Macroeconomic Uncertainty and Investment Specific Technical Change

PRELIMINARY AND INCOMPLETE

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Abstract

The impact of macroeconomic uncertainty is related to the underlying rate of investment-specific technical change (ISTC). Empirically, we estimate a state-dependent local projection model and show that when ISTC is rapid, uncertainty shocks have a more significant negative impact on the aggregate economy. Additionally, firm-level evidence suggests that this ISTC-uncertainty nexus is largely driven by the response of investment. Finally, we develop a DSGE model that incorporates ISTC and uncertainty shocks, confirming that more rapid ISTC exacerbates the effect of uncertainty shocks on delaying investment. ISTC affects how much capital a unit of foregone consumption generates, so uncertainty makes investors more apprehensive in the face of uncertainty when ISTC is rapid due to their increased exposure.

Keywords: Uncertainty, investment-specific technical change, business cycles.

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La machine, qui semblait d'abord l'en écarter, le soumet avec plus de rigueur encore, aux grands problèmes naturels.

The machine does not isolate man from the great problems of nature but plunges him more deeply into them. Antoine de Saint-Exupéry, *Terre des hommes.*

1 Introduction

Business cycle research finds that uncertainty shocks can have a significant macroeconomic impact. A key channel is the "wait and see" impact of uncertainty, whereby agents are reluctant to invest in an uncertain environment in the presence of investment adjustment costs.[1]

We argue that the importance of the "wait and see" effect may depend on technological conditions. In particular, it is well known that a key factor of both economic growth and business cycle fluctuations is the rate at which investment translates into capital goods - the rate of *investment-specific technical change* (ISTC). We argue that the aggregate impact of uncertainty shocks depends on the prevailing rate of ISTC, since this rate affects the extent to which a given investment today turns into future productive capacity - thus impacting the benefit of "waiting and seeing" in an uncertain environment. This relationship is important because, aside from improving our understanding of the channels through which uncertainty shocks affect the economy, it also suggests that the extent to which policymakers need to be aware of uncertainty shocks depends on the technological context - in particular, the rate of ISTC.

We begin by exploring empirically whether there is a link between the rate of ISTC and uncertainty shocks, by studying whether the impact of uncertainty shocks depends on the prevailing rate of ISTC. Estimating a state-dependent local projection model, we find that the negative impact of uncertainty shocks on aggregate activity is greater in times when ISTC is more rapid. Furthermore, we study the impact of aggregate uncertainty shocks on

[1]For example, see Dixit and Pindyck (1994).

firm-level investment in industries that vary in the rate of ISTC experienced by the capital they use. We find robust evidence in all cases that uncertainty shocks have a higher negative impact on investment in environments were ISTC is more rapid - both across time and across industries.

Then, we show that the impact of uncertainty shocks on investment, and thus aggregate activity, is indeed greater when ISTC is more rapid in an otherwise standard DSGE framework with uncertainty. To do this, we extend the macroeconomic model with uncertainty shocks of Basu and Bundick (2017) to allow for ISTC. In their model, uncertainty is due to changes in the time-varying second moment of discount factors - not due to technological factors. This form of uncertainty directly affects investment decisions, by making the anticipated payoff of current investment more volatile.

In the model economy, we explore the uncertainty-ISTC link in two ways. First, we compare the impact of uncertainty shocks for different balanced growth path-rates of ISTC. Second, we compare the impact of uncertainty shocks after a permanent shift from a higher to lower rate of ISTC or vice-versa.

We also find that a key role in these differences is played by endogenous capital utilization. When utilization is adjustable, it influences the response to uncertainty by amplifying uncertainty shocks when ISTC is high. At the same time, when utilization is adjustable, the interaction between uncertainty and ISTC turns out to be weaker.

The results are important for our understanding of the manner in which uncertainty shocks affect the economy. Furthermore, our measure of ISTC - the rate of decline in the relative price of capital - is known to have accelerated in recent decades, from about 1.6 percent per year before 1982 to about 2.6 percent per year afterwards, according to the Federal Reserve Bank of St. Louis.[2] As a result, our findings indicate that the economy is likely more vulnerable to uncertainty shocks than it used to be. It also suggests that, to accurately assess the impact of uncertainty shocks, emprical and theoretical work needs to

[2]See also Greenwood and Yorukoglu (1997).

take into account the potential influence of ISTC shocks.

Our paper is related to the growing literature on the impact of uncertainty on macroeconomic dynamics - see Bloom (2014) for a survey. The link between the impact of uncertainty and the rate of ISTC has not been made before, however.[3] We also contribute to the literature on the heterogeneous impact of uncertainty, such as Samaniego and Sun (2019) who emphasize capital depreciation and Alfaro et al (2024) who emphasize financial frictions. In our case, uncertainty shocks have differential impact depending on the rate of ISTC at the time.

Our paper is also related to the literature on the macroeconomic impact of ISTC. This literature has focused on the impact of the rate of ISTC on economic growth rates or the impact of shocks to ISTC on business cycle dynamics - see Greenwood et al (1997, 2000) or Justiniano et al (2010, 2011). Our paper adds a new dimension to this literature: we show that the rate of ISTC interacts with uncertainty shocks to generate greater or lesser severity of these shocks.

Section 2 outlines our empirical strategy and describes the data we employ. Section 3 describes our empirical findings. Section 4 presents and analyzes the model economy. Section 5 concludes.

2 Empirical Strategy

We employ two empirical strategies for linking ISTC to the impact of uncertainty shocks. First, we use time series data to show that the macroeconomic impact of uncertainty shocks depends on the rate of ISTC. Second, we show that the impact of uncertainty shocks affects firm investment differently depending on the rate of ISTC in the industry where they operate.

[3]Ma and Samaniego (2022) suggest a link between ISTC and uncertainty by showing that the presence of ISTC can affect business cycle dynamics when the level of ISTC is imperfectly observable. However, there are no uncertainty shocks. Instead, their mechanism relates to imperfect information about ISTC as a source of uncertainty, not to the rate of ISTC exacerbating the impact of uncertainty shocks.

2.1 Impulse Response Analysis

Macroeconomists primarily use two methods to develop empirical impulse response functions: local projection and VAR models. The VAR model relies on restrictive assumptions, as its identification strategies require strict variable ordering, solid economic theory, or a valid instrumental variable, which is not always available. Local projection, on the other hand, is more flexible, requiring fewer prior assumptions than VAR. Additionally, the lag length in local projection does not need to be the same for each horizon h and it can be estimated using individual univariate regressions. We proceed with the local projection method.

Standard local projection developed by Jorda (2005) is written as:

$$y_{t+h} = \beta_0^h + \beta^h d_{t-1} + \boldsymbol{\gamma}^h \boldsymbol{w}_t + u_{t+h} \tag{1}$$

y_{t+h} denotes the response variable at period $t+h$, such as log-transformed indices like industrial production and investment performance, which is measured by manufacturers' new orders of capital goods, adjusted for inflation using the PCE index. d_{t-1} is the lagged uncertainty level and $\boldsymbol{w}_t$ is a vector of control variables, including several lags of the dependent variable. β^h measures the response of variables on uncertainty at the period h, forming the impulse response trajectory based on the values of β^h across different horizons. Following Jordà and Taylor (2024), the coefficient β^h is defined as

$$\beta^h \equiv E[y_{t+h}|d_{t-1} = d_0 + \delta; \boldsymbol{w}_t] - E[y_{t+h}|d_{t-1} = d_0; \boldsymbol{w}_t] \tag{2}$$

where δ represents the size of the uncertainty level. We use the Newey–West method to address the potential bias of the standard error estimator due to potential autocorrelation@@@@.

Furthermore, we wish to see whether the rapid and slow ISTC would cause the impact of uncertainty to behave differently in the sense that one has a more significant aggregate effect during rapid periods than the low periods, as reflected in the difference in coefficients

across states. To analyze this, we modified the standard local projection model into a state-dependent version, similar to Ramey and Zubairy (2014):

$$y_{t+h} = I_t[\beta^h_{a,0} + \beta^h_a d_{t-1} + \boldsymbol{\gamma}^h_a \boldsymbol{w}_t] + (1 - I_t)[\beta^h_{b,0} + \beta^h_b d_{t-1} + \boldsymbol{\gamma}^h_b \boldsymbol{w}_t] + u_{t+h} \tag{3}$$

where I_t is a dummy variable that is equal to 1 if the relative price of capital is growing at a rate below its average, and 0 otherwise. Since the growth rate of the relative price of capital is the inverse of the rate of ISTC, this means that $I_t = 1$ when ISTC is relatively slow, and that $I_t = 0$ when ISTC is rapid. This distinction allows us to identify the differential impact of uncertainty shocks depending on the rate of ISTC, as parameters may vary based on the value of I_t, yielding distinct impulse responses. More specifically, β^h_a and β^h_b captures the impulse response when the economy is under the slow and rapid ISTC regimes, respectively.

This method employs a direct projection approach that produces less biased impulse response estimates, a property empirically proved by existing literature, such as Li et al. (2024), even though this comes at the cost of increased variance, particularly in the long run. Despite this tradeoff, the reduction in bias is often considered more critical, as it ensures more reliable estimates and greater robustness to the model's misspecification. While the resulting impulse responses become more sensitive to new observations over longer horizons, this is less of a concern for our analysis, as our primary focus is on comparing the magnitude of responses in the short and medium run rather than tracking long-run dynamics.

We tried different sets of control variables and measures of uncertainty series in both standard local projection and state-dependent local projection in the appendix for the robustness check. The main conclusions still hold.

2.2 Panel specification

In addition to developing time series evidence, we ask whether there are independent sources of evidence supporting the idea that uncertainty shocks might have greater impact when

ISTC is more rapid by looking at *firm level* data. It is well known since Cummins and Violante (2002) that the rate of ISTC varies across *industries*. If so, we might expect uncertainty shocks to have a higher impact on firms in industries with relatively higher rates of ISTC.

To check this, we use data from Compustat from 1960 to 2023 in order to see whether uncertainty shocks have this disproportionate effect on investment by firms in industries with different ISTC rates.

The specification is

$$\Delta \ln Investment_{i,t} = \delta_i + \delta_t + \beta \times ISTC_{j(i)} \times Uncertainty_t + \varepsilon_{i,t}$$

where $\Delta \ln Investment_{i,t}$ is the change in log investment at firm i, δ_i is a firm fixed effect, δ_t is a time dummy to capture the effect of uncertainty shocks, business cycle conditions and other quarter-specific effects on investment, and $ISTC_{j(i)} \times Uncertainty_t$ is an interaction between the average rate of ISTC in the industry j where firm i participates and $Uncertainty_t$ is the uncertainty shock measure.

2.3 Data Sources

2.3.1 Macroeconomic Data

We measure uncertainty using the macroeconomic uncertainty measure in Jurado et al (2015). The principle behind their measurement strategy is to define uncertainty as the unforecastable component of macroeconomic time series. They provide this measure for different time horizons: we use the one-month horizon as our benchmark.

For measuring an aggregate time series for ISTC, we use the relative price of capital series PIRIC reported by the Federal Reserve of St. Louis Economic Data (FRED). The advantage of this series is that it is available until late 2023 at the time of writing.

The time series models in the empirical sections are estimated using monthly data. The

variables included in the impulse response analysis are the Standard and Poor's 500 Index, the industrial production index, investment measured by real capital orders, the federal funds rate which is replaced by the shadow rate developed by Wu and Xia (2016) during periods of unconventional monetary policy, wages, price level, working hours, and employment. All variables are log-transformed except for the growth rate of money supply, interest rate, and working hours.

Additionally, for robustness checks, we incorporate real consumption, the PCE deflator, real new orders, and the growth rate of the money supply. All time series data are sourced from CEIC and FRED.

2.3.2 Firm and Industry Data

For our panel specification, we measure ISTC at the industry level using the data from Cummins and Violante (2002). They partition the private economy into 62 non-overlapping industries, and construct ISTC rates for each industry by weighing measures of ISTC for each type of capital using the composition of investment in each industry from the US capital flow tables.

Firm level data on investment are obtained for US firms from Compustat, using the change in log net property plant and equipment and deflated using the CPI. We also use firm size as a control variable, measured using log sales which is also reported in Compustat.

3 Empirical Results

3.1 Time series results

Figure 1 illustrates the dynamic relationships between real activity and macro uncertainty developed by Jurado et al. (2015), defined as the volatility of the unforecastable component of macroeconomic indicators. The impulse response indicates that macro uncertainty significantly and negatively affects industrial production and investment, particularly in the short

run, which is consistent with existing empirical evidence.

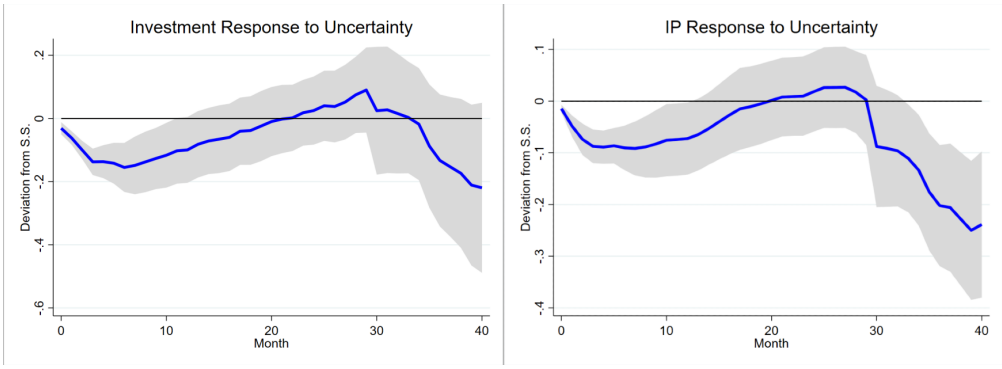


Figure 1: The Impact of Uncertainty

The left panel shows the impulse response of the investment to the uncertainty shock. The right panel shows the impulse response of the industrial production index (IP) to the uncertainty shock. The vertical axis shows percent deviation from the steady state. The horizontal axis shows time in months. The shaded areas show the one standard deviation confidence band.

Figure 2 compares the impulse response functions across two distinct states. The control variables are consistent with those in VAR-8 from Jurado et al. (2015). The shaded areas represent 68 percent confidence intervals, corresponding to one standard error band. Positive macro uncertainty sharply reduces industrial production activity and investment in both states, particularly in the short run. Notably, these negative impacts are more significant in both magnitude and persistence when the dummy variable is equal to zero, i.e., during periods of rapid ISTC growth. For example, in high ISTC growth periods, the negative effect of uncertainty on industrial production peaks around 12 months, resulting in a deviation of about -0.41 from the production activity's long run trend. A second peak occurs around 36 months, reaching nearly -0.42. In contrast, during low ISTC growth periods, the peaks occur at roughly 3 and 38 months, with values around -0.11 and -0.21, respectively, indicating weaker effects compared to periods of high ISTC growth. Moreover, in these slow ISTC growth periods, the industrial production's medium run response to positive uncertainty shocks is not statistically different from zero. Investment response shows similar response patterns. The heightened magnitude and persistence of the negative effects during rapid ISTC growth indicate a strong linkage between ISTC growth rates and macroeconomic

uncertainty.

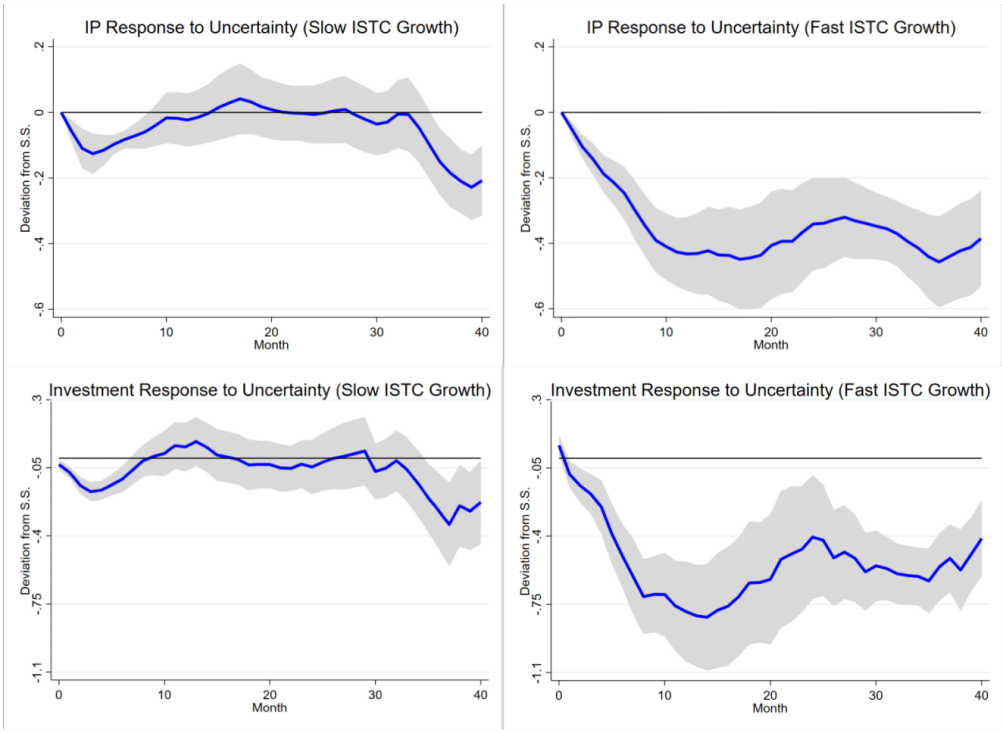


Figure 2: The State-Dependent Impact of Uncertainty

This figure shows the impulse response of the industrial production index (IP) and investment to the uncertainty shock. The left column displays the impulse response during periods of slow ISTC growth, while the right column shows the response during periods of fast ISTC growth. The vertical axis shows the percent deviation from the steady state. The horizontal axis shows time in months. The shaded areas show the one standard deviation confidence band.

3.2 Panel results

Table 1 Column 1 shows clearly that uncertainty shocks have a negative impact on investment at firms in high-ISTC industries. Column 2 conditions on firm size, measured by log sales, since it is known since at least Evans (1987) that firm growth is faster for smaller firms: the results are consisten. Column 3 includes time dummies, to account for the business cycle, uncertainty shocks themselves, the state of ISTC or any other time-varying factors that might affect investment in general. Again, the results are consistent.

A concern in panel data is the possibility of autocorreated errors. In our context, allowing for autocorrelated errors could be important since investment decisions may be spread over

Table 1: Uncertainty and Investment

Specification	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ISTC_j$	-2.922^{***}	-1.983^{***}	-2.019^{**}	-31.69^{***}	-32.19^{***}	-38.93^{***}	-17.34^{***}	-32.61^{***}
$\times Uncertainty_t$	(0.391)	(0.303)	(0.975)	(0.449)	(0.412)	(0.423)	(0.274)	(0.452)
$LogSales_{it}$	–	-0.039^{***}	-0.026^{***}	-0.045^{***}	-0.043^{***}	-0.038^{***}	$-.047^{***}$	$-.044^{***}$
		(.005)	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	N	Y	Y	Y	Y	Y	Y
Autoreg. err.	N	N	N	Y	Y	Y	Y	Y
Uncertainty	Macro 1	Macro 1	Macro 1	Macro 1	Macro 3	Macro 12	Fin 1	Real 1
Obs	849,105	807,138	807,138	786,151	786,151	786,151	786,151	786,151
Groups	21,738	20,987	20,987	20,573	20,573	20,573	20,573	20,573
R^2	0.001	0.004	0.064	0.054	0.056	0.058	0.053	0.055

Notes: Table reports results of the regression of log investment growth on the interaction of the industry rate of ISTC with uncertainty at date t. Specifications 1 thru 4 use our benchmark measure of uncertainty, the Jurado et al (2015) macroeconomic uncertainty measure computed with 1 month data. Specifications 5 and 6 use the 3 and 12 month measures respectively. Specifications 7 and 8 use the financial and real uncertainty measures from Jurado et al (2015) respectively. Specifications 1-3 cluster errors by industry.

time due to the possibility of investment adjustment costs, a common feature of DSGE models required for shock propagation. We reject the hypothesis of no autocorrelation with about ten percent confidence, using the test of Wooldridge (2002) and Drukker (2003). Nonetheless, in column 4 we estimate the specification again allowing for autocorrelated errors using the method of Baltagi and Wu (1999), finding that the coefficient of interest maintains its sign and significance. We also find that results are robust to different measures of uncertainty as reported in Jurado et al (2015), including their measures using unforecastable macroeconomic data at different frequencies, as well as their financial and real uncertainty measures. The results are consistent.

To sum up, the empirical results based on the impulse responses and the panel regression both suggest that uncertainty can have different effects on economic activities dependent on the level of ISTC. Furthermore, this difference is likely due to the different responses of investment. In the next section, we interpret these empirical results through a theoretical framework.

4 Theoretical Analysis

In this section, we develop a DSGE model to rationalize our empirical findings. We build on the model of Basu and Bundick (2017) and extend it to allow for shocks to the rate of ISTC.

4.1 Model

4.1.1 Households

There is a continuum of households, who make the same optimal decisions in equilibrium. Each household consumes, works, invests in capital and rents it to firms, receiving wages and rental payments. The representative household maximizes lifetime discounted utility following the Epstein and Zin (1989) preferences, which distinguish between the coefficient of risk aversion and the intertemporal elasticity of substitution. The value function V_t of this maximization is:

$$V_t = \max[a_t(C_t^{\eta}(1-L_t)^{1-\eta})^{(1-\sigma)/\theta_v} + \beta(E_t V_{t+1}^{1-\sigma})^{1/\theta_v}]^{\theta_v/(1-\sigma)} \tag{1}$$

where C_t is consumption and $1 - L_t$ is leisure. η is the inverse Frisch elasticity, σ is the relative risk aversion, and $\theta_v \equiv (1-\sigma)(1-1/\psi)^{-1}$ reflects the household preference over certainty, where ψ is the intertemporal elasticity of substitution. a_t is preference shock, whose variance is time-varying. Their dynamics follow

$$\log(a_t) = \rho_a \log(a_{t-1}) + \varepsilon_{a,t}, \quad \varepsilon_{q,t} \sim N(0, (\sigma_t^a)^2)$$

$$\log(\sigma_t^a) = (1-\rho_{\sigma^a})\log(\sigma^a) + \rho_{\sigma^a}\log(\sigma_{t-1}^a) + \varepsilon_{\sigma^a,t}, \quad \varepsilon_{\sigma^a,t} \sim N(0, \sigma_{\sigma^a}^2)$$

where $\varepsilon_{\sigma^a,t}$ is an innovation to the volatility of preference, and is the uncertainty shock in

the modeled economy.[4]

The representative household makes choices on consumption C_t, labor L_t, investment I_t, capital utilization rate U_t, and risk-free government bonds B_{t+1} to maximize its utility function, given the (gross) nominal interest rate on bonds R_t^R, the aggregate consumption price index P_t, the nominal wage rate W_t, and the nominal capital rental rate R_t^K. The budget constraint of the household is:

$$P_t C_t + P_t I_t + \frac{B_{t+1}}{R_t^R} = W_t L_t + R_t^K U_t K_t + B_t + D_t + T_t \tag{2}$$

where D_t is the nominal profits from firms owned by the household, and T_t is the nominal net government transfers. Newly invested goods I_t contribute to the accumulation of capital stock K_{t+1}, whose evolution is given by:

$$K_{t+1} = \left(1 - \delta(U_t) - \frac{\phi_I}{2}\left(\frac{I_t}{K_t} - (\gamma_K - 1 + \delta)\right)^2\right) K_t + \gamma_q q_t I_t \tag{3}$$

where ϕ_I captures the magnitude of the investment adjustment cost, $\delta(U_t)$ is the capital depreciation rate, following

$$\delta(U_t) = \delta + \delta_1(U_t - U) + \frac{\delta_2}{2}(U_t - U)^2 \tag{4}$$

γ_K and γ_q are the growth rates of capital and investment specific technology, respectively. q_t is a stochastic shock to the level of investment specific technology, evolving as:

$$\log(q_t) = \rho_q \log(q_{t-1}) + \varepsilon_{q,t}, \quad \varepsilon_{q,t} \sim N(0, \sigma_q^2)$$

[4]We follow Basu and Bundict (2017) and define uncertainty shock in the framework of a stochastic volatility model. We obtain similar results when defining it as a volatility shock to productivity.

4.1.2 Final Goods Firm

The final goods firm produces Y_t by combining a continuum of intermediate goods $Y_t(i)$ indexed by $i \in [0, 1]$ as:

$$Y_t = \left(\int_0^1 Y_t(i)^{\frac{\epsilon-1}{\epsilon}} di \right)^{\frac{\epsilon}{\epsilon-1}} \tag{5}$$

where ϵ is the elasticity of substitution between different varieties of intermediate goods. This implies the relationship between the price of final goods P_t and that of each intermediate good $P_t(i)$ is:

$$P_t = \left(\int_0^1 P_t(i)^{1-\epsilon} di \right)^{\frac{1}{1-\epsilon}} \tag{6}$$

4.1.3 Intermediate Goods Firm

We assume each intermediate goods firm i has a Cobb-Douglas production function:

$$Y_t(i) = Z_t K_t(i)^{\alpha_k} L_t(i)^{\alpha_l} \tag{7}$$

where the quantity of capital and labor as inputs is $K_t(i)$ and $L_t(i)$ respectively. α_k and α_l represent their income shares out of the intermediate output. Z_t is the stochastic total factor productivity, whose dynamics is characterized by an AR(1) process:

$$\log(Z_t) = \rho_z \log(Z_{t-1}) + \varepsilon_{z,t}, \quad \varepsilon_{z,t} \sim N(0, \sigma_z^2)$$

Each firm producing intermediate goods makes two decisions. First, given the demand by final goods firms $Y_t(i)$, it minimizes production cost by optimally choosing the quantity of inputs. In particular, the optimality condition for $K_t(i)$ and $L_t(i)$ are:

$$R_t^K = MC_t \alpha_k Z_t K_t(i)^{\alpha_k - 1} L_t(i)^{\alpha_l} \tag{8}$$

$$W_t = MC_t \alpha_l Z_t K_t(i)^{\alpha_k} L_t(i)^{\alpha_l - 1} \tag{9}$$

where MC_t is the nominal marginal cost. After the marginal cost is determined, intermediate goods firm then optimally chooses its output price $P_t(i)$ to maximize its lifetime profits, following the Rotemberg (1982) style:

$$\max_{P_{t+s}(i)} E_t \sum_{s=0}^{\infty} \Lambda_{t,t+s} \left[\left(\frac{P_{t+s}(i)}{P_{t+s}} - \frac{MC_{t+s}}{P_{t+s}} \right) Y_{t+s}(i) - \frac{\phi_p}{2} \left(\frac{P_{t+s}(i)}{P_{t+s-1}} - 1 \right)^2 Y_{t+s}(i) \right]$$

subject to the demand constraint: $Y_{t+s|t}(i) = \left(\frac{P_{t+s}(i)}{P_{t+s}} \right)^{-\epsilon} Y_{t+s}$, where $\Lambda_{t,t+s} \equiv \frac{\partial V_t / \partial C_{t+s}}{\partial V_t / \partial C_t}$ is the stochastic discount factor of the household, and ϕ_p is the parameter capturing the adjustment cost associated with changing price, which reflects the degree of price rigidity.

Intermediate goods firms choose the same price and produce the same quantity in equilibrium, as they have the same technology and profit maximization problem. The optimal price $P_{Y,t}$ can be derived as

$$\phi_p \left(\frac{P_t}{P_{t-1}} - 1 \right) \frac{P_t}{P_{t-1}} = \phi_p E_t \Lambda_{t,t+s} \left(\frac{P_{t+1}}{P_t} - 1 \right) \frac{P_{t+1}}{P_t} \frac{Y_{t+1}}{Y_t} + 1 - \epsilon + \epsilon \frac{MC_t}{P_t} \tag{10}$$

In addition, the economy-wide unique price-cost markup μ_t can be defined as the inverse of the real marginal cost, i.e., $\mu_t \equiv P_t / MC_t$.

4.1.4 Government

First, monetary authority decides the net nominal policy rate according to a variant of the Taylor rule in order to stabilize the economy:

$$\log(R_t) = \log(R) + \phi_\pi (\log(\Pi_t) - \log(\Pi)) + \phi_Y (\log(Y_t) - \log(Y_{t-1})) \tag{11}$$

where R_t is the nominal policy rate, and R is its steady state level. Π_t is the consumer price inflation, defined as P_t / P_{t-1}, and Π is its steady state. ϕ_π and ϕ_Y are respectively the weights on inflation and output growth.

Second, a balanced budget is assumed for the government:

$$B_t + G_t + T_t = \frac{B_{t+1}}{R_t^R}$$

where G_t denotes the nominal government expenditure.

4.2 Quantification

4.2.1 Calibration

We calibrate the model to match important moments in the U.S. economy during the same sample periods as the empirical exercise.

On the household side, following Basu and Bundick (2017), we set σ at 2 and ψ at 0.95 in the Epstein and Zin utility function. η is 0.5, matching the Frisch elasticity of 2. The discount factor β is 0.994, suggesting that the equilibrium real interest rate is 2.4% at annual frequency. For the capital accumulation function, we assume the investment adjustment cost parameter ϕ_I is 2.09, and the steady state depreciation rate is 0.025.

On the firm side, the elasticity of substitution between differentiated goods ϵ is 6, implying the steady state level of the markup 20%. The share of capital and labor out of output, α_k and α_l, are 0.33 and 0.67 respectively. The price adjustment cost ϕ_p is 100.

In the monetary policy rule, the steady state gross inflation rate Π is 1.005, matching an annual net inflation rate of 2% during the sample periods. The coefficient in front of inflation gap and output gap, ϕ_π and ϕ_y are 1.5 and 0.2, respectively.

Finally, uncertainty shocks in the model are represented by a shock to the volatility of the preference shock, similar to Basu and Bundick (2017). We set the persistence of the shock ρ_{σ^a} at 0.74, and its standard deviation σ_{σ^a} at 0.25%.

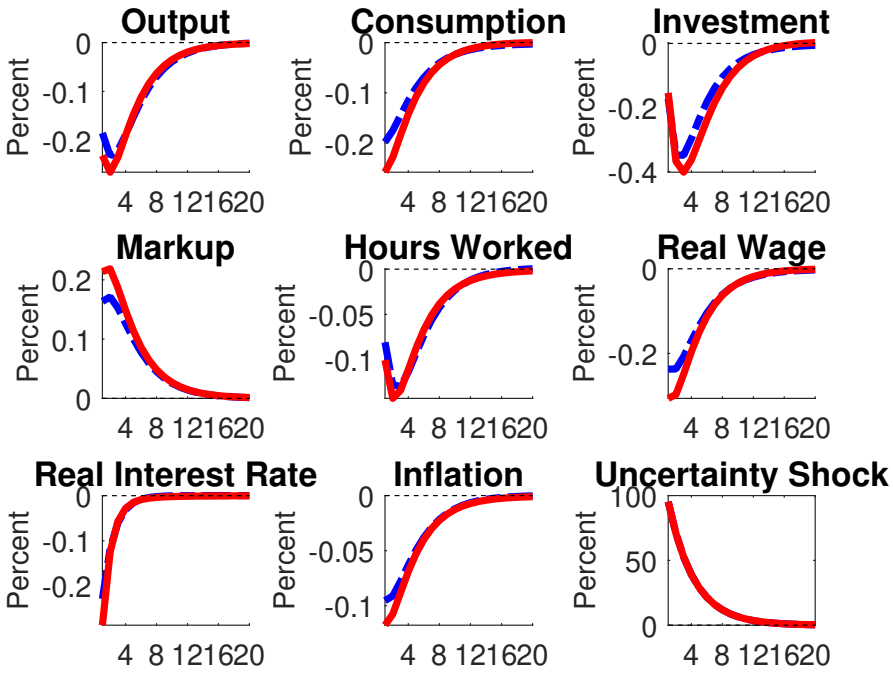


Figure 3: The Impact of Uncertainty Shocks under Different ISTC

Notes: The figure plots impulse responses to a one-standard-deviation positive shock to preference volatility, estimated when ISTC growth is at 3.55% (solid lines) and at 1.65% (dashed lines) respectively.

4.2.2 Simulation

To illustrate the impact of uncertainty shocks under different levels of investment-specific technological progress, we compare the impulse responses of the modeled economy to the same uncertainty shock under two scenarios, with the ISTC growth rates at 3.55% and 1.65% respectively, which are calculated based on the inverse of the growth rate of relative capital prices during the sample periods. The results are shown in Figure 3. It is evident that uncertainty shocks have a bigger negative effect on inflation and economic activities when the growth of ISTC is accelerated. This is likely because investment responds more sensitively to uncertainty shocks when improvement of capital efficiency is faster, i.e., the transmission channel of "wait and see" under uncertainty is mitigated with slower growth of ISTC. This is because, when ISTC accelerates, the option to delay investment due to uncertainty becomes more valuable, as investing later enhances the ability to capitalize on

any positive opportunities.

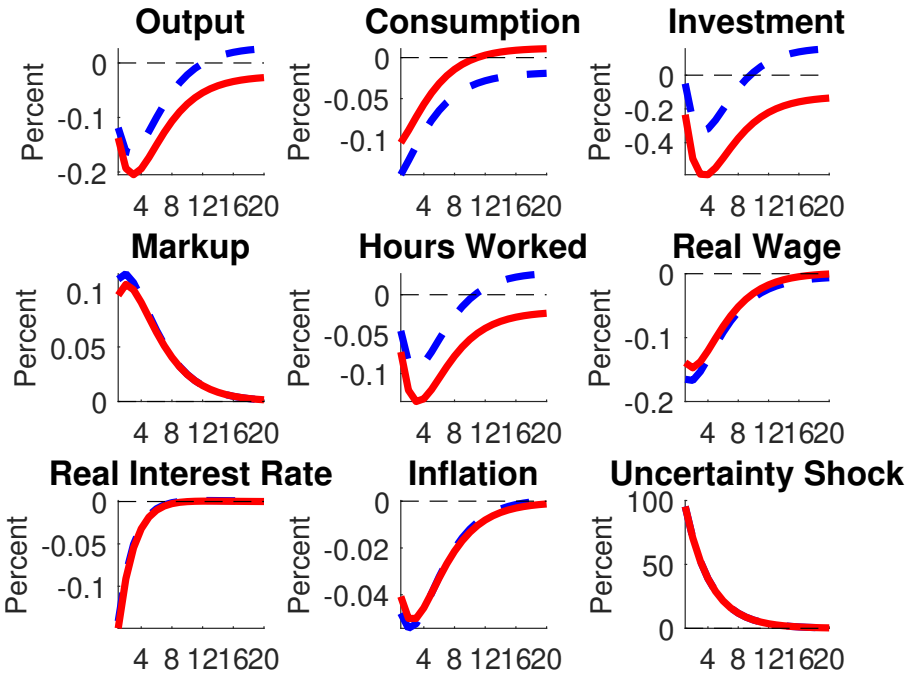


Figure 4: The Impact of Uncertainty Shocks under Permanent Shock to ISTC

Notes: The figure plots impulse responses to a one-standard-deviation positive shock to preference volatility, when ISTC growth is at 3.55% (solid lines) and at 1.65% (dashed lines) respectively. The results are estimated in a model where capital utilization rate is fixed at 100%.

We also explore the effects of uncertainty shocks when positive (negative) permanent shocks to ISTC happen at the same time. Different from the first exercise, the variation in ISTC growth is stochastic, attributed to a permanent increase or decrease in the rate at which ISTC evolves. The results shown in Figure 4 suggest that our baseline conclusion still holds. That is, uncertainty shocks have a more significant impact on economic activities under a higher ISTC growth (due to permanent ISTC shocks). This disproportionate impact is mainly due to the different responses of investment.

The implication of ISTC for the effects of uncertainty is sensitive to the capital utilization rate in production. Figure 5 plots the uncertainty-iSTC nexus estimated in a model where the capital utilization rate is fixed at 100%. First, the aggregate effects of uncertainty are still more negative when ISTC growth is accelerated, as that shown in Figure 3. In particular, the

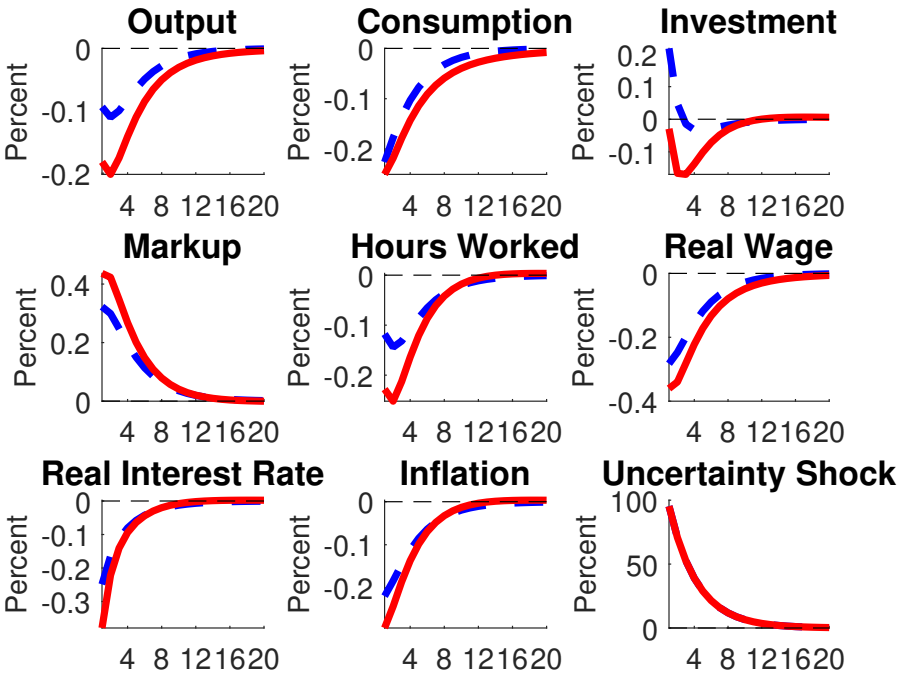


Figure 5: The Impact of Uncertainty Shocks under Fixed Capital Utilization Rate

Notes: The figure plots impulse responses to a one-standard-deviation positive shock to preference volatility, when ISTC growth is at 3.55% (solid lines) and at 1.65% (dashed lines) respectively. The results are estimated in a model where capital utilization rate is fixed at 100%.

response of investment is even positive for a short period in the model where ISTC growth is low at 1.65%. However, the magnitude of both are smaller than the baseline model, which suggests that flexibility in adjusting capital utilization can propagate the negative effect of uncertainty, as it allows a larger reduction of capital when facing higher uncertainty. Second, the difference in the impact of uncertainty under different ISTC growth rates is more evident than that in the baseline model. This shows that the relationship between ISTC and the impact of uncertainty can be strengthened when there is less scope to adjust the rate at which capital is utilized. In other words, variable capital utilization can mitigate the extent to which ISTC influences the effects of uncertainty.

5 Conclusion

We argue that the impact of uncertainty shocks depends on the pervailing rate of ISTC. When ISTC is rapid, the option to wait before investing is more valuable, since a given investment tomorrow results in an enhanced ability to take advantage of any positive opportunities. We show that this holds empirically, and also in a standard DSGE framework with uncertainty. Thus, our paper is the first to show a link between two time-varying factors of macroeconomic dynamics: uncertainty shocks and the rate of ISTC.

The paper suggests that the impact of uncertainty shocks might depend on the state of other fundamentals at the moment of impact. Our focus is on ISTC, since this is directly related to the costs and benefits of delaying investment. However, there may be others. In particular, there is a literature on the cyclicality of R&D, such as Barlevy (2007). The interaction of R&D and uncertainty is a topic for potential future research.

In addition, we find that the uncertainty-ISTC interaction is sensitive to the ease with which capital utilization can be adjusted, as variable utilization provides an alternative way of managing uncertainty shocks that is unrelated to the rate of ISTC. This underlines the potential importance of further research into the topic of capital utilization: not only is it important for business cycle dynamics, but it may also be key for the ability of the economy to adjust to uncertainty shocks.

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7 Appendix

Figure 6 presents the impulse response generated by the state-dependent local projection model, with additional control variables outlined in the data source section. Our main conclusions still hold.

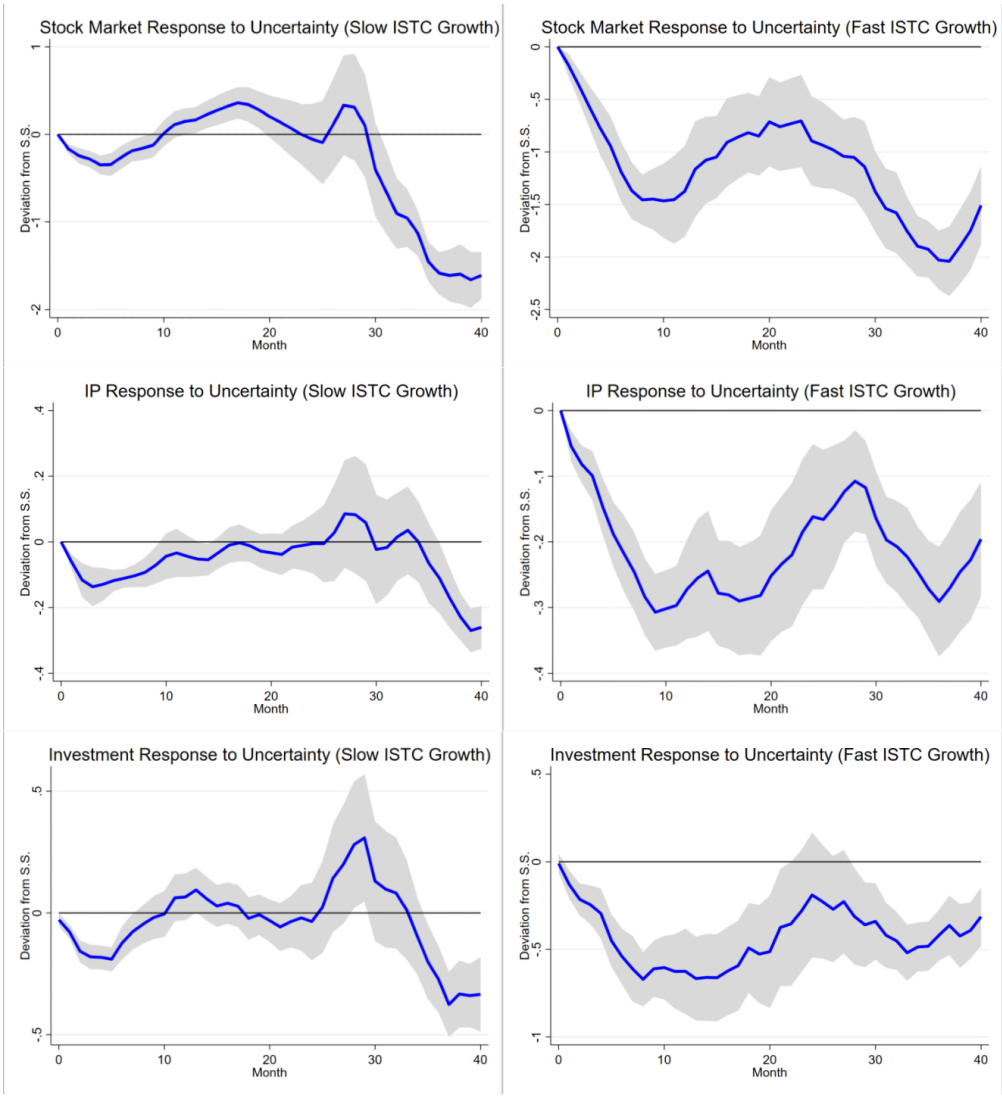


Figure 6: The State-Dependent Impact of Uncertainty

This figure shows the impulse response of stock market performance, the industrial production index (IP), and investment to the uncertainty shock. The left column displays the impulse response during periods of slow ISTC growth, while the right column shows the response during periods of fast ISTC growth. The vertical axis shows percent deviation from the steady state. The horizontal axis shows time in months. The shaded areas show the one standard deviation confidence band.