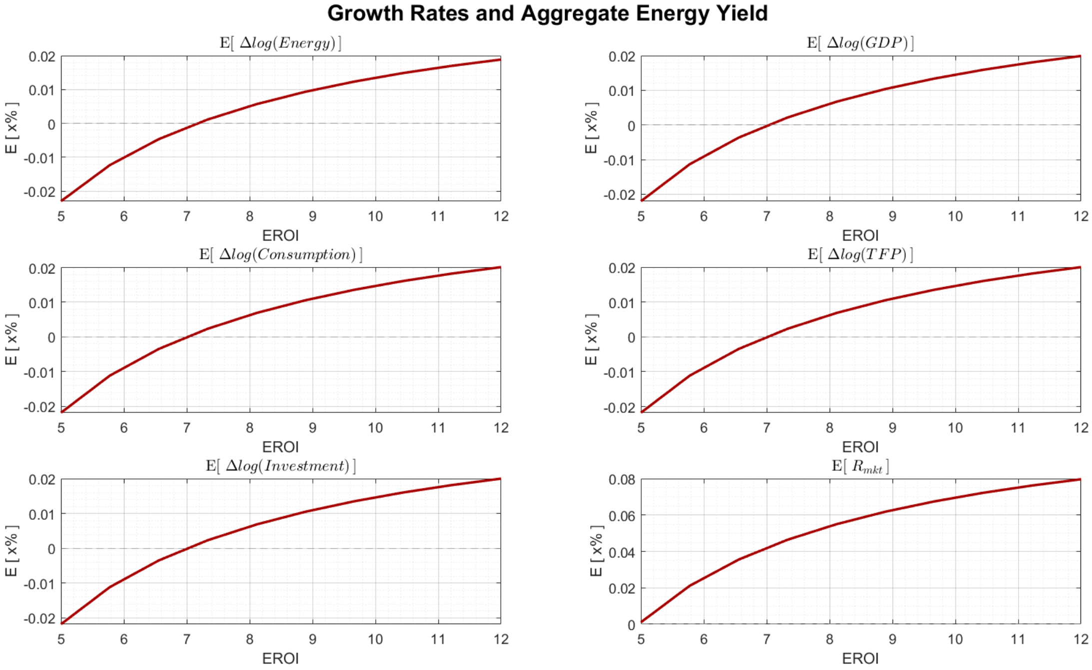

Fig. 13: Growth Rates and Aggregate Energy Yield connection

Notes - The figure reports expected value of GDP, growth rates and market return, calculated over 120 simulation periods, depending on the value of aggregate EROI.

6 Conclusion

This paper reinterprets the production side of the macroeconomy through the lens of fundamental physical symmetry - energy conservation - and places it as a foundational element of modelling production. Conventional production functions are shown to be incomplete because they omit the physical symmetry that governs all matter transformations. Economic growth is reinterpreted as energy-conversion chain. Convenient application of energy balances formalizes the Energy Differential - *Net Useful Energy* after extraction and conversion losses - as the core state variable governing both long-run trends and cyclical dynamics of the economy. his allows for unifying natural science foundation to think about broader environmental damage and other economic challenges.

When applied to endogenous growth setting, energy balances result in Total Factor Productivity emerging endogenously from flow of useful energy through intermediate goods optimization, framing growth as a process of transforming energy gradients into ordered output. The model implies that transitions to lower-EROI energy sources - such as renewables - may constrain growth via several channels, unless offset by large energy-efficiency gains.

Empirically, the Energy Differential explains over 94% of TFP variation, outperforms TFP in tracking business-cycle dynamics, and subsumes its role in long-run growth predictions. Both model simulations and structural VARs show that energy shocks generate impulse responses nearly identical to traditional TFP shocks, indicating that much of measured productivity fluctuations reflects underlying energy flows. In Macro-Finance, Energy Differential becomes the main driver of long-run consumption growth, thus affecting asset prices - providing a fundamental physical interpretation for long-run risk models.

At its core, this paper advocates for a materialist outlook on macroeconomics - unifying growth theory with natural sciences - approach that unifies sustainability, inequality and finance under a single principle - all economic motion is energy transformation.

References

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous, 2012, The Environment and Directed Technical Change, *American Economic Review* 102, 131–166.

Aghion, Philippe, and Peter Howitt, 1992, A Model of Growth Through Creative Destruction, *Econometrica* 60, 323.

Apostolakis, Bobby E., 1990, Energy—capital substitutability/ complementarity, *Energy Economics* 12, 48–58.

Arkolakis, Costas, and Conor Walsh, 2023, Clean Growth, Working paper, National Bureau of Economic Research.

Atkeson, Andrew, and Patrick J Kehoe, 1999, Models of Energy Use: Putty-Putty Versus Putty-Clay, *American Economic Review* 89, 1028–1043.

Ayres, Robert U., Leslie W. Ayres, and Benjamin Warr, 2003, Exergy, power and work in the US economy, 1900 – 1998, *Energy* 28, 219–273.

Ayres, Robert U., and Benjamin Warr, 2005, Accounting for growth: The role of physical work, *Structural Change and Economic Dynamics* 16, 181–209.

Backus, David, Mikhail Chernov, and Stanley Zin, 2014, Sources of entropy in representative agent models, *The Journal of Finance* 69, 51–99.

Bansal, Ravi, Dana Kiku, and Marcelo Ochoa, 2016, Price of Long-Run Temperature Shifts in Capital Markets, Working paper, National Bureau of Economic Research.

Bansal, Ravi, Dana Kiku, and Amir Yaron, 2016, Risks for the Long Run: Estimation with Time Aggregation, *Journal of Monetary Economics* 82, 52–69.

Bansal, Ravi, and Marcelo Ochoa, 2011, Temperature, Aggregate Risk, and Expected Returns, Working paper, National Bureau of Economic Research.

Bansal, Ravi, and Amir Yaron, 2004, Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles, *The Journal of Finance* 59, 1481–1509.

Barlevy, Gadi, 2004, The Cost of Business Cycles under Endogenous Growth, *American Economic Review* 94, 964–90.

Barsky, Robert B., and Lutz Kilian, 2004, Oil and the Macroeconomy since the 1970s, *The Journal of Economic Perspectives* 18, 115–134.

Belo, Frederico, Santiago Bazdresch, and Xiaoji Lin, 2014, Labor Hiring, Investment, and Stock Return Predictability in the Cross Section, *Journal of Political Economy* 122, 129–177.

Belo, Frederico, Vito Gala, Juliana Salomao, and Maria Ana Vitorino, 2022, Decomposing Firm Value, *Journal of Financial Economics* 143, 619–639 Lead Article, Editor's choice.

Belo, Frederico, Xiaoji Lin, and Fan Yang, 2018, External Equity Financing Shocks, Financial Flows, and Asset Prices, *Review of Financial Studies* 32, 3500–3543.

Bianchi, Francesco, Cosmin Ilut, and Martin Schneider, 2012, Uncertainty shocks, asset supply and pricing over the business cycle, Working paper.

Bilal, Adrien, and Diego Känzig, 2024, The Macroeconomic Impact of Climate Change: Global vs. Local Temperature, Working paper, National Bureau of Economic Research.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Campanale, Claudio, Rui Castro, and Gian Luca Clementi, 2010, Asset pricing in a production economy with Chew–Dekel preferences, *Review of Economic Dynamics* 13, 379–402.

Comin, Diego, and Mark Gertler, 2006, Medium-Term Business Cycles, *American Economic Review* 96, 523–551.

Comin, Diego A, Mark Gertler, and Ana Maria Santacreu, 2009, Technology innovation and diffusion as sources of output and asset price fluctuations, npublished working paper. National Bureau of Economic Research.

Corhay, Alexandre, Howard Kung, and Lukas Schmid, 2015, Competition, Markups and Predictable Returns., Unpublished working paper. Duke University.

Croce, Max, 2014, Long-run productivity risk: A new hope for production-based asset pricing?, *Journal of Monetary Economics* 66, 13–31.

Diercks, Anthony M., Alex Hsu, and Andrea Tamoni, 2024, When It Rains It Pours: Cascading Uncertainty Shocks, *Journal of Political Economy* 132, 694–720.

Engle, Robert F, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging Climate Change News, *The Review of Financial Studies* 33, 1184–1216.

Favero, Carlo Ambrogio, Arie Gozluklu, and Andrea Tamoni, 2011, Demographic Trends, the Dividend-Price Ratio and the Predictability of Long-Run Stock Market Returns, *Journal of Financial and Quantitative Analysis* 46, 1493–1520.

Favero, Carlo Ambrogio, Arie Gozluklu, and Haoxi Yang, 2016, Demographics and the Behaviour of Interest Rates, *IMF Economic Review* 64, 732–776.

Finn, Mary G, 2000, Perfect Competition and the Effects of Energy Price Increases on Economic Activity, Working paper, .

Gao, Lin, Steffen Hitzemann, Ivan Shaliastovich, and Lai Xu, 2022, Oil volatility risk, *Journal of Financial Economics* 144, 456–491.

Gavazzoni, Federico, and Ana Maria Santacreu, 2015, International R&D Spillovers and Asset Prices., Unpublished working paper. INSEAD.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate Change and Long-Run Discount Rates: Evidence from Real Estate, *The Review of Financial Studies* 34, 3527–3571.

Grossman, Gene M., and Elhanan Helpman, 1991, Trade, knowledge spillovers, and growth, *European Economic Review* 35, 517–526.

Hassler, John, Per Krusell, and Conny Olovsson, 2021, Directed technical change as a response to natural resource scarcity, *Journal of Political Economy* 129, 3039–3072.

Heal, Geoffrey, 2009, The Economics of Renewable Energy, Working paper, National Bureau of Economic Research.

Holechek, Jerry L., Hatim M.E. Geli, Mohammed N. Sawalhah, and Raul Valdez, 2022, A Global Assessment: Can Renewable Energy Replace Fossil Fuels by 2050?, *Sustainability* 14.

Hsu, Po Hsuan, Kai Li, and Chi Yang Tsou, 2023, The Pollution Premium, *Journal of Finance* 78, 1343–1392.

Jermann, Urban Joseph, 1998, Asset Pricing in Production Economies, *Journal of Monetary Economics* 41, 257–275.

Jermann, Urban Joseph, 2010, The Equity Premium Implied by Production, *Journal of Financial Economics* 98.

Jo, Soojin, Lilia Karnizova, and Abeer Reza, 2019, Industry effects of oil price shocks: A re-examination, *Energy Economics* 82, 179–190.

Kaltenbrunner, Georg, and Lars A. Lochstoer, 2010, Long-Run Risk through Consumption Smoothing, *Review of Financial Studies* 23, 3190–3224.

Kilian, Lutz, 2008, The economic effects of energy price shocks, *Journal of Economic Literature* 46, 871–909.

Kim, In-Moo, and Prakash Loungani, 1992, The role of energy in real business cycle models, *Journal of Monetary Economics* 29, 173–189.

Kogan, Leonid, and Dimitris Papanikolaou, 2009, Growth Opportunities and Technology Shocks, .

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, 2012, Technological Innovation, Resource Allocation and Growth, *Working Paper, MIT*.

Kogan, Leonid, Dimitris Papanikolaou, and Noah Stoffman, 2013, Technologial Innovation: Winners and Losers, *Working Paper, MIT*.

Komatsu, Momo, 2024, To Cap or Not to Cap? Energy Crises in a Currency Union, Working paper, .

Kuehn, Lars Alexander, 2008, Asset Pricing and Real Investment Commitment., Unpublished working paper. Carnegie Mellon University.

Kuehn, Lars Alexander, 2009, Disentangling Investment Returns and Stock Returns: the Importance of Time-to-Build., Unpublished working paper. Carnegie Mellon University.

Kung, Howard, and Lukas Schmid, 2015, Innovation, Growth, and Asset Prices, *Journal of Finance* 70, 1001–1037.

Kydland, Finn E., and Edward C. Prescott, 1982, Time to Build and Aggregate Fluctuations, *Econometrica* 50, 1345.

Lucas, Robert E., 1987, *Models of Business Cycles*. (Oxford: Basil Blackwell).

Lustig, Hanno, Stijn Van Nieuwerburgh, and Adrien Verdelhan, 2013, The Wealth-Consumption Ratio, *Review of Asset Pricing Studies* 3, 38–94.

Nath, Ishan, Valerie Ramey, and Peter Klenow, 2024, How Much Will Global Warming Cool Global Growth?, Working paper, National Bureau of Economic Research.

Popp, David, 2002, Induced Innovation and Energy Prices, *American Economic Review* 92, 160–180.

Prigogine, Ilya, and Isabella Stengers, 1984, *Order Out of Chaos*. (Toronto ; New York, N.Y. : Bantam Books).

Romer, Paul M, 1990, Endogenous technological change, *Journal of Political Economy* 98, 71–102.

Rotemberg, Julio J, and Michael Woodford, 1996, Imperfect Competition and the Effects of Energy Price Increases on Economic Activity, Working paper, .

Schlenker, Wolfram, and Charles A. Taylor, 2021, Market expectations of a warming climate, *Journal of Financial Economics* 142, 627–640.

Stern, David I., and Astrid Kander, 2012, The Role of Energy in the Industrial Revolution and Modern Economic Growth, *The Energy Journal* 33, 125–152.

Tallarini, Thomas D., 2000, Risk Sensitive Real Business Cycles, *Journal of Monetary Economics* 45, 507–532.

A Other Implications of Energy Balances

Finiteness of Growth.

Each act of production is an energy transformation. This renders growth ultimately constrained by the planet's finite capacity to provide concentrated energy gradients. Every new production layer - be it digital services or AI inference - rests on a foundation of physical operations and energy use . In case of exhaustion of existing energy sources, higher energy extraction costs and lower aggregate energy yield (declining EROIs), the system uses larger share of available energy just to maintain itself.

Thus, economic growth is not an abstract extrapolation of productivity curves; it is a chain of physical conversions - each subject to conversion losses and inefficiencies.

A thought experiment clarifies the point: suppose a scenarion where fossil and nuclear stocks are exhausted, and society relies solely on solar radiation.

Radiation inflow has certain energy density ($\frac{\Delta_t E_{env}}{V_t}$), V_t would be the volume of economic system. Given the fixed deployable volume for harvesting sun radiation, peak conversion efficiencies - there is only a fixed amount of energy incoming into the macro-economy, and therefore fixed amount of energy value of goods produced. This would naturally lead to de-growth.

$$
\begin{aligned}
[\Delta_t E_{ext} \cdot \eta_t^e - \Delta_t E_{Y_E}] \cdot \eta_t^P &= \Delta_t E_Y \\
[\Delta_t E_{ext} \cdot \eta_t^e - \Delta_t E_{Y_E}] \cdot \eta_t^P \cdot \varpi_t^P &= Y_{real} \\
\textit{while } \Delta_t E_{ext} &= \frac{\Delta_t E_{env}}{V_t} \cdot V_t
\end{aligned}
$$

This example convincingly illustrates that infinite endogenous technological growth is not possible. It is a transient force of economic growth. Expansion of production is harshly dependent on the rate of expansion of economic system, and the exogenously determined energy-density of the environment. In the long run, growth is ultimately volumetric: expanding the system's reach (e.g. into space) is the only route to maintain the flow of energy and resources.

It is a well-known tenet in some models - that everything grows with productivity. Oftentimes, assumption of infinite exponential productivity is introduced. However the latter serves only as approximation to luckily constellation of energy inflow since 19th Century and development of thermal engines.

It is of interest to examine the parameter ϖ_t^P, which translates the energy value of production into a real bundle of consumable items. It can be interpreted either as an energy–productivity coefficient in the production chain, or as the conversion rate between energy inflows and entropy reduction. In either case, physical law imposes an upper bound.

To assume ϖ_t^P can grow without limit is to claim that a finite quantity of energy can produce infinite structure - either through unbounded entropy reduction or mass generation. Both violate core physical constraints: no system can yield infinite output from finite inputs. This would imply, absurdly, that no consistent mapping exists between mass (or service-carrying conduits of mass) and energy, contradicting both thermodynamic and relativistic principles. Empirically and theoretically, a one-to-one relationship between mass and energy seems to hold so far.

Ultimately, economy as an open thermodynamic system, grows in volume at the expense of inflow of energy. Therefore describing growth without energy as enabling, augmenting and balancing factor may lead to undesirable outcomes.

Money as a claim on Energy.

Since all the goods we exchange are forms of derived energy, and we use money for exchanging those - each monetary unit can be interpreted as a claim on energy-equivalent of output. The quantity of money in circulation - whether issued by the state, banks, or other entities - does not alter energy value at given period. Expansion of monetary mass (M_t) reduces the energy-content per unit of currency, effectively diluting the claim each unit has on real energy-equivalent of wealth.

$$M_{t,Gov} + M_{t,H} + M_{t,Firms} + M_{t,Banks} = M_t \approx \Delta_t E_Y \tag{32}$$

From this standpoint, credit issuance and inflation act as redistribution channels of energy value. Monetary and financial mechanisms can shift claims across sectors or households, but cannot bypass the energy constraints embedded in the real economy. This has implications for understanding fiat money credibility, energy-price pass-throughs, and financial fragility.

Energy-dimension of Inequality.

Energy Value Theory also introduces a natural lens for studying economic inequality.

$$\Delta_t ED_C^{total} = \int_{h=1}^{H} [\Delta_t E_C^h - \Delta_t E_L^h] \cdot \underbrace{f_H(h)\partial h}_{distribution\ of\ households} \tag{33}$$

Equation (8) defines each household's net consumption in Joules: the energy equivalent of goods acquired minus the energy value of labor supplied. Since human physical output is bounded and similar across individuals, large disparities in net energy consumption reflect the extent to which some agents are placed within energy-intensive processes - via capital ownership, wealth, or institutional claims. This reconceptualization allows to study inequality not only in income or wealth space, but in energy-consumption space, offering a universal, physical metric. Inequality becomes a question of who controls access to energy-mediated conversion chains.

B Alternative model structure with imperfect energy market clearing

In alternative version of the model, energy market may not cleer perfectly.

Then realized production of intermediate goods is given by the minimum - approximated in the model via $\ln(X) = -\frac{1}{\lambda} \cdot \log\left(e^{-\lambda \ln(X^{en})} + e^{-\lambda \ln(X')}\right)$ - between energetically-achievable production (X_t^{en}) and optimal amount (X_t'):

$$X_t^{en} = ED_{S,t} \cdot \eta_t^p \cdot \varpi_t$$

$$X_t = \min(X_t', X_t^{en})$$

$$\omega_t \equiv \frac{X_t}{X_t'} \in [0, 1]$$

ω_t - is an auxillary variable that describes the achieved share of potential optimum.

C Extra Figures

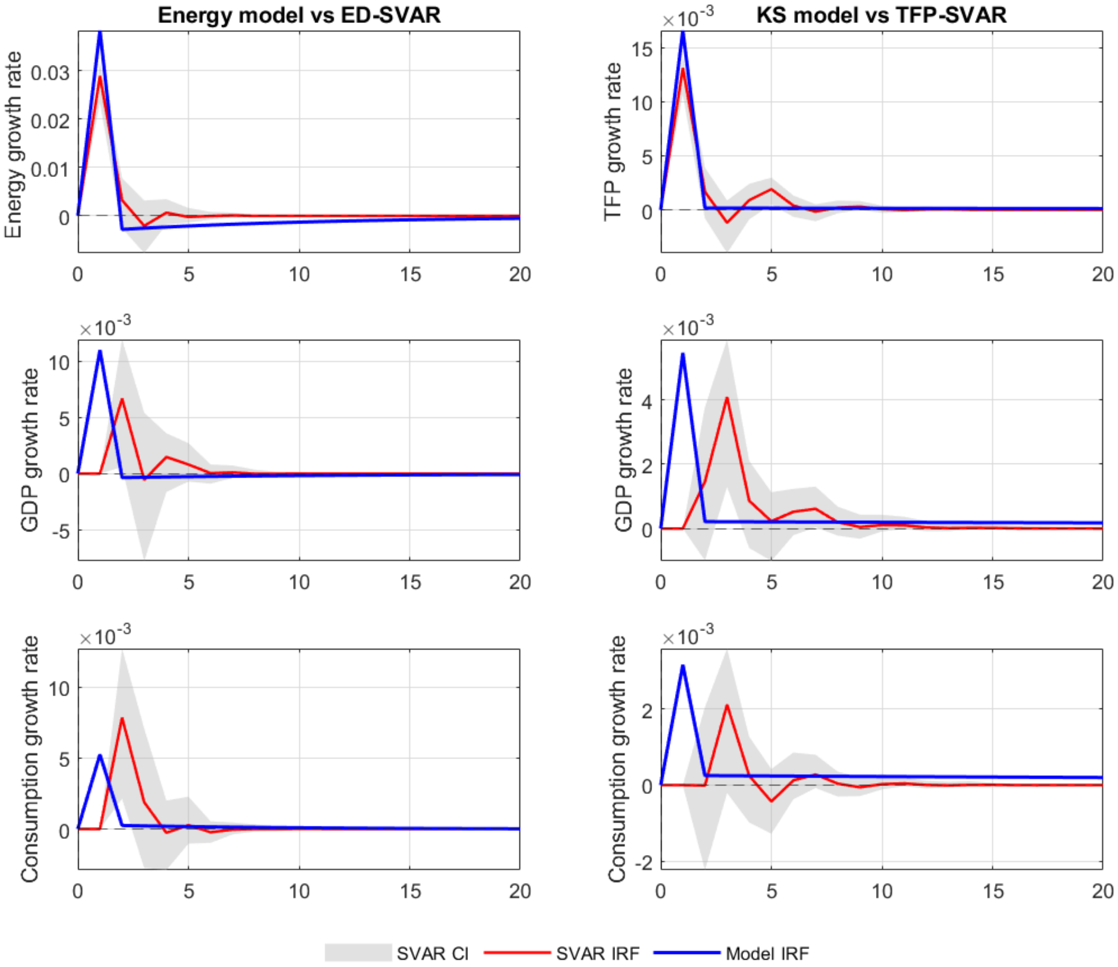

Fig. 14: Impulse Response Functions from KS and Energy models vs. SVARs

Notes - figure displays impulse response functions of real GDP and consumption growth rates to structural shocks in either Energy Differential or TFP (right). Red line is empirical estimate from a Structural-VAR. Cholesky decomposition assumes the ordering $[TFP/ED] \rightarrow GDP \rightarrow Consumption$. KS stands for Kung and Schmid (2015) model, Energy stands for endogenous growth model with energy as single exogenous component. In KS model, productivity shock is downscaled with $\kappa_a = 10$ Model simulations replicate the shock ordering in empirical SVARs. The specification is estimated using yearly U.S. data for 1949–2023, to improve signal-to-noise ratio. Confidence intervals are at the 10% significance level with Newey-West adjusted standard errors.

What is the Relationship between Biodiversity and the Frequency of Financial Crises? Global Evidence

Mikhail Stolbov[*], Maria Shchepeleva[†], Daniil Parfenov[‡]

Abstract

The paper studies the relationship between the state of world's biodiversity proxied by the Living Planet Index and the frequency of financial crises, conditional on global economic growth and the total number of biodiversity-related environmental policy instruments, during 1970-2018. We find that the increased frequency of banking crises as well as triple crises, i.e. simultaneously occurring banking, sovereign debt and currency crises, has a detrimental effect on biodiversity. Moreover, this relationship appears bidirectional. Thus, our findings call for a joint implementation of environmental and macroprudential policies to better align the goals of biodiversity conservation and financial stability worldwide.

JEL classification: biodiversity, financial crisis, Living Planet Index, local projections
Keywords: G01, C32, E44.
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1 Introduction

Biodiversity has now been studied from an interdisciplinary perspective, increasingly catching the attention of scholars in social sciences, including economics and finance (Dasgupta, 2021). Against this backdrop, the biodiversity-finance nexus represents an important, yet burgeoning research program with multiple gaps. They are identified in the recent conceptual works and reviews (Flammer, Giroux, and Heal, 2025; Karolyi and Tobin-de la Puente, 2023; Hutchison and Lucey, 2024) and are to be filled in by the research community. One of the key strands of research on the biodiversity-finance nexus deals with biodiversity-related financial risks, as biodiversity loss creates physical and transition risks for financial institutions (Network for Greening the Financial System , NGFS; Hudson, 2024). In particular, several recent studies document that biodiversity loss adversely affects credit portfolios and equity holdings of financial institutions (Calice, Diaz, Dunz, and Miguel, 2023; Hadji-Lazaro, Salin, Svartzman, Espagne, Gauthey, Berger, Calas, Godin, and Vallier, 2024; Mundaca and Heintze, 2024). Furthermore, Giglio, Kuchler, Stroebel, and Zeng (2023) and Bassen, Buchholz, Lopatta, and Rudolf (2024) show that biodiversity-related risks can potentially entail stock price crashes.

Although biodiversity-related financial risks represent a serious concern for central banks (Kedward, Ryan-Collins, and Chenet, 2023), little is known about the relationship between biodiversity and financial stability once financial risks have materialized, i.e., in terms of financial crises. Does the frequency of financial crises affect biodiversity? Is this relationship unidirectional, running from the frequency of crises to biodiversity or vice versa? Which types of financial crises are more related to biodiversity? These questions naturally extend the studies focused on the link between financial crises and various manifestations of environmental degradation. For example, Pacca, Antonarakis, Schröder, and Antoniades (2020) investigate the impact of financial crises on air-pollutant emissions, while Antonarakis, Pacca, and Antoniades (2022) explore their effect on deforestation. In the spirit of these works, the above questions build on the premise that there can be a deterioration in biodiversity, since environmental protection is weakened due to a financial crisis. This detrimental effect may be exacerbated in case different types of financial crises overlap.

To our knowledge, this paper is the first to explore the link between financial crises and biodiversity on the global level. We carry out the analysis for the period 1970–2018, using the Living Planet Index as a proxy for the state of world biodiversity and considering the annual frequency of banking, sovereign debt, and currency crises as well as their combinations, i.e., twin crises and triplets. We also account for the role of conditioning variables, i.e., world real GDP per capita growth and the total number of environmental policy instruments applied worldwide, specifically aimed at safeguarding biodiversity.

2 Data

We adopt the Living Planet Index (LPI) as a measure of the state of world biodiversity. This indicator captures population trends of vertebrate species from terrestrial, freshwater, and marine habitats. It currently encompasses 31,821 populations of 5,230 species. The LPI can be retrieved from https://www.livingplanetindex.org/latest_results and is available on an annual basis for the period 1970–2020, [1] exhibiting a persistent downward trend over this span.

Regarding the frequency of financial crises, we exploit the dataset on banking (BANK), sovereign debt (SOVDEBT), currency (CUR), as well as complex crises—twin (banking and currency episodes, TWIN) and triple crises (TRIPLE)—provided by Nguyen, Castro, and Wood (2022). They updated and extended the well-established financial crisis database by Laeven and Valencia (2020).

We also include world real GDP per capita growth (GDP) and the total number of environmental policy instruments (NEPI) applied worldwide, covering various taxes and

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[1] Although there are other measures assessing the state of global biodiversity—such as the Red List Index (https://www.iucnredlist.org) or the Biodiversity Intactness Index (https://www.nhm.ac.uk/our-science/services/data/biodiversity-intactness-index.html)—the Living Planet Index (LPI) covers the longest time span without missing values and has been adopted by the Convention on Biological Diversity as an official indicator of progress toward the goals set by the UN Biodiversity Conference (COP15) held in 2022.

fees as well as permits and subsidies specifically aimed at safeguarding biodiversity. Both indicators are alleged to co-vary with biodiversity, while global economic growth should also relate to the frequency of financial crises. Thus, GDP and NEPI are likely to mediate the relationship between LPI and the frequency of financial crises. GDP comes from the World Development Indicators, while NEPI is based on the OECD Policy Instruments for the Environment (PINE) database.

Given the length of the time series for LPI and the data on financial crises, our empirical analysis is confined to the period between 1970 and 2018. Descriptive statistics of all variables are represented in Table 1.

Table 1: Descriptive statistics of main variables

	Mean	Maximum	Minimum	Std. Dev.	Observations
GDP	1.7	4.3	-2.6	1.4	49
LPI	0.6	1.0	0.3	0.2	49
NEPI	213.1	470.0	26.0	157.0	49
BANK	3.1	22.0	0.0	4.4	49
SOVDEBT	3.7	13.0	0.0	2.8	49
CUR	7.1	25.0	0.0	5.4	49
TWIN	1.5	7.0	0.0	1.7	49
TRIPLE	0.4	3.0	0.0	0.7	49

Notes – Table reports descriptive statistics for the main variables used in the empirical analysis. GDP denotes world real GDP per capita growth rate (%), LPI refers to the Living Planet Index (annual change), NEPI represents the total number of biodiversity-related environmental policy instruments applied worldwide, and BANK, SOVDEBT, CUR, TWIN, and TRIPLE correspond to the annual frequencies of banking, sovereign debt, currency, twin, and triple crises, respectively.

3 Methodology

We employ local projections (LPs) proposed by Jordá (2005). This method provides an alternative approach to deriving impulse responses and, in several respects, appears superior to conventional vector autoregressions (VAR). LPs obtain impulse responses by estimating forecasts at each horizon rather than extrapolating from a single estimated system as in

VARs. Moreover, LPs are more flexible, since they do not rely on a specific preliminary specification of a multivariate dynamic system. They are also robust to model misspecification, non-linearities, and short time series. Another advantage is that lag-augmented LPs are asymptotically valid under both stationary and non-stationary data (Olea and Plagborg-Møller, 2021). Overall, given that our time series are relatively short and bi-directional relationships among variables cannot be ruled out, we regard LPs as preferable to VAR estimation.

The general setup of the LP equation is given by:

$$y_{i,t+s} = \alpha_{i,s} + D^{\text{shock}}_{i,t-1}\beta_s + D^{x}_{i,t-1}\gamma_s + u_{i,t+s} \tag{1}$$

where $y_{i,t+s}$ refers to the dependent variable, which iteratively takes on the value of one of the indicators in the following vector: [the total number of environmental policy instruments aimed at safeguarding biodiversity (NEPI), the Living Planet Index (LPI), the frequency of financial crises (BANK, SOVDEBT, CUR, TWIN, and TRIPLE), and world real GDP per capita growth (GDP)]. $\alpha_{i,s}$ denotes country fixed effects. $D^{\text{shock}}_{i,t-1}$ is one of the first-differenced variables from the above-mentioned vector, while $D^{x}_{i,t-1}$ contains the control variables—the same first-differenced variables excluding the one regarded as the shock. The impulse response $y_{i,t+s}$ is estimated with respect to changes in the shock and control variables over the horizon $s = 0, \dots, 12$.

For instance, in the case of the relationship between the Living Planet Index and the frequency of banking crises, we estimate the following set of equations:

$$NEPI_{i,t+s} = \gamma_{i,s} + \lambda_1 D^{NEPI}_{t-1} + \lambda_2 D^{LPI}_{t-1} + \lambda_3 D^{BANK}_{t-1} + \lambda_4 D^{GDP}_{t-1} + \mu_{i,t+s} \tag{2}$$

$$LPI_{i,t+s} = \beta_{i,s} + \mu_1 D^{NEPI}_{t-1} + \mu_2 D^{LPI}_{t-1} + \mu_3 D^{BANK}_{t-1} + \mu_4 D^{GDP}_{t-1} + \epsilon_{i,t+s} \tag{3}$$

$$BANK_{i,t+s} = \omega_{i,s} + \zeta_1 D_{t-1}^{NEPI} + \zeta_2 D_{t-1}^{LPI} + \zeta_3 D_{t-1}^{BANK} + \zeta_4 D_{t-1}^{GDP} + \varepsilon_{i,t+s} \tag{4}$$

$$GDP_{i,t+s} = \alpha_{i,s} + \eta_1 D_{t-1}^{NEPI} + \eta_2 D_{t-1}^{LPI} + \eta_3 D_{t-1}^{BANK} + \eta_4 D_{t-1}^{GDP} + u_{i,t+s} \tag{5}$$

In each of these equations, one regressor is treated iteratively as a shock, while the remaining variables serve as controls. We use Cholesky identification with the following variable ordering: total number of environmental policy instruments → Living Planet Index → frequency of banking (sovereign debt, currency, twin, and triple crises) → global economic growth. This ordering captures increasing degrees of endogeneity across variables. The total number of environmental policy instruments is treated as the most exogenous variable, largely determined by policymakers, whereas global economic growth may have bidirectional linkages with the remaining variables, making it the most endogenous. Ordinary Least Squares (OLS) is used to estimate this system of equations.

We implement the R package for LPs developed by Adämmer (2019) [2]. Based on this package, impulse response functions (IRFs) are obtained, revealing lead–lag relationships among the variables. The IRFs are reported with 95% confidence intervals for 12 periods following the initial shock.

4 Results

The results are presented in Figures 1 - 5 below.

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[2] The package is publicly available at https://cran.r-project.org/web/packages/lpirfs/lpirfs.pdf

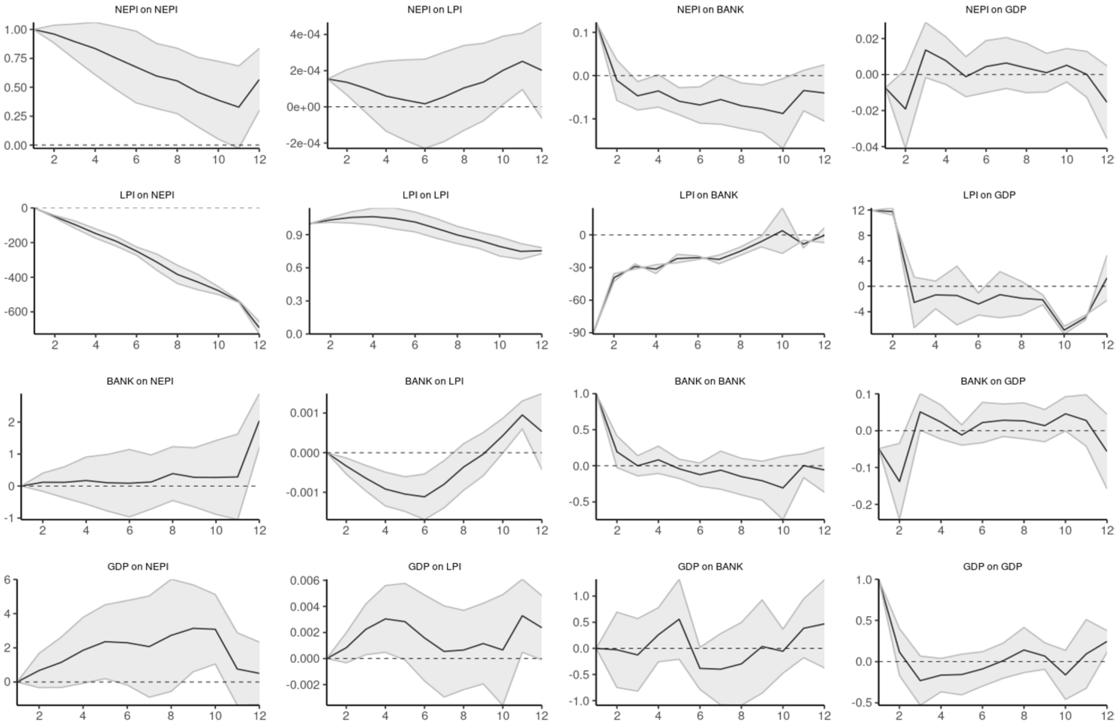

Fig. 1: IRFs for BANK, LPI, NEPI and GDP.

Notes – the impulse is associated with the variable mentioned first in the pairwise graphs above, the second variable represents the response. The shaded area corresponds to the 95% confidence bands of the impulse response function.

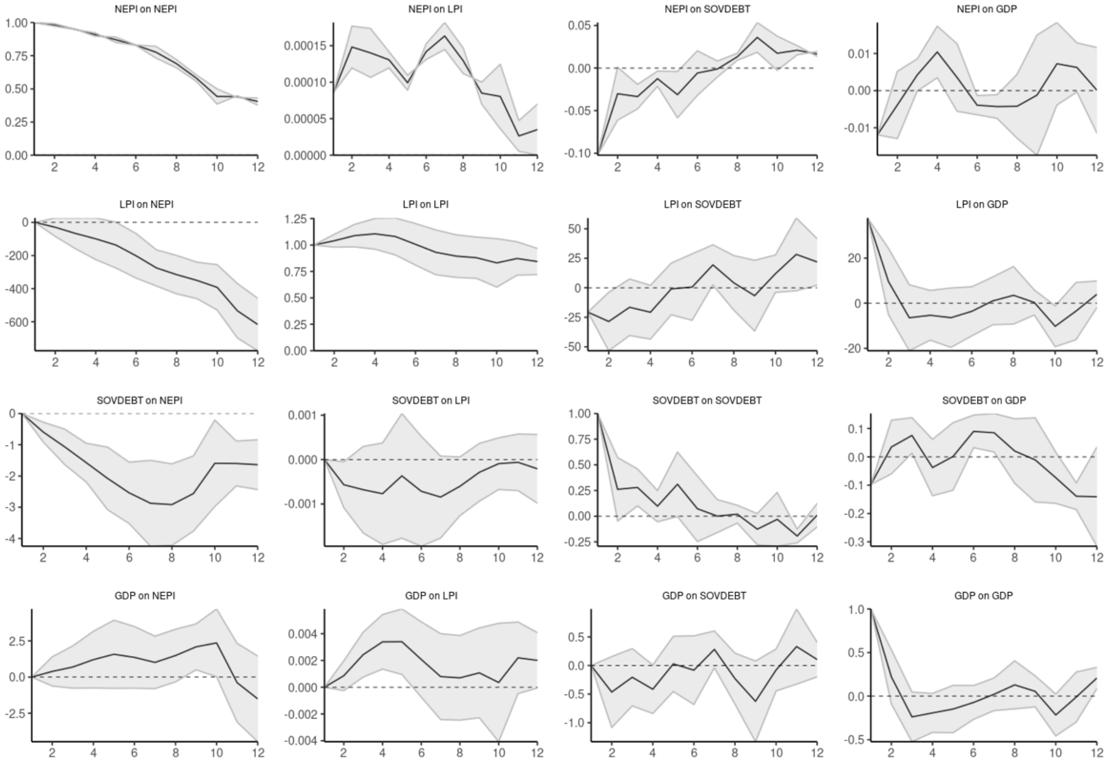

Fig. 2: IRFs for SOVDEBT, LPI, NEPI and GDP.

Notes – the impulse is associated with the variable mentioned first in the pairwise graphs above, the second variable represents the response. The shaded area corresponds to the 95% confidence bands of the impulse response function.

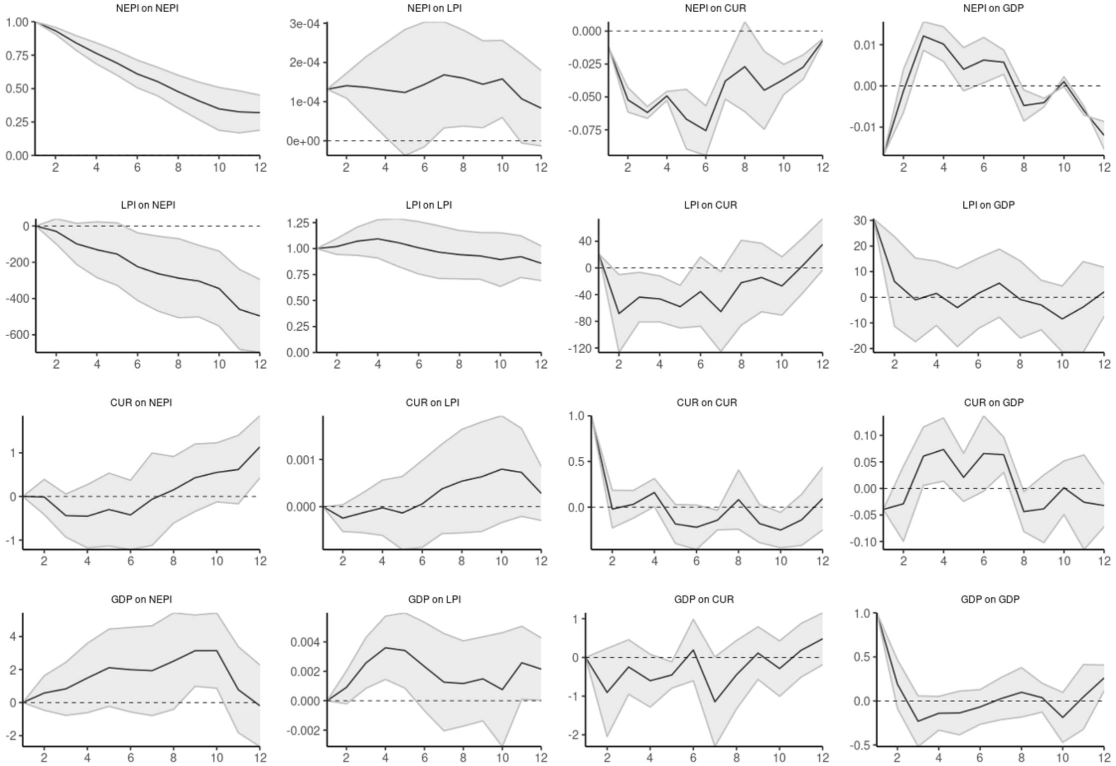

Fig. 3: IRFs for CUR, LPI, NEPI and GDP.

Notes – the impulse is associated with the variable mentioned first in the pairwise graphs above, the second variable represents the response. The shaded area corresponds to the 95% confidence bands of the impulse response function.

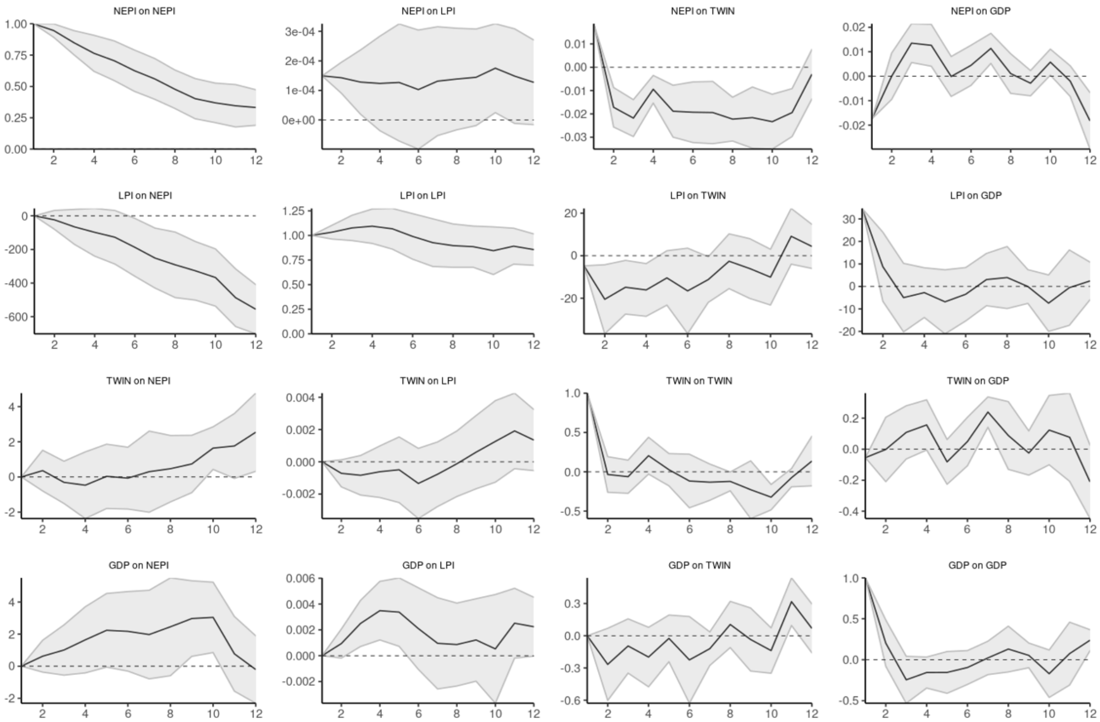

Fig. 4: IRFs for TWIN, LPI, NEPI and GDP.

Notes – the impulse is associated with the variable mentioned first in the pairwise graphs above, the second variable represents the response. The shaded area corresponds to the 95% confidence bands of the impulse response function.

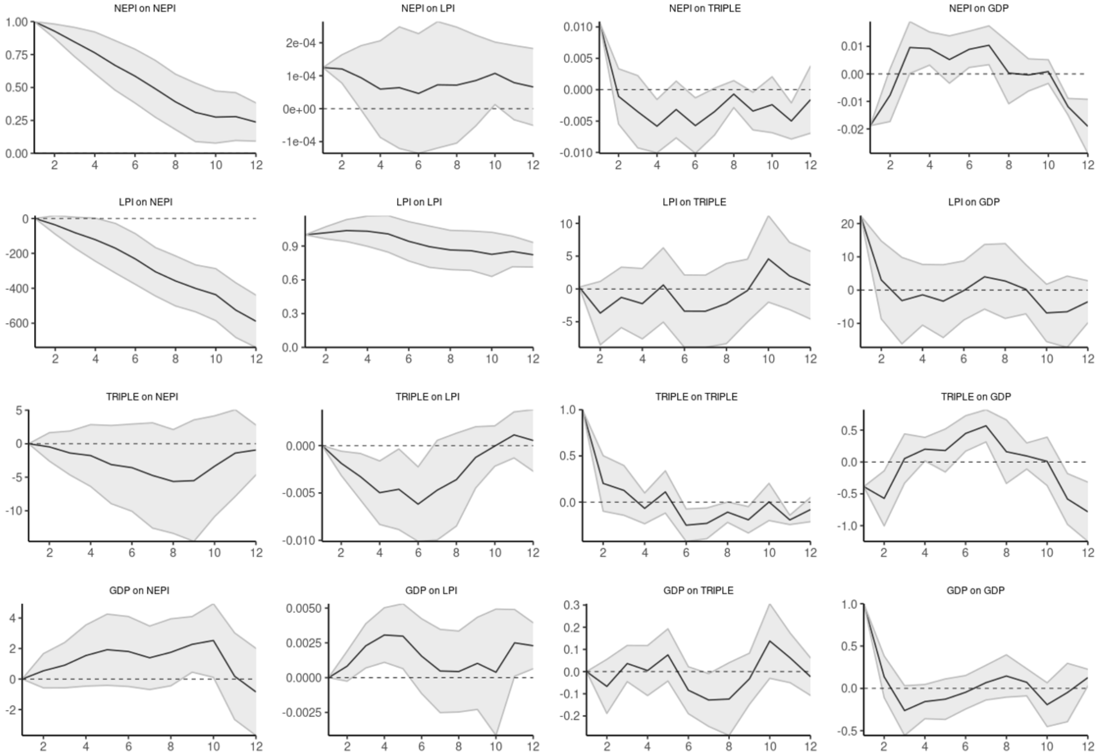

Fig. 5: IRFs for TRIPLE, LPI, NEPI and GDP.

Notes – the impulse is associated with the variable mentioned first in the pairwise graphs above, the second variable represents the response. The shaded area corresponds to the 95% confidence bands of the impulse response function.

Of all the crisis types, the frequency of banking crises and triplets exerts a direct detrimental effect on the Living Planet Index. Since sovereign debt and currency crises do not drive the latter directly[3], the adverse impact of triplets on the state of world biodiversity must also be shaped by the frequency of banking crises. In contrast to other crisis types, the frequency of banking crises involves a statistically significant decline in world real GDP per capita growth. Since the latter is positively related to the total number of environmental policy instruments aimed at safeguarding biodiversity, the increased occurrence of banking crises worldwide can entail a depletion of funding available for biodiversity conservation through the contraction of global economic growth.

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[3] The effect of sovereign debt crises on LPI is roundabout: the increased frequency of such crises adversely affects NEPI first. Meanwhile, there is no evidence of the frequency of currency and twin crises affecting LPI in a direct or indirect way.

Apart from causing a shortage of funding for biodiversity conservation, banking crises adversely impact innovation and technological adoption (Hardy and Sever, 2021), thereby impeding the replacement of outdated equipment which can damage biodiversity even when operated by benevolent and environmentally oriented firms. Also, banking crises lead to the expansion of the informal sector in the economy (Colombo, Onnis, and Tirelli, 2016). The latter extensively exploits low-productive technologies hampering biodiversity, while it is hard to impose and enforce fines and other restrictions on informal firms due to their opacity[4].

Our findings have a policy implication showcasing that macroprudential policy measures aimed at averting banking crises and triplets may bring about a positive externality, allowing for greater financing of biodiversity-related environmental policy instruments[5]. Namely, if macroprudential policy measures successfully prevent a worldwide wave of banking crises, no global recession occurs. Hence, more funds can be allocated to increase the number of biodiversity-related environmental policy instruments. Similarly, firms are more likely to adopt technologies safeguarding biodiversity.

Importantly, a decline in the LPI in turn undermines financial stability by increasing the frequency of all crises except triplets. This impact should be offset by increasing NEPI. Hence, it is vital to align the goals of biodiversity conservation and financial stability worldwide. To this end, environmental and macroprudential policies need to be perceived as complements. The need for such complementarity is emphasized by Lee, Wang, Hong, and Lin (2024) and Luo, Sun, and Zhang (2024), albeit in a framework distinctive from ours. Namely, Luo, Sun, and Zhang (2024) consider a sample of 11 largest economies during 1992–2020 and conclude that environmental policy strengthens the positive impact of macroprudential mea-

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[4] Against this backdrop, it is no surprise that there is empirical evidence of an increasing number of biodiversity crimes committed during economic and financial crises, such as illegal logging and hunting (Troumbis and Zevgolis, 2020).

[5] Delving into specific macroprudential policy instruments is beyond the scope of this study, though we conjecture that, apart from conventional macroprudential measures, green macroprudential instruments may facilitate the financing of biodiversity-related environmental policies. See, for example, D'Orazio and Popoyan (2019) for a taxonomy of green macroprudential policies.

sures on environmental sustainability. Based on a sample of banks from 28 countries over 2004–2020, Lee, Wang, Hong, and Lin (2024) argue that environmental policy effectively decreases bank risk under tighter capital and leverage regulation.

Thus, our study appears to be the first to provide empirical evidence that the complementarity between environmental and macroprudential policy is also essential for biodiversity conservation on a global scale.

5 Conclusion

Building on local projections as an estimation method, we shed light on the relationship between the state of world biodiversity proxied by the Living Planet Index and the frequency of financial crises during 1970–2018, also accounting for the role of global economic growth and the total number of biodiversity-related environmental policy instruments applied worldwide.

We find that the frequency of banking crises and triplets appears most hazardous for the state of world biodiversity. The effect of sovereign debt crisis frequency is transmitted through a decrease in the total number of biodiversity-related environmental policy instruments. In the case of currency and twin crises, no impact on the Living Planet Index is found. However, a deterioration in the Living Planet Index increases the frequency of all financial crises except triplets. Thus, our findings provide evidence in favor of joint implementation of environmental and macroprudential policies to reconcile the goals of biodiversity conservation and financial stability.

References

Adämmer, Philipp, 2019, lpirfs: An R Package to Estimate Impulse Response Functions by Local Projections, *The R Journal* 11, 421–438.

Antonarakis, A., L. Pacca, and A. Antoniades, 2022, The Effect of Financial Crises on Deforestation: A Global and Regional Panel Analysis, *Sustainability Science* 17, 1037–1057.

Bassen, A., D. Buchholz, K. Lopatta, and A. R. Rudolf, 2024, Biodiversity Management and Stock Price Crash Risk, *Business Strategy and the Environment* 33, 4788–4805.

Calice, P., F. Diaz, K. N. Dunz, and F. Miguel, 2023, Biodiversity and Finance: A Preliminary Assessment of Physical Risks for the Banking Sector in Emerging Markets, Working paper, Policy Research Working Paper 10432 World Bank.

Colombo, E., L. Onnis, and P. Tirelli, 2016, Shadow Economies at Times of Banking Crises: Empirics and Theory, *Journal of Banking and Finance* 62, 180–190.

Dasgupta, P., 2021, *The Economics of Biodiversity: The Dasgupta Review.* (HM Treasury).

D'Orazio, P., and L. Popoyan, 2019, Fostering Green Investments and Tackling Climate-related Financial Risks: Which Role for Macroprudential Policy?, *Ecological Economics* 160, 25–37.

Flammer, C., T. Giroux, and G. Heal, 2025, Biodiversity Finance, *Journal of Financial Economics* 164, 103987.

Giglio, S., T. Kuchler, J. Stroebel, and X. Zeng, 2023, Biodiversity Risk, Working paper, Working Paper 31137 NBER.

Hadji-Lazaro, P., M. Salin, R. Svartzman, E. Espagne, J. Gauthey, J. Berger, J. Calas, A. Godin, and A. Vallier, 2024, Biodiversity Loss and Financial Stability as a New Frontier for Central Banks: An Exploration for France, *Ecological Economics* 223, 108246.

Hardy, B., and C. Sever, 2021, Financial Crises and Innovation, *European Economic Review* 138, 103856.

Hudson, R., 2024, Biodiversity and Risk in the Financial Sector, *Journal of Sustainable Finance and Accounting* 2, 100009.

Hutchison, M., and B. Lucey, 2024, A Bibliometric and Systematic Literature Review of Biodiversity Finance, *Finance Research Letters* 64, 105377.

Jordá, Ó., 2005, Estimation and Inference of Impulse Responses by Local Projections, *American Economic Review* 95, 161–182.

Karolyi, A., and J. Tobin-de la Puente, 2023, Biodiversity Finance: A Call for Research into Financing Nature, *Financial Management* 52, 231–251.

Kedward, K., J. Ryan-Collins, and H. Chenet, 2023, Biodiversity Loss and Climate Change Interactions: Financial Stability Implications for Central Banks and Financial Supervisors, *Climate Policy* 23, 763–781.

Laeven, L., and F. Valencia, 2020, Systemic Banking Crises Database II, *IMF Economic Review* 68, 307–361.

Lee, C.-C., C.-W. Wang, P.-H. Hong, and W. Lin, 2024, Environmental Policy Stringency and Bank Risks: Does Green Economy Matter?, *International Review of Financial Analysis* 91, 103040.

Luo, H., Y. Sun, and L. Zhang, 2024, Effects of Macroprudential Policies on Ecological Footprint: The Moderating Role of Environmental Policy Stringency in the Top 11 Largest Countries, *Scientific Reports* 14, 7423.

Mundaca, L., and J.-N. Heintze, 2024, Banking on Ecosystem Services, *Ecological Economics* 224, 108284.

Network for Greening the Financial System (NGFS), 2021, Biodiversity and Financial Stability: Building the Case for Action, Working paper, NGFS Occasional Paper, October 2021.

Nguyen, T. C., V. Castro, and J. Wood, 2022, A New Comprehensive Database of Financial Crises: Identification, Frequency and Duration, *Economic Modelling* 108, 105770.

Olea, J., and M. Plagborg-Møller, 2021, Local Projection Inference Is Simpler and More Robust Than You Think, *Econometrica* 89, 1789–1823.

Pacca, L., A. Antonarakis, P. Schröder, and A. Antoniades, 2020, The Effect of Financial Crises on Air Pollutant Emissions: An Assessment of the Short vs. Medium-term Effects, *Science of the Total Environment* 698, 133614.

Troumbis, A., and Y. Zevgolis, 2020, Biodiversity Crime and Economic Crisis: Hidden Mechanisms of Misuse of Ecosystem Goods in Greece, *Land Use Policy* 99, 105061.