Uncertainty, Risk, and Capital Growth

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Abstract

We find that high productivity-based macroeconomic uncertainty is associated with greater accumulation of physical capital despite a reduction in investment and valuations. To reconcile this puzzling evidence, we show that uncertainty predicts lower aggregate depreciation of existing capital, which dominates the investment slowdown. We explain these findings by developing a quantitative production-based model in which firms implement precautionary savings through reducing utilization rather than raising investment. Through this novel intensive-margin mechanism, uncertainty shocks command a quarter of the equity premium in general equilibrium. Flexibility in utilization adjustments also helps explain uncertainty risk exposures in the cross-section of industry returns. (*JEL* G12, E32, D81, D50)

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Extensive empirical evidence suggests that high macroeconomic uncertainty coincides with adverse times for the real economy and financial markets. Indeed, an increase in aggregate uncertainty is associated with a business cycle trough and a persistent decline in consumption, investment, and output. At the same time, firm valuations decline and the market risk increases. These findings have spurred a large and growing literature aiming to reconcile the dynamic interactions between uncertainty, economic growth, and asset markets.

In this study, we present novel empirical evidence that enriches and challenges the prevailing view on the propagation of uncertainty shocks in capital markets. We document that even though productivity-based uncertainty is associated with lower investment, it is not associated with a decline in the future capital stock. In fact, future capital may even increase following a rise in uncertainty. This fundamental result is surprising at first glance, as investment and capital growth are typically synonymous.

Investment in new capital, however, only governs the extensive margin of capital formation. The intensive margin, driven by the time-varying depreciation of the existing capital, may also respond to uncertainty shocks, reconciling the divergent dynamics of capital and investment. Indeed, we find that both aggregate investment and capital depreciation rates persistently decrease following a rise in aggregate economic uncertainty. The decline in depreciation cushions the investment slowdown and is quantitatively large enough to induce a capital buildup during periods of heightened uncertainty.

We next develop and estimate a production-based macrofinance model to explain our novel empirical findings alongside existing evidence on uncertainty and economic growth. We also use the model to explain and quantify the effects of uncertainty spillovers from real to financial capital markets for aggregate and cross-sectional risk premia.

Our model incorporates empirically driven extensive and intensive margins of capital accumulation, which give rise to endogenous time variation in depreciation. Specifically, since our focus is on aggregate moments, we devise a one-good, single-sector framework with flexible capacity utilization, extending the tradition of New Keynesian models.

A key insight of our model is that lowering capital utilization can substitute for higher investment for precautionary saving, with the benefit of avoiding the costs associated with new capital installation. Specifically, a rise in aggregate uncertainty drives firms to build up capital as a buffer against downside moves in future productivity. In the model, underutilization of capital persistently decreases its depreciation rate. As a result, firms substantially lower the utilization rate of the capital already installed, preserving it for future use. Investment, on the other hand, is driven by two opposing forces. A positive uncertainty shock persistently reduces utilization, which lowers the expected marginal product of capital and discourages investment. At the same time, the equilibrium risk-free rate falls, which stimulates investment. Quantitatively, in our setup, the impact of lower effective productivity dominates. Consequently, aggregate investment declines while future capital increases, as in the data. Thus, the model can rationalize a surprising buildup of capital at times of economic slowdown triggered by heightened uncertainty.[1] Lastly, lower utilization also decreases the level of current and future output. The decline in output is larger than the decline in investment. As a result, consumption decreases as well, resulting in a full business-cycle trough and an increase in the marginal utility of investors.

Importantly, our utilization-driven channel for explaining the impact of uncertainty on capital formation, in general, and suppressing investment, in particular, is novel and differs from existing mechanisms, such as real options or time-varying markups. It does not require imperfect competition or non-convex adjustment costs and can be easily incorporated into any neoclassical or New Keynesian framework. Furthermore, existing frameworks either fail to eliminate the precautionary savings effect of uncertainty on investment (ipso facto, leading to a divergence between investment and consumption) or, alternatively, depress both investment and future capital growth in response to high uncertainty, contrary to the data.[2]

[1] This divergence of investment and capital growth occurs only with respect to second-moment productivity shocks. Negative first-moment productivity shocks lower both investment and capital, so that capital and investment are procyclical, in both the data and our model.

[2] To help further assess the contribution of our mechanism vis-à-vis existing channels, we extend our baseline model and incorporate flexible utilization and persistent depreciation dynamics into a New Keynesian model featuring nominal price rigidity. We show that, depending on the dynamics of aggregate productivity, our mechanism is either necessary to induce a drop in investment following a rise in uncertainty or, at the very least, substantially

While our framework does not target asset-price data, it can capture salient features of the aggregate and sectoral asset valuations. With a preference for early resolution of uncertainty, uncertainty shocks increase marginal utility and thus bear a negative price of risk. Further, the firm's investment rate and stock prices comove, a standard implication of q-theory. Because high uncertainty decreases investment in our benchmark setting with flexible utilization, equity price exposure to uncertainty risks is negative. Coupled with a negative market price of risk, uncertainty shocks thus contribute positively to the model-implied equity premium, accounting for about a quarter of its magnitude. In addition, the mechanism helps generate empirically consistent predictive power of market variance for future returns. In contrast, when the utilization rate is constant, as in the off-the-shelf production model, high uncertainty increases investment and firm valuations. Counterfactually, equities become hedges against uncertainty fluctuations, demand less than a third of the original risk compensation, and are virtually unpredictable by the market variance.

In addition to the aggregate risk premium, the model delivers specific cross-sectional predictions for the relationship between the uncertainty exposures of firms' returns and their capital utilization rates. In particular, firms whose utilization is more volatile, more sensitive to aggregate uncertainty fluctuations, or less persistent compared to their depreciation rate should have a higher asset-price exposure to uncertainty risk. Thus, the flexibility of adjusting the utilization rate helps microfound the observed sensitivities of stock returns to uncertainty shocks. We confirm these model implications using cross-sectional data on manufacturing and utility industries.

The theoretical literature on the impact of uncertainty shocks primarily focuses on the negative relationship between uncertainty and investment. The studies of McDonald and Siegel (1986) and, more recently, Bloom, Bond, and Van Reenen (2007), Bloom (2009) and Alfaro, Bloom, and Lin (2018) use a real options channel (or "bad news" principle) to explain why uncertainty suppresses investment. Importantly, the positive effect of uncertainty on capital stock, which we focus on, differs from the investment overshoot effect in real options models.

amplifies the adverse effect of higher uncertainty on real variables above and beyond the countercyclical markup channel.

In a real options model, future capital growth increases because of a simultaneous overshoot in investment. In our model, capital rises while the contemporaneous investment declines, leading to a divergence between the two.

A number of studies have confirmed, empirically and theoretically, that high uncertainty increases firms' cost of capital, making investment more costly (see, e.g., Christiano, Motto, and Rostagno 2010; Gilchrist, Sim, and Zakrajšek 2014; Arellano, Bai, and Kehoe 2019; Bretscher, Hsu, and Tamoni 2022; or Fernández-Villaverde et al. 2011 in the context of an open economy). Di Tella and Hall (2021) feature uninsurable idiosyncratic risk, which creates a time-varying risk premium wedge that suppresses investment and hiring. We differ from these studies in two ways. First, in all of the aforementioned papers depreciation rate is constant. Thus, they cannot account for our new evidence on the response of the depreciation rate to uncertainty shock or for the divergence between investment and capital growth following higher uncertainty. Second, in all these studies, except Di Tella and Hall (2021), uncertainty decreases investment but does not generate positive contemporaneous comovement between consumption and investment.

Fernández-Villaverde et al. (2015) and Basu and Bundick (2017) rely on a New Keynesian framework with monopolistic competition and sticky prices to generate a drop in consumption and investment in response to uncertainty shocks. Both studies feature flexible utilization; however, as in the other New Keynesian models, utilization only affects the contemporaneous depreciation rate and mainly serves to extend the duration of price stickiness. Without our channel of added persistence in depreciation, the existing models cannot fully account for our novel empirical evidence.[3]

Our paper further contributes to the production-based asset-pricing literature.[4] In a standard production setting, uncertainty shocks lower the equity premium and increase stock prices, in contrast to the endowment economies and the data.[5] We show that in our model, uncertainty

[3] Under the parameters of Basu and Bundick (2017), the investment decline following an uncertainty shock dominates the drop in utilization and depreciation, so that future capital growth falls, in contrast to our empirical evidence (see Figure IA.3.13 in the Internet Appendix).

[4] See, e.g., Berk, Green, and Naik (1999); Boldrin, Christiano, and Fisher (2001); Zhang (2005); Wu, Zhang, and Zhang (2010); İmrohoroğlu and Tüzel (2014); Favilukis and Lin (2016); Belo et al. (2017).

[5] See, e.g., Bansal and Yaron (2004); Boguth and Kuehn (2013); Buraschi, Trojani, and Vedolin (2014); Johannes, Lochstoer, and Mou (2016); Ai and Kiku (2016), among many others.

shocks decrease stock prices, increase the marginal utility, and contribute positively to the market risk premium. Thus, our channel complements other production-based approaches in which discount rate shocks suppress investment and raise equity premium, such as resource reallocation (e.g., Gao et al. 2022; Bansal et al. 2019; Basu et al. 2021), endogenous growth (e.g., Kung and Schmid 2015), uninsurable idiosyncratic risk (e.g., Dou 2017; Herskovic et al. 2016), debt overhang (e.g., Chang, d'Avernas, and Eisfeldt 2024), or multiple sectors and uncertainties (e.g., Segal, Shaliastovich, and Yaron 2015; Segal 2019). Our study also shows that flexible utilization is important for return predictability using uncertainty. Related, Bandi, Bretscher, and Tamoni (2023) explore return predictability due to uncertainty shocks in an endogenous growth setup. Our paper is also related to studies that incorporate flexible utilization in asset pricing (see, e.g., Garlappi and Song 2017; Grigoris and Segal 2022; Ai, Li, and Tong 2025). These studies do not consider the interaction between utilization and second-moment shocks.

Finally, a recent strand of the empirical literature aims to assess and quantify the causal nature of uncertainty shocks on economic fundamentals. In particular, Berger, Dew-Becker, and Giglio (2020) and Ludvigson, Ma, and Ng (2021) question the role of macroeconomic uncertainty to induce recessions. We follow the instrumental variables (IV) approach of Baker, Bloom, and Terry (2024) and the inequality-constraint structural vector autoregression (SVAR) approach of Ludvigson, Ma, and Ng (2021) to identify exogenous variation in productivity-based volatility, and we show that it induces a negative effect on investment and positive on capital, similar to our benchmark results. These mixed effects can potentially shed light on the ambiguous role of macro uncertainty for aggregate economic indices.

1 Empirical Evidence

In this section, we examine the relationship between macroeconomic uncertainty and key determinants of capital accumulation. We establish the following novel findings: (i) high uncertainty is associated with lower depreciation of existing capital, and (ii) high uncertainty is associated with higher (or at least not lower) future capital.

The second finding does not follow directly from the former. As is well known in the literature, high uncertainty is associated with a reduction in investment, which slows down capital accumulation. We argue that a drop in capital depreciation quantitatively outweighs the reduction in investment, so higher uncertainty predicts an increase in the capital stock.

1.1 Data and measurements

We provide a brief description of the data and methodology to construct our benchmark measures (labeled "Benchmark" henceforth) of capital accumulation, productivity, and macroeconomic uncertainty. We refer the reader to Internet Appendix IA.1.1 for full details. Real capital growth, depreciation rate, and investment rate, are constructed based on data from the Bureau of Economic Analysis (BEA) Fixed assets accounts, and correspond to private nonresidential capital. Based on availability of fixed assets data, all variables are sampled at an annual frequency from 1948 to 2022.

The main driving forces in our theoretical framework in Section 2 are related to the first and second moments of aggregate productivity. To ensure a tight connection between the model and the data, we use the utilization-adjusted measure of total factor productivity (TFP) growth, constructed by Basu, Fernald, and Kimball (2006) and Fernald (2014) and available at the Federal Reserve Bank of San Francisco, as a proxy for aggregate productivity (that is, its first moment). Consistent with our model, we measure second-moment shocks through the time-varying conditional volatility of productivity shocks. To construct our benchmark measure of macroeconomic variance, we estimate a parametric AR(1)-GARCH model. Specifically, we filter out the time-varying volatility of these innovations via a conditional heteroscedasticity model. We employ the Glosten-Jagannathan-Runkle ($GJR(p,q)$) model. It nests a standard generalized autoregressive conditional heteroscedasticity (GARCH) framework, but accounts for an asymmetry in the volatility response to positive and negative shocks. For accurate measurement, we use the highest frequency available for the utilization-adjusted TFP data, which is quarterly. We set $p = 4$ and $q = 1$ to account for any seasonal effects in quarterly data and take the end of the fourth quarter volatility estimate to form annual observations.

We consider alternative measures to corroborate our main empirical evidence. We provide a brief description, and refer the reader to Internet Appendix IA.1.2 for full details.[6] We examine three alternative measures of capital stock, investment, and depreciation: (i) BEA-based measures related to private nonresidential equipment and structures (labeled "Capital: Equip & Struct"); (ii) BEA-based measures related to total private capital (labeled "Capital: Total Priv"); (iii) replacing capital and investment from BEA with their accounting equivalents from Compustat (labeled "Capital: Compustat").[7]

Since our framework features tangible capital, we construct two alternative Solow residuals that capture Hicks-Neutral productivity. We employ the same methodology as the San Francisco Fed but in the computation process, we replace their capital growth with the growth in tangible capital only. First, we exclude from capital growth forms of capital that relate to organizational capital (e.g., R&D and artistic stocks, labeled "Productivity: Solow(Ex R&D)"). Second, we narrow the capital growth definition further, using only the stock of equipment and structures (labeled "Productivity: Solow(Equip & Struct)"). Lastly, we consider replacing the benchmark TFP measure with labor productivity published by the Bureau of Labor Statistics (labeled "Productivity: Labor Prod").

Finally, we consider several alternatives to our benchmark uncertainty measure. First, we implement a stochastic volatility (labeled "Uncertainty: SV") model which features a separate AR(1) process for log volatility with potentially heavy-tailed shocks, via the methodology of Chan and Hsiao (2014). Second, we replace the GJR model with an exponential GARCH (labeled "Uncertainty: E-GARCH") volatility.

1.2 Empirical framework

The main goal of our empirical analysis is to establish the relation between macro uncertainty and components of capital accumulation. Specifically, we are interested in measuring

$$\frac{\partial}{\partial v_t} E_t \Delta K_{t+h}, \ \frac{\partial}{\partial v_t} E_t \delta_{t+h}, \ \text{and} \ \frac{\partial}{\partial v_t} E_t [I/K]_{t+h}, \tag{1}$$

[6] Table IA.2.2 in the Internet Appendix shows the correlation between the different measures of capital, productivity and uncertainty.

[7] For the Compustat case, we infer the economic impact of depreciation from the observed capital and investment rates, as the accounting depreciation is missing for a nonnegligible number of firms in Compustat.

where ΔK is the growth in the capital stock, δ is the depreciation rate, I/K is the investment rate, and v is uncertainty. The econometric measurements face potential challenges due to deep structural relationships between the current and future components of capital accumulation and the selection of economic predictors. Later we describe how our empirical framework integrates the economic intuition of a standard neoclassical growth framework to determine a consistent set of predictive variables. We further discuss how our analysis combines the fundamental restrictions on the components of capital formation, imposed by the capital accumulation equation.

1.2.1 Predictors.

We draw on key principles from the extensive macroeconomic literature to provide a sufficient set of core variables for predicting future margins of capital accumulation. The standard growth model satisfies a Markov property so that the only information needed at time t to predict any endogenous policy—to be realized in the future—is fully spanned by the model's current state variables. Across most neoclassical models featuring stochastic volatility in existing literature, these state variables include (i) the current stock of capital, (ii) the current TFP, and (iii) the current TFP volatility. Notably, our economic model in Section 2 generalizes the neoclassical framework, and suggests another important state variable: (iv) the lagged value of depreciation rate.[8] These four predetermined state variables are both necessary and sufficient to capture the evolution of the economy. We denote these core variables that constitute the full information set in the model by Γ_t.

The model determines an endogenous and time-invariant law of motion Λ such that

$$\Gamma_{t+1} = \Lambda(\Gamma_t, \epsilon_{t+1}), \tag{2}$$

where ϵ_{t+1} refers to exogenous innovations (e.g., to the level and volatility of TFP).

Since all shocks are independent over time, it follows from Equation (2) that the conditional expectation of the next-period state variables depends only on the current states Γ_t. By the law of iterated expectations, this is also true at any future horizon h :

$$E_t(\Gamma_{t+h}) = E_t\left(E(\Gamma_{t+h}|\Gamma_{t+h-1})\right) = E_t\left(\left(E(\Gamma_{t+h}|\Gamma_{t+h-1}\right)|\Gamma_{t+h-2}\right)\ldots|\Gamma_t) = E(\Gamma_{t+h}|\,\Gamma_t).$$

[8] See Bellman Equation (16) for the full specification.

Given that the stock of installed capital in h periods, k_{t+h}, is in the vector Γ_{t+h}, it follows that the core predictors Γ_t provide all information needed to form an unbiased estimate for ΔK_{t+h} at time t. That implies that,

$$\frac{\partial}{\partial v_t} E_t \Delta K_{t+h} = \frac{\partial}{\partial v_t} E(\Delta K_{t+h} | \Gamma_t).$$

Moreover, the endogenous policies for investment rate and depreciation in h periods are a function of Γ_{t+h} only.[9] It then follows that the predictors Γ_t yield unbiased estimates for the expected effects of uncertainty on the investment and depreciation rates:

$$\frac{\partial}{\partial v_t} E_t [I/K]_{t+h} = \frac{\partial}{\partial v_t} E([I/K]_{t+h} | \Gamma_t), \text{ and } \frac{\partial}{\partial v_t} E_t \delta_{t+h} = \frac{\partial}{\partial v_t} E(\delta_{t+h} | \Gamma_t)$$

Consequently, in the empirical implementation, we set Γ_t to include all four state variables in their covariance-stationary form: TFP volatility and the log growth rates of TFP, capital, and one-period lagged depreciation.[10] With a slight change of notation vis-à-vis the model, in the empirical analysis, K_t refers to the end of period capital at time t, to be consistent with the timing of other variables. The results are robust to replacing this predictor with the beginning of period log capital growth (see Table IA.2.3) or the Hodrick-Prescott (HP)–filtered level of k_t (see Table IA.2.4).

1.2.2 Capital accumulation restriction.

Capital stock, investment, and depreciation are linked through an accounting identity, which is the capital accumulation law of motion. In growth rate form, we can express it as follows:

$$\Delta K = 1 - \delta + \phi(I/K), \tag{3}$$

where ΔK is the growth rate in future capital, and ϕ is the capital adjustment function. Let $\overline{X}$ be the steady-state value of the variable X, and define $\tilde{x} \equiv \log X - \log \overline{X}$ its deviation from the steady state. We can then log-linearize Equation (3) in the following way:

$$\Delta \tilde{k} = -\frac{\overline{\delta}}{1 - \overline{\delta} + \overline{I/K}} \tilde{\delta} + \frac{\overline{I/K}}{1 - \overline{\delta} + \overline{I/K}} \tilde{ik}. \tag{4}$$

[9] Importantly, all other time-t variables (e.g., the market return, the risk-free rate, contemporaneous investment rate, etc.) are endogenous to Γ_t. Up to a first-order approximation, they are completely collinear with the set of variables in Γ_t, making them "bad" controls through the lens of the model. Nonetheless, for robustness purposes, we shall incorporate additional predictors in empirical extensions.

[10] While not a unit root, (lagged) depreciation level is too autocorrelated (see Table 5) to be used as a standalone predictor. To avoid estimation biases in the point estimates and/or the standard errors, we employ its lagged log first difference as a predictor. While not tabulated, the results are materially robust to using the level of lagged depreciation after stripping away non business-cycle fluctuations, using a Baxter-King filter.

That is, log capital growth is approximately a scaled linear combination of the log investment and depreciation rates, where the scale coefficients depend on the average depreciation and investment. We can rearrange to solve for the depreciation rate:

$$\tilde{\delta} = a_{ik}\tilde{ik} - a_{\Delta K}\Delta\tilde{k}, \quad \text{for} \quad a_{ik} = \frac{\overline{I/K}}{\overline{\delta}}; \quad a_{\Delta k} = \frac{1-\overline{\delta}+\overline{I/K}}{\overline{\delta}}. \tag{5}$$

All together, this approach allows to map the response of depreciation rate to any variable of interest, including uncertainty, to the corresponding responses of the log capital growth and log investment rate:

$$\frac{\partial}{\partial v_t}E_t\delta_{t+h} = a_{ik}\frac{\partial}{\partial v_t}E_t ik_{t+h} - a_{\Delta K}\frac{\partial}{\partial v_t}E_t\Delta k_{t+h}, \tag{6}$$

where the last term corresponds to the growth rate of the end-of-period capital.

In our empirical analysis, we use observed data to estimate the responses for capital growth and investment rates to uncertainty shocks. The responses for depreciation are inferred in one of two ways: (i) Direct—using observed depreciation rate data, and (ii) implied—consistent with Equation (6). The "direct" and "implied" responses are quite similar, as they should be in theory subject to approximation and measurement errors.[11]

1.3 Empirical results

We proceed by documenting the interaction between macro uncertainty and capital accumulation margins using a correlation analysis (Section 1.3.1), a projection analysis (Section 1.3.2), an SVAR analysis (Section 1.3.3), followed by additional robustness checks (Section 1.3.4). We caution the reader that the results in these subsections only indicate an association between macroeconomic uncertainty and measures of capital, investment, and depreciation. In Section 1.3.5 we discuss the potential limitations of our analysis including possible endogeneity concerns, and attempt to alleviate them using instrumental variables and inequality-constraints approaches.

[11] In principle, any margin of capital accumulation can be inferred from the other two. For example, the capital growth response could be inferred from the response of depreciation and investment rates. We prefer to solve for the implied depreciation rate because capital and investment rate are more familiar variables in the macroeconomic research.

Table 1
Uncertainty and capital accumulation: Correlations

	(1) Benchmark	(2) Capital: Equip & Struct	(3) Capital: Total Priv	(4) Capital: Compustat	(5) Uncertainty: SV
corr($v, I/K$)	-0.62 [-7.24]	-0.40 [-3.29]	-0.60 [-6.89]	-0.44 [-3.33]	-0.52 [-3.81]
corr(v, δ(direct))	-0.62 [-7.02]	-0.63 [-7.36]	-0.63 [-7.16]	–	-0.52 [-3.67]
corr(v, δ(implied))	-0.65 [-7.26]	-0.62 [-7.02]	-0.65 [-7.37]	-0.55 [-4.31]	-0.57 [-4.29]
corr($v, \Delta K$)	0.39 [4.31]	0.43 [5.00]	0.51 [4.69]	0.39 [3.11]	0.34 [3.41]

	(6) Uncertainty: E-GARCH	(7) Productivity: Solow(Ex R&D)	(8) Productivity: Solow(Equip&Struct)	(9) Productivity: Labor Prod	(10) Sample: 1965-
corr($v, I/K$)	-0.57 [-9.77]	-0.63 [-7.48]	-0.61 [-7.24]	-0.38 [-3.65]	-0.54 [-4.08]
corr(v, δ(direct))	-0.58 [-9.51]	-0.63 [-7.18]	-0.62 [-7.08]	-0.38 [-3.72]	-0.51 [-3.72]
corr(v, δ(implied))	-0.60 [-9.58]	-0.66 [-7.47]	-0.65 [-7.37]	-0.40 [-3.68]	-0.53 [-3.97]
corr($v, \Delta K$)	0.37 [4.32]	0.39 [4.34]	0.40 [4.44]	0.24 [2.60]	0.30 [2.01]

The table shows the correlations of macro uncertainty v with components of capital accumulation, such as the investment rate I/K, the depreciation rate δ, and the growth rate in stock of nonresidential capital ΔK. Newey–West t-statistics are in brackets. Data are annual from 1948 to 2022, except for columns (4) and (10), which start in 1964 and 1965, respectively.

1.3.1 Correlations.

We start the analysis with pairwise correlations. Table 1 shows contemporaneous correlations of macro uncertainty v with variables of capital accumulation: investment rate I/K, depreciation rate δ, and the growth rate in stock of capital K. To compute depreciation rate correlations, we use the raw depreciation data directly or back out the implied correlations through the capital accumulation equation, $Corr(\delta(\text{implied}), v) \approx \alpha_{ik} Corr(\Delta k, v) - \alpha_{\Delta k} Corr(ik, v)$.

Under the benchmark (column (1)), macroeconomic uncertainty has a negative correlation with I/K. This is generally consistent with a common view that macroeconomic uncertainty causes and/or deepens recessions. More surprisingly, the correlation between v and the growth of the capital stock K is positive and sizable at about 0.4. This finding is robust across various configurations, spanning different capital measures and methodologies for volatility extraction (columns (2) – (10)). Finally, the table shows that uncertainty comoves strongly and negatively with the depreciation rate δ, which can explain the divergence of capital and investment with respect to volatility. Averaged across all the specifications, the correlation of uncertainty with depreciation is -0.56 (direct) and -0.58 (implied), while it is -0.53 for the investment rate.

Empirically, second-moment shocks are negatively correlated with first-moment shocks to productivity. We account for this correlation and other theoretically driven controls in the following subsections.

1.3.2 Projections. As discussed in Section 1.2.1, Γ_t denotes the minimal set of covariance-stationary variables that are sufficient to form unbiased expectations, capital, lagged depreciation, and first and second moments of productivity. Consider a standard linear projection of the future components of capital accumulation on Γ_t:

$$\begin{aligned}
\Delta k_{t+h} &= \beta^h_{k,0} + {\beta^h_{\Delta k}}'\Gamma_t + \varepsilon^h_{k,t+h}, \\
ik_{t+h} &= \beta^h_{ik,0} + {\beta^h_{ik}}'\Gamma_t + \varepsilon^h_{ik,t+h}, \\
\delta_{t+h} &= \beta^h_{\delta,0} + \beta^{h\prime}_{\delta}\Gamma_t + \varepsilon^h_{\delta,t+h}.
\end{aligned} \tag{7}$$

Let e_v be the selection vector of v_t in Γ_t.[12] The impact of uncertainty on h-periods-ahead capital growth and investment rate are given by ${\beta^h_{\Delta k}}'e_v$ and ${\beta^h_{ik}}'e_v$, respectively. The effect of uncertainty on log cumulative capital growth, $\Delta k_{t\to t+h}$, is given by $\sum_{j=1}^h {\beta^j_{\Delta k}}'e_v$. To compute standard errors, we use a bootstrap method, which accommodates the correlation of error terms across the projections in Equation (7) and over time by resampling residuals in blocks. Resampled residuals are combined with the estimated ordinary least squares (OLS) equations to form new data paths, which are then used to bootstrap the slope coefficients and derive standard errors.

The effect on depreciation can be estimated in two ways: "direct" using the projection above, $\beta^{h\prime}_{\delta}e_v$, or "implied" using the capital accumulation restriction in Equation (6), $(\alpha_{ik}\beta^h_{ik} - \alpha_{\Delta k}\beta^h_{\Delta k})'e_v$. The latter ensures that the capital accumulation equation is satisfied state by state.

Table 2 shows the responses of expected cumulative capital growth, investment rate, and depreciation to macro uncertainty, where the predictive horizon is $h \in \{1, 3, 5\}$ years ahead. For interpretability, the projection coefficients are scaled by the standard deviation of macro uncertainty used in the regression, and multiplied by 100; for instance, a 0.61 benchmark slope estimate for capital growth at the five-year horizon suggests that a one-standard-deviation increase in uncertainty is associated with a 0.61% increase in the five-year-ahead cumulative log

[12] That is, if v_t is in the jth place of Γ_t, then e_v takes a value of one at the jth place and zero otherwise.

capital growth. This normalization facilitates the comparison of regression coefficients across different volatility specifications or data samples, and makes them comparable to the impulse response estimates in the subsequent section.

Consistent with the correlation evidence in Table 1, Table 2 shows that higher uncertainty predicts greater accumulation of physical capital. Under the benchmark and across all robustness configurations, the slope coefficient on uncertainty is always positive and statistically significant at horizons of three to five years ahead. Furthermore, the slope coefficient rises with the predictive horizon. In terms of economic magnitudes, in samples starting in 1948 (all columns of Table 2 except (4) and (10)), a one-standard-deviation rise in macro uncertainty is associated with an increase in five-year-ahead cumulative log capital growth ranging from 0.5% to 1.1%. This is equivalent to a 0.14- to 0.3-standard-deviation change in cumulative capital growth. Interestingly, the effects are stronger in the later part of the sample. Using data from the mid-1960s (columns (4) and (10)), a one-standard-deviation increase in macro uncertainty is associated with a 1.7% to 2.7% increase in the five-year-ahead log capital growth. At the same time, the slope coefficient on uncertainty when predicting investment rates is always negative and significant one year ahead, and in almost all cases – including the benchmark – remains significant up to five years ahead.

The described effects of uncertainty present a challenge to the existing literature. How can the capital stock grow (or at a minimum, not decline) when investment falls at times of high uncertainty? To satisfy the capital accumulation equation, the only available margin is the change in capital depreciation. Indeed, the regression results confirm that depreciation rates significantly drop at times of high uncertainty. The slope coefficients are always negative, and with the exception of column (4), statistically significant at all predictive horizons. Quantitatively, the estimated decreases in the log depreciation and investment rates are of a similar magnitude. For example, under the benchmark, a one-standard-deviation increase in macro uncertainty is associated with a 10.2% drop in the one-year-ahead log investment rate. For log depreciation rate, the corresponding decline is estimated at 10.4% (direct) or 13.7% (implied). To help interpret the relative effects, recall that according to the capital accumulation equation, the

Table 2
Uncertainty and capital accumulation: Projections

	(1) Benchmark	(2) Capital: Equip & Struct	(3) Capital: Total Priv	(4) Capital: Compustat	(5) Uncertainty: SV
$\Delta k_{t\to t+1}$	0.04 [0.71]	0.07 [1.54]	0.05 [1.09]	1.28 [3.70]	0.00 [0.07]
$\Delta k_{t\to t+3}$	0.38 [3.28]	0.52 [5.49]	0.41 [3.88]	2.21 [4.99]	0.43 [4.03]
$\Delta k_{t\to t+5}$	0.61 [5.76]	0.99 [11.33]	0.72 [7.48]	2.68 [5.73]	1.08 [11.14]
ik_{t+1}	−10.19 [−3.87]	−3.41 [−2.74]	−5.07 [−3.50]	−7.41 [−1.83]	−11.06 [−5.40]
ik_{t+3}	−9.31 [−3.48]	−0.59 [−0.43]	−3.27 [−1.93]	−10.15 [−2.14]	−9.98 [−4.65]
ik_{t+5}	−9.73 [−5.52]	−0.42 [−0.35]	−4.04 [−3.60]	−5.49 [−1.23]	−10.45 [−6.62]
δ_{t+1} (implied)	−13.71 [−4.06]	−6.29 [−4.22]	−8.37 [−3.92]	−15.67 [−4.51]	−14.05 [−5.43]
δ_{t+3} (implied)	−14.85 [−4.11]	−6.01 [−3.72]	−9.62 [−3.58]	−14.60 [−4.70]	−17.77 [−5.73]
δ_{t+5} (implied)	−13.56 [−4.31]	−4.75 [−3.16]	−8.57 [−3.11]	−13.61 [−4.92]	−18.93[−7.66]
δ_{t+1} (direct)	−10.41 [−4.32]	−5.37 [−5.19]	−6.45 [−4.17]	–	−10.70 [−5.88]
δ_{t+3} (direct)	−10.57 [−4.27]	−5.13 [−4.20]	−6.52 [−3.44]	–	−11.96 [−5.71]
δ_{t+5} (direct)	−10.11 [−5.36]	−4.71 [−4.44]	−6.42 [−3.99]	–	−12.69 [−8.17]

	(6) Uncertainty: E-GARCH	(7) Productivity: Solow(Ex R&D)	(8) Productivity: Solow(Equip&Struct)	(9) Productivity: Labor Prod	(10) Sample: 1965-
$\Delta k_{t\to t+1}$	0.04 [0.66]	0.05 [0.72]	0.05 [0.72]	0.02 [0.37]	0.08 [1.09]
$\Delta k_{t\to t+3}$	0.28 [2.29]	0.39 [3.35]	0.38 [3.15]	0.33 [3.80]	0.83 [7.92]
$\Delta k_{t\to t+5}$	0.47 [3.76]	0.63 [5.94]	0.59 [5.84]	0.58 [5.81]	1.66 [18.27]
ik_{t+1}	−7.36 [−3.06]	−10.62 [−4.05]	−10.38 [−3.83]	−5.60 [−2.65]	−5.05 [−2.44]
ik_{t+3}	−7.26 [−2.93]	−9.71 [−3.61]	−9.52 [−3.57]	−3.88 [−1.52]	−1.87 [−0.70]
ik_{t+5}	−6.81 [−2.67]	−10.10 [−5.63]	−9.99 [−5.66]	−4.84 [−2.95]	−1.01 [−0.56]
δ_{t+1} (implied)	−10.13 [−2.89]	−14.27 [−4.27]	−13.98 [−4.05]	−7.38 [−2.56]	−7.70 [−2.81]
δ_{t+3} (implied)	−11.28 [−3.57]	−15.47 [−4.26]	−15.12 [−4.24]	−8.16 [−2.57]	−9.89 [−2.35]
δ_{t+5} (implied)	−10.29 [−2.38]	−14.19 [−4.48]	−13.76 [−4.46]	−7.32 [−2.26]	−7.68 [−3.23]
δ_{t+1} (direct)	−7.54 [−3.16]	−10.84 [−4.50]	−10.60 [−4.35]	−5.65 [−2.62]	−5.36 [−2.79]
δ_{t+3} (direct)	−8.03 [−3.40]	−11.01 [−4.44]	−10.78 [−4.45]	−5.33 [−2.27]	−5.62 [−1.96]
δ_{t+5} (direct)	−7.37 [−2.71]	−10.55 [−5.66]	−10.33 [−5.68]	−5.25 [−2.57]	−4.35 [−2.58]

The table shows the estimated slope coefficients on macroeconomic uncertainty in projections of future cumulative capital growth, Δk, investment rate, ik, and depreciation rate, δ, controlling for the remaining core state variables. The predictive horizon is one, three, and five years ahead. For interpretability, the slopes are multiplied by the standard deviation of macro uncertainty (times 100). Bootstrapped t-statistics are in brackets. Data are annual from 1948 to 2022, except for columns (4) and (10), which start in 1964 and 1965, respectively.

next-period log capital growth is approximately a scaled linear combination of the investment and depreciation rates; see Equation (4). Using the scale parameters a_{ik} and $a_{\Delta k}$ used in the computations of the implied depreciation effects, a 13.7% drop in the depreciation rate implies a 0.73% increase in capital, while a 10.2% decrease in investment rate is associated with a

0.68% decrease in capital. Together, the two offsetting effects lead to a 0.04% increase in log capital growth, consistent with the evidence in Table 2. While at each specific horizon h the associated effect on depreciation is only mildly larger than investment, these increments cumulate over time and ensure that future cumulative capital growth does not fall, and even slightly rises.[13]

It is important to contrast our findings with well-established channels connecting uncertainty and capital. First, Bloom (2009) documents that uncertainty shocks lead to an investment overshoot in the long run. In Bloom (2009), however, capital growth increases because future investment rises (i.e., ΔK and I/K *comove*), while in our empirical findings, as well as in the subsequent model, the capital stock increases despite of a simultaneous investment slowdown (i.e., ΔK and I/K *diverge*). Second, the Oi-Hartman-Abel effect can similarly induce an expansion in the capital stock but also predicts a counterfactual comovement between capital growth and investment following second-moment shocks. Consequently, we formalize a novel quantitative mechanism to reconcile the evidence in Section 2.

1.3.3 Structural vector auto-regression.

To further illustrate the dynamic impact of uncertainty shocks on capital accumulation, we employ a structural vector auto-regression (SVAR) analysis. As prescribed in Section 1.2.1, we let Γ_t denote the core vector of the covariance-stationary variables, which proxy for the model state variables. We assume that the vector Γ_t satisfies the following autoregressive law of motion:

$$\Gamma_{t+1} = const + \Phi \cdot \Gamma_t + \varepsilon_{\Gamma,t+1}, \tag{8}$$

[13] The relative magnitudes of the intensive and extensive margins are assessed using the log-linearized capital accumulation equation (4), which links cumulative capital growth to investment and depreciation responses. Up to horizon h, for the cumulative capital growth response $\frac{\partial}{\partial v_t}\sum_{i=1}^{h}\mathbb{E}_t[\Delta k_{t+i}]$ to be statistically significantly positive, and the cumulative investment response $\frac{a_{ik}}{a_{\Delta k}}\cdot\frac{\partial}{\partial v_t}\sum_{i=1}^{h}\mathbb{E}_t[ik_{t+i}]$ to be statistically significantly negative — as shown in Table 2 — the cumulative depreciation effect $\frac{1}{a_{\Delta k}}\cdot\frac{\partial}{\partial v_t}\sum_{i=1}^{h}\mathbb{E}_t[\delta_{t+i}]$ must be statistically significantly larger in absolute value than the investment effect. This implication follows directly from the identity and supports our interpretation that depreciation is the dominant margin offsetting the investment decline. Furthermore, across all the rows and columns of Table 2, we verify that the slope coefficients for the direct and indirect measures of δ all fall in each other confidence intervals, which suggests that the estimated effects of uncertainty on $\delta(direct)$ and $\delta(implied)$ are not statistically distinct. Consequently, the sizable drop in $\frac{1}{a_{\Delta k}}\frac{\partial}{\partial v_t}\sum_{i=1}^{h}\mathbb{E}_t\delta_{t+i}$ is statistically equivalent when using the direct or the indirect depreciation slope coefficients.

where Φ is an $N \times N$ persistence matrix with $N = 4$ in the benchmark analysis, and $\varepsilon_{\Gamma,t+1} \sim N(0, \Sigma)$. Equation (8) is a first-order approximation of the general law of motion in Equation (2). We refer to Equation (8) as the "core" VAR. Due to the Markov property, the next period values of the variables in Γ are only driven by their realized values Γ_t and the set of shocks $\varepsilon_{\Gamma,t+1}$. The state variables in the VAR are placed in the following order: first-moment TFP growth, second-moment TFP (uncertainty), capital growth, and lagged depreciation growth. This order ensures that under Cholesky decomposition, structural uncertainty shocks, $Chol(\Sigma)\varepsilon'_{\Gamma,t+1}e_v$, are orthogonal to first-moment effects. At the same time, volatility shocks can have a contemporaneous impact on capital. The impulse response of structural uncertainty shocks on capital growth in h periods is given by $e_{\Delta k}\Phi^h Chol(\Sigma)' e_v$.

To obtain the impulse-response functions of uncertainty shocks to non-core variables y, such as investment rate, we use an auxiliary VAR, which extends the core VAR to include the non-core variable y :

$$\begin{bmatrix} \Gamma_{t+1} \\ y_{t+1} \end{bmatrix} = const + \Phi^{aux} \cdot \begin{bmatrix} \Gamma_t \\ y_t \end{bmatrix} + \varepsilon^{aux}_{\Gamma,t+1}, \tag{9}$$

where:

$$\Phi^{aux} = \begin{bmatrix} \Phi_{N\times N} & \mathbf{0}_{N\times 1} \\ \phi_{y,1\times N} & 0 \end{bmatrix}_{(N+1)\times(N+1)}.$$

The Φ_{aux} is an $(N+1)\times(N+1)$ persistence matrix of the auxiliary VAR, which restricts the top left component to the core VAR persistence matrix Φ, and the last column to zero. In line with the assumption that Γ_t determines a sufficient set of economic predictors, the structure of Φ^{aux} ensures that the auxiliary variable y_t does not affect the transition of the core state variables. At the same time, its own law of motion is determined only by the core economic states Γ. The impulse response to the variable y_t in h periods is obtained by $e_y\Phi^h Chol(\Sigma^{aux})' e_v$, where Σ^{aux} is the covariance matrix of the auxiliary VAR innovations.

Figure 1 shows the impulse responses of log capital growth, log investment rate, and log depreciation to one-standard-deviation macro uncertainty shocks. To conserve space, we focus on four key measurement configurations: the benchmark, using an alternative capital measure pertaining to total private capital, using an alternative volatility model (E-GARCH), and using

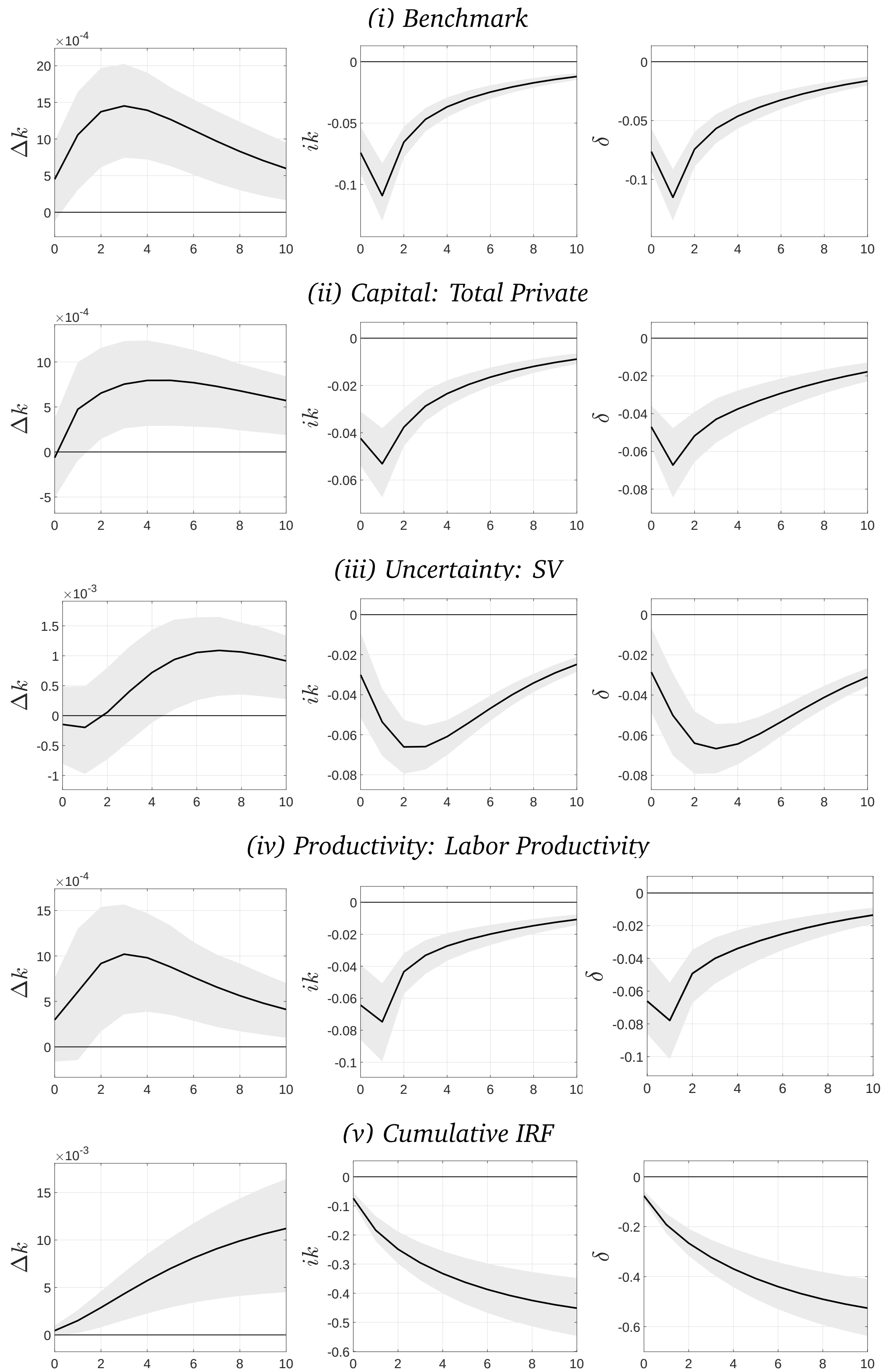

Figure 1
Uncertainty shock impulse responses

The figure shows one-standard-deviation uncertainty shock impulse responses of log capital growth Δk, investment rate ik, and depreciation rate δ, based on the benchmark and alternative configurations.

Alt Text: Graphs depicting uncertainty shocks' impulse-response functions, showing their impact on capital growth, investment, and depreciation rates.

an alternative productivity metric, such as labor productivity. Impulse responses for other configurations are relegated to the Internet Appendix Figure IA.2.5.

In line with the previous evidence, a one-standard-deviation uncertainty shock is associated with an increase in capital growth starting two years ahead, and this positive and significant impact persists for at least 10 years. While the contemporaneous effect is insignificant, it is nonetheless non-negative despite the significant negative effect on investment rates. Across all configurations, the impact on capital growth peaks around four years ahead. Under the benchmark scenario, the peak magnitude amounts to 0.15% higher capital growth.

Importantly, this effect accumulates over time. The last row of Figure 1 displays cumulative impulse responses under the benchmark. Ten (five) years after the initial uncertainty shock, cumulative capital growth increases by approximately 1.12% (0.6%). For comparable horizons, these effects are of similar magnitude to the evidence presented in column (1) of Table 2.

1.3.4 Empirical robustness. We perform additional checks for our main empirical results. In the interest of space, we provide the evidence in the Internet Appendix. First, in Table IA.2.5 we confirm that the capital, investment, and depreciation projection results remain similar in sign and significance within recessions and expansions, which mitigates concerns about volatility mean reversion during recoveries.

Second, in Internet Appendix Section IA.2.1, we consider several methodological variations to the VAR estimation of Section 1.3.3, which includes (i) changing the order of the variables in the vector Γ_t, (ii) restricting the matrix Φ such that uncertainty only depends on its own lag, (iii) using the hp-filtered level of capital rather than its growth, (iv) using a narrative identification of uncertainty shocks following Bloom (2009), (v) expanding the core variables in the vector Γ_t to include a host of other controls consistent with Bloom (2009).[14] The impulse-response evidence remains robust to these alterations.

Third, Salgado, Guvenen, and Bloom (2019) find that skewness plays a role for business cycles beyond second-moment shocks. Related, Segal, Shaliastovich, and Yaron (2015) show

[14]We also augment the core variables in the VAR with proxies of financial frictions and show in Figure IA.2.7 this does not have a material impact on the impulse responses vis-à-vis the benchmark.

that "good" and "bad" uncertainties, which measure conditional variations in the right and left tails of macroeconomic fundamentals, have differential impact for future real growth and asset prices. In the context of our study that examines higher-order fluctuations in productivity, we consider cross-sectional skewness in the firm-level TFP, constructed using the granular TFP data from İmrohoroğlu and Tüzel (2014). We augment the core VAR to include this cross-sectional skewness time series and show in Figure IA.2.6 that the impulse responses are quite close to the benchmark. Table IA.2.6 shows that controlling for skewness, macro uncertainty still positively predicts future capital growth. Interestingly, cross-sectional skewness on its own also predicts an increase in capital growth.

Lastly, in Internet Appendix Section IA.2.3, we source data on UK TFP and capital accumulation margins from Penn World Table (PWT), compiled by Feenstra, Inklaar, and Timmer (2015). We follow the benchmark approach to construct macro uncertainty and core controls using UK data. Similarly to the U.S. evidence, the slope coefficients on UK macro uncertainty are positive and significant (at the 10% level or higher) when predicting future capital growth, but negative and significant for future investment and depreciation rates.

1.3.5 Causality and empirical limitations. Our benchmark empirical analysis demonstrates that an increase in macro uncertainty is associated with higher expectations about future capital despite being associated with lower expectations about investment rates. To isolate these relations as accurately as possible, our econometric approach relied on a sufficient set of economic predictors according to classical macroeconomic theory. Nonetheless, such analysis cannot establish strict causality, and it may be subject to potential biases as well.

First, while our set of controls captures the current state of the economy, any departure of the data-generating process from the model's assumptions could lead to an omitted variable bias. For example, our model highlights that the dynamics of the depreciation rate are highly persistent, and follow an autoregressive process of the first order. In principle, the depreciation rate may depend on other lags as well. This omission could potentially inflate (deflate) the effect of uncertainty on depreciation, if the omitted lag is negatively (positively) correlated with uncertainty. A similar argument could be made for other lags of investment. As the slope coefficients on depreciation, investment, and capital growth are jointly determined (see Equations (6) and (7)), any potential bias in the estimates for depreciation or investment would directly affect the estimates for capital growth.

Second, the OLS and VAR estimates could suffer from reverse causality. A negative first moment can decrease depreciation and investment while simultaneously increasing uncertainty. Given the persistence of the capital accumulation measures, or data issues in accurately capturing first-moment controls, the estimated effects of uncertainty could instead capture the impact of first-moment shocks.

Consequently, the baseline results only point to an economic interaction. They should only be interpreted in a causal way from a theoretical standpoint — through the lens of the model that we present in Section 2. We lend further support for this causal interpretation by testing the model's predictions in Section 5.

In addition, we consider several strategies, which, to the best of our knowledge, represent state-of-the-art methods for identifying exogenous uncertainty shocks using aggregate data. While each approach, separately, could be subject to its own shortcomings, the bulk of the evidence, collectively, helps alleviate biased-inducing endogeneity concerns.

First, we follow the identification strategy of Baker, Bloom, and Terry (2024), who argue that uncertainty could be instrumented using exogenous disaster shocks, including natural disasters, terrorist attacks, coups, and political shocks; see Section IA.2.2.2 for further details. These shocks could pertain to the United States only ("domestic") or pertain to linked economies ("trade-weighted"). We consider the full sample for which these instruments are available, as well as a recent subsample starting in the mid-1980s. For brevity, the full implementation details are relegated to the Internet Appendix. Adopting the IV approach for macro uncertainty, Table 3 reports that the slope coefficients for capital growth on instrumented uncertainty are always positive, increase with the predictive horizon, and are statistically significant at horizons of three to five years ahead. Using the full sample period in which the instruments are available (columns (1) and (3)), a one-standard-deviation increase in instrumented macro uncertainty increases the five-year-ahead log capital growth by 2.9% to 6.6%. These effects are considerably

Table 3
Instrumented uncertainty: Capital accumulation projections

	(1)	(2)	(3)	(4)
	Domestic instruments		Trade-weighted instruments	
	Full sample	Recent sample	Full sample	Recent sample
$\Delta k_{t\to t+1}$	0.35 [1.27]	0.27 [1.42]	−0.10 [−0.20]	0.35 [1.97]
$\Delta k_{t\to t+3}$	1.56 [3.51]	1.61 [5.73]	2.52 [3.32]	1.88 [8.40]
$\Delta k_{t\to t+5}$	2.87 [6.31]	3.61 [13.41]	6.62 [8.91]	3.56 [15.06]
ik_{t+1}	−10.63 [−1.19]	−19.09 [−2.70]	−32.98 [−3.47]	−14.88 [−2.26]
ik_{t+3}	−8.14 [−1.48]	−13.55 [−2.33]	−17.59 [−1.09]	−9.66 [−1.86]
ik_{t+5}	−4.51 [−0.71]	−5.64 [−1.25]	−13.03 [−1.10]	−4.93 [−1.20]
δ_{t+1} (implied)	−18.89 [−1.65]	−27.45[−3.15]	−39.49 [−2.84]	−23.50 [−2.97]
δ_{t+3} (implied)	−21.14 [−2.24]	−27.67 [−3.97]	−50.57 [−2.39]	−23.58 [−3.66]
δ_{t+5} (implied)	−15.15 [−1.38]	−23.19 [−2.98]	−46.49[−2.56]	−19.37 [−3.11]
δ_{t+1} (direct)	−12.23 [−1.54]	−19.23 [−3.06]	−30.02 [−3.21]	−16.07 [−2.64]
δ_{t+3} (direct)	−11.22[−1.70]	−17.88 [−3.43]	−29.73[−1.95]	−14.71 [−2.99]
δ_{t+5} (direct)	−7.40 [−1.03]	−13.34 [−2.57]	−26.05[−2.17]	−11.03 [−2.73]

The table shows the estimated slope coefficients on instrumented macroeconomic uncertainty in projections of future cumulative capital growth (Δk), investment rate (ik), and depreciation rate (δ), controlling for the remaining core state variables. The predictive horizons are one, three, and five years ahead. For interpretability, the slopes are multiplied by the standard deviation of macro uncertainty times 100. The instruments are obtained from Baker, Bloom, and Terry (2024) and encompass both domestic instruments and trade-weighted instruments, surrounding disaster shocks (natural disasters, terrorist attacks, coups, and revolutions). We use a two-stage bootstrapping method to obtain robust standard errors. For the full sample, data are annual from 1973 to 2021, and for the recent subsample, the data start in 1985.

larger than the corresponding OLS ones, shown in columns (1) and (10) of Table 2, which utilize the same measures of capital and uncertainty. This echoes the findings of Baker, Bloom, and Terry (2024) that instrumentation amplifies the estimated effect of uncertainty shocks. In the recent subsample (columns (2) and (4)), the impact on capital growth is about 3.6%, using both sets of instruments. The slope coefficients for the investment rate and the depreciation rates on the instrumented uncertainty are negative, with greater statistical significance at shorter horizons. Importantly, the instrumentation reveals a more pronounced asymmetry in the impact of uncertainty shocks on depreciation versus investment rates, compared to plain OLS. For example, in columns (1), (2), and (4), a one-standard-deviation increase in uncertainty drops the five-year-ahead log investment rate by about 5%, whereas the direct decrease in log depreciation ranges from 7.4% to 13.3%.

Second, we follow Ludvigson, Ma, and Ng (2021) and use "inequality constraints" to identify the causal impact of macroeconomic uncertainty shocks; see Section IA.2.2.1 for further details. This specific SVAR methodology does not rely on recursive identification. Rather, it requires that uncertainty shocks exhibit appropriate sign and magnitude during key historical periods, in which unexpected and arguably exogenous events elevate macro uncertainty. It also requires the time series of uncertainty shocks to exhibit a negative (positive) correlation with stock (gold) prices. We find that these structural uncertainty shocks induce a positive and significant impact on capital growth, whose magnitude is even larger than in the benchmark.

Last but not least, we can approach the endogeneity problem theoretically, from the perspective of the model presented in Section 2. In Internet Appendix Section IA.3.3, we shut down the stochastic volatility of TFP from this model, so that the economy is driven solely by persistent shocks to the TFP growth. We simulate finite paths from this economy and filter the conditional volatility of TFP in the same way as in the data (i.e., through GRJ-GARCH). In this case, fluctuations in "uncertainty" are driven only by random large and persistent first-moment shocks — which are identified as uncertainty fluctuations in finite samples. We then perform a "falsification" test and check whether such specification can explain the empirical finding where capital growth and investment rate diverge in response to elevated measured uncertainty. We show that if the economic environment is driven only by first-moment shocks, then it cannot account for this pattern — at all predictive horizons, the uncertainty effects on future capital growth are of the same sign as for the investment rates, contrary to the data. From the perspective of our model, the observed uncertainty-related patterns cannot be obtained in the absence of exogenous second-moment shocks.

2 Model

We construct a general-equilibrium model that can quantitatively account for our novel empirical findings, along with standard macroeconomic and asset-pricing moments. The economy is composed of a representative household that owns a representative firm. The firm uses capital and labor to produce aggregate output and faces permanent productivity shocks whose conditional volatility is time-varying. In addition to investment and labor choices, the firm makes decisions about the utilization of existing capital. Utilization persistently correlates with future capital depreciation, which is a key novel channel in our model.

2.1 Firm

The representative firm produces its output, Y_t, using a constant return to scale Cobb-Douglas production function over capital, K_t, and a flow of labor, L_t:

$$Y_t = A_t^{1-\alpha}(u_t K_t)^{\alpha} L_t^{1-\alpha}, \tag{10}$$

where α is the capital share of output, and A_t is the firm's productivity level. The firm owns its capital stock, K_t, which evolves according to the following law of motion:

$$K_{t+1} = (1-\delta_t)K_t + \phi\left(\frac{I_t}{K_t}\right)K_t. \tag{11}$$

I_t represents investment, δ_t is a time-varying and endogenous depreciation rate, and $\phi(\cdot)$ is a positive, concave function capturing adjustment costs, specified as in Jermann (1998):

$$\phi\left(\frac{I_t}{K_t}\right) = \alpha_1 + \frac{\alpha_2}{1-\frac{1}{\xi}}\left(\frac{I_t}{K_t}\right)^{1-\frac{1}{\xi}}. \tag{12}$$

The parameter ξ captures the elasticity of the investment rate. The limiting case $\xi \to \infty$ ($\xi \to 0$) represents frictionless (infinitely costly) adjustment. The parameters α_1 and α_2 are set so there are no adjustment costs in the deterministic steady state.[15]

The control variable $u_t > 0$ denotes the capacity utilization rate of the firm. This variable governs the intensity with which the firm utilizes its assets in place. We assume that increasing utilization causes existing equipment to erode faster, and therefore, a positive change in utilization is akin to a positive depreciation shock. This ingredient is common in extant modeling approaches (see, e.g., Basu and Bundick (2017) Garlappi and Song (2017), among others). The current depreciation shock is given by:

$$\varepsilon_\delta(u_t) = \sigma_u\left[\frac{u_t^{1+\zeta}-1}{1+\zeta}\right]. \tag{13}$$

[15] Specifically, $\alpha_1 = (\mu - 1 + \delta)^{\frac{1}{\xi}}$ and $\alpha_2 = \frac{1}{\xi-1}(1-\delta-\mu)$, where μ is the constant drift of productivity defined in Section 2.3.

The parameter ζ controls the elasticity of current depreciation innovation to utilization and determines how costly it is for a firm to alter its utilization rate. All else equal, larger values of ζ imply that increasing the capacity utilization rate is more costly, and ensures that firms choose a finite level of utilization. Without loss of generality, we normalize the steady-state level of utilization in the model to 1, using the scaling parameter σ_u, so that the steady-state value of $\varepsilon_\delta(u_t)$ is zero. When $\zeta \to \infty$, utilization is fixed at its steady state.

A key ingredient is the dynamics of the depreciation rate:

$$\delta_t = (1-\rho_\delta)\delta_0 + \rho_\delta \delta_{t-1} + \varepsilon_\delta(u_t). \tag{14}$$

The parameter δ_0 is the steady-state level of the depreciation rate. The parameter $\rho_\delta \in [0,1)$ captures additional persistence in the depreciation dynamics beyond that of the endogenous utilization rate, determined by the term $\varepsilon_\delta(u_t)$.

The depreciation specification in Equation (14) builds on traditional modeling in which the response of depreciation to utilization is static, that is, $\rho_\delta = 0$.[16] Our paper argues that this assumption is unnecessarily restrictive, empirically and economically: the data strongly reject the null hypothesis of $\rho_\delta = 0$, which we subsequently show through model estimation in Section 2.5 and via direct empirical tests in Section 5.3.[17]

Thus, introducing a lag of depreciation in Equation (14) represents a simple yet empirically and economically relevant way to separate the persistence of utilization from that of the depreciation rate, and is a novel element that distinguishes our model from other neoclassical and New Keynesian specifications. In Section 3.2, we show how this extra persistence in depreciation plays a key role in qualitatively accounting for the impact of uncertainty on capital dynamics and risk premia.

The dividend of the firm at time t is given by:

$$D_t = Y_t - I_t - W_t L_t, \tag{15}$$

[16] See, e.g., Jaimovich and Rebelo (2009); Fernández-Villaverde et al. (2015), among many others.

[17] Furthermore, Internet Appendix Section IA.4.3 discusses potential microfoundations for the aggregate depreciation dynamics in Equation (14). For example, we show an isomorphism between the aggregate depreciation dynamics in Equation (14) and those that endogenously arise in an extended model with multiple types of capital goods with different depreciation rates, and where economic shocks persistently change the relative composition of the underlying goods.

where W_t is the equilibrium wage rate. At each date t, the manager of the representative firm chooses how much to invest I_t and hire L_t, and capacity utilization u_t in order to maximize firm value given the current stock of capital K_t, the state of depreciation δ_{t-1}, wage W_t, and the stochastic discount factor of the household $M_{t,t+1}$. We can write the firm's maximization program recursively as follows:

$$V(K_t, \delta_{t-1}, A_t, \sigma_{a,t}) = \max_{L_t, I_t, u_t, K_{t+1}} \quad D_t + \mathbb{E}_t\left[M_{t,t+1} V(K_{t+1}, \delta_t, A_{t+1}, \sigma_{a,t+1})\right] \tag{16}$$
$$\text{s.t.} \qquad (11), (14), (10), (15).$$

The realized unlevered return of the firm at time t is given by $R_{d,t}^{\text{UNLEV}} = \frac{V_t}{V_{t-1} - D_{t-1}}$.

2.2 Household

The preferences of the representative household over the future consumption stream are characterized by the recursive utility of Epstein and Zin (1991):

$$U_t = \left[(1-\beta) C_t^{1-\frac{1}{\psi}} + \beta \mathbb{E}_t \left[U_{t+1}^{1-\gamma}\right]^{\frac{1-\frac{1}{\psi}}{1-\gamma}}\right]^{\frac{1}{1-\frac{1}{\psi}}}, \tag{17}$$

where γ denotes the coefficient of relative risk aversion, and ψ denotes the intertemporal elasticity of substitution (IES). When $\psi = \frac{1}{\gamma}$, Equation (17) collapses to constant relative risk aversion (CRRA) preferences. We assume that $\psi > \frac{1}{\gamma}$ so that the household exhibits a preference for early resolution of uncertainty, while for $\psi < \frac{1}{\gamma}$ it has a preference for late uncertainty resolution.

The household is endowed with one unit of labor, and can hold a fraction Θ_t of the firm, which pays a dividend D_t as in Equation (15). The household maximizes its utility by supplying labor and participating in financial markets, subject to:

$$C_t + \Theta_{t+1} V_t = W_t L_t + \Theta_t (V_t + D_t), \tag{18}$$

where L_t is the hours worked, and V_t is the stock price of the representative firm, defined in Equation (16). Since the household does not derive disutility from labor, it supplies labor inelastically and $L_t = 1$ in equilibrium. The first-order condition of the household's maximization program implies that the stochastic discount factor (SDF) is given by:

$$M_{t+1} = \beta \left(\frac{C_{t+1}}{C_t} \right)^{1-\frac{1}{\psi}} \left(\frac{U_{t+1}}{\mathbb{E}_t \left[U_{t+1}^{1-\gamma} \right]^{\frac{1}{1-\gamma}}} \right)^{\frac{1}{\psi}-\gamma}. \tag{19}$$

2.3 Productivity

Let A_t be the level of aggregate productivity, and $\Delta a_{t+1} = \log\left(\frac{A_{t+1}}{A_t}\right)$. We assume that log productivity growth, Δa, follows an AR(1) process with time-varying conditional volatility governed by a process $\sigma_{a,t}$ as follows:

$$\Delta a_{t+1} = (1-\rho_a)\mu + \rho_a \Delta a_t + e^{\sigma_{a,t}} \sigma_a \varepsilon_{a,t+1}, \tag{20}$$

$$\sigma_{a,t+1} = \rho_\sigma \sigma_{a,t} + \sigma_w \varepsilon_{w,t+1}, \tag{21}$$

where $0 < \rho_a, \rho_\sigma < 1$, and the productivity and volatility shocks $\varepsilon_{a,t+1}$ and $\varepsilon_{w,t+1}$ are i.i.d. standard normal, uncorrelated with each other.[18] μ is the drift of productivity. The log volatility σ_a is exponentiated in Equation (20) to ensure that conditional volatility is strictly positive.[19] Without loss of generality, the unconditional mean of $\sigma_{a,t}$ is 0 so that the steady-state volatility of productivity growth is σ_a.

2.4 Optimal utilization choice

Section IA.3.1 of the Internet Appendix details the definition of an equilibrium as well as standard first-order conditions. Equilibrium utilization u_t is determined by the following optimality condition:

$$\frac{MPU_t}{\varepsilon_\delta'(u_t)} = q_t K_t + \mathbb{E}_t \left[M_{t,t+1} \rho_\delta \frac{MPU_{t+1}}{\varepsilon_\delta'(u_{t+1})} \right], \tag{22}$$

[18]In the Internet Appendix, we augment the innovation to aggregate productivity with a skewed term to match a mild negative skewness of the TFP in the data. In this case, $\sigma_{a,t}$ governs variation in the conditional second and third moments jointly. This does not have a large impact on our results and serves mainly to amplify the decline in investment following an increase in second and higher moments (see Figure IA.3.12).

[19]The log volatility modeling follows existing general-equilibrium literature, such as Croce (2014) and Basu and Bundick (2017). At the estimated parameter values, the solution does not run into convergence issues due to the exponentiation of the uncertainty process. We further checked that switching to a square-root process does not affect model results.

where q_t is the shadow price of installed capital, and MPU_t is the marginal product of utilization given by $\alpha Y_t/u_t$. Iterating forward on the right-hand side of Equation (22), one obtains:

$$\frac{MPU_t}{\varepsilon'_\delta(u_t)} = \mathbb{E}_t\left[\sum_{s=0}^{\infty}\rho_\delta^s M_{t,t+s}q_{t+s}K_{t+s}\right]. \tag{23}$$

When depreciation shocks are not persistent ($\rho_\delta = 0$), the utilization choice is static:

$$MPU_t = q_t K_t \varepsilon'_\delta(u_t). \tag{24}$$

The benefit of raising utilization is its marginal contribution to output, specified on the left-hand side of the equation. The cost of raising utilization on the right-hand side is that it causes capital to depreciate faster, creating a cost per dollar of capital at a rate of ε'_δ.

When $\rho_\delta > 0$, the utilization choice is dynamic, because increased utilization raises not only the current depreciation δ_t, but also its future values $\{\delta_s\}_{s>t}$. In this case, optimal utilization can be derived from Equation (23), by plugging in the expressions for output, the market clearing condition $L_t = 1$, and $\varepsilon_\delta(u_t)$:

$$u_t = \left\{u_0 A_t^{1-\alpha}K_t^{\alpha}\mathbb{E}\left[\sum_{s=0}^{\infty}\rho_\delta^s M_{t,t+s}q_{t+s}K_{t+s}\right]^{-1}\right\}^{\frac{1}{\zeta+1-\alpha}}, \tag{25}$$

where $u_0 = \alpha\sigma_u^{-1}$. Note that when discount rates fall, the net present value of future capital increases, which creates a larger cost for utilization. The utilization choice is directly affected by the precautionary saving motive, via discount rates, similar to the investment choice.

2.5 Estimation

Table 4 shows the benchmark model parameters. Following Christiano, Eichenbaum, and Evans (2005) and Basu and Bundick (2017), we classify the parameters into two sets. The first set includes a small number of parameters that are calibrated based on existing studies. Specifically, the capital share of output, governed by α, is about 33%. We adopt a standard preference parameter configuration in the production-based asset-pricing literature: γ is set to 10, and the IES ψ is set to two. These are similar to the values employed in Bansal and Yaron (2004) and Croce (2014), among others.

Table 4
Model parameters

Parameter	Value	Description
Technology.		
μ	0.0015	Productivity growth
ρ_a	0.8919	Aggregate productivity's persistence
σ_a	0.0013	Aggregate productivity shock volatility
ρ_σ	0.9951	Log volatility's persistence
σ_w	0.0903	Log Volatility shocks' volatility
Capital.		
α	**0.34**	Capital's share of output
ξ	2	Capital adjustment cost
Depreciation and Utilization.		
δ_0	0.0075	Unconditional depreciation rate
ρ_δ	0.9908	Depreciation's persistence
ζ	0.9323	Elasticity of depreciation to utilization
Preferences.		
γ	**10**	Relative risk aversion
ψ	**2**	Intertemporal elasticity of substitution
β	0.9988	Time discount factor

The table shows the model parameters under the benchmark case (monthly frequency). All non-bold parameters are estimated. Bold parameters are calibrated.

The second set, which includes the vast majority of the model parameters, is estimated using SMM. We denote the second set by $\theta = \{\mu, \rho_a, \sigma_a, \rho_\sigma, \sigma_w, \xi, \delta_0, \rho_\delta, \zeta, \beta\}$. Our estimate of θ minimizes the SMM objective function:

$$\hat{\theta} = \text{argmin}_\theta \left[\Psi(\theta) - \hat{\Psi}\right]' V^{-1} \left[\Psi(\theta) - \hat{\Psi}\right],$$

where $\hat{\Psi}$ are the empirical moments used in the estimation, $\Psi(\theta)$ are their model-implied equivalents that depend on the monthly parameters θ, and V is a diagonal matrix with the empirical variances of each moment along its main diagonal. Given a set of parameters, the model is solved using a third-order perturbation method. We compute model-implied moments based on 200 simulations of short sample paths of 612 months each. Each model-implied path is time-aggregated to annual observations spanning 51 years, which matches a modern empirical sample starting in 1968 for which utilization growth data are available.

Table 5 shows the moment conditions used to estimate the model. We group the moments into two categories.[20] (i) Unconditional annual moments: the mean, standard deviation, and autocorrelation of consumption growth, output growth, investment growth, depreciation rate,

[20]The table shows all macro-related moments used in the estimation. See Table 6 for the risk-free rate.

Table 5
Model-implied macroeconomic moments

		Model		Data
A. Unconditional annual moments				
Consumption growth	Mean (%)	1.82	[0.60, 3.69]	1.81
	Std. dev. (%)	2.16	[1.20, 4.73]	1.22
	AC(1)	0.46	[0.15, 0.71]	0.47
Output growth	Mean (%)	1.85	[0.54, 3.81]	1.78
	Std. dev. (%)	2.43	[1.37, 5.63]	1.92
	AC(1)	0.47	[0.16, 0.68]	0.25
Investment growth	Mean (%)	1.86	[0.35, 3.93]	1.25
	Std. dev. (%)	3.31	[1.70, 7.77]	5.83
	AC(1)	0.39	[0.11, 0.63]	0.27
Depreciation rate	Mean (%)	8.18	[7.23, 9.51]	8.34
	Std. dev. (%)	0.32	[0.12, 0.72]	0.51
	AC(1)	0.98	[0.93, 0.99]	0.96
Utilization rate	Std. dev. (%)	4.74	[2.86, 8.55]	4.17
	AC(1)	0.77	[0.39, 0.92]	0.62
B. Realized volatility moments				
Consumption growth	Std. dev. (%)	0.19	[0.08, 0.54]	0.14
	AC(1)	0.97	[0.91, 0.99]	0.97
Output growth	Std. dev. (%)	0.26	[0.10, 0.78]	0.30
	AC(1)	0.98	[0.94, 0.99]	0.98
Investment growth	Std. dev. (%)	0.48	[0.17, 1.38]	0.63
	AC(1)	0.98	[0.91, 0.99]	0.96

The table shows model-implied moments along with their empirical counterparts. Panel A shows unconditional moments for macroeconomic growth rate variables. Panel B shows realized volatility moments computed using a five-year rolling window standard deviation. For each moment of interest, the table shows the median value and the 5th and 95th percentiles based on 200 simulations of short sample paths 612 months each. In panel A (B), each model-implied path is aggregated to form annual (quarterly) observations spanning 51 years (204 quarters).

and the real risk-free rate; the standard deviation and autocorrelation of utilization rate. (ii) Realized volatility moments: the standard deviation and autocorrelation of rolling window realized volatility time series for consumption, output, and investment growth rates. In all, we use 23 moment conditions to identify 10 parameters.

Importantly, we deliberately refrain from identifying any parameter by directly targeting TFP data or the impulse responses of uncertainty shocks to capital or investment. This serves two purposes. First, as discussed in Section 1.1, there are multiple methodologies for eliciting productivity's first and second moments, yielding potentially different targets. Second, by excluding these targets, we ensure that any model-implied increase in the capital stock following higher uncertainty is not mechanically hardwired by either specific measurement or the broader estimation exercise.

In our model estimation, the means of annual consumption, output, and investment growth jointly help to identify the parameter μ. We estimate μ to be about 0.15%, which implies an annual real consumption growth rate of 1.82%, consistent with its empirical value of 1.81%. The standard deviation (autocorrelation) of consumption growth is directly governed by σ_a (ρ_a). Under the estimated values, the model-implied volatility of consumption growth is about 2%. The lower bound of the model confidence interval is about 1.2%, which aligns with the data from 1968 onward. Moreover, consumption growth volatility is about 2% in the long sample starting in 1930. The autocorrelation of consumption growth is 0.46 and 0.47 in the model and the data, respectively. The capital adjustment cost ξ is identified by targeting the volatility and the autocorrelation of output and investment growth rates. These empirical moments fall within the model confidence intervals.

To identify the parameters that govern the uncertainty process, σ_w and ρ_w, we construct realized volatility time series for quarterly (three months) consumption, output, and investment growth rates, using a five-year (20 quarters) rolling window standard deviation. We then compute the standard deviation of these realized volatilities. If the data featured constant conditional volatility, the standard deviations of the five-year rolling realized volatilities would be close to zero. By contrast, these standard deviations are statistically significant and amount to 0.14%, 0.3%, and 0.63% for the realized volatility of consumption, output, and investment growth, respectively. The model equivalents are 0.19%, 0.26%, and 0.48%, respectively, all close to the data.

To help identify ρ_w separately from σ_w, the estimation also includes the autocorrelation of these realized volatility time series. The estimated uncertainty process is highly persistent and implies that the autocorrelations of the five-year rolling window standard deviations are all above 0.97 in the model, similar to the data.

The parameters δ_0 and ρ_δ are identified using the mean and the autocorrelation of depreciation, respectively. δ_0 is estimated to be 0.75%, suggesting that the model-implied annualized average depreciation rate is 8.18%, closely matching the empirical rate. ρ_δ is estimated to be about 0.99 at the monthly frequency, consistent with modeling the depreciation dynamics as persistent. Given this estimate, the autocorrelation of the annual depreciation rate is 0.98 in the model versus 0.96 in the data. At the same time, the autocorrelation of the utilization rate is 0.77 in the model versus 0.62 in the data, with an upper bound of 0.92. Thus, both empirically and theoretically, the autocorrelations of the depreciation and the utilization rates are statistically distinct, with the former being more persistent than the latter.[21] Importantly, if ρ_δ is set to zero, as in other existing frameworks, the model-implied autocorrelation of utilization and depreciation would be counterfactually identical.

The parameter ζ, which governs the elasticity of depreciation to utilization, is identified by targeting the unconditional volatility of the utilization rate, which amounts to 4.2% in the data, jointly with the volatility of the depreciation rate, which is 0.5%. Both volatilities fall within the model confidence interval. Lastly, the estimate of β is 0.998, identified using the mean, standard deviation, and autocorrelation of the risk-free rate. The risk-free rate is 0.91% (1.04%) in the model (data).

3 Implications for the Macroeconomy

We show that our model can account for the key empirical evidence, specifically (i) the negative association between uncertainty and depreciation and (ii) the positive association between uncertainty and future capital, in spite of a drop in investment. We start by showing the failure of the model with fixed utilization to generate these findings, and then explain how flexible utilization coupled with persistence in depreciation resolves these failures.[22]

[21] The difference in the persistence between utilization and depreciation also holds at the cross-section. In Internet Appendix Table IA.2.7, we report the autocorrelation of utilization and depreciation rates for a collection of industries for which both utilization and depreciation data are available. For all industries, the point estimate of the persistence in the depreciation rate is higher than that of the utilization rate, and Wald tests reject the null that the persistence parameters are equal.

[22] The Internet Appendix provides additional model results. In Internet Appendix Section IA.3.2, we compare the model-implied capital growth impulse response to the data. In Section IA.3.4, we nest our mechanism in a New Keynesian model with time-varying markups. Incorporating flexible utilization and extra persistence in depreciation remains quantitatively important: it is necessary to generate uncertainty-driven contractions if productivity shocks are permanent.

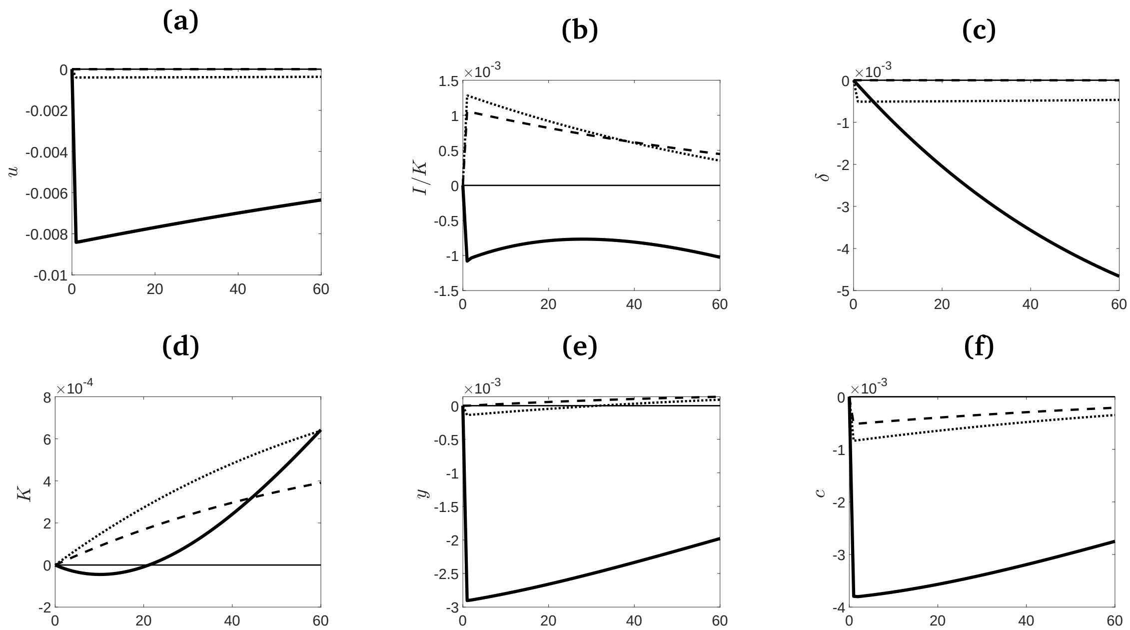

Figure 2
Model-implied IR to uncertainty shocks: Macro variables
The figure shows the impulse responses of (a) utilization rate u, (b) investment rate I/K, (c) depreciation rate δ, (d) detrended capital stock K, (e) detrended output y, and (f) detrended consumption c to uncertainty shocks. The solid line shows the responses using the benchmark model parameters. The dotted line shows the results when $\rho_\delta = 0$ (no extra persistence in depreciation). The dashed line shows the results when $\zeta \to \infty$ (fixed utilization). The horizontal axis represents months. The vertical axis represents deviations from the steady-state values.
Alt Text: Graphs depicting uncertainty shocks' impulse-response functions in the model, contrasting their impact under the benchmark against the cases of no extra persistence in depreciation and fixed utilization.

3.1 Case I: A model with fixed utilization

We show that a model with fixed utilization ($\zeta \to \infty$) cannot explain the empirical evidence. Figure 2 shows model-implied impulse responses (IR) of the key macroeconomic variables to a one-standard-deviation uncertainty shock. The dashed line shows the results for a model with fixed utilization.

A surge in uncertainty raises the volatility of future productivity, and increases the likelihood of future output declines. A risk-averse household has strong incentives to create a buffer to smooth out future consumption fluctuations. When utilization is fixed, the firms optimally implement precautionary savings by investing and building up a stock of capital that can be used for consumption in the future.

To see this mechanism through the optimality conditions, note that an increase in the uncertainty raises the volatility of the SDF $M_{t,t+1}$ and decreases the equilibrium risk-free rates, consistent with the precautionary savings channel. This drop in the discount rate increases the present value of the expected marginal product of capital.[23] Thus, an immediate implication of the Euler equation (IA.3) is that the firm increases its investment I_t. This is consistent with the model-implied impulse response in panel (b) of Figure 2 , but is contrary to the empirical evidence presented in Table 2, or Figure 1.

Because utilization is fixed, the depreciation rate is constant and is unaffected by uncertainty. Accordingly, panels (a) and (c) of Figure 2 show no impact of uncertainty shocks on u_t or δ_t. This is at odds with the evidence in Table 2.

Given that investment rises and depreciation is unaltered, capital must rise, as shown in panel (d) of the figure. The increase in capital, however, occurs because of an increase in investment (panel b), which is contrary to the data. Because capital K_t is predetermined, labor supply is inelastic, and current productivity A_t is unaffected by uncertainty, the current output Y_t does not react on impact to the uncertainty shocks (see dashed line in panel (e) of Figure 2). Future output increases due to the capital buildup induced by precautionary saving. This goes against existing evidence that uncertainty is associated with a drop in future output (e.g., Ludvigson, Ma, and Ng (2021), among others). We note that elastic labor supply would not resolve this counterfactual. With flexible labor, uncertainty would induce a precautionary labor supply, which would raise not only the future output but also the contemporaneous one.

Since contemporaneous output is unaffected and investment increases due to uncertainty shocks, consumption must drop for the goods market to clear. Future consumption is persistently negative due to the fact that the volatility process is persistent, suggesting persistence in the precautionary saving motive (see panel (f) of the figure). While a decrease in consumption is

[23]Notably, similar to a classical framework, high economic uncertainty unambiguously raises the conditional risk premium in our model. However, this does not override the precautionary saving motive under decreasing absolute risk aversion (see, e.g., Kimball 1990). A rise in uncertainty stimulates aggregate demand for savings, which, in the absence of any other frictions or channels, is fulfilled through aggregate investment. To support savings, the equilibrium prices adjust so that the expected return on capital falls, but by a smaller amount than the risk-free rate that accommodates an increase in the risk premium.

consistent with the empirical evidence (see, e.g., Bansal et al. 2014), its negative correlation with investment is counterfactual.

3.2 Case II: Flexible utilization and persistent depreciation

Next, we show that flexible utilization and persistent depreciation dynamics resolve the counterfactual implications of the restricted model and allow us to account for the empirical evidence. The solid lines in panels (a)–(f) of Figure 2 show model-implied impulse responses to an uncertainty shock under the benchmark model parameters.

3.2.1 Utilization and depreciation. Equation (25), describing the optimal choice of capacity utilization, explicitly links utilization to the depreciation rate: higher utilization erodes capital faster. When depreciation effects are persistent, utilization costs are intertemporal – and take into account not just the value of the existing capital stock, but also its expectations of future realizations. The more persistent depreciation is, the greater the present value of the affected stock of capital and the larger the cost of utilization.

As explained in Subsection 3.1, a positive uncertainty shock ε_w causes the risk-free rate to persistently decline. The net present value of future capital stock in Equation (25) increases. Based on Equation (25), the cost of utilization rises. The firm can benefit by lowering its utilization rate, which persistently lowers depreciation and, therefore, increases the capital stock in future periods. The future capital stock becomes more valuable in present value due to the decline in discount rates. Because the uncertainty process is persistent, the same logic applies to future periods leading to a drop in both the contemporaneous and the future utilization rate $\{u_s\}_{s\geq t}$, as seen in the solid line of panel (a) of Figure 2.

As a direct result of Equation (14), and the fact that u_t declines, the depreciation rate also declines following an uncertainty shock, as illustrated in panel (c) of Figure 2. This is consistent with the empirical evidence in Table 2 and Figure 1. The persistence parameter $\rho_\delta > 0$ magnifies the contemporaneous drops in utilization and depreciation and generates long-lasting effects of uncertainty on these variables.

3.2.2 *Investment and capital.*

Under flexible utilization, the uncertainty shock ε_w renders two opposite forces on investment: (i) as in Subsection 3.1, the risk-free rate R_f falls, which increases the expected discounted value of the future MPK_{t+s}, all else equal. This is part of the precautionary saving motive, and it operates to increase I_t. (ii) The future utilization rate declines, based on panel (a). A decline in u_{t+s} is isomorphic to a drop in future productivity. To see this, note that the equilibrium MPK_{t+s} can be rewritten as $SR_{t+s}K_{t+s}^{\alpha-1}$, where the Solow residual, SR_{t+s}, is $\alpha A_{t+s}^{1-\alpha}u_{t+s}^{\alpha}$. Thus, lower u_{t+s} decreases the future value of MPK_{t+s}, and this operates to decrease I_t. In our benchmark parametrization, the effect of (ii) dominates.[24] Hence, the investment rate persistently declines following an increase in uncertainty, as shown in panel (b) of Figure 2, consistent with the empirical evidence in Table 2. Importantly, this decline in investment is attributable to the intensive margin of utilization and not to any real options or countercyclical markups, as commonly featured in the literature.

Thus, our channel, relying on flexible utilization coupled with persistent depreciation, alters the qualitative effects of uncertainty shocks, vis-à-vis the restricted model in Section 3.1. When utilization is flexible, and can be lowered at times of high uncertainty, it replaces an increase in investment for executing precautionary saving. Lowering utilization decreases capital depreciation rate, preserves capital for future periods as a buffer against bad productivity shocks, and eliminates the need to pay an installation cost associated with purchasing new capital goods (i.e., adjustment costs). This substitution between utilization and investment for saving allows us to account for the empirical evidence, and explain the joint dynamics of output and consumption, as shown later.

Panel (d) of Figure 2 shows the impact of an uncertainty shock on the detrended capital level in the model. Capital overshoots after about 20 months, whereas the initial effect of uncertainty on capital is close to zero. This pattern resembles the data: the empirical analysis shows that following an uncertainty shock, capital either increases in future periods or, at a minimum, is unaffected in the immediate run. In particular, all columns of Table 2 show that the effect of

[24] Specifically, the utilization rate immediately drops by 0.8% after an uncertainty shock, whereas R_f (not shown in Figure 2) drops by 0.01%.

uncertainty on capital growth is indistinguishable from zero in the very short term, but turns positive thereafter. Therefore, the model dynamics are consistent with our novel evidence that uncertainty does not decrease capital in the longer run (see further details on the model fit in Section IA.3.2).

Two channels affect the sign of capital in the model: First, keeping depreciation constant, the decrease in investment in response to uncertainty leads to a drop in capital. Second, keeping investment constant, the decrease in depreciation in response to uncertainty increases capital. The parameter that governs the magnitude of the impact of utilization on depreciation is σ_u (see Equations (13) and (14)). In our model, it is set to a relatively small value to match the utilization and depreciation moments in the data (in particular, it disciplines the mean of utilization). Thus, the immediate effect of utilization on depreciation is sufficiently small that the first channel dominates in the short run. However, the impact of uncertainty on utilization is much more long-lasting than on investment. Coupled with a persistent effect of utilization on depreciation, the cumulative effect of underutilizing capital intensifies over time. In one to two years following the uncertainty shock, the effect of a decrease in depreciation dominates the decrease in investment and boosts medium- to long-term capital.

Existing papers that produce a decline in investment following an uncertainty shock (e.g., using real options, Bloom 2009, or an increase in the risk premium, Di Tella and Hall 2021) typically assume that the depreciation rate is constant and, consequently, are unable to reconcile the divergence between investment and capital following uncertainty shocks.[25]

The divergence between capital and investment occurs only with respect to the second-moment shocks. While such divergence can potentially arise from first-moment shocks, the quantitative impact of these shocks on investment is larger than on depreciation, generating comovement between investment and capital. Hence, capital is procyclical, as in the data.

[25] Even if depreciation is time-varying, existing channels for uncertainty-induced recessions can fail to deliver this finding. For example, Basu and Bundick (2017) use countercyclical markups to make investment drop in response to uncertainty. Their model features flexible utilization, which induces time-varying depreciation. Utilization in their model has only a quantitative but not a qualitative impact on the results. In particular, because the authors do not assume that depreciation dynamics are persistent, we confirm in Internet Appendix Figure IA.3.13 that an uncertainty shock leads to a drop in both investment and future capital growth in their model, in contrast to our evidence.

3.2.3 *Output and consumption.*

In contrast to a model with fixed utilization, contemporaneous output can decrease with uncertainty because of the immediate drop in the utilization rate. The future output depends on the balance between the decrease in future utilization and investment rates and the increase in future capital due to a fall in the depreciation rate. The impulse responses show that a drop in utilization (panel a) dominates an increase in capital (panel b), which leads to a decline in output in the future (panel e)). Lastly, via market clearing, consumption is the difference between output and investment. Following an uncertainty shock, output falls more strongly than investment, causing consumption to decrease. Intuitively, investment is driven by two countervailing forces – a precautionary saving motive versus a drop in the future effective productivity caused by lower utilization. This weakens the response of investment to uncertainty shocks compared to the response of output to these shocks. While consumption also decreases in the model with fixed utilization (see Subsection 3.1), the drop is smaller compared to the flexible utilization model.

3.3 The role of persistence in depreciation

We show that persistent depreciation ($\rho_\delta > 0$), in excess of the endogenous persistence in utilization, is a key ingredient for our results. Flexible utilization alone is not sufficient for the model to fully explain the novel features of the data. The dotted line in panels (a)–(f) of Figure 2 shows model-implied impulse responses to an uncertainty shock ε_w with flexible utilization but no additional persistence in depreciation ($\rho_\delta = 0$).

There are two major differences in uncertainty impulse responses in the restricted model ($\rho_\delta = 0$) compared to the benchmark. First, while some of the responses remain qualitatively similar, the quantitative magnitudes are minuscule compared to the benchmark case of $\rho_\delta > 0$. For example, utilization immediately declines by 0.02% versus 0.6% when $\rho_\delta = 0$ and $\rho_\delta = 0.99$, respectively. Similarly, consumption falls by 0.05% (0.25%) without (with) additional persistence in depreciation dynamics.

As shown in Section 2.4, when $\rho_\delta = 0$ the utilization choice is static. The benefit of reducing utilization is that it slows down the depreciation rate when a capital buildup is beneficial to the agent. With $\rho_\delta = 0$, this benefit pertains only to the contemporaneous stock. The precautionary effect, which creates a dynamic link among utilization, discount rates, and the capital stock in future periods, disappears. Thus, the decline in utilization following an uncertainty shock is much smaller, which qualitatively affects the investment dynamics. Panel (b) shows that if $\rho_\delta = 0$, the investment rate increases, despite the decrease in utilization. Recall that investment is determined by the trade-off between a drop in discount rates and a drop in the Solow residual, which positively depends on utilization. If the change in utilization is minor, the discount rate effect dominates, leading to precautionary saving primarily through higher investment, contrary to the data.

4 Implications for Asset Prices

We show that our model is capable of producing a sizable equity premium, and that a considerable component of the equity premium is due to the uncertainty shocks.

4.1 Unconditional pricing moments

In the model, firms are all-equity financed, there is no operating leverage due to fixed costs, and the dividend cash flow is the residual output net of investment and wages. In reality, firms take substantial financial and operating leverage, and distributions to the shareholders can be subject to firm-specific payout shocks. To bring the model closer to the data, we follow Croce (2014) and consider the following levered return as a proxy for the market excess return: $R^e_{m,t} = \phi_{lev}(R^{\text{UNLEV}}_{d,t} - R_{f,t-1}) + \sigma_d \varepsilon_{d,t}$, where $\varepsilon_{d,t} \sim N(0,1)$ captures the effect of idiosyncratic dividend shocks. García-Feijóo and Jorgensen (2010) estimate that the total degree of leverage (joint operating and financial leverage) implies $\phi_{lev} = 3.5$. This estimate is consistent with the leverage parameter in Abel (1990), and Bansal and Yaron (2004). The shocks $\varepsilon_{d,t}$ do not covary with the marginal utility and do not affect the equity premium. These shocks only affect excess return volatility. We set σ_d to target the volatility of excess returns in the data.

Panel (a) of Table 6 shows the model-implied moments of the excess equity returns and the risk-free rate. Accounting for financial leverage and idiosyncratic dividend shocks, the model can match the key features of the equity return in the data. In the data, the mean of the excess

Table 6
Model-implied asset prices

A. Asset pricing moments

	Model		Data
Market excess return			
Mean (%)	7.29	[2.43, 12.97]	4.58
Std. dev. (%)	17.78	[13.94, 22.47]	17.09
AC(1)	−0.01	[−0.23, 0.26]	−0.05
Risk-free rate			
Mean (%)	0.91	[-0.33, 1.79]	1.04
Std. dev. (%)	1.20	[0.69, 2.20]	1.71
AC(1)	0.58	[0.29, 0.77]	0.79

B. Equity premium decomposition

	$E[R_m^e]$ (%)	First-moment contribution	Second-moment contribution	$\sigma(\Delta c)$ (%)
(1) Data	4.58	–	–	1.22
(2) Benchmark	7.29	73.24%	26.75%	2.16
(3) Fixed utilization	2.21	196.82%	−96.82%	1.89
(4) No extra persistence in depreciation	2.20	207.07%	−107.07%	1.97

Panel A of the table shows model-implied asset-pricing moments along with their empirical counterparts. Panel B of the table shows the empirical and model-implied moments for the equity premium $E[R_m^e]$ and the decomposition of the equity premium to the first and second moments of productivity shocks. The risk-premium contribution of each shock is computed as the multiplication of the unconditional market exposure to the shock multiplied by the average market risk price of the shock. To compute the share of each shock, we divide the shock's risk premium by the total market risk premium. For ease of comparison across calibrations, we also report consumption growth's volatility $\sigma(\Delta c)$. The results are shown for calibration under the benchmark parameter values and restricted calibrations with feature fixed utilization ($\zeta \to \infty$) or flexible utilization but no extra persistence in depreciation dynamics ($\rho_\delta = 0$). For each moment of interest, the table shows the median value and the 5th and 95th percentiles based on 200 simulations of short sample monthly paths. Each model-implied path is aggregated to an annual horizon.

returns is 4.58% (with a 95% confidence interval of [0.18%, 9.47%]). The model-implied average excess return is 7.29%, close to the data and well inside the empirical confidence interval. In the data, the volatility of the market excess returns is 17.09% per annum, which is nearly identical to the volatility of excess returns in the model. The autocorrelation of the returns in both the model and the data is close to zero. The risk-free rate is about 1% in both the model and the data. The risk-free rate in the model is sufficiently smooth and features similar persistence as in the data.

4.2 First-moment shocks contribution

Panel (B) in Table 6 shows that about three-quarters of the equity premium contribution originates from first-moment productivity shocks. As demonstrated in Croce (2014), attaining a sizable equity premium is a considerable challenge in general equilibrium, in the absence of a slow-moving productivity process. Our model can endogenously generate sizable variation in long-run consumption risk through two channels. As shown by Kaltenbrunner and Lochstoer (2010), investment can create long-run risk. That is, consumption smoothing via investment implies that expected consumption growth is time-varying. Unique to our setup, flexible utilization can also create long-run risk because of our depreciation dynamics in Equation (14). Indeed, any change in utilization creates a small but persistent effect on depreciation. This causes a slowly decaying response to capital, which translates into a small predictable component in expected consumption growth.

4.3 Uncertainty shocks contribution

Panel (a) of Figure 3 shows that in our benchmark model, uncertainty shocks increase the marginal utility. Notably, the quantitative impact of uncertainty shocks on the stochastic discount factor—that is, the market price of uncertainty risks—remains quite similar in model specifications with fixed utilization ($\zeta \to \infty$) or with no extra persistence in depreciation $\rho_\delta = 0$.

Intuitively, with Epstein and Zin (1991) utility and a preference for early resolution of uncertainty, the continuation utility decreases with a more volatile consumption profile, which increases $M_{t-t,t}$. In our model, the firm production function features constant returns to scale, and consequently, valuation and investment comove. Simply put, Tobin's q is a sufficient statistic for the (ex-dividend) firm value, and Equation (IA.5) suggests that q_t depends positively on I_t/K_t. Consider Case I from section 3.1, in which utilization is fixed. The section shows that uncertainty shocks increase investment due to a precautionary saving motive. This implies that the firm valuation increases with uncertainty; indeed, the dashed line in panel (b) in Figure 3 shows that the firm realized excess return increases after an uncertainty shock, producing

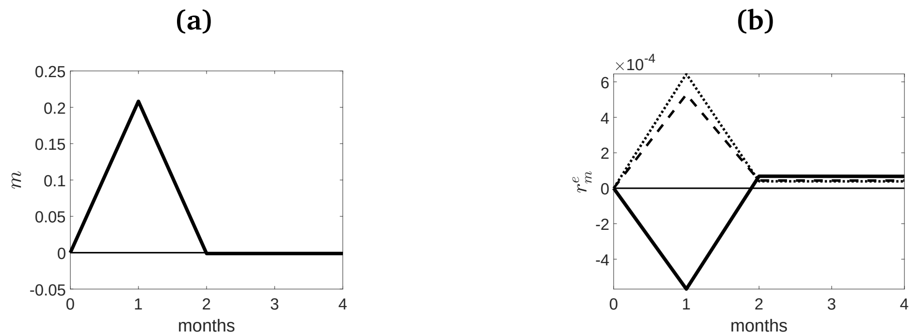

Figure 3
Model-implied IR to uncertainty shocks: Prices
The figure shows impulse responses of (a) the marginal utility m and (b) excess returns r_d^e to uncertainty shocks. The solid line shows the results using the benchmark model parameters. The dotted line shows the results when $\rho_\delta = 0$ (no extra persistence in depreciation). The dashed line shows the results when $\zeta \to \infty$ (fixed utilization). The horizontal (vertical) axis represents months (deviations from the steady-state values).
Alt Text: Graphs depicting uncertainty shocks' impulse-response functions in the model, showing their effect on the stochastic discount factor and excess returns.

a positive risk exposure.[26] Since the firm value is a hedge against uncertainty shocks, the uncertainty shocks contribute negatively to the risk premium. The quantitative contribution of uncertainty shocks to the equity premium in the steady state can be approximated by the negative of the product of the impulse response of the marginal utility and the impulse response of the excess return at time $t = 1$ (i.e., contemporaneously with the uncertainty shock). Row (3) of panel (B) in Table 6 shows that with fixed utilization, the contribution of uncertainty shock to the equity premium is -96.8%. The equity premium is considerably lower than the benchmark equity premium, despite the fact that the two specifications feature nearly identical consumption volatility; see Table 6.

Panel B of Figure 3 further shows that in the case of no extra persistence in depreciation, the firm beta to uncertainty risks is positive and even larger than with fixed utilization. Hence, the risk premium for uncertainty shocks remains negative, and the overall equity premium is well below the benchmark specification. In contrast, when utilization turns flexible and has a persistent effect on depreciation, precautionary saving is no longer accomplished by investment, but rather by decreasing utilization. Since investment drops, the firm risk exposure

[26]The impulse responses in Figure 3 are to the unlevered equity return, $R_{d,t}^{\mathrm{UNLEV}}$. The impulse responses to the levered return R_m are identical up to the scale factor ϕ_{lev}.

to uncertainty shocks is negative, as shown by the drop in realized return in panel (b) of Figure 3. As shown in row (2) of panel (B) in Table 6, in the benchmark specification uncertainty shocks contribute sizably to the total equity premium, at just over 26%.

4.4 Return predictability

In the model, the conditional equity premium is time-varying, and in particular, it is affected by fluctuations in uncertainty. To evaluate the dynamic impact of uncertainty on the equity premium, we run the following predictive regression:

$$R^e_{t+1\to t+k} = const + \beta_{rv} RV_t + error,$$

where $R^e_{t\to t+h}$ is the future market excess return up to horizon h and RV_t is the current 12-month rolling window realized volatility of market returns. We compare model predictions across three cases: the benchmark ($\rho_\delta > 0$), when we shut down the excess depreciation persistence ($\rho_\delta = 0$), and when we shut down flexible utilization ($\zeta \to \infty$).

The results are shown in Internet Appendix Table IA.3.9. In the data, the realized variance of market returns can account for 2% of future return variation at a one-year horizon, and up to 8% at five years. When $\rho_\delta = 0$, or when utilization is fixed, the restricted model is unable to generate a sufficient amount of return predictability, and the $R^2 s$ are 2% or below at all the horizons. In contrast, under the benchmark, the R^2s are substantially higher, reaching 5% at a five-year horizon. Although the R^2s in the model are slightly lower than in the data, they are quite similar: both increase with the predictive horizon.

5 Assessing the Mechanism

5.1 Utilization and volatility risk

Our mechanism provides testable predictions for the connection between utilization, uncertainty, and asset prices that we can assess in the cross-section of returns. The model predicts that the uncertainty exposure of firm return is connected to flexibility in its utilization adjustments. Specifically, firms that have (i) higher sensitivity of capital utilization to aggregate uncertainty,

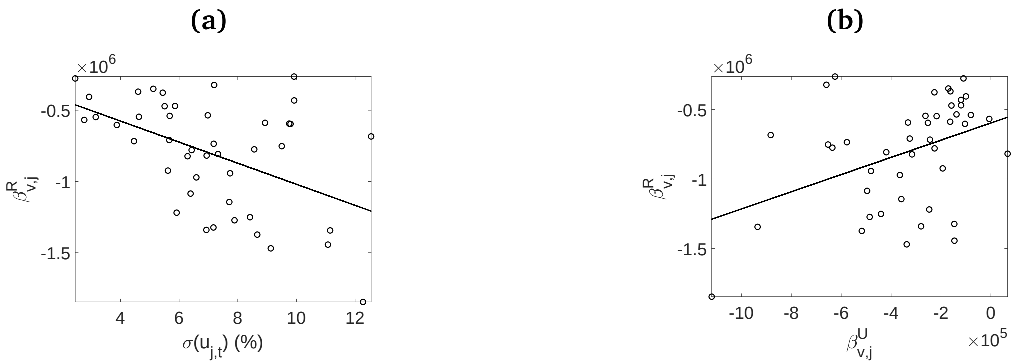

Figure 4
Uncertainty risk exposures and utilization
The figure shows scatter plots of industry j return beta to uncertainty risks, $\beta^R_{v,j}$, against industry j standard deviation of utilization rate, $\sigma(u_j)$ (panel a), or industry j utilization beta to uncertainty risks, $\beta^U_{v,j}$. The solid line indicates the best linear fit.
Alt Text: Charts depicting industries' risk exposures to uncertainty risk against their utilization rates' volatility and utilization rates' sensitivity to uncertainty shocks.

(ii) more volatile utilization, or (iii) higher persistence in depreciation relative to utilization feature stronger (more negative) exposure to aggregate uncertainty.

Intuitively, cutting utilization in response to an uncertainty shock benefits the firm by conserving capital against future bad shocks. When utilization is more flexible (i.e., $\uparrow \sigma(u)$, more volatile utilization governed by lower ζ), the firm can drop its utilization rate more aggressively, implying higher sensitivity of utilization to uncertainty. A sharper drop in utilization lowers the expected MPK more strongly. This yields a larger decrease in investment and in Tobin's q (valuation), leading to a more negative exposure to uncertainty shocks. Further, if depreciation is more persistent than utilization, then the stock return exposure to uncertainty risk should be more negative. To see this, assume that there is no excess persistence. This is equivalent to the case where $\rho_\delta = 0$. In this case, utilization alone cannot serve as a quantitatively relevant vehicle for precautionary savings, as the drop in utilization would induce only a transitory decline in depreciation. As a result, the uncertainty risk exposure is positive. On the other hand, when ρ_δ is higher, then utilization can substitute investment for precautionary savings and the exposure to uncertainty shocks turns negative.

We verify these predictions using annual industry-level utilization rates from the Federal Reserve Board (FRB) report on Industrial Production and Capacity Utilization (report G.17).

The cross-section encompasses durable producers (17 industries), nondurable producers (17 industries), and mining and utilities (10 industries). The cross-sectional data start in 1972.

Our model features two exogenous shocks to the driving forces, productivity level and its volatility. Their structural empirical proxies, as implied by the VAR system in Equation (8), are given by $\eta_{TFP,t} \equiv Chol(\Sigma)\varepsilon'_{\Gamma,t}e_{TFP}$ and $\eta_{v,t} \equiv Chol(\Sigma)\varepsilon'_{\Gamma,t}e_{v}$, respectively. To be consistent with the theory, we estimate for each industry j its macro uncertainty exposure using a time-series regression of the industry stock return on these shocks:

$$R_{j,t} = const + \beta^R_{v,j}\eta_{v,t} + \beta^R_{g,j}\eta_{TFP,t} + error. \tag{26}$$

Similarly, for each industry j we estimate the sensitivity of its utilization growth rate to uncertainty shocks, $\beta^U_{v,j}$, using the following projection:

$$\Delta u_{j,t} = const + \beta^U_{v,j}\eta_{v,t} + \beta^U_{g,j}\eta_{TFP,t} + error, \tag{27}$$

where $\Delta u_{j,t}$ is the log growth of industry j's utilization rate. $\beta^R_{v,j}$ ($\beta^U_{v,j}$) is the return (utilization) exposure of industry j to macro uncertainty. We also estimate the standard deviation of the capacity utilization rate for each industry j, $\sigma(u_j)$.

Panel A (B) of Figure 4 shows a scatter plot of $\{(\beta^R_{v,j}, \sigma(u_j))\}_j$ ($\{(\beta^R_{v,j}, \beta^U_{v,j})\}_j$) pairs along with the linear fit. First, for almost all industries, the uncertainty risk exposure is negative, in line with existing studies. Almost all utilization elasticities to uncertainty are negative as well. Second, the cross-sectional correlation between $\{\beta^R_{v,j}\}_j$ and $\{\sigma(u_j)\}_j$ is -0.47 with p-value$<$ 1%. The correlation between $\{\beta^R_{v,j}\}_j$ and $\{\beta^U_{v,j}\}_j$ is 0.40 with p-value$<$ 1%, confirming the predictions that utilization is key for determining uncertainty risk exposures.

To test the relationship between uncertainty exposure and excess persistence in depreciation, we use a subsample of 18 industries for which depreciation rate is also available from the BEA. Recall that extra persistence in depreciation relative to utilization is a key novel ingredient of our model, and we devoted a large part of the empirical analysis and model interpretation to make this point in the aggregate data.[27] Remarkably, the difference in the persistence of depreciation over utilization lines up well with the uncertainty exposures of industry returns.

[27] We can provide further support for our aggregate results in the cross-section of industries. In Table IA.2.7 in the Internet Appendix we show that across all the 18 matched industries, the persistence in industry utilization rate is always below that in depreciation, and the difference is statistically significant with all p-values below 1%.

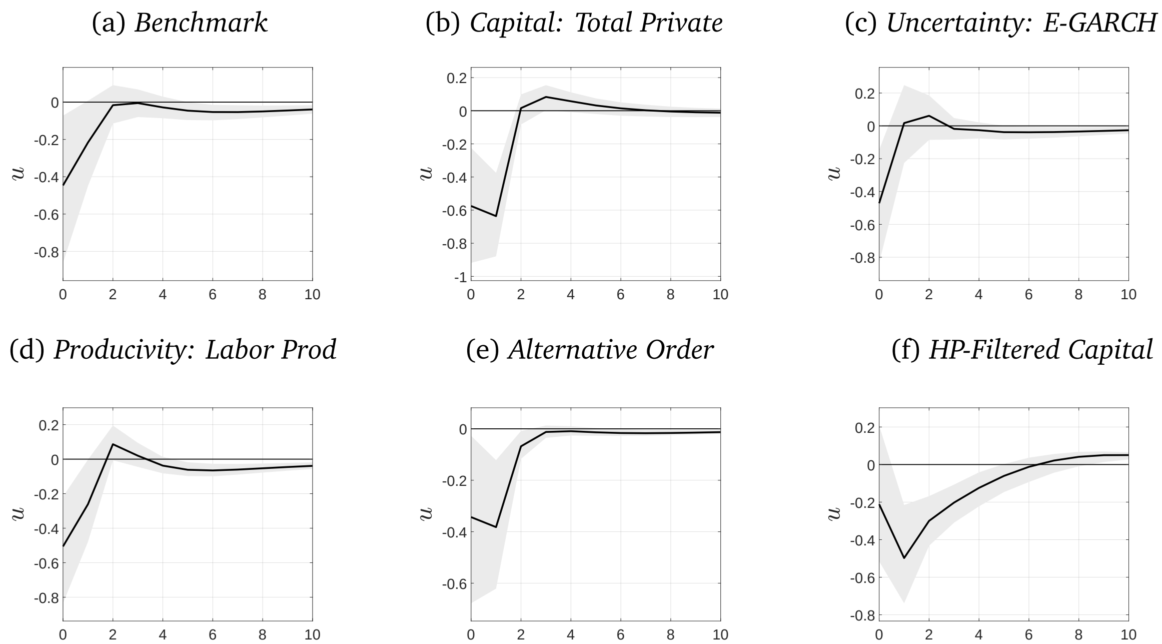

Figure 5
Uncertainty shocks and utilization
The figure shows one-standard-deviation uncertainty shock impulse responses of utilization, based on the benchmark and across alternative measures and methodologies.
Alt Text: Graphs depicting uncertainty shocks' impulse-response functions, showing their impact on capacity utilization rates.

Figure IA.2.8 in the Internet Appendix shows that as the gap in persistence coefficients increases, the uncertainty risk exposure becomes more negative.

5.2 Utilization and uncertainty

Our model predicts that uncertainty shocks should have a negative impact on the current and future utilization growth rates. Data on capacity utilization are sourced from St. Louis Federal Reserve Economic Data (FRED) and span annually from 1968 to 2022.[28] To examine the dynamic impact of uncertainty shocks on the utilization rate we use the auxiliary VAR methodology, as described in Equation (9).

We consider the results for the benchmark case, as well as other cases representing key departures along measurements and methodologies. The results are shown in Figure 5. Across

[28]While the utilization rate is stationary for most of the sample period, allowing us to compute its unconditional moments, studying its dynamic impact is more subtle. Utilization time series shows a slight downward trend starting in the very last part of our sample, beginning in 1989 (see José Gahn 2020). To ensure that no spurious result stems from later years, we hp-filter the raw data for subsequent time-series analysis.

all specifications, the uncertainty shock drops utilization in the short run. Across all horizons, whenever significant, the effect is negative. In some specifications, the effect persists at longer horizons as well, broadly consistent with the model.

5.3 Utilization and depreciation

Our model assumes a positive and persistent link between capacity utilization and future depreciation rates. In Section IA.4 of the Internet Appendix we test this restriction in the data. Projecting future depreciation rates on lagged utilization rates shows that the predictive effect of utilization on future depreciation is persistent. We further clarify how measurement practices by Compustat and the BEA could give rise to this empirical observation. Moreover, we discuss how the dynamic link between utilization and depreciation rate at the aggregate level can be microfounded in a model featuring one of the following factors: changes in the composition of capital goods, capital reallocation, or vintage effects.

6 Conclusion

We provide novel evidence for the propagation of uncertainty shocks in real and financial capital markets. We show that elevated macroeconomic uncertainty is associated with higher future capital growth. This is quite surprising, given ample evidence that uncertainty suppresses investment. To reconcile this, we show that high uncertainty leads to lower depreciation of existing capital, which dominates the adverse impact of uncertainty on investment.

We develop a parsimonious framework to account for our empirical evidence. Our economic explanation hinges on flexible capital utilization and persistence of capital depreciation, and provides novel insights on the implementation of precautionary saving in a production setting. Under our mechanism, uncertainty shocks are associated with a high marginal utility and a decrease in equity valuations. This implies that uncertainty shocks contribute substantively to the level and variation in the equity premium. Moreover, the mechanism induces low-frequency variations in expected consumption growth. The model also provides implications for the uncertainty betas of equity returns and utilization rates, which we verify in the data.

Overall, our empirical evidence and the theoretical model highlight the key role of intensive margins for explaining the macroeconomic and asset-price data jointly. Our mechanism is simple to incorporate into any production model, and it gives rise to a rich interplay between time-varying risk and capital accumulation, as well as realistic implications for asset pricing.

Code Availability: The replication code is available in the Harvard Dataverse at https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/V1HZGI

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