Supply Chain Uncertainty: Pricing, Growth & Blockchains

S. Boldrini M. Croce T. Nguyen D. Parfenov C. Tebaldi*

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.

JEL classification: E1; E2; G1; O33; O41.

Keywords: Supply Chain Uncertainty, FinTech, Blockchain, Cross Section of Stock Returns, R&D, Growth

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*Boldrini is a PhD student in the Finance Department of Bocconi University. Croce is affiliated with Bocconi University, CEPR, IGIER and Baffi Center. Nguyen is affiliated with the Federal Reserve Board. Parfenov is a PhD student in the Finance Department of Bocconi University. Tebaldi is affiliated with Bocconi University, IGIER and Baffi Center. The views expressed in this paper are ours alone and not necessarily those of the Board of Governors of the Federal Reserve System or its staff. We are grateful for feedback from Agostino Capponi and Fiorella De Fiore. We are grateful to our discussants: B Dumas. We thank the seminar participants at the SED Conference, the University of Luxemburg 5th Corporate Policies and Asset Prices Conference, the Global Financial Conference, IFABS 2025 Oxford Conference, Melbourne Business School, Monash University, UNSW, Palermo University, Bocconi University, Alabama University, the Warwick University Gillmore Centre Fintech Conference, and the FRB (USA). This paper was shortlisted for the IFABS 2025 Best Paper Award. Any remaining errors are our own. The research team gratefully acknowledges financial support from Fintech Lab Baffi Centre Bocconi University. This research project is part of the joint scientific and applied industrial actions supported by PNRR Musa Spoke 4 Workpackage Fintech.

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

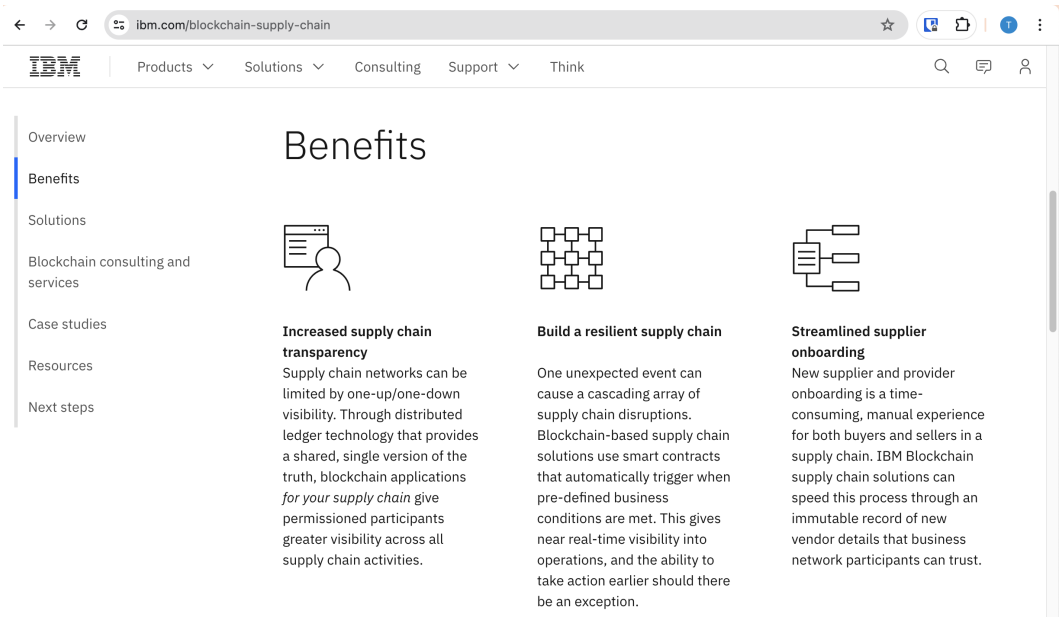


Fig. 1: Supply Chain Blockchains: Key Features

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

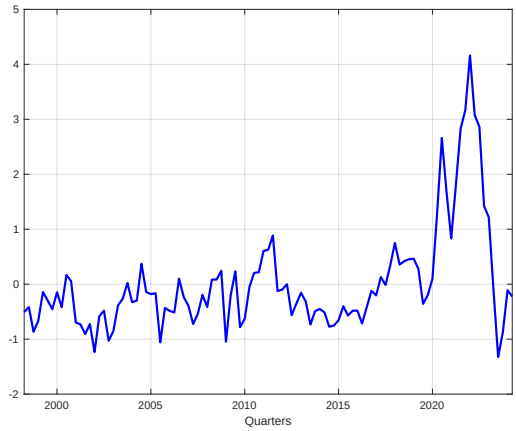


Fig. 2: Global Supply Chain Pressure Index

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:

$$R^{ex,i}_{rnd,t} = \left(\sum_f \left(\beta^f_0 + \beta^f_{rnd} \overline{\frac{R\&D}{Assets}} i \right) \cdot F_{f,t} \right) + e_{i,t} \tag{1}$$

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%.

[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

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

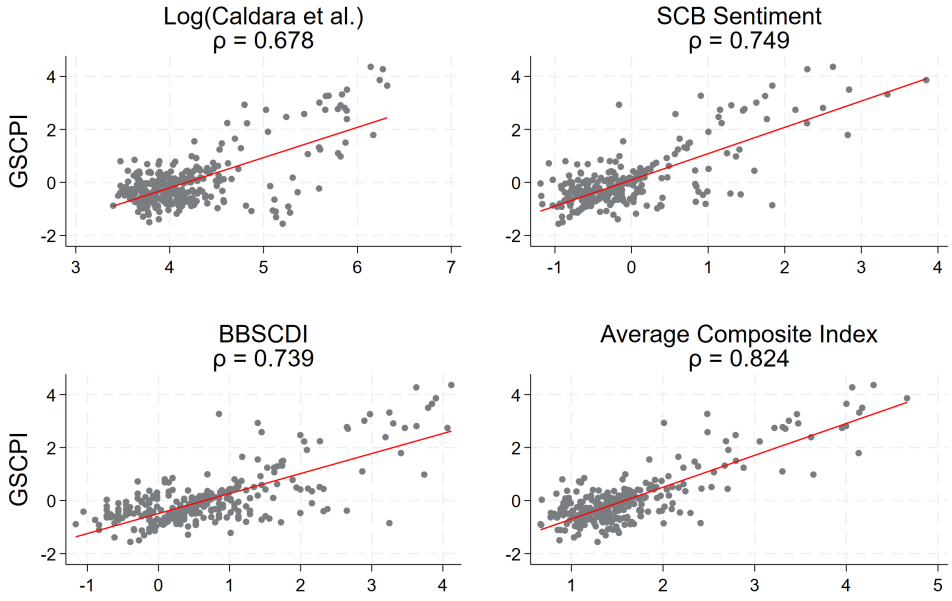


Fig. 3: Correlation between Supply Chain Indexes

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)

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 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

[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.

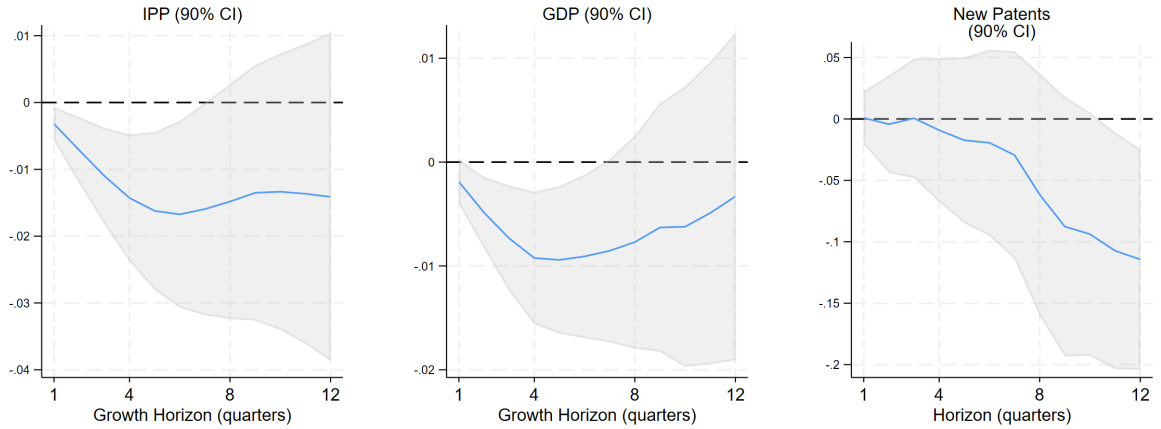


Fig. 4: US IPP, GDP, and Patents Response to Shortage Shock

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.

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:

$$\Gamma_t = \left[\int_0^{\lambda_t \cdot N_t} X_{i,t}^{\nu} di + \int_{\lambda_t \cdot N_t}^{N_t} (\theta X_{i,t})^{\nu} di\right]^{\frac{1}{\nu}} \tag{6}$$

$$= \{\underbrace{(\lambda_t + (1-\lambda_t)\theta^{\nu})}_{\omega_t} N_t\}^{\frac{1}{\nu}} X_t \tag{7}$$

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

[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.

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:

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

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. We assume that $\psi > \frac{1}{\gamma}$ so that the agent has a preference for early resolution of uncertainty

[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.

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 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

[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.

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

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

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
$E[R^{HML}_{R\&D}]$	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; $R^{MHL}_{R\&D}$ 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]

[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

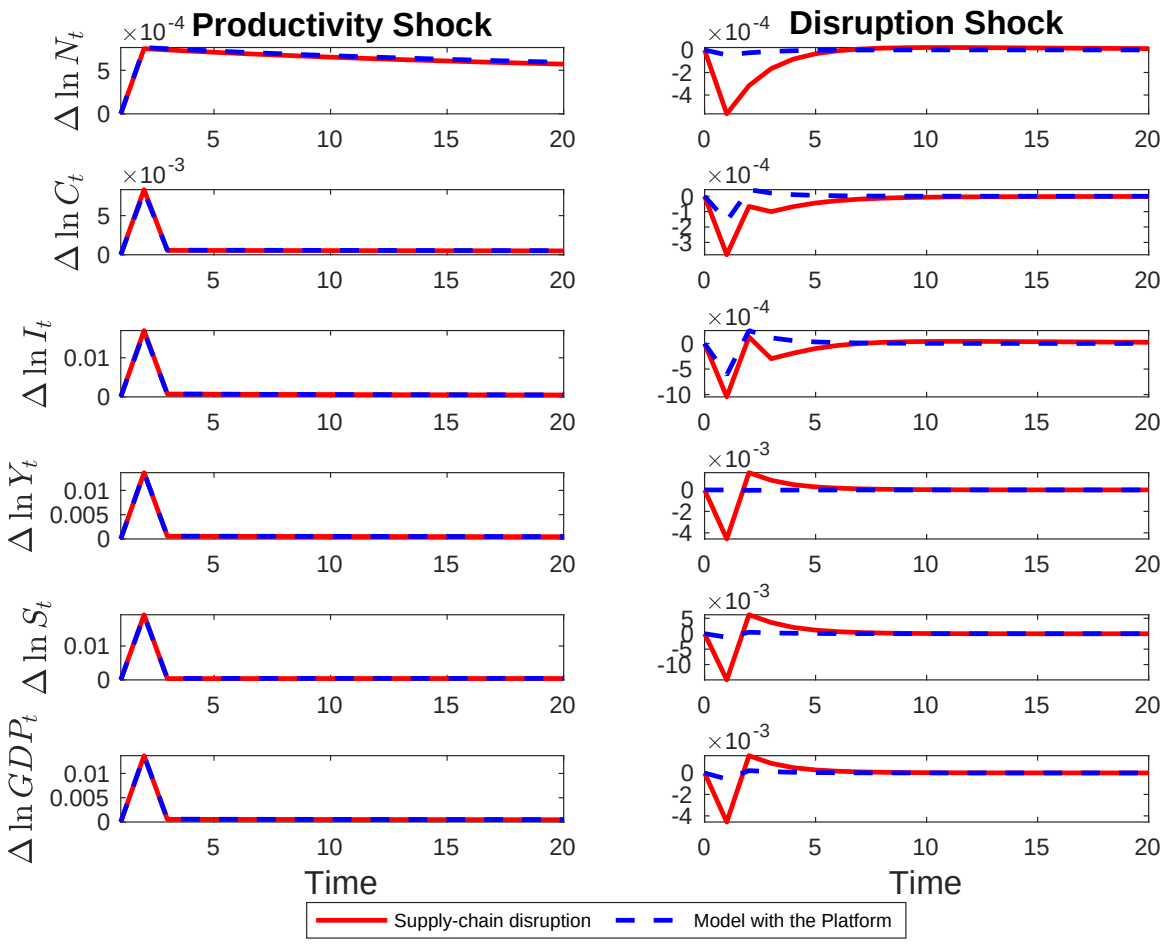


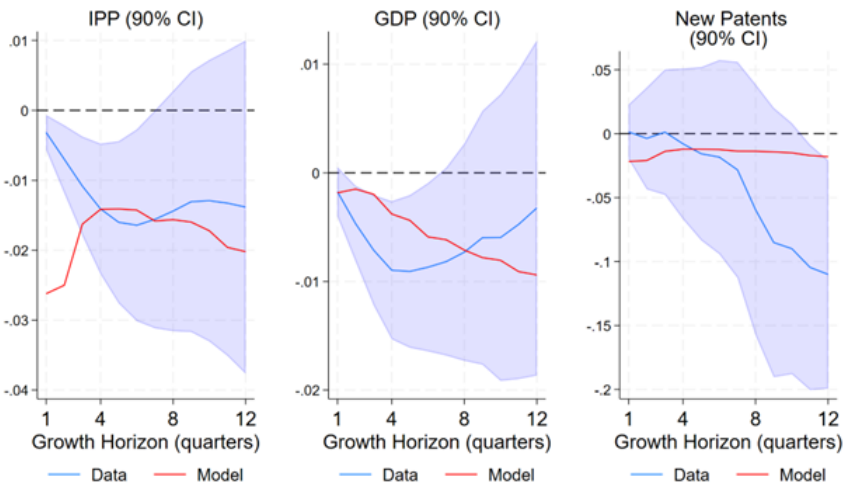
Fig. 5: Impulse responses to structural shocks

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.

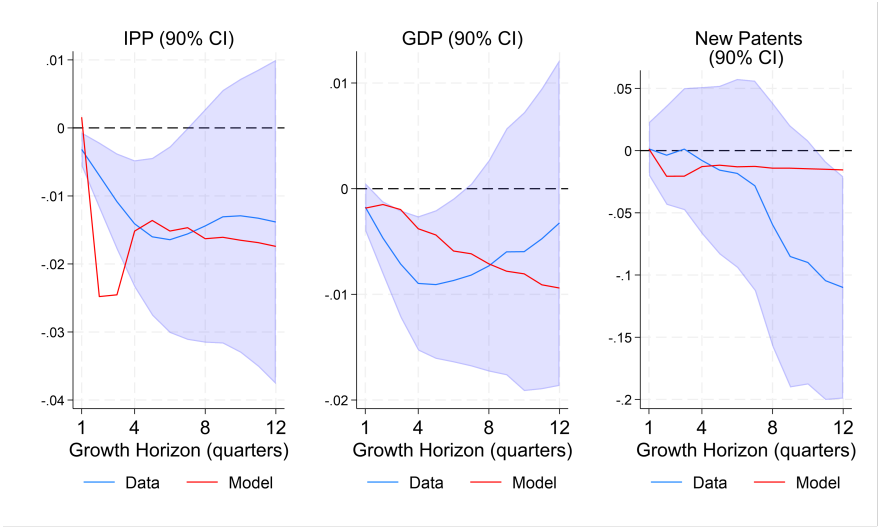
disruption to GDP is almost null.

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

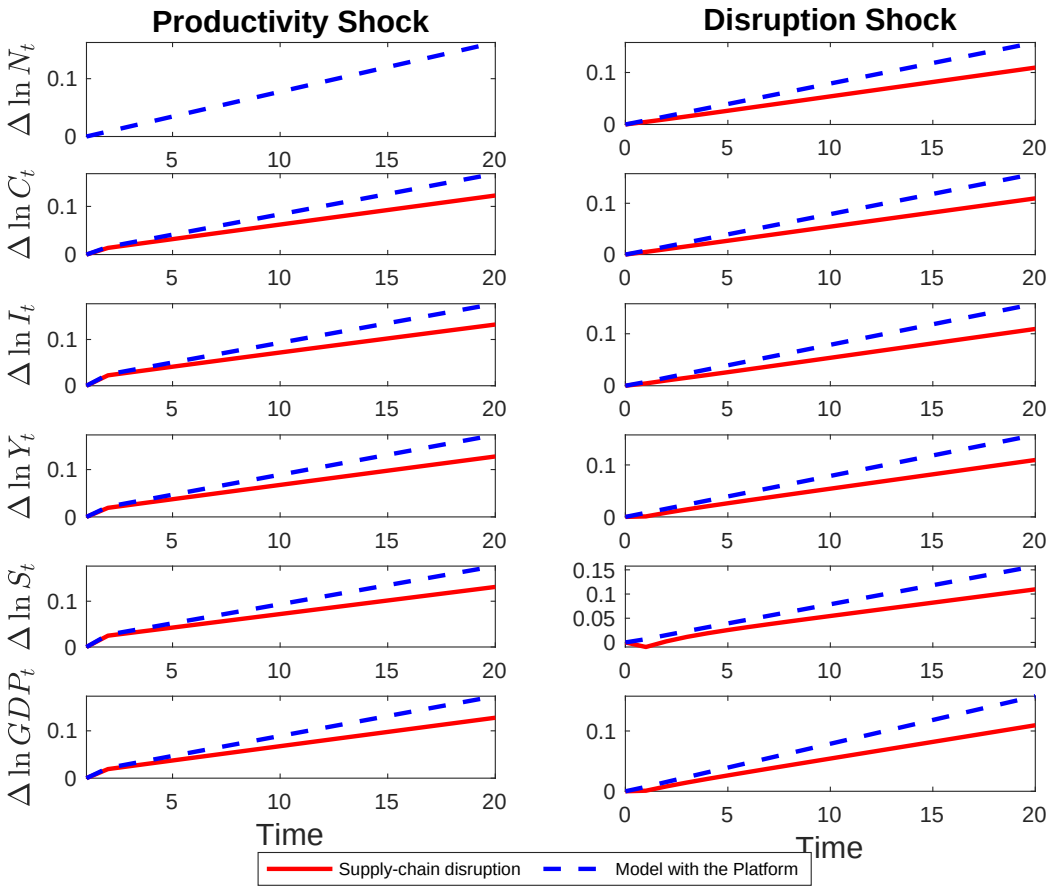


Fig. 7: Cumulative impulse responses to structural shocks

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,

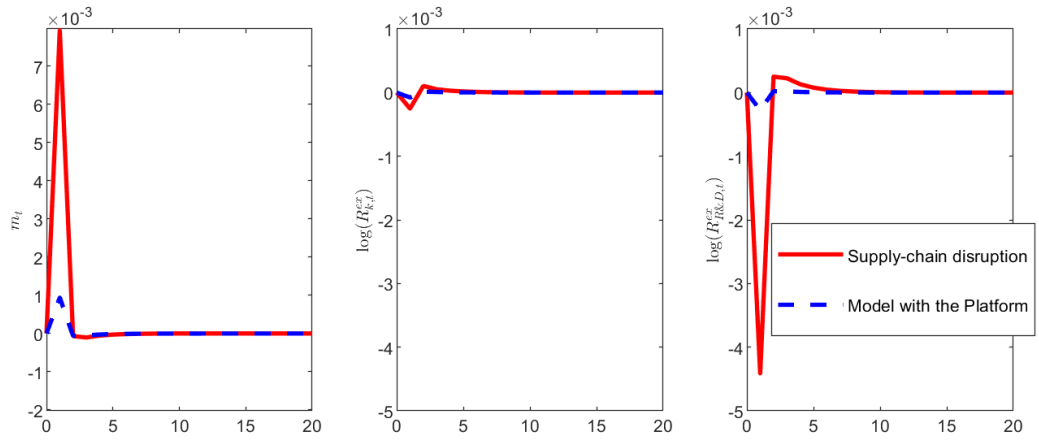


Fig. 8: Impulse responses to a one-standard-deviation disruption shock

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.

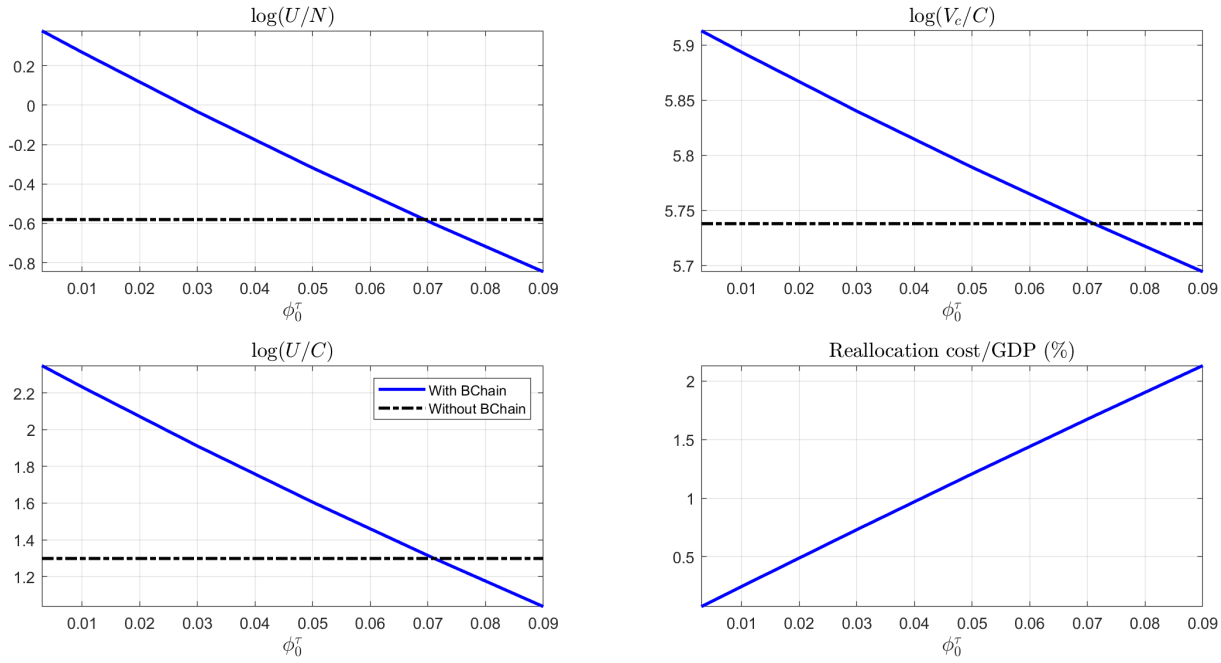


Fig. 9: The Role of Supply Chain Blockchain Efficiency

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.

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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

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

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

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