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Uncertainty shocks in an intangible economy

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ABSTRACT

This paper studies uncertainty shocks in the context of an intangible economy. I build a two-sector dynamic stochastic general equilibrium (DSGE) model to understand a shift in investment composition and its implications for the transmission of uncertainty shocks. The model is motivated by the role of intangible capital as a cushion, mitigating the adverse effects of uncertainty on investment, as suggested by firm-level data. The quantitative analysis shows that heightened uncertainty directs resources toward the intangible sector, making the economy more intangible-intensive. The rising importance of intangibles diminishes aggregate volatility in the uncertainty-driven business cycle.

1. Introduction

Technology advancements are driving many countries towards more intangible-intensive production, characterized by an increasing reliance on non-physical assets such as knowledge derived from research and development (R&D), intellectual property, organizations, brands, and business strategy. The increasing importance of intangibles raises an essential question: what role do intangibles play in business cycles? While existing literature has made commendable strides in studying level (or first-moment) shocks, much less is known about how intangibles interact with uncertainty shocks which are recognized as a pivotal source of macroeconomic fluctuations (Leduc and Liu, 2016; Basu and Bundick, 2017; Fernández-Villaverde and Guerrón-Quintana, 2020).

To investigate the macroeconomic implications of intangibles in a uncertainty-driven business cycle, this paper adopts a micro-to-macro approach by motivating a macro model using micro empirical evidence. By employing a US firm-level dataset between 2000Q1 and 2023Q2, my first analysis investigates the effects of uncertainty on investment and its components, and further explores the roles of intangible capital in shaping the relationship between uncertainty and investment. The empirical results document (1) negative relationships between uncertainty and both physical and intangible investment albeit the latter displaying less sensitivity to uncertainty, and (2) the observation that firms with more intangible capital exhibit a relative resilience in the face of uncertainty, evidenced by less pronounced impacts on their investment.

The analysis progresses to a rationalization of the empirical findings using a theoretical framework, quantitatively evaluating the macroeconomic implications of the growing importance of intangibles in business cycles. To this end, I build a two-sector Dynamic Stochastic General Equilibrium (DSGE) model with time-varying volatility in the preference shifter (i.e., the uncertainty shock).[1] This model underscores the production of both tangible and intangible goods, highlighting three key differences between the two sectors. In line with existing literature (McGrattan and Prescott, 2010; Mitra, 2019), intangible capital is non-rival in that it can be used to

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[1] See Basu and Bundick (2017), among others. Bianchi et al. (2023) label time-varying volatility in the preference shifter as a demand-side or preference uncertainty shock.

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produce two types of goods simultaneously while physical capital is rival and, hence, can only be used to produce one type of good at a time. Moreover, intangible capital has lower pledgeability and is, thus, disadvantaged in securing collateral (Lopez and Olivella, 2018; Deng and Liu, 2024). Departing from prior work, the model accounts for the sophistication required in producing intangible goods, which involves inputs from skilled labor. While unskilled labor contributes to output contemporaneously, the contribution of skilled labor has a delay, implying a long-term feature in the intangible sector.

Consistent with the empirical evidence, the model yields relatively less responsive intangible investment to the uncertainty shock. Two important forces are behind this pattern–capital reallocation and the delayed contribution of skilled labor. Elevated uncertainty triggers precautionary saving effects, lowering demands for tangible goods and reducing returns of input factors. Given the long-term nature of intangible production, the effects of the uncertainty shock are partially absorbed by the tangible sector, resulting in a weakened transmission to the intangible sector. Consequently, returns of physical capital and labor in the intangible sector are less responsive than their counterparts in the tangible sector. The former leads to a gap in the return of physical capital, prompting capital reallocation towards the intangible sector. The latter widens the wage gap between skilled and unskilled labor, further strengthening precautionary labor supply motive (Basu and Bundick, 2017) toward skilled labor. Further empirical evidence is provided to support the model predictions, showing that skilled labor is indeed less sensitive to uncertainty than unskilled labor.

In light of the model mechanisms, this paper further assesses the macroeconomic implications of the increasing importance of intangibles. The quantitative analysis suggests that intangibles act as a cushion to mitigate the contractionary effects of heightened uncertainty–reducing investment volatility on the real side and curbing stock market volatility on the financial side. This macro theoretical finding echoes the micro empirical evidence, presenting a counterpoint to the amplification role traditionally ascribed to intangibles in the transmission of financial shocks (Lopez and Olivella, 2018; Anzoategui et al., 2019; Ikeda and Kurozumi, 2019).[2]

Finally, this paper differentiates between "good uncertainty" and "bad uncertainty". It shows that uncertainty in the production of intangibles leads to expansionary effects on the economy in the mid-to-long run. However, the positive effects are quantitatively modest and incomparable to the recessionary effects from the preference uncertainty. This finding provides insight into why scholars mainly observe negative effects of uncertainty based on aggregate measures.

This paper contributes to two major strands of emerging literature, i.e., the macroeconomic consequences of uncertainty (Bloom, 2007; Bloom et al., 2007; Fernández-Villaverde et al., 2015; Segal et al., 2015; Leduc and Liu, 2016; Basu and Bundick, 2017; Segal, 2019; Fasani et al., 2023; Alfaro et al., 2024) and the role of intangibles in business cycles (Lopez and Olivella, 2018; Mitra, 2019; Döttling and Ratnovski, 2023). This paper provides a crossroad between the two areas by incorporating intangibles into a framework with uncertainty to investigate the uncertainty-intangible relationships and their implications. Specifically within the uncertainty literature, this paper aligns with Basu and Bundick (2017) by studying the transmission of the uncertainty shock and underscoring the importance of households' precautionary motives. Departing from the common ingredients, I incorporate intangible production, a factor gaining increased prominence in advanced economies. Additionally, the model differentiates between skilled and unskilled labor, allowing for a nuanced exploration of precautionary labor motives specific to each type of labor. Focusing on the knowledge component of intangibles, Bloom (2007) studies uncertainty-R&D relationships by exploring R&D adjustment costs in a single-sector model. The current paper is related to Bloom (2007) in that the delayed-labor mechanism is akin to a micro-foundation for the reduced-form adjustment cost of intangible investment. Furthermore, by highlighting the long-term features of intangibles, this paper studies intangible-specific uncertainty shocks, which propagate as good uncertainty. Segal (2019) also studies the positive effects of uncertainty, focusing on an investment volatility shock. My paper complements the literature by differentiating two types of investment and building connections between tangible and intangible sectors to explain the consequences of the intangible uncertainty shock. In addition to the theoretical contributions, my empirical analysis not only confirms weak responses of intangible investment to short-run uncertainty as found in the literature (see Barrero et al. (2017), among others), but also shows that firms with higher intangible capital and skilled-labor shares exhibit more resilient investment behavior under uncertainty.

Regarding the intangible literature, there is an ongoing debate on whether the shift toward an intangible economy amplifies or dampens macroeconomic fluctuations. Previous research by Lopez and Olivella (2018), Anzoategui et al. (2019), and Ikeda and Kurozumi (2019) focusing on financial or liquidity shocks broadly suggests an amplification effect of intangibles. In addition, Mitra (2019) shows that the rising importance of intangibles could increase hours volatility. This paper provides a reconciliation by showing that both amplification and dampening effects are possible, but the latter is more likely to hold if the business cycle is dominated by the uncertainty shock.

This paper also connects to the broader literature studying the secular change in corporate investment and its implications. Existing literature, such as Bianchi et al. (2019), Caggese and Pérez-Orive (2022), and Deng and Liu (2024), explores the interactions between financial conditions[3] and differential pledgeability between tangible and intangible capital. While much of the focus has been on the ability to serve as collateral, my model also highlights non-rivalry and long-term features of intangibles. These elements are more important in explaining the consequences of uncertainty shocks, whereas limited pledgeability plays a relatively larger role in the propagation of financial shocks. This paper complements the literature by highlighting uncertainty as another important determinant

[2] Anzoategui et al. (2019), Ikeda and Kurozumi (2019) focus on technology innovation which is often referred to as a knowledge component of intangibles.

[3] Bianchi et al. (2019) study different implications of debt and equity conditions focusing on different crisis episodes; Caggese and Pérez-Orive (2022) explore how different pledgeability affects the sensitivity of the two types of investment to interest rates; Deng and Liu (2024) investigate the implications of sovereign debt crisis for the investment composition.

of the investment composition and by developing a macroeconomic model to interpret the different impacts of uncertainty on the two types of investment.

The rest of the paper is organized as follows. Section 2 empirically examines the implications of intangibles for the effects of uncertainty. Section 3 presents the DSGE model with intangible production and the uncertainty shock, followed by calibration of parameters in Section 4. Sections 5 and 6 report the main theoretical results. In Section 7, I investigate the potential expansionary effects of uncertainty. Finally, Section 8 concludes with comments.

2. Empirical evidence

This section provides motivational empirical evidence to investigate the relationship between uncertainty and investment, while also exploring the role of intangibles in shaping this relationship. The empirical investigation is divided into two stages. In the first stage, a structural VAR model is estimated to extract the exogenous components of uncertainty measures. Taking the adjusted uncertainty as the primary independent variable, I merge it with a firm-level panel dataset to study the effects of aggregate uncertainty in the second stage.

2.1. Data

In the first stage, I consider a six-variable VAR with the following variables: real GDP, real private investment, CPI inflation, federal fund rate, excess bond premium, and uncertainty measured by either the VIX index or Jurado et al. (2015) macroeconomic uncertainty (henceforth JLN index). In the baseline estimation, uncertainty is ordered as the last variable and contributions of each variable to uncertainty are identified according to a Cholesky decomposition. Then, contributions from non-uncertainty shocks to uncertainty are removed to obtain an adjusted uncertainty index u_t. I also find that different ordering schemes would not fundamentally change the results.

The firm-level variables used in the second-stage analysis are from Compustat based on quarterly financial statement of public firms between 2000Q1 and 2023Q2.[4] Following Peters and Taylor (2017) and Döttling and Ratnovski (2023), intangible investment is defined as the sum of research and development (R&D) expense and 30 % of selling, general and administrative (SG&A) expense. This measure includes not only technology but also organization capital, another important component of intangibles. When constructing intangible capital, estimated off-balance sheet intangibles are added to the on-balance component (Intan). The off-balance sheet component is estimated using R&D and SG&A based on a perpetual inventory method (Peters and Taylor, 2017). I find that the off-balance sheet component accounts for an average of 74 % of intangible capital, indicating the important role of unmeasured intangibles in shaping firms' intangible assets. This finding is consistent with Peters and Taylor (2017), who show that off-balance sheet intangible capital–largely created internally–constitutes the majority of intangible assets. Moreover, I find that intangible investment represents about 40 % of total investment on average, in line with other estimates (Aghion et al., 2010; Corrado and Hulten, 2010; Lopez and Olivella, 2018; Döttling and Ratnovski, 2023).

Following a commonly used sampling procedure (see Peters and Taylor (2017) and Döttling and Ratnovski (2023), among others), I exclude firms in utility (SIC 4900–4999), finance (SIC 6000–6999), and public service (SIC 9000 and above). Observations with missing or negative assets, sales, CAPX, R&D, or SG&A expenditure are also removed. Furthermore, very small firm with physical capital under $5 million are excluded. In order to correctly match firm-level variables and the uncertainty index, fiscal quarters are mapped to calendar quarters using information on firms' fiscal-year end. Finally, I manually check and drop duplicated observations. Table A2 in Appendix A presents descriptive statistics including mean, median, standard deviation, 10th percentile and 90th percentile.

Fig. 1 compares investment based on the aggregated Compustat series (Micro measures) and macroeconomic sources. While the former offers broader coverage of intangibles based on publicly listed firms, the latter is limited to technology activities but encompasses all establishments. Despite the different statistical coverage, the two total investment growth series display similar movement over time. The right panel depicts the increasing shares of intangible investment based on both measures, a trend that persists even during the COVID pandemic period.

2.2. Investment regressions

To investigate the overall effects of uncertainty on investment, I consider the following regression specifications:

$$I_{it} = \alpha_i + \beta u_t + \gamma' \mathbf{Z}_{it-1} + \psi_{fq} + \epsilon_{it} \tag{1}$$

where I_{it} is a measure of investment. $\mathbf{Z}_{it-1}$ is a set of lagged control variables, including Tobin's Q, leverage ratio, cash holding, cash flow, size, and age (see Döttling and Ratnovski (2023), among others). α_i are firm fixed effects and ψ_{fq} are quarter fixed effects to control for seasonality. To account for potential implications of intangibles for the effects of uncertainty, Specification (1) is expanded with an interaction term between uncertainty and an intangible capital ratio k^{int}_{it-1}, defined as intangible capital over total capital. The main coefficients of interest in Specification (2) are β_1 and β_2, which jointly capture the effect of uncertainty conditional on the

[4] Intangible investment data became extensively available in the 2000s.

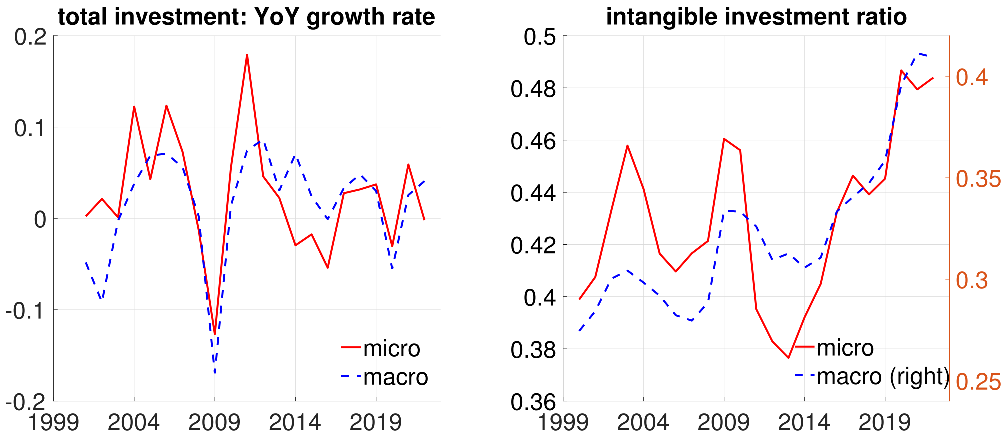

Fig. 1. Investment Comparison. *Notes:* This figure compares total investment (in the left panel) and intangible investment ratio (in the right panel) based on Compustat (i.e., Micro) and Macro series. The total investment includes both intangible and tangible investment. The intangible investment ratio is defined as intangible investment over total investment. The Micro series defines tangible investment as capital expenditure (CAPX) and intangible investment as that in R&D and organizational capital (measured as a portion of SG&A expenditures). The Macro series measures tangible investment as that in non-residential fixed investment, and intangible investment as that in intellectual property products.

Table 1
Investment regression results–total investment.

	[1]	[2]	[3]	[4]	[5]
u	-0.0593***	-0.2743***	-0.2798***		
	(0.008)	(0.037)	(0.038)		
u × k^{int}		0.2563***	0.2605***	0.2386***	0.2514***
		(0.046)	(0.047)	(0.045)	(0.051)
$k^{int} \times rec$			-0.0721*	-0.0205	-0.0447
			(0.037)	(0.037)	(0.042)
Observations	107,439	97,746	97,756	97,202	97,075
Adj. R^2	0.413	0.429	0.429	0.309	0.335
Controls & Firm FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	No	No
Rec. Dummy	No	No	Yes	No	No
Time FE	No	No	No	Yes	Yes
Ind-Time FE	No	No	No	No	Yes

Notes: The dependent variable–total investment rate is measured as the log of sum of tangible and intangible investment divided by lagged total assets. u is measured as the adjusted VIX index. Total assets are book assets plus off-balance intangible capital estimated based on the perpetual inventory method. k^{int} is the firm's intangible-to-total capital ratio. rec is the recession dummy. Firm-level controls include Tobin's Q, leverage ratio, cash holding, cash flow, size, and age. For regressions in columns [2]-[5], k^{int} is added as an additional control variable. Detailed descriptions about variables can be found in Appendix A. Robust standard errors are shown in parentheses. ***, **, and * represent significance level at 1 %, 5 %, and 10 %, respectively.

firm's intangible capital. Given the fact that uncertainty tends to rise sharply in recession, one might be concerned that uncertainty-investment relationships are mainly driven by recession times. Thus, a recession dummy rec_t[5] and its interaction with the intangible capital ratio $k^{int}_{it-1} \times rec_t$ are added to Specification (2) to ensure that the role of intangible capital in transmitting uncertainty shocks is not confounded by other recessionary shocks. This treatment is also helpful if stage-one estimations do not fully orthogonalize the exogenous components of uncertainty.

$$I_{it} = \alpha_i + \beta_1 u_t + \beta_2 u_t \times k^{int}_{it-1} + \beta_3 k^{int}_{it-1} \times rec_t + \beta_4 k^{int}_{it-1} + \beta_5 rec_t + \gamma' \mathbf{Z}_{it-1} + \psi_{fq} + \epsilon_{it} \tag{2}$$

To address the potential influence of outliers which are often presented in firm-level studies, I adopt the Hampel Identifier (Wilcox, 2011), an outlier detection approach based on median absolute deviation (MAD) statistics. MAD is a more robust statistic than standard deviation, making the detection procedure resilient to the presence of outliers. Detailed explanations of this method can be found in Appendix B.

Table 1 reports the results based on overall investment rates, defined as the sum of tangible and intangible investment divided by firm's lagged assets. Uncertainty is measured as the adjusted VIX index. Column [1] shows a negative coefficient for u_t which

[5] The recession dummy is equal to one for recession time according to NBER's Business Cycle Dating, and zero otherwise.

Table 2
Investment regression results–alternative uncertainty measure (JLN index).

	[1]	[2]	[3]	[4]	[5]
u	-0.2176***	-0.8560***	-0.9627***		
	(0.019)	(0.088)	(0.091)		
u × k^{int}		0.7570***	0.8507***	0.9150***	0.7130***
		(0.110)	(0.114)	(0.115)	(0.121)
$k^{int} \times rec$			-0.1194***	-0.0966***	-0.0973**
			(0.038)	(0.037)	(0.044)
Observations	107,437	97,776	97,783	97,234	97,068
Adj. R^2	0.415	0.433	0.434	0.310	0.335
Controls & Firm FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	No	No
Rec. Dummy	No	No	Yes	No	No
Time FE	No	No	No	Yes	Yes
Ind-Time FE	No	No	No	No	Yes

Notes: u is measured as the adjusted JLN index. The others are the same as above.

Table 3
Investment regression results–investment components.

	VIX		JLN	
	Intangible Inv. Rate [1]	Tangible Inv. Rate [2]	Intangible Inv. Rate [3]	Tangible Inv. Rate [4]
u	-0.0369***	-0.0949***	-0.1658***	-0.3156***
	(0.006)	(0.013)	(0.016)	(0.034)
Observations	107,735	107,029	107,724	107,060
Adj. R^2	0.278	0.565	0.281	0.566
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Notes: The dependent variables are intangible investment rate in columns [1] and [3], and tangible investment rate in columns [2] and [4]. The intangible investment rate is measured as the log of Compustat item *R&D* plus $0.3 \times$ *SG&A* scaled by lagged total assets. The tangible investment rate is measured as the log of Compustat item *CAPX* scaled by lagged total asset. In columns [1] and [2], u is measured as the adjusted VIX index while the adjusted JLN index is used in columns [3] and [4]. The others are the same as above.

is significant at the 1 % level, indicating an adverse effect of uncertainty on overall investment. Columns [2] and [3] confirm this result and further show positive and significant coefficients for the interaction term $u_t \times k^{int}_{it-1}$, implying that the negative effect of uncertainty can be weakened by a higher intangible capital ratio. This mitigation effect of intangibles is robust after controling for $k^{int}_{it-1} \times rec_t$, indicating that the role of intangible capital in transmitting uncertainty shocks is not driven by other recessionary shocks.

$$I_{it} = \alpha_i + \beta_1 u_t \times k^{int}_{it-1} + \beta_2 k^{int}_{it-1} \times rec_t + \beta_3 k^{int}_{it-1} + \gamma' \mathbf{Z}_{it-1} + \eta_t + \eta_{st} + \epsilon_{it} \tag{3}$$

To further confirm the implication of intangibles, I include time fixed effects η_t and industry-by-time fixed effects η_{st} in Specification (3)[6], and investigate whether the weakened response of investment is driven by time-varying factors or industry-specific trends which cannot be accounted for in Specification (2). The main interest is the coefficient of $u_t \times k^{int}_{it-1}$, β_1. The results based on Specification (3) are reported in columns [4] and [5] in Table 1. I find that the presence of time or industry-time fixed effects does not alter the mitigation role provided by intangibles. Table 2 reports the investment regression results with uncertainty measured as the adjusted JLN index, confirming the negative relationship between total investment and uncertainty. This adverse relationship could be mitigated by a higher intangible capital ratio.

Next, I examine the effects of uncertainty on different components of total investment, including physical and intangible investment based on Specification (1). Table 3 suggests that increased uncertainty reduces both types of investment; yet physical investment tends to be more considerably affected compared to its intangible counterpart. For example, columns [1] and [2] show that a 1 % increase in the adjusted VIX index reduces the physical investment rate by 0.095 %, while intangible investment is reduced by 0.037 %. This finding implies that intangible investment is relatively less sensitive to changes of uncertainty levels. The insensitivity of intangible investment to uncertainty can be further corroborated based on macro-level evidence. Fig. 2 plots impulse responses of physical and intangible investment measured at the macro level to uncertainty shocks. Based on both measures of uncertainty, Fig. 2 suggests that the responses of intangible investment are relatively muted compared to physical investment. My results based on aggregate uncertainty are broadly consistent with the literature studying micro uncertainty. Based on firm-level uncertainty and annual data,

[6] Note that it is unnecessary to include u_t and rec_t in Specification (3) because η_t or η_{st} would absorb all time-series variations.

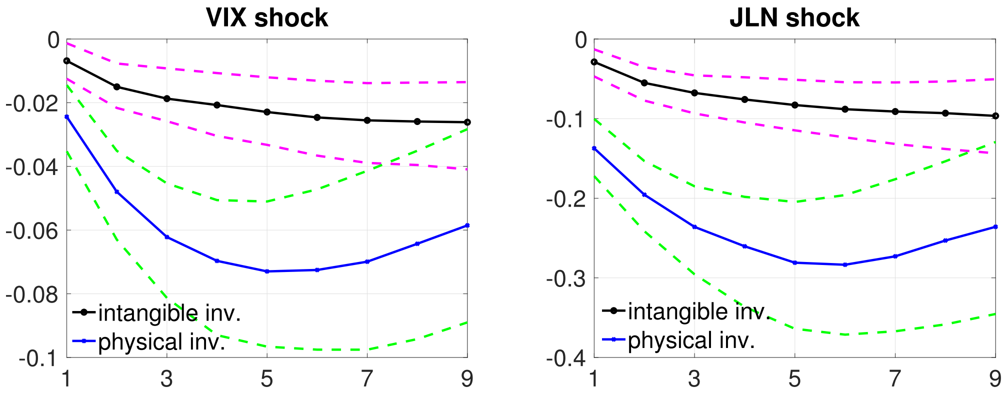

Fig. 2. Responses of Investment based on the Macro Measure to Uncertainty Shocks. *Notes:* This figure compares impulse responses of physical investment and intangible investment to a 1 % increase in uncertainty based on either the VIX index or the JLN index. Physical investment is measured as non-residential fixed investment, and intangible investment is measured as investment in intellectual property products. Dashed lines show 68 % probability density intervals. Impulse responses are expressed as percentage deviations.

Alfaro et al. (2024) also find negative effects of uncertainty on firm investment. Similarly, Barrero et al. (2017) show that R&D–as one narrow proxy of intangible investment–is less sensitive to short-term uncertainty than physical investment. Since my uncertainty measures also focus on the short term (near-term stock volatility or 1-month-ahead macroeconomic uncertainty), the finding of low sensitivity of intangible investment is in line with Barrero et al. (2017).

Overall, the empirical evidence based on total investment and its components mirror each other, suggesting that intangible firms, which hold relatively more intangible capital and also make substantial intangible investment, tend to be more resilient during episodes of elevated uncertainty.

To test the robustness of the main findings, I conduct a series of extended estimations. First, I use log-differenced capital to measure intangible and physical investment, which includes not only internal capital accumulation but also external acquisitions of capital, thereby offering a broader measure of investment. Second, I use the R&D investment rate as an alternative outcome variable in intangible investment regressions. Third, I re-estimate the VAR model from the first stage by ordering uncertainty indices as the leading variable to extract their exogenous components. This alternative ordering is motivated by the theoretical implications that uncertainty shocks contemporaneously affect other variables. In the baseline estimation, uncertainty is ordered as the last variable to avoid overestimating its effects. Fourth, I run regressions without applying the Hampel Identifier. Finally, an alternative measure of investment rates–dividing investment by capital–is used. Across all these specifications, I consistently find that uncertainty exerts a negative effect on investment, while intangible capital mitigates this effect. Additional empirical results are reported in Appendix C.

To sum up, the firm-level results, alongside the macro-level evidence, provide empirical support to the main theoretical findings–the presence of intangibles weakens the adverse effects of uncertainty–which are explored in Sections 5 and 6.

3. The model

This section outlines the theoretical framework which is used to analyze uncertainty shocks in an economy producing intangible goods and accumulating intangible capital. Taking a medium-scale single-good DSGE model as the benchmark, e.g., Basu and Bundick (2017), I augment it with production of intangible goods, incorporating skilled labor, and quantity-based financial frictions (i.e, a borrowing constraint).

3.1. Households

The representative household derives utility from consumption C_t and leisure, and saves in the form of deposits D_t and equity shares S_t. It supplies two types of labor (Anzoategui et al., 2019), including unskilled labor which is used to produce tangible goods Y_t and skilled labor which is used in the production of intangibles X_t. The supply of two types of labor is measured by working hours H_t^u and H_t^s. Following Gourio (2012), Basu and Bundick (2018), and Pellegrino et al. (2023), the preference is given by a Epstein-Zin structure.

$$V_t = [(1-\beta)U_t^{(1-\sigma)/\theta_v} + \beta(E_t V_{t+1}^{1-\sigma})^{1/\theta_v}]^{\theta_v/(1-\sigma)} \tag{4}$$

where the utility kernel U_t is

$$U_t = \varepsilon_t^d (C_t - h\bar{C}_{t-1}) e^{-\frac{\psi^u (H_t^u)^{1+\eta} + \psi^s (H_t^s)^{1+\eta}}{1+\eta}} \tag{5}$$

The distributional weights add up to one in Eq. (4), which is required to avoid the asymptote suggested by De Groot et al. (2018). The household maximizes lifetime utility (4) subject to the budget constraint

$$P_t C_t + D_t + P_t^E S_t = R_{t-1} D_{t-1} + (D_{t-1}^E + P_{t-1}^E) S_{t-1} + W_t^u H_t^u + W_t^s H_t^s + \Pi_t^f \tag{6}$$

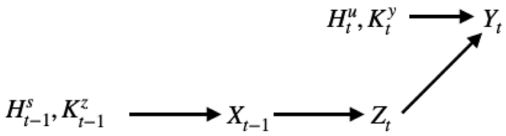

Fig. 3. Contributions of the input factors to Y_t.

where R_t denotes interest rate, P_t aggregate price level, W_t^u unskilled wages, W_t^s skilled wages, and Π_t^f profits due to owning the final goods firms. Equity shares have a price of P_t^E and pay dividends D_t^E for each share owned. h measures the degree of external habits in consumption and η measures the elasticity of labor supply. ε_t^d is a preference shock following an AR(1) process $\varepsilon_t^d = (1-\rho_d)\varepsilon^d + \rho_d \varepsilon_{t-1}^d + \sigma_{t-1}^d \epsilon_t^d$ and ϵ_t^d follows an i.i.d $N(0,1)$. σ_t^d is a uncertainty shock evolving as $\sigma_t^d = (1-\rho_u)\sigma^d + \rho_u \sigma_{t-1}^d + \sigma^u \epsilon_t^u$ and ϵ_t^u follows an i.i.d $N(0,1)$. Following Basu and Bundick (2017), the stochastic discount factor $M_{t,t+1}$ is defined as

$$M_{t,t+1} = \frac{\partial V_t / \partial C_{t+1}}{\partial V_t / \partial C_t} = \beta(\frac{U_{t+1}}{U_t})^{(1-\sigma)/\theta_v}(\frac{C_t - h\bar{C}_{t-1}}{C_{t+1} - h\bar{C}_t})(\frac{V_{t+1}^{1-\sigma}}{\mathbb{E}_t V_{t+1}^{1-\sigma}})^{\theta_v/(1-\sigma)} \tag{7}$$

3.2. Intermediate goods producers

There is a continuum of monopolistic intermediate goods firms j, each of which produces tangible and intangible goods, accumulates physical capital and intangible capital, and finances business by debts and equity. The tangible goods Y_{jt}^m are sold to final goods producers. The intangible goods X_{jt}, which is an investment good, are used for accumulating intangible capital. Production functions of the two types goods for firm j are given by

$$Y_{jt}^m = A_t Z_{jt}^\zeta (u_{jt} K_{jt}^y)^\alpha (H_{jt}^u)^{1-\alpha-\zeta} \tag{8}$$

$$X_{jt} = \chi Z_{jt}^\zeta (u_{jt} K_{jt}^z)^\alpha (H_{jt}^s)^{1-\alpha-\zeta} \tag{9}$$

where Z_{jt} is intangible capital, K_{jt}^y is physical capital used for Y_{jt}^m production, K_{jt}^z is physical capital used for X_{jt} production, and u_{jt} is a utilization rate of physical capital. χ is the intangible-specific productivity. ζ and α are income shares of the two types of capital in the production functions. A_t is a productivity shock following an AR(1) process $A_t = (1-\rho_a)A + \rho_a A_{t-1} + \sigma^a \epsilon_t^a$ and ϵ_t^a follows an i.i.d $N(0,1)$.

Eqs. (8) and (9) suggest two key differences in producing the two types of goods. In line with the literature (McGrattan and Prescott, 2010; Mitra, 2019), I assume that physical capital, such as machines, can only be used to produce one type of good at a time while intangible capital, such as patents and brands, is non-rival in that it can be used to produce two types of goods simultaneously. In other words, Z_{jt} provides a spillover effect in the production activities. Departing from the literature, I also consider that the production of intangible goods, such as technology innovation, is sophisticated and requires inputs from skilled labor.

The firm j accumulates physical and intangible capital according to the following laws of motions:

$$K_{j,t+1} = [1-\delta(u_{jt})]K_{jt} + \Omega_{j,t}^k I_{jt} \tag{10}$$

$$Z_{j,t+1} = (1-\delta_z)Z_{jt} + X_{jt} \tag{11}$$

where I_{jt} is physical investment and δ_z is a depreciation rate of intangible capital. Denoting δ_k as the depreciation rate of physical capital in the steady state, depreciation of physical capital $\delta(u_{jt})$ depends on the utilization rate in the following functional form:

$$\delta(u_{jt}) = \delta_k + \delta_1(u_{jt}-1) + \frac{\delta_2}{2}(u_{jt}-1)^2 \tag{12}$$

The physical investment adjustment cost $\Omega_{j,t}^k$ is given by

$$\Omega_{j,t}^k = 1 - \frac{\phi_k}{2}[\frac{I_{jt}}{(1+g^y)I_{j,t-1}} - 1]^2 \tag{13}$$

where g^y is the net growth rate of the economy in the steady state.

The capital accumulation and production functions (8)–(11) suggest different contributions of the input factors to tangible goods over different horizons. Taking labor as an example, while unskilled labor contributes to tangible production contemporaneously, the contribution of skilled labor has a delay (see Fig. 3). Such a difference implies that skilled labor tends to have a long-term nature. When the aggregate demand is subject to disturbances, the effect could be partially absorbed by the tangible sector before being transmitted to the skilled labor market and, hence, the intangible sector.

The firm j maximizes the expected present discounted value of the current and future dividends D_{jt}^E:

$$\max \mathbb{E}_t \sum_{s=0}^{\infty} M_{t+s,t+s+1} D_{j,t+s}^E \tag{14}$$

subject to the two production functions (8) and (9), the budget constraint (15), the borrowing constraint (16), the demand scheme of tangible goods (17), and the evolution of two types of capital (10) and (11).

$$W_t^u H_{jt}^u + W_t^s H_{jt}^s + P_t I_{jt} + P_t \Phi(D_{jt}^E) + R_{t-1}^b B_{j,t-1} = P_{jt}^m Y_{jt} + B_{jt} \tag{15}$$

$$B_{jt} \leqslant \xi_t (P_t K_{jt} + \nu P_t Z_{jt}) \tag{16}$$

$$Y_{jt}^m = Y_t^m (\frac{P_{jt}^m}{P_t^m})^{-\theta_m} \tag{17}$$

where P_{jt}^m is the price of intermediate tangible goods and θ_m is the elasticity of substitution for intermediate tangible goods. $\nu \in (0,1)$ captures limited pledgeability of intangible capital compared with physical capital. Following Jermann and Quadrini (2012), each firm uses debts and equity, and debts are preferred to equity due to their tax advantage. The gross lending rate is $R_t^b = 1 + (1-\tau)(R_t - 1)$, where $\tau \in (0,1)$ denotes the tax rate. The equity issuance is subject to a quadratic adjustment cost with $\Phi(D_{jt}^E) = D_{jt}^E + \kappa/2(D_{jt}^E/(1+g_y)^t - d^E)^2$ where $(1+g_y)^t$ is a scaling factor to ensure a balanced growth path, $d^E = D^E/(1+g_y)$ is the detrended dividend in the steady state, and κ is the dividend payment cost parameter. ξ_t is a financial shock following an AR(1) process $\xi_t = (1-\rho_f)\xi + \rho_f \xi_{t-1} + \sigma^f \epsilon_t^f$ and ϵ_t^f follows an i.i.d $N(0,1)$.

3.3. Final goods producers

There is a continuum of monopolistic competitive final goods producers i, each of which is like a retailer who buys intermediate goods Y_{it}^m and transfers them into differentiated final goods Y_{it} in a linear way, which is further used for consumption, physical investment, and government spending. The final goods firms face nominal price adjustment costs following Rotemberg's approach $\frac{\phi_p}{2}(\frac{P_{it}}{\pi P_{i,t-1}} - 1)^2 Y_t$.

The final goods producer i maximizes expected present discounted value of the current and future profit:

$$\max \mathbb{E}_t \sum_{s=0}^{\infty} M_{t+s,t+s+1}[(\frac{P_{i,t+s}}{P_{t+s}} - \frac{P_{t+s}^m}{P_{t+s}})Y_{i,t+s} - \frac{\phi_p}{2}(\frac{P_{i,t+s}}{\pi P_{i,t+s-1}} - 1)^2]Y_{t+s} \tag{18}$$

subject to the demand of final goods:

$$Y_{it} = Y_t (\frac{P_{it}}{P_t})^{-\theta_f} \tag{19}$$

where θ_f is elasticity of substitution for final goods. The maximization yields the following New-Keynesian Phillips Curve in the equilibrium:

$$p_t^m = \frac{\theta_f - 1}{\theta_f} + \frac{\phi_p}{\theta_f}(\frac{\pi_t}{\pi} - 1)\frac{\pi_t}{\pi} - \mathbb{E}_t M_{t,t+1}\frac{\phi_f}{\theta_f}(\frac{\pi_{t+1}}{\pi} - 1)\frac{\pi_{t+1}}{\pi}\frac{Y_{t+1}}{Y_t} \tag{20}$$

where $p_t^m = P_t^m / P_t$ is the real price of intermediate goods (and also real marginal cost for final goods firms).

3.4. Equilibrium

In the symmetric equilibrium, all intermediate goods firms and final goods firms have the same decisions, respectively. Hence,

$$Y_t = Y_t^m = A_t Z_t^{\zeta} (u_t K_t^y)^{\alpha} (H_t^u)^{1-\alpha-\zeta} \tag{21}$$

$$X_t = \chi Z_t^{\zeta} (u_t K_t^z)^{\alpha} (H_t^s)^{1-\alpha-\zeta} \tag{22}$$

The resource constraint is given by

$$Y_t = C_t + I_t + G_t + \frac{\phi_p}{2}(\frac{P_t}{\pi P_{t-1}} - 1)^2 Y_t + \frac{\kappa}{2}[\frac{D_t^E}{(1+g_y)^t} - d^E]^2 \tag{23}$$

where government spending G_t follows an AR(1) process: $G_t/(1+g_y)^t = (1-\rho_g)g + \rho_g G_{t-1}/(1+g_y)^{t-1} + \sigma_g \epsilon_t^g$ and ϵ_t^g follows i.i.d $N(0,1)$. $g = G/(1+g_y)$ is the detrended government spending in the steady state.

In equilibrium, capital markets are clear.

$$K_t = K_t^y + K_t^z \tag{24}$$

The central bank sets the nominal interest rate according to a Taylor rule:

$$R_t = R_{t-1}^{\rho_r}[R(\frac{\pi_t}{\pi})^{\rho_\pi}(\frac{Y_t}{(1+g^y)Y_{t-1}})^{\rho_y}]^{1-\rho_r} \tag{25}$$

Table 4
Calibrated parameters.

Parameters	Description	Value
α	physical capital share	0.3
ζ	intangible capital share	0.13
β	discount factor	0.995
h	degree of habit formation	0.75
η	inverse labour elasticity	2
δ_k	physical capital depreciation	0.025
δ_z	intangible capital depreciation	0.04
δ_2/δ_1	capital utilization cost	0.1
κ	equity adjustment cost	0.15
ϕ_k	investment adjustment cost	2
ϕ_p	price adjustment cost	100
ψ	intertemporal elasticity of substitution	0.5
σ	risk aversion	80
τ	tax rate	0.35
θ_m	IG elasticity of substitution	10
θ_f	FG elasticity of substitution	10
ρ	Taylor smoothing	0.7
ρ_π	Taylor parameter	1.85
ρ_y	Taylor parameter	0.25
ν	intangible pledgeability	0.2
$1+g_y$	ss per capita GDP growth	1.005
G/Y	ss exo. demand share	0.15
H^u	ss unskilled hours worked	1/3
H^s	ss skilled hours worked	0.017
ξ	ss financial constraint	0.4
ρ_u	per. of uncertainty	0.75
σ_u	std. of uncertainty	0.03

Following Basu and Bundick (2017), the stock return R_t^E and model-implied stock market volatility in the annualized term V_t^M are defined as

$$R_t^E = \frac{P_t^E + D_t^E}{P_{t-1}^E} \tag{26}$$

$$V_t^M = 100\sqrt{4\mathbb{VAR}(R_{t+1}^E)} \tag{27}$$

GDP is defined as the sum of consumption, two types of investment, and government spending:

$$GDP_t = C_t + I_t + X_t + G_t \tag{28}$$

Appendix D lists all equilibrium conditions in the baseline model.

4. Solution and calibration

Following the existing literature (see Born and Pfeifer (2014), Fernández-Villaverde et al. (2015), and Basu and Bundick (2017), among others), the model is solved by a third-order perturbation around the balanced growth path. The third-order approximation is required to separate the effects of the uncertainty shock from the corresponding level shock.

Table 4 presents the calibrated parameters. The physical capital share α is set as 0.3, in line with other US-based DSGE studies. The intangible capital share ζ is calibrated as 0.13, which falls in the range suggested by the literature (Lopez and Olivella, 2018; Mitra, 2019). The discount factor β is calibrated as 0.995 to match the quarterly interest rate. The habit parameter h is set as 0.75, a moderate value reported by the literature (see Born and Pfeifer (2014) and Bianchi et al. (2023), among others). The physical capital depreciation rate δ_k is calibrated as 0.025. Following Kung and Schmid (2015) and Jinnai (2015), the intangible capital depreciation rate δ^a is set as 0.04. The combination of α, ζ, δ^k, and δ^a delivers the intangible-to-output (X/Y) ratio as 9 % and intangible investment share ($X/(X+I)$) as 31 %, consistent with empirical observations and the estimates of Aghion et al. (2010) and Lopez and Olivella (2018). The inverse labor elasticity η is calibrated as 2, consistent with Smets and Wouters (2007) and Basu and Bundick (2017). Following Born and Pfeifer (2014), the capital utilization cost δ_2/δ_1 is calibrated as 0.1. The physical capital adjustment cost ϕ_k is calibrated as 2 which falls in the range suggested by the literature.[7] Following Basu and Bundick (2017), the price adjustment cost ϕ_p and risk aversion σ are set as 100 and 80, respectively. Regarding the intertemporal elasticity of substitution ψ, it is set as 0.5, in line with Gourio (2012) and Basu and Bundick (2018). Following Jermann and Quadrini (2012), the equity adjustment cost κ,

[7] Born and Pfeifer (2014) find a relative low value for ϕ_k (1.6), while Bianchi et al. (2023) find a relatively high value (7.3). As will be shown shortly in Section 6, the inclusion of intangibles dampens investment volatility. In order to match the data, a relatively low value of physical capital adjustment cost is chosen.

Table 5
Empirical and model-implied moments.

Moment	Data	Model Baseline	Model w/o Uncertainty shock
$\sigma(\Delta y)$	0.63	0.62	0.52
$\sigma(\Delta c)$	0.55	0.53	0.28
$\sigma(\Delta i)$	2.27	2.27	1.62
$\sigma(x/(x+i))$	3.59 (macro) 2.92 (micro)	2.83	2.27
$\sigma(h)$	1.23	1.32	0.92

Notes: The sample period is 1986–2019 at quarterly frequency for macro variables. The empirical counterpart of tangible output y is defined as GDP excluding intellectual property products (IPP) investment. The empirical counterpart of tangible investment i is defined as fixed private investment excluding IPP investment.

and tax rate τ are set as 0.15 and 0.35, respectively. The two elasticities of substitution parameters θ^m and θ^f are calibrated as 10, implying markup as 1.1 in the final goods and intermediate goods sectors. Regarding the three Taylor parameters ρ, ρ_π, and ρ_y, they are calibrated as commonly used values of 0.7, 1.85, and 0.25, respectively.

The lower part of Table 4 displays the calibrated values of the steady-state parameters and the uncertainty shock. The average per capita GDP growth rate is about 0.5 %, implying g_y as 0.005. The government spending-to-output ratio is calibrated as 15 %. The unskilled dis-utility parameter ψ^u is set to match 1/3 unskilled worked hours. The skilled dis-utility parameter ψ^s is set such that the productivity of intangibles χ is normalized to unity.[8] Regarding the two financial constraint parameters, the intangible pledgeability ν is set as 0.2, implying that 20 % of intangible capital is pledgeable, in line with empirical observations (Mann, 2018; OECD, 2021; Caggese and Pérez-Orive, 2022). Finally, the financial constraint ξ in the steady state is calibrated as 0.4, implying private debt-to-output ratio as 3.3 at quarterly frequency. Regarding the uncertainty shock, a moderately high persistence is chosen ($\rho_u = 0.75$), in line with suggestions from existing literature (see Leduc and Liu (2016) and Basu and Bundick (2017), among others). Following the approach adopted by Basu and Bundick (2017), I calibrate σ_u such that a one-standard-deviation increase in the uncertainty shock raises stock market volatility by 15 %. This implies σ_u as 0.03.

In order to assess how the calibrated model fits the data, a comparison is made between model-implied moments of key macroeconomic variables and their empirical counterparts. Table 5 shows that the model closely matches the volatility of output growth, consumption growth, physical investment growth, and hours worked observed in the data. Table 5 also reports volatility of the intangible investment ratio, $\sigma(x/(i+x))$, which captures relative variations of intangible investment. The result indicates that the volatility of the intangible investment ratio is well aligned with the data, particularly at the micro level, which provides broader statistical coverage of intangible investment than at the macro level. Furthermore, the last column in Table 5 also reports model-implied moments when the uncertainty shock is shut down. In this case, all variables become substantially less volatile compared to the baseline case and the data. For example, the standard deviation of physical investment growth falls to 71 % of its baseline value. Overall, these findings suggest the important role of the uncertainty shock in driving business cycles, consistent with the argument of Fernández-Villaverde and Guerrón-Quintana (2020).

5. Uncertainty shock in an intangible economy

This section investigates transmission of the uncertainty shock in an intangible economy based on impulse response analysis.

5.1. Transmission of uncertainty shock with intangibles

Fig. 4 plots impulse responses to a one-standard-deviation increase in the uncertainty shock. Elevated uncertainty triggers households' precautionary saving motives, which suppresses consumption demand. The decline in consumption reduces tangible goods in the sticky-price economy, further depressing the marginal product of labor, leading to decreased wages and hours worked. The contraction in tangible goods also reduces return on all types of capital, discouraging capital accumulation in both tangible and intangible sectors. As a result, physical investment and intangible investment both decline, although the response of intangible investment is relatively muted. This asymmetry is consistent with the empirical evidence documented in Section 2, where intangible investment is less sensitive to uncertainty shocks compared with its tangible counterpart. Moreover, the results are also consistent with findings and implications in the existing literature. In particular, Fig. 4 suggests a comovement pattern between major macroeconomic aggregates, consistent with Basu and Bundick (2017). It also shows that rising uncertainty reduces aggregate demand and inflation, implying that the transmission of uncertainty resembles a demand-side shock, in line with Leduc and Liu (2016). Focusing on firm decisions, Kumar et al. (2023) find that heightened uncertainty reduces employment and investment, including technology innovation as one form of intangible investment. These results are reflected in my model. Furthermore, the model predicts less responsive intangible investment than physical investment, a pattern broadly consistent with Bloom (2007).

[8] I find that dynamic responses of hours worked to uncertainty do not depend on ψ^u and ψ^s.

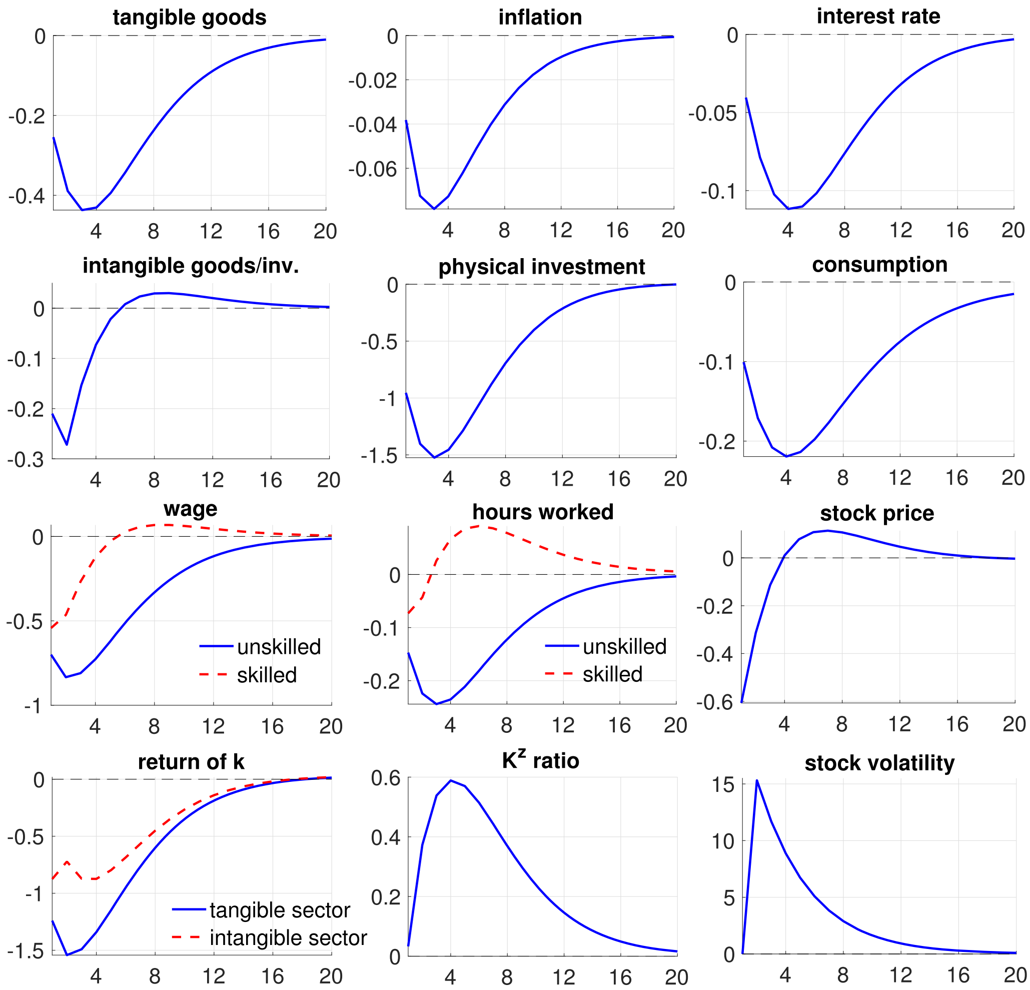

Fig. 4. Uncertainty Shock. *Notes:* This figure plots impulse response functions (IRFs) of key variables to a one-standard-deviation increase in the uncertainty shock. The shock hits the model in period one. Intangible goods are also the output measure of intangible investment. Variables are expressed as percentage deviations from the trend.

Next, I further assess the model's performance against the data by comparing the model-implied IRFs with the empirical counterparts. To do so, I augment a VAR model estimated in Section 2 to include a broader set of macroeconomic variables. Fig. 5 plots the model-implied IRFs (the blue circled lines), along with their empirical counterparts (the red solid lines). Overall, the model-implied IRFs are close to the empirical counterparts. In particular, the model closely matches the decline in GDP and physical investment. It also reproduces the initial drop in intangible investment, although less persistent as in the data. Due to various definitions and challenges in measuring intangibles, it is not feasible to perfectly capture the responses of intangible investment in the data. Nevertheless, Fig. 1 and Table 5 suggest that intangible investment ratios based on the alternative measures tend to closely comove with similar volatility. Thus, the intangible investment ratio appears to be less influenced by measurement issues. Fig. 5 shows that the intangible investment ratio matches the data well based on both VIX and JLN uncertainty shocks, supporting the model's ability to capture the relative sensitivity of intangible investment to uncertainty.

To explain the less responsive pattern of intangible investment, the model highlights two important forces–the delayed contribution of skilled labor and capital reallocation. Given the long-term nature of intangible production, effects of the uncertainty shock are partially absorbed by the tangible sector, resulting in a weakened transmission to the intangible sector. Hence, firms tend to maintain demand for skilled labor. The skilled labor demand curve shifts inward, yet less significant than the unskilled counterpart, leading to a smaller fall of skilled wages compared to unskilled wages. Consequently, households are likely to favor skilled labor supply and strive to maintain skilled hours, inducing a precautionary labor motive (Basu and Bundick, 2017) specifically for skilled hours. This suggests that the precautionary motive for skilled labor is stronger than for unskilled labor. As a result, skilled hours are less affected upon impact of the uncertainty shock, as suggested by Fig. 4.

Similarly, physical capital in the intangible sector K_t^z also exhibits long-term characteristics (see Fig. 3). The downward pressure on return of K_t^z is relatively low and, hence, $R_t^{k,z}$ has a limited fall. Consequently, deploying physical capital in the intangible sector becomes more attractive than in the tangible sector. The return gap between K_t^y and K_t^z drives a capital reallocation effect toward

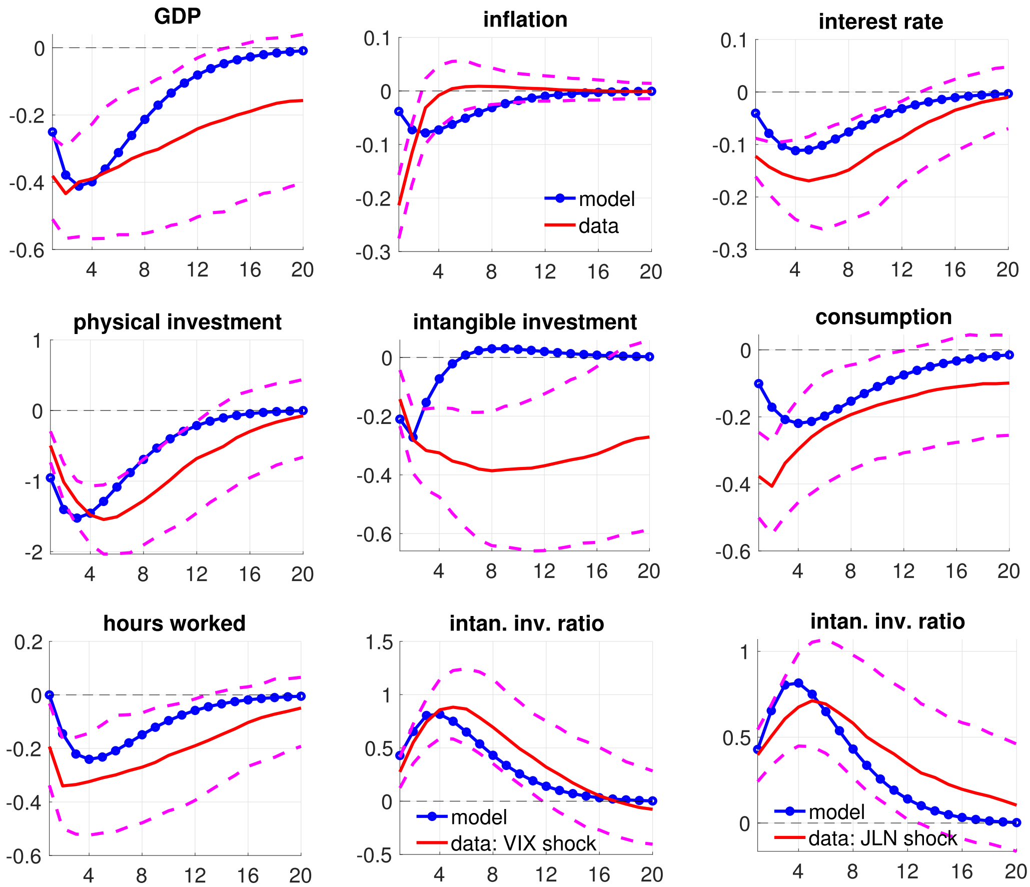

Fig. 5. Empirical and Model-implied IRFs to Uncertainty Shock. *Notes:* This figure compares model-implied IRFs with the empirical counterparts based on the VIX shock unless otherwise specified. Two VAR models are estimated. The first one includes a measure of uncertainty, GDP, consumption, fixed private investment excluding IPP investment, IPP investment, hours worked, CPI inflation, federal fund rate, and excess bond premium. In the second VAR model, IPP investment is replaced by its ratio to total investment. Dashed lines show 68 % probability density intervals. Impulse responses are expressed as percentage deviations.

the intangible sector and, hence, the K^z ratio rises. With the dampening forces from both skilled labor and capital reallocation, the production of intangible goods experiences relatively limited disruptions, making intangible investment less responsive to uncertainty.

Overall, the results suggest that elevated uncertainty channels resources toward the intangible sector, rendering the economy relatively more intangible-intensive. A pertinent example can be found from the COVID pandemic period when uncertainty levels rose substantially. OECD (2021) documents that firms shifted their investment composition toward intangibles, such as adopting digital technology to weather the COVID-19 crisis. Given the sophistication of intangible production, such a shift also altered firms' labor demand to be more skilled-based.

5.2. *Inspecting the mechanisms*

The analysis emphasizes capital reallocation and the delayed contribution of skilled labor in interpreting the results. It is useful to quantitatively assess the importance of the two factors in driving the weak response of intangible investment. To this end, I compare impulse responses based on the baseline model and counterfactual cases. One option is to remove skilled labor from the model and assume that unskilled labor is also used for intangible production (labeled as Reference Model I). By doing so, the skilled labor precautionary motive is shut down. Based on Reference Model I, I further consider a case that assumes a constant k^z ratio, thereby closing the capital reallocation channel (labeled as Reference Model II). Fig. 6(a) compares impulse responses of different types of investment based on the baseline model and the two Reference Models. In Reference Model I (red dash-dot line), the peak decline of x_t becomes 0.4 %, 60 % larger than in the baseline model (0.25 %). If the capital reallocation channel is further closed (green-dash line), the peak decline of x_t increases to 0.45 %, the same as that of tangible goods y_t.

The model also incorporates other heterogeneity between tangible and intangible sectors, as well as nominal and real frictions. To better understand the drivers of the results, I further examine how these additional elements affect the responses of intangible investment. These elements are partitioned into two groups. The first group includes other heterogeneity or factors potentially more important for intangible investment–i.e., different depreciation rates, equity adjustment costs, and the financial constraint.

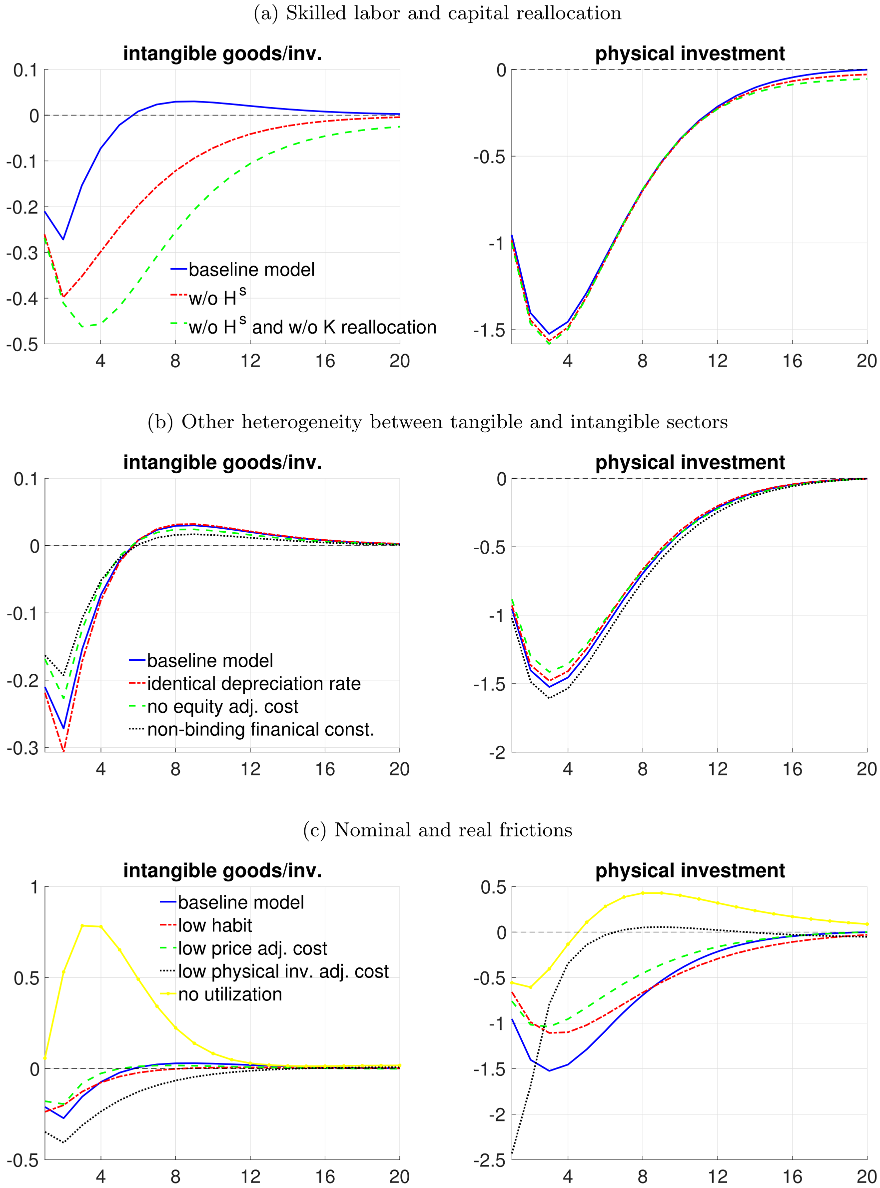

Fig. 6. Uncertainty Shock: Roles of Model Elements. *Notes:* This figure compares IRFs in alternative models with the baseline model. Fig. (a) highlights the role of skilled labor and capital reallocation. Fig. (b) focuses on elements which are potentially more important for intangible investment. Fig. (c) focuses on nominal and real frictions. Variables are expressed as percentage deviations from the trend.

Overall, Fig. 6(b) suggests that changing elements in the first group has slightly larger impacts on intangible investment than on physical investment. Starting with depreciation, I reduce δ_z such that it is equal to δ_k. The red dash-dot line in the left panel indicates a larger decline in intangible investment. A lower δ_z makes intangible capital more long-lived, increasing its sensitivity to uncertainty shocks. This result is consistent with Barrero et al. (2017). Second, I remove the equity adjustment cost, implying that firms can flexibly issue equity. In this case, the green-dash line suggests a smaller decline in intangible investment. Without frictions in equity issuance, firms can raise equity quickly, which provides a buffer against the downward pressure of uncertainty. The result is consistent with Brown et al. (2009) who highlight equity as a key financing source for technology innovation. In the third case, the financial constraint is removed. The black-dot lines show that intangible investment falls more, while physical investment declines less. In the presence of the financial constraint, higher uncertainty tightens the financial constraint, generating a substitution effect: because intangible capital is less pledgeable, firms prefer to cut intangible capital and try to retain physical capital. Removing the financial constraint eliminates this substitution effect.[9] Overall, the elements in the first group explain some of the responses of intangible

[9] The substitution effect is also consistent with my results based on the financial shock ξ_t, which is explored in Appendix E.

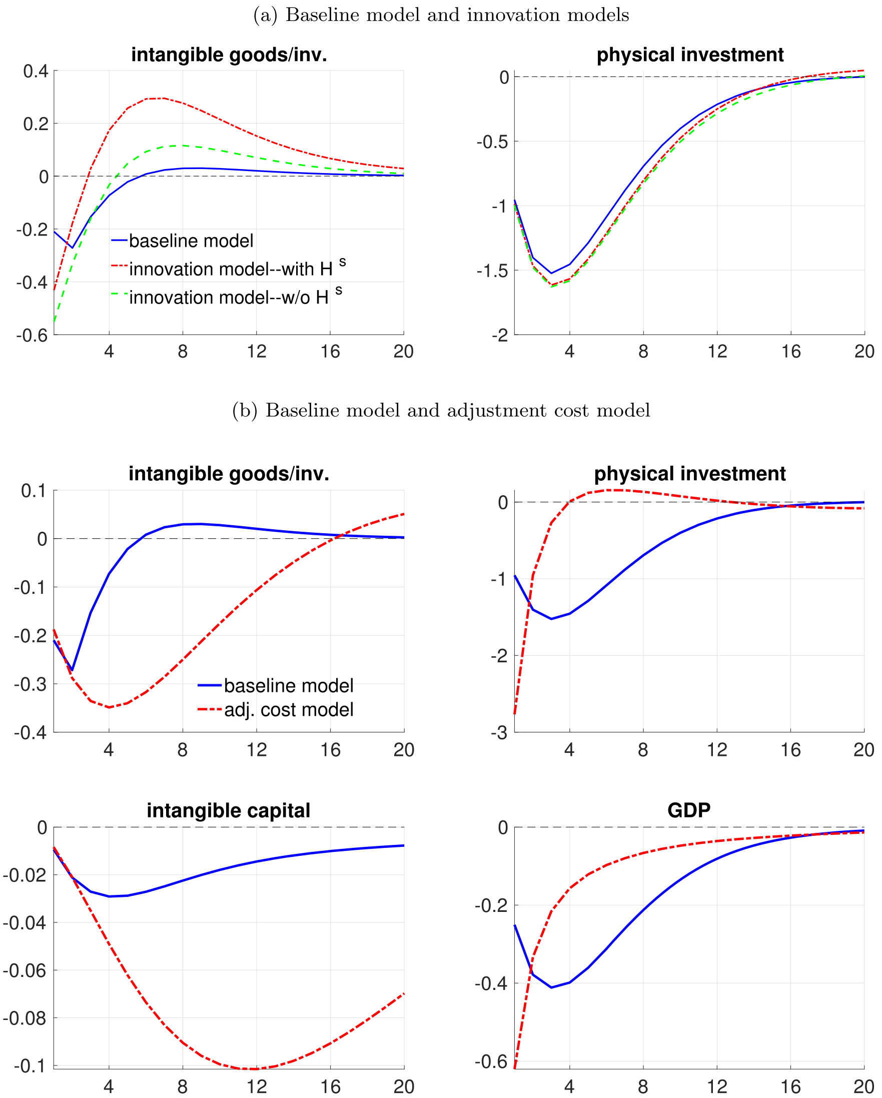

Fig. 7. Uncertainty Shock: Model Comparisons. *Notes:* This figure compares IRFs of key variables in the baseline model with innovation models or the adjustment cost model. Variables are expressed as percentage deviations from the trend.

investment. However, their effects are quantitatively incomparable with the capital reallocation effect and the delayed skilled labor mechanism.

The second group includes habit formation, price rigidity, physical investment adjustment costs, and capital utilization. These frictions are documented as important factors for shock transmissions in business cycles (Smets and Wouters, 2007; Basu and Bundick, 2017; Fernández-Villaverde and Guerrón-Quintana, 2020). Fig. 6(c) depicts that altering or removing these elements affects responses of both physical and intangible investment simultaneously. This contrasts with Fig. 6(a), where capital reallocation and skilled labor primarily affect responses of intangible investment only. Thus, these frictions generally shape the propagation of the uncertainty shock rather than uniquely affect the responses of intangible investment. Moreover, Fig. 6(c) suggests that frictions in the second group tend to exacerbate the decline of investment. In contrast, delayed labor and capital reallocation work against the recessionary pressure, hence weakening the responses of intangible investment.

5.3. Model comparisons

Focusing on technology components of intangibles, previous studies incorporate endogenous growth in business cycle models (Comin and Gertler, 2006; Anzoategui et al., 2019; Ikeda and Kurozumi, 2019; Queralto, 2020). I consider modeling features as in these studies to examine the response of intangibles (or, narrowly, technology innovation). In particular, I consider that intangible production (or technology creation) is carried out by using either tangible goods (see Comin and Gertler (2006), among others) or both tangible goods and skilled labor (see Queralto (2020), among others). Fig. 7(a) suggests more significant responses of intangible investment based on the two innovation models[10] compared to the baseline model. These two models can be treated as additional exercises to assess the importance of capital reallocation and the delayed contribution of skilled labor in shaping the response of intangible investment. In both innovation models, the capital reallocation channel and/or the delayed-labor mechanism are absent. Consistent with the implications from Fig. 6(a), Fig. 7(a) further confirms the importance of the two channels in leading to the insensitivity of intangible investment to uncertainty.

In addition to the endogenous growth framework, some studies focus on adjustment costs to explore the dynamics of intangible investment. Bloom (2007) suggests that knowledge and physical capital have different adjustment costs, which could lead to heterogeneous investment-uncertainty relationships. While physical capital adjustment costs arise from changing capital stock, knowledge adjustment is subject to a flow cost, i.e., costs from changing the investment level. The knowledge adjustment cost reflects the expenses of changing equipment and paying skilled labor, providing a reduced-form representation to capture costs involved in producing intangible goods. Given that the delayed-labor mechanism is akin to a micro-foundation for the reduced-form adjustment cost of intangible investment, I further carry out a comparison with an adjustment cost model to provide further robustness checks to the key findings.

To compare the implications of the baseline model with the adjustment cost model, I distinguish between flow and stock adjustment cost functions. In the adjustment cost model, I incorporate a flow adjustment cost function for intangible investment: $\frac{\phi_z}{2}[\frac{X_t}{(1+g^y)X_{t-1}}-1]^2$, and adopt a stock-based adjustment cost for physical capital: $\frac{\phi_k}{2}(\frac{I_t}{K_t}-\frac{I}{K})^2$. These forms of adjustment costs are commonly used in the business cycle literature (see Smets and Wouters (2007), Basu and Bundick (2017), and Bianchi et al. (2019), among others). Additionally, I remove the intangible sector and assume that firms accumulate intangible capital using tangible goods. Hence, the adjustment cost model is effectively a one-sector model.

Based on the adjustment cost model, Fig. 7(b) shows that intangible investment initially declines less than physical investment. It also adjusts more slowly, with both intangible investment and intangible capital displaying gradual slowdown, whereas physical investment and GDP exhibit faster declines and quicker recoveries. These results are in line with the implications of Bloom (2007). Overall, both the adjustment cost model and the baseline model generate a pattern of less responsive intangible investment to uncertainty in the short run. However, the baseline model explicitly incorporates the production process of intangibles and, hence, provides more structural interpretations, such as resource allocation across sectors. Moreover, the baseline model distinguishes between skilled and unskilled labor, which allows for analysis of the delayed contributions from skilled labor. Further empirical evidence on the uncertainty-labor relationships, and their implications for intangible investment are explored in Section 5.4.

5.4. *Empirical validations*

The quantitative analysis predicts that skilled labor is less responsive than unskilled labor to the uncertainty shock, which is an important force behind the weak response of intangible investment. This subsection provides empirical evidence to validate this mechanism. In detail, I first examine how different types of labor respond to uncertainty shocks. In the second step, I investigate the implications of skilled labor for the transmission of uncertainty shocks. To begin with, I measure skilled and unskilled employment based on macro-level data, and include the two extra variables into the VAR model to compare their impulse responses to uncertainty shocks. Following the commonly-used definitions (see Acemoglu and Autor (2011), among others), skilled labor is defined as labor forces with at least a college degree, while unskilled labor is defined as labor forces without a college degree. The upper panels of Fig. 8 show the responses of the two types of employment to uncertainty shocks. Although both skilled and unskilled employment have negative responses, the latter appears to have a larger and faster decline when uncertainty rises. The different response is more pronounced when uncertainty is measured by the JLN index. To better visualize different responses of the two labor types, I estimate an alternative VAR model including skilled-to-unskilled employment ratios. Adding the latter is useful to capture the relative sensitivity of skilled employment. The lower panels of Fig. 8 show that the skilled-employment ratio rises following uncertainty shocks. Since both types of employment contract, the increase in the skilled-employment ratio suggests that skilled employment is less affected by uncertainty, providing support for the quantitative results.

Next, I turn to the implications of skilled labor for the effects of uncertainty. Following Döttling and Ratnovski (2023), I split firms by a skilled-labor share to examine how skilled labor may shape relationships between uncertainty and employment or intangible investment. Skilled-labor shares are constructed using the Specific Vocational Preparation (SVP) index[11] based on Occupational Employment Statistics (OES) from the Bureau of Labor Statistics. Following Belo et al. (2017), I classify an occupation as high skilled if SVP is strictly greater than 6. These are occupations mainly requiring bachelor's or postgraduate degrees and, hence, consistent with the macro-level definition. Based on skilled employment at the industry-occupation level, I aggregate it to the industry level and compute the industry-level skilled-labor share. Industries with skilled-labor share above the median are classified as heavy reliance on skilled labor, labeled as a *high-skilled* group. To name some examples, I find that the following industries have relatively high skilled-labor shares: scientific research and development services, engineering and architectural services, accounting and tax preparation services, and radio and television broadcasting. Examples of industries with relatively low skilled-labor shares include restaurants and

[10] Technical details of the two innovation models and an adjustment model discussed shortly are reported in Appendix DII.

[11] OES provides industry-occupation-level data, and occupations can be classified as high skilled or low skilled based on the Specific Vocational Preparation (SVP) index. The SVP measures the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. The SVP ranges from 1 to 9 with a higher value indicating more considerable preparation needed. More details can be found from the SVP page at O*NET Online.

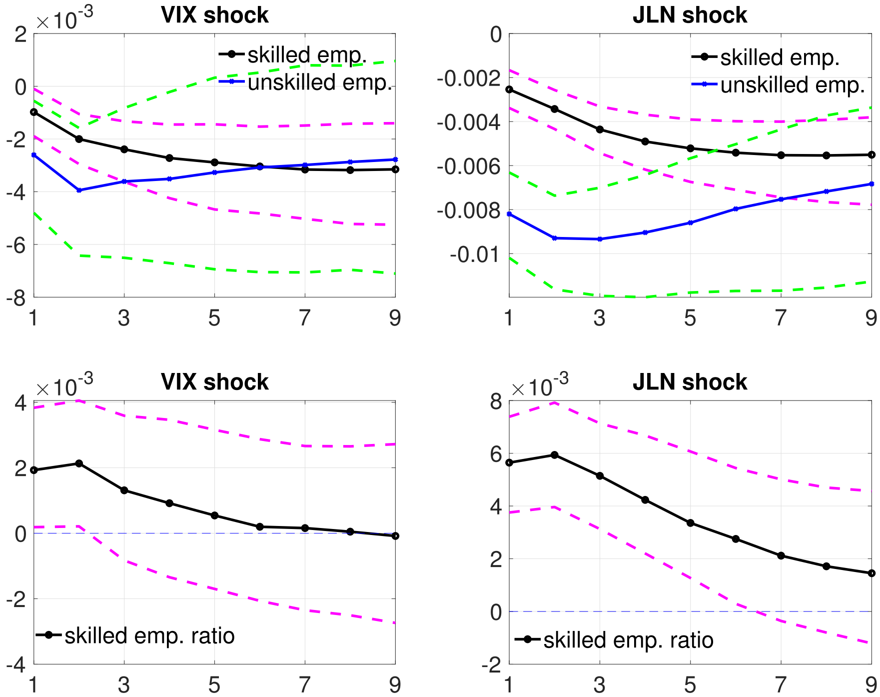

Fig. 8. Responses of Different Types of Labor to Uncertainty Shocks. *Notes:* This figure compares the impulse responses of skilled labor and unskilled labor to a 1 % increase in uncertainty based on either the VIX index or the JLN index. Skilled labor is measured as employment aged over 16 with college or higher degrees. Unskilled labor is measured as employment aged over 16 having lower than a college degree. The dashed lines show the 68 % probability density intervals. Impulse responses are expressed as percentage deviations.

Table 6
Employment regression results.

	VIX		JLN	
	All Firms [1]	High Skilled [2]	All Firms [3]	High Skilled [4]
u	-0.0526***	-0.0152	-0.1487***	-0.1051***
	(0.008)	(0.012)	(0.018)	(0.028)
Observations	37,586	15,483	37,598	15,486
Adj. R^2	0.364	0.405	0.365	0.406
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: Regressions are based on firm-level annual data between 2000 and 2023. The dependent variable is the log of employment scaled by lagged total assets. Columns [2] and [4] report the results based on the group with high skilled-labor shares. Sample split is based on the median of skilled-labor shares. Firm-level controls include Tobin's Q, leverage ratio, cash holding, cash flow, size, and age. Robust standard errors are shown in parentheses. ***, **, and * represent significance level at 1 %, 5 %, and 10 %, respectively.

other eating places, gasoline stations, department stores, and services to buildings. These findings are consistent with the literature (see Ghaly et al. (2017), among others). Since the skilled-labor share and firm employment are only available annually, I perform regressions based on annual data. The uncertainty shocks are averaged to annual frequency, and I included the same set of firm-level controls as in the baseline regressions.

Table 6 reports the employment regression results. Focusing on columns [1] and [3], we first confirm negative uncertainty-employment relationships which are also found in the literature (Barrero et al., 2017; Kumar et al., 2023). According to the quantitative analysis and VAR results, skilled labor has relatively weak responses to uncertainty. Thus, I expect that firms heavily relying on skilled labor should experience a smaller decline in total employment. This expectation is confirmed by columns [2] and [4] which document weaker effects of uncertainty for the High Skilled group relative to the average. This evidence complements the VAR results, providing support for the weak response of skilled labor to uncertainty at both micro and macro levels.

Table 7
Intangible investment regression results.

	VIX		JLN	
	All Firms [1]	High Skilled [2]	All Firms [3]	High Skilled [4]
u	-0.0899***	-0.0717***	-0.1973***	-0.1892***
	(0.007)	(0.012)	(0.016)	(0.027)
Observations	38,467	15,632	38,480	15,643
Adj. R^2	0.310	0.345	0.310	0.347
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Notes: Regressions are based on firm-level annual data between 2000 and 2023. The dependent variable is intangible investment rate. Columns [2] and [4] report the results based on the group with high skilled-labor shares. Sample split is based on the median of skilled-labor shares. Firm-level controls include Tobin's Q, leverage ratio, cash holding, cash flow, size, and age. Robust standard errors are shown in parentheses. ***, **, and * represent significance level at 1 %, 5 %, and 10 %, respectively.

In addition to studying the implications of skilled labor for the uncertainty-employment relationships, I proceed to investigate whether high reliance on skilled labor contributes to weaker responses of intangible investment. Table 7 compares the impact of uncertainty on intangible investment for the full sample and for firms with high skilled-labor intensity. Similar to the employment analysis, we can interpret that the effects of uncertainty based on the full sample as averaged effects which serve as a benchmark for comparison. Comparatively, firms' intangible investment in the High Skilled group tends to be less affected by uncertainty, indicating a dampening role of skilled labor in transmitting uncertainty shocks. Such a finding is consistent with the theoretical prediction in Section 5.2.

6. The rise of intangibles

Given the importance and transmission of the uncertainty shock established in Sections 4 and 5, this section proceeds to study the implications of rising intangibles through the lens of the model.

Fig. 9 compares the responses of output, investment, and stock market volatility to the uncertainty shock while setting the intangible share ζ at alternative values. When there are almost no intangibles in the economy, the red-dash lines show the largest decline in both types of goods, physical investment, and the largest increase in stock market volatility in response to the uncertainty shock.

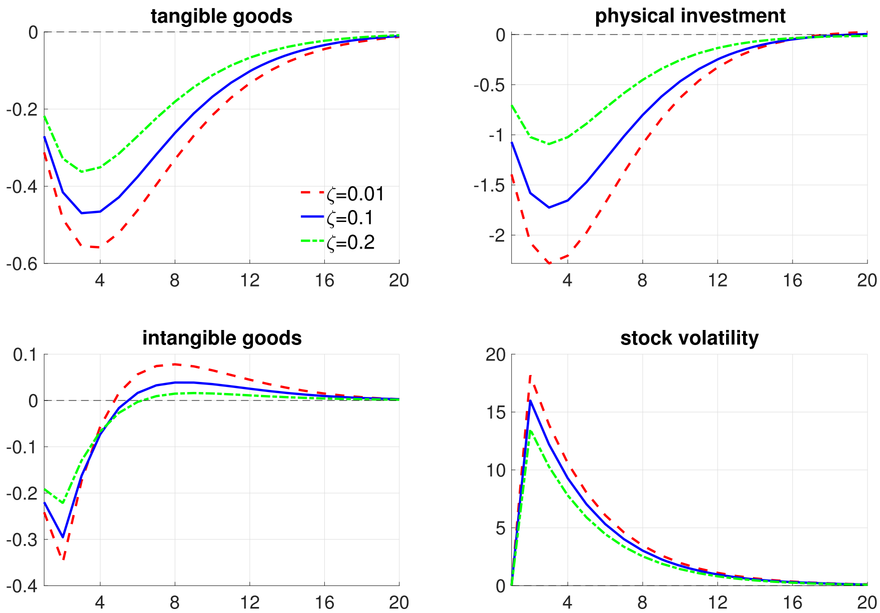

Fig. 9. Uncertainty Shock: Alternative Intangible Ratios. *Notes:* This figure compares IRFs to the uncertainty shock at different values of the intangible share ζ. Variables are expressed as percentage deviations from the trend.

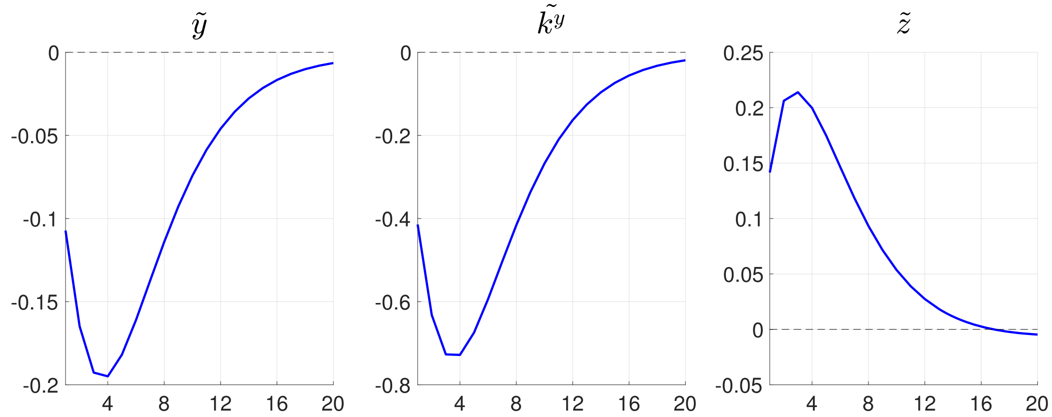

Fig. 10. Uncertainty Shock: per Hour Term. *Notes:* This figure shows IRFs to the uncertainty shock with $\tilde{y}_t = Y_t/H_t^u$, $\tilde{k^y}_t = u_t K_t^y/H_t^u$, and $\tilde{z}_t = Z_t/H_t^u$. Variables are expressed as percentage deviations from the trend.

Table 8
Effects of intangibles on aggregate volatility.

Variable	Fin. Shock only	All Level Shocks	All Shocks
y	1.93	1.03	0.93
c	1.88	1.04	0.99
i	1.55	0.87	0.82
x	1.47	0.93	0.85
h	1.64	0.94	0.84

Notes: This table contains the relative volatility of key macroeconomic aggregates between an intangible economy ($\zeta = 0.13$) and a tangible economy ($\zeta = 0.01$). Volatility is measured with model-implied standard deviation. An entry below (above) 1 implies that intangibles dampens (amplifies) the volatility of a variable.

As the intangible share increases to 0.1, the responses of output, investment, and stock market volatility all become dampened. This dampening effect becomes even more pronounced as the intangible share rises to 0.2. These results, illustrated in Fig. 9, suggest that an increase in intangible shares contributes to volatility reduction on both the real and financial sides of the economy. This finding echoes the empirical evidence that firms with more intangible capital tend to be less affected by uncertainty.

To better understand how the dampening effects work, it is convenient to rewrite the tangible production function in terms of hours worked.

$$\tilde{y}_t = A_t \tilde{z}_t^{\zeta} \tilde{k^y}_t^{\alpha} \tag{29}$$

where $\tilde{y}_t = Y_t/H_t^u$, $\tilde{k^y}_t = u_t K_t^y/H_t^u$, and $\tilde{z}_t = Z_t/H_t^u$. Given a constant productivity level, Eq. (29) suggests that per-hour output $\tilde{y}_t$ depends on the product of per-hour physical capital $\tilde{k^y}_t$ and per-hour intangible capital $\tilde{z}_t$. Fig. 10 shows that elevated uncertainty reduces $\tilde{y}_t$ and $\tilde{k^y}_t$. However, since the intangible sector suffers less from uncertainty, intangible capital has inertia responses, thereby leading to an increase in $\tilde{z}_t$. The opposite movement of $\tilde{z}_t$ against $\tilde{k^y}_t$ provides a dampening force which mitigates the adverse effect of uncertainty. As ζ increases, the intangible sector becomes more sizeable, further enhancing the mitigation effect, and resulting in the dampening pattern as found in Fig. 9.

To investigate the overall implications of intangibles in the business cycle, I compare model-implied moments of key macroeconomic aggregates at alternative values of intangible shares. Table 8 reports relative volatility between two cases: a benchmark intangible economy ($\zeta = 0.13$) and a tangible economy with very low intangible share ($\zeta = 0.01$). When only the financial shock is active, Table 8 suggests amplification effects of the intangibles on output, investment, and hours worked. After including all level shocks, the relative volatility of two types of investment and hours becomes less than one, indicating some dampening effects provided by the intangibles. Further incorporating the uncertainty shock reduces the relative volatility of all variables to below unity, indicating important interactions between intangibles and uncertainty. Intangibles can, thus, act as cushions in an uncertainty-driven business cycle.

7. Good vs. bad uncertainty shock

The majority of the literature suggests that uncertainty typically has recessionary effects. However, it is also possible for an uncertainty shock to deliver expansionary effects, which is often referred as good uncertainty (Bloom, 2014; Segal et al., 2015). Some

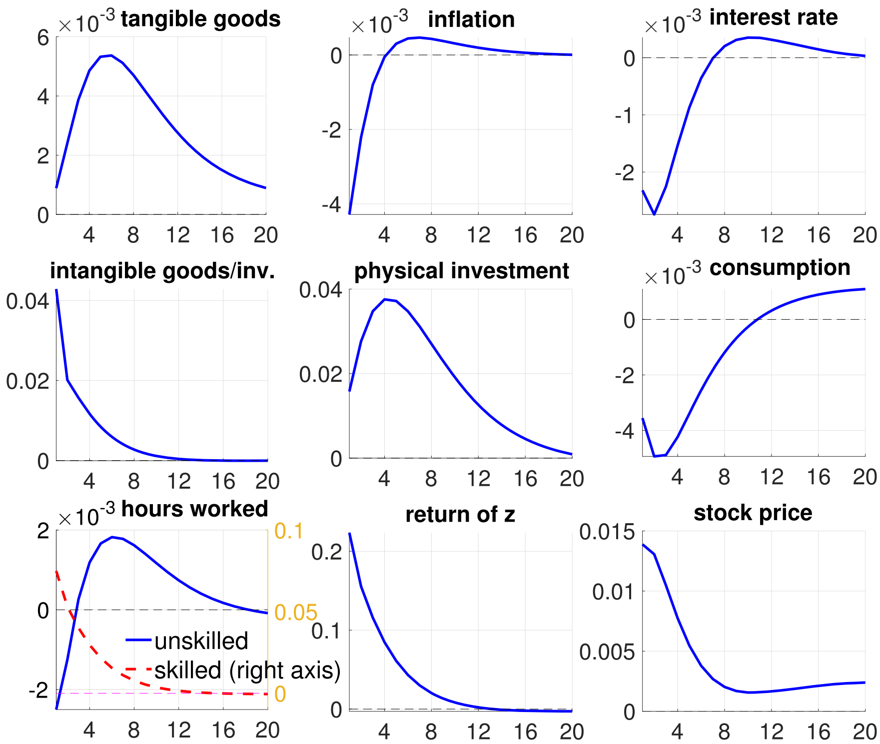

Fig. 11. Intangible Uncertainty Shock. *Notes:* This figure plots IRFs of key variables to a one-standard-deviation increase in the intangible-specific uncertainty shock. Variables are expressed as percentage deviations from the trend.

types of uncertainty may bring promising investment opportunities, leading to potentially high expected return in the future. Firms are encouraged to expand to pursue these future opportunities and, as a result, uncertainty can have expansionary effects.[12] Segal (2019) suggests that uncertainty could lead to a fear of suboptimal investment. In order to avoid a lack of physical capital in the future, more investment is made as a buffer to saving.

Although different studies have different foci, they commonly stress that long-term features of a project could be the key, leading to expansionary effects of uncertainty. Motivated by implications from the literature and historical experiences, this section explores the potential expansionary effects of uncertainty in the model with intangible production as an extended analysis. To this end, I incorporate an intangible-specific uncertainty shock and investigate its transmission. In particular, I allow the intangible productivity χ in Eq. (9) to follow an AR(1) process $\chi_t = (1-\rho_x)\chi + \rho_x \chi_{t-1} + \sigma^x_{t-1}\epsilon^x_t$. σ^x_t is the intangible-specific uncertainty shock evolving as $\sigma^x_t = (1-\rho_{ux})\sigma^x + \rho_{ux}\sigma^x_{t-1} + \sigma^x \epsilon^{ux}_t$ and ϵ^{ux}_t follows an i.i.d $N(0,1)$. Increased volatility in χ_t suggests more dispersed productivity in producing intangible goods, which leads to uncertain outcomes in the intangible production.

The information about intangible productivity and related uncertainty shocks is limited in the literature, particularly for the latter. I set the persistence of the intangible productivity shock ρ_x as 0.95 and that of the intangible uncertainty shocks ρ_{ux} as 0.75 based on values of ρ_a and ρ_u. In Appendix E, a range of values for ρ_x and ρ_{ux} are used to conduct a sensitivity analysis. Following the approach used by Mitra (2019), the volatility of intangible productivity shock in the steady state σ^x is calibrated to match the volatility of intangible investment rate (x_t/z_t).

Fig. 11 displays impulse responses to the positive intangible uncertainty shock (rise of σ^x_t). Unlike the recessionary effects as shown in Sections 5 and 6, the intangible-specific uncertainty shock leads to expansionary effects on investment, output, and stock prices. In the short run, the intangible uncertainty shock triggers the precautionary saving effect which lowers consumption and unskilled hours worked, hence imposing downward pressure on the tangible sector. Conversely, intangible uncertainty stimulates intangible production for two motives. Increased σ^x_t suggests that intangible productivity is more likely to take extreme values. There could be promising business opportunities with high productivity, which raises the return of intangible capital and encourages firms to produce more intangible goods. On the other hand, firms are also concerned with very low productivity. To compensate for this potential bad situation, firms increase their intangible production. Both two motives, which concern either upward or downward risks, lead to an expansion in the intangible sector. Owing to the complementarity between tangible and intangible capital, the accumulation of intangible capital spills over into the tangible sector, which further eases the downward pressure on the return of physical capital,

[12] One typical example used to explain this intuition is the hi-tech boom in the 1990s.

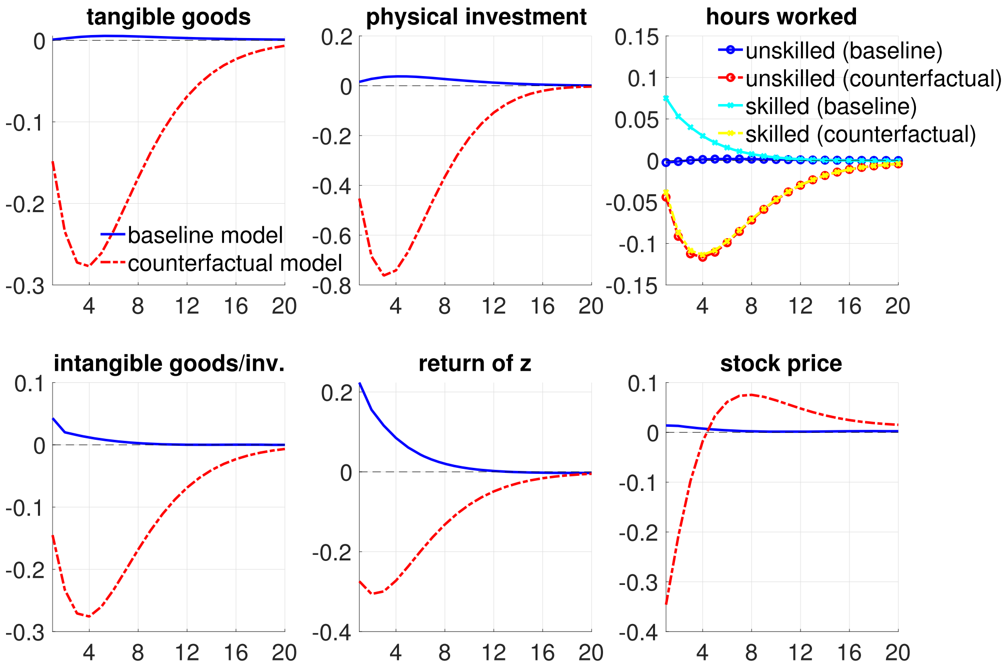

Fig. 12. Intangible Uncertainty Shock: Model Comparisons. *Notes:* This figure compares the responses of some key macroeconomic aggregates in the baseline case with the counterfactual case that intangible production does not have the long-term feature. Variables are expressed as percentage deviations from the trend.

gradually increasing physical investment and unskilled hours worked. Overall, the economy enters a expansion in the mid-to-long run.

Essentially, the positive effects of the intangible uncertainty shock rely on the long-term feature of projects which is particularly relevant for intangible production. To further corroborate the role of the long-term feature of intangibles in explaining the results, I compare the baseline results with a counterfactual case in which intangibles do not have the long-term feature. In details, I consider that intangible goods contribute to tangible production contemporaneously. The tangible production function becomes

$$Y_t = A_t X_t^{\zeta}(u_t K_t^y)^{\alpha}(H_t^u)^{1-\alpha-\zeta} \tag{30}$$

Eq. (30) also implies that output is a function of the contemporaneous term of the intangible-specific uncertainty shock $Y_t = f(\sigma_t^x, H_t^s, K_t^z, \ldots)$ and, hence, σ_t^x immediately affects output. This contrasts with the baseline model where σ_t^x primarily affects output in the future. Fig. 12 compares the responses of some key macroeconomic aggregates in the baseline model with those in the counterfactual model. In the latter case, the return of intangible capital declines, discouraging intangible investment. Moreover, since skilled labor in the counterfactual model contributes to tangible production contemporaneously, the responses of the two types of labor (the red dash-dot line and the yellow-cross line) become almost identical. Overall, Fig. 12 shows that the expansionary effects disappear once the long-term feature of intangibles is removed.

If an uncertainty shock could potentially lead to expansionary effects, it raises a question of why such effects are rarely observed in empirical evidence. The analysis provides two explanations. First, the expansionary effects could be quantitatively incomparable to the recessionary effects as shown in Section 5. Fig. 11 suggests that the magnitude of responses remains small. This is due to the two competing effects (i.e., the adverse effects on the tangible sector and the expansionary effects on the intangible sector) which tend to counteract each other. Thus, when considering multiple sources of uncertainty at the aggregate level, the expansionary effect would be dominated by the recessionary effect. Second, the expansionary effect tends to materialize in the mid-to-long run, whereas short-run responses of variables might dominate the results under business cycle frequency. Both reasons contribute to the predominantly recessionary pattern found in the existing empirical literature.

8. Conclusion

The rapid growth of intangible investment, which may exceed tangible investment in the recent two decades (Corrado and Hulten, 2010), raises an important question–what implications do intangibles hold for business cycle fluctuations? Focusing on uncertainty shocks, this paper adds to the literature another set of macroeconomic consequences of rising intangibles. An essential finding is that intangibles dampen the transmission of the uncertainty shock, in contrast to the amplification role in the financial shock. These results imply that intangibles act as a cushion in the uncertainty-driven business cycles.

To study the macroeconomic consequences of intangibles, I develop a two-sector DSGE model featuring both tangible and intangible goods production. The model is motivated by empirical observations that intangible investment is less sensitive to uncertainty compared to tangible investment. Moreover, firms with more intangible capital experience less pronounced effects of uncertainty on their investment decisions.

The quantitative analysis based on the DSGE model highlights two key mechanisms shaping the response of intangibles to uncertainty shocks: delayed contribution of skilled labor and capital reallocation effects. As the share of intangibles in production increases, aggregate volatility is further dampened. Finally, this paper investigates the effects of an intangible-specific uncertainty shock, i.e., uncertainty surrounding the productivity in the intangible sector. Owing to the long-term features of intangibles, uncertainty in the intangible sector could bring promising business opportunities, leading to expansion in the medium-to-long run. The last finding suggests that intangible-specific uncertainty can be a source of good uncertainty.

In conclusion, this paper contributes insights into the intricate relationship between intangibles and business cycle dynamics. The results not only highlight the stabilizing role of intangibles in uncertainty-driven business cycles but also sheds light on the potential positive impacts stemming from intangible-specific uncertainty.

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Supplementary material

Supplementary material associated with this article can be found in the online version at 10.1016/j.jedc.2025.105230.

References

Acemoglu, D., Autor, D., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Handbook of Labor Economics. Elsevier. Vol. 4, pp. 1043–1171.
Aghion, P., Angeletos, G.-M., Banerjee, A., Manova, K., 2010. Volatility and growth: credit constraints and the composition of investment. J. Monet. Econ. 57 (3), 246–265.
Alfaro, I., Bloom, N., Lin, X., 2024. The finance uncertainty multiplier. J. Politic. Econ. 132 (2).
Anzoategui, D., Comin, D., Gertler, M., Martinez, J., 2019. Endogenous technology adoption and R&D as sources of business cycle persistence. Am. Econ. J.: Macroecon. 11 (3), 67–110.
Barrero, J.M., Bloom, N., Wright, I., 2017. Short and long run uncertainty. Technical Report. National Bureau of Economic Research.
Basu, S., Bundick, B., 2017. Uncertainty shocks in a model of effective demand. Econometrica 85 (3), 937–958.
Basu, S., Bundick, B., 2018. Uncertainty shocks in a model of effective demand: reply. Econometrica 86 (4), 1527–1531.
Belo, F., Li, J., Lin, X., Zhao, X., 2017. Labor-force heterogeneity and asset prices: the importance of skilled labor. Rev. Financ. Stud. 30 (10), 3669–3709.
Bianchi, F., Kung, H., Morales, G., 2019. Growth, slowdowns, and recoveries. J. Monet. Econ. 101, 47–63.
Bianchi, F., Kung, H., Tirskikh, M., 2023. The origins and effects of macroeconomic uncertainty. Quant. Econom. 14 (3), 855–896.
Bloom, N., 2007. Uncertainty and the dynamics of R&D. Am. Econ. Rev. 97 (2), 250–255.
Bloom, N., 2014. Fluctuations in uncertainty. J. Econ. Perspect. 28 (2), 153–176.
Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. Rev. Econ. Stud. 74 (2), 391–415.
Born, B., Pfeifer, J., 2014. Policy risk and the business cycle. J. Monet. Econ. 68, 68–85.
Brown, J.R., Fazzari, S.M., Petersen, B.C., 2009. Financing innovation and growth: cash flow, external equity, and the 1990s R&D boom. J. Finance 64 (1), 151–185.
Caggese, A., Pérez-Orive, A., 2022. How stimulative are low real interest rates for intangible capital? Eur. Econ. Rev. 142, 103987.
Comin, D., Gertler, M., 2006. Medium-term business cycles. Am. Econ. Rev. 96 (3), 523–551.
Corrado, C.A., Hulten, C.R., 2010. How do you measure a “technological revolution”? Am. Econ. Rev. 100 (2), 99–104.
De Groot, O., Richter, A.W., Throckmorton, N.A., 2018. Uncertainty shocks in a model of effective demand: comment. Econometrica 86 (4), 1513–1526.
Deng, M., Liu, C., 2024. Sovereign risk and intangible investment. J. Int. Econ., 104009.
Döttling, R., Ratnovski, L., 2023. Monetary policy and intangible investment. J. Monet. Econ. 134, 53–72.
Fasani, S., Mumtaz, H., Rossi, L., 2023. Monetary policy uncertainty and firm dynamics. Rev. Econ. Dyn. 47, 278–296.
Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., Rubio-Ramírez, J., 2015. Fiscal volatility shocks and economic activity. Am. Econ. Rev. 105 (11), 3352–3384.
Fernández-Villaverde, J., Guerrón-Quintana, P.A., 2020. Uncertainty shocks and business cycle research. Rev. Econ. Dyn. 37, S118–S146.
Ghaly, M., Anh Dang, V., Stathopoulos, K., 2017. Cash holdings and labor heterogeneity: the role of skilled labor. Rev. Financ. Stud. 30 (10), 3636–3668.
Gourio, F., 2012. Disaster risk and business cycles. Am. Econ. Rev. 102 (6), 2734–2766.
Ikeda, D., Kurozumi, T., 2019. Slow post-financial crisis recovery and monetary policy. Am. Econ. J.: Macroecon. 11 (4), 82–112.
Jermann, U., Quadrini, V., 2012. Macroeconomic effects of financial shocks. Am. Econ. Rev. 102 (1), 238–271.
Jinnai, R., 2015. Innovation, product cycle, and asset prices. Rev. Econ. Dyn. 18 (3), 484–504.
Jurado, K., Ludvigson, S.C., Ng, S., 2015. Measuring uncertainty. Am. Econ. Rev. 105 (3), 1177–1216.
Kumar, S., Gorodnichenko, Y., Coibion, O., 2023. The effect of macroeconomic uncertainty on firm decisions. Econometrica 91 (4), 1297–1332.
Kung, H., Schmid, L., 2015. Innovation, growth, and asset prices. J. Finance 70 (3), 1001–1037.
Leduc, S., Liu, Z., 2016. Uncertainty shocks are aggregate demand shocks. J. Monet. Econ. 82, 20–35.
Lopez, J.I., Olivella, V., 2018. The importance of intangible capital for the transmission of financial shocks. Rev. Econ. Dyn. 30, 223–238.
Mann, W., 2018. Creditor rights and innovation: evidence from patent collateral. J. Financ. Econ. 130 (1), 25–47.
McGrattan, E.R., Prescott, E.C., 2010. Unmeasured investment and the puzzling US boom in the 1990s. Am. Econ. J.: Macroecon. 2 (4), 88–123.
Mitra, S., 2019. Intangible capital and the rise in wage and hours volatility. J. Econ. Dyn. Control 100, 70–85.
OECD, 2021. Bridging the gap in the financing of intangibles to support productivity: Background paper. Technical Report. OECD Publishing, Paris.
Pellegrino, G., Castelnuovo, E., Caggiano, G., 2023. Uncertainty and monetary policy during the great recession. Int. Econ. Rev. (Philadelp.) 64 (2), 577–606.
Peters, R.H., Taylor, L.A., 2017. Intangible capital and the investment-q relation. J. Financ. Econ. 123 (2), 251–272.
Queralto, A., 2020. A model of slow recoveries from financial crises. J. Monet. Econ. 114, 1–25.
Segal, G., 2019. A tale of two volatilities: sectoral uncertainty, growth, and asset prices. J. Financ. Econ. 134 (1), 110–140.
Segal, G., Shaliastovich, I., Yaron, A., 2015. Good and bad uncertainty: macroeconomic and financial market implications. J. Financ. Econ. 117 (2), 369–397.
Smets, F., Wouters, R., 2007. Shocks and frictions in US business cycles: a bayesian DSGE approach. Am. Econ. Rev. 97 (3), 586–606.
Wilcox, R.R., 2011. Introduction to Robust Estimation and Hypothesis Testing. Academic press.