Product Life Cycle Heterogeneity in the Transmission of Uncertainty[*]

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February 16, 2026

Abstract

I show that firms at different stages of the product life cycle respond differently to increases in economic uncertainty, and that this heterogeneity matters for understanding the aggregate implications of uncertainty for the economy. In response to higher uncertainty, early-stage firms increase investment, leading to greater innovation output (e.g., product patents). In contrast, late-stage firms reduce both investment and innovation. Using highly granular product-level data, I find that when uncertainty rises, early-stage firms increase product entry and exit, shifting their portfolios toward newer products, whereas late-stage firms scale back portfolio adjustments by reducing entry and exit activity. A real-options model with product life-cycle heterogeneity rationalizes these patterns: uncertainty boosts investment, innovation, and product experimentation when firms hold valuable growth options but discourages such activity when projects are mature and less scalable. My findings reconcile mixed results in the literature and provide the first evidence that a firm's product life cycle stage is crucial for understanding how economic uncertainty affects corporate investment and product markets.

KEYWORDS: Innovation, investment, product cycle, product markets, uncertainty.
JEL CLASSIFICATION: G31, G32, D22, D25.

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[*] I am thankful to Heitor Almeida, Dan Bernhardt, Yuchen Chen, Jaewon Choi, and Josef Zechner for their invaluable guidance and support. I would also like to thank Murillo Campello, Daniel Carvalho, Danilo Cascaldi-Garcia, Ian Dew-Becker, François Gourio, Gerard Hoberg, Greg Howard, Rustom Irani, Dalida Kadyrzhanova, Gaurav Kankanhalli, Mete Kilic, Hyunseob Kim, Emilio Osambela, Dino Palazzo, Vicenzo Quadrini, Joy Tong, Selale Tuzel, Michael Weisbach, Youngsuk Yook, Miao Ben Zhang, Nick Zarra, and Yucheng Zhou for helpful comments. Disclaimer: *Researchers' own analyses calculated (or derived) based in part on data from Nielsen Consumer LLC and marketing databases provided through the NielsenIQ data sets at the Kilts Center for Marketing Data Center at the University of Chicago Booth School of Business. Conclusions drawn from the NielsenIQ data are those of the researchers and do not reflect the views of NielsenIQ. NielsenIQ is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.*

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1. Introduction

How firms respond to economic uncertainty has been a central question in economics and finance, but clear answers have yet to emerge.[1] While a large body of research finds that higher uncertainty dampens investment and innovation by increasing the value of waiting, other studies argue that growth opportunities can lead firms to invest more when uncertainty rises. Consequently, the effect of uncertainty on firm behavior remains unclear. Moreover, most existing work has focused on financial and investment policies, overlooking how uncertainty shapes product entry, exit, and portfolio adjustments, decisions that are central to firms' growth trajectories and competitive dynamics.

This paper establishes that the research on corporate decision-making under uncertainty misses important nuances by just focusing on whether uncertainty hurts or boosts firms' investment, innovation, and product-market outcomes: both outcomes obtain in the data. I posit that firms' reactions to increased uncertainty vary with their stage in the product life cycle. Early-stage firms, with high growth potential but uncertain prospects, may view uncertainty as an opportunity to innovate and expand. By contrast, late-stage firms, whose products are mature and cash flows more predictable, may treat uncertainty primarily as a risk that justifies caution and delay. Consistent with my hypothesis, I find heterogeneous effects on investment and financing policies, innovation, and product-market decisions across the product life cycle.

I show that early-stage firms respond to higher uncertainty by increasing R&D and capital expenditures, leading to more innovation (e.g., patent applications). In contrast, late-stage firms cut back on investment and reduce innovation. In the product market, early-stage firms expand experimentation via greater product entry and exit, while late-stage firms retrench and prioritize portfolio stability. These heterogeneous responses help reconcile prior conflicting findings in the literature. They also have important aggre-

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[1] I review the literature in Section 2. See also Campello and Kankanhalli (2022) for a discussion of uncertainty and corporate decisions.

gate implications: the expansionary behavior of early-stage firms offsets a sizable share of the decline in investment that would occur if all firms behaved like late-stage firms.

To understand these results and derive new insights, I develop a real-options model of firm investment under uncertainty with product life-cycle heterogeneity. Firms allocate resources across three project types: exploratory (growth-option) R&D, incremental (process-improvement) R&D, and mature capital investment; in addition, they choose innovative capacity that scales the returns of successful exploratory projects. Uncertainty enters as a mean-preserving spread in project payoffs. Exploratory R&D is multi-stage: firms invest upfront, receive an interim signal, abandon unpromising projects, and scale successful ones using innovative capacity. Incremental R&D and mature investments, by contrast, are irreversible but can be delayed, giving rise to an option-to-wait. Firms differ by life-cycle stage in both the composition of their opportunity sets and the strength of complementarities between innovative capacity and growth, which are strong for early-stage firms and weak for late-stage firms.

In the model, the effect of uncertainty on investment depends on which project margins dominate firm behavior. For exploratory growth options, higher uncertainty raises expected value through the abandonment option and the convex scaling of payoffs via innovative capacity, encouraging both R&D and capacity investment, especially for early-stage firms with strong growth complementarities. By contrast, for incremental R&D and mature projects, higher uncertainty increases the value of delaying commitment, reducing immediate investment. Because early-stage firms' portfolios are tilted toward exploratory projects and scalable opportunities, the expansionary growth-option channel dominates, leading uncertainty to raise both R&D and Capex. Late-stage firms, whose portfolios are concentrated in mature and incremental activities with limited scalability, are instead governed by the option-to-delay mechanism, so uncertainty lowers their overall investment. The model thus generates life-cycle–dependent, opposite investment responses to uncertainty, providing a unified explanation for the empirical heterogeneity that I document.

I start my empirical analysis by examining how uncertainty affects investment and innovation. For this analysis, I use a text-based measure to classify firms by product life cycle stage. This measure builds on Hoberg and Maksimovic (2022) to decompose a firm's product life cycle into four stages: product development stage (life1), process optimization stage (life2), mature product stage (life3), and product decline stage (life4). To measure uncertainty, I follow Alfaro, Bloom, and Lin (2024) and use instrumented firm-level option-implied volatility. This instrumentation strategy allows me to isolate second-moment uncertainty effects from correlated first-moment effects. As the relationship between the moments may not be linear, I further refine this strategy by controlling for nonlinearities in the upside, which may be particularly important for early-stage firms. I complement this analysis by using a comprehensive set of uncertainty proxies in order to remain agnostic about the specific source of uncertainty.

I show that following a one standard deviation increase in uncertainty, early-stage firms increase their R&D and capital expenditures by 4.6 and 1.0 percentage points, respectively. The positive effect on capital expenditures underscores that the heterogeneity of the impact of uncertainty does not depend only on the type of investment. Of note, this increase in capital expenditures is much smaller than the increase in R&D expenses, consistent with capital expenditures being a type of investment that is more costly to reverse, making the associated growth option less valuable. In contrast, for firms in later product life cycle stages, a one standard deviation increase in uncertainty leads to decreases of 1 and 5.5 percentage points in R&D and capital expenditures, respectively.

To assess the aggregate implications of these heterogeneous responses, I conduct a simple back-of-the-envelope exercise. I convert the estimated investment changes into dollar terms using firms' average total assets and then scaling by the number of firms in each group to obtain aggregate effects. I show that early-stage firms help offset the aggregate negative effect of uncertainty on investment. In particular, their expansionary response offsets about 27 percent of the total decline that would occur if all firms behaved like late-stage firms. This highlights the importance of accounting for product life cycle heterogeneity when evaluating the macroeconomic consequences of uncertainty and indicates how the composition of firms in the economy shapes the overall sensitivity of investment to uncertainty.

I next investigate the impacts of uncertainty on innovation. In line with these effects on firms' innovation inputs, I find significant effects of uncertainty on firms' innovation outputs. For early-stage firms, after three years, a one standard deviation increase in uncertainty increases both the probability of filing a patent and the number of patents filed by 4.58 and 1.3 percentage points, respectively. I decompose this analysis following the categorization in Ganglmair, Robinson, and Seeligson (2022), and define "product patents" as patents with over 50% of the claims being product claims. Early-stage firms significantly increase product patents relative to other patents, consistent with being in the product innovation stage, so their innovation should be concentrated in product patents. The opposite holds for later-stage firms, highlighting the important role of the product cycle in transmitting uncertainty to firms' innovation.

Uncertainty can also affect firms' product market strategies. Investment decisions determine the resources and incentives available for developing, launching, and discontinuing products. As a result, heterogeneity in investment behavior should naturally translate into heterogeneity in how firms manage their product portfolios. To examine the product market consequences of uncertainty, I use highly granular product-level data from NielsenIQ's Retail Scanner, which covers the universe of products of both public and private firms in the consumer-goods sector. I link the product-level data to firm identifiers and construct each firm's product portfolio. This lets me measure the age of firms' product portfolios and track how uncertainty affects product entry, exit, and the overall composition of portfolios across different stages of the life cycle.

A key challenge in studying how uncertainty affects firms' product portfolios is the lack of firm-level uncertainty measures.[2] To overcome this challenge, I construct a new firm-level measure of product-market uncertainty (PMU). Each firm-quarter, I compute the rolling standard deviation of log revenue growth for each product over a four-quarter window, and then aggregate these volatilities to the firm level using product revenue shares as weights. This measure captures a firm's exposure to volatile product markets by incorporating both the intrinsic risk of each of its products and a product's importance in the firm's portfolio. Unlike traditional measures of firm-level sales volatility, which reflect ex-post fluctuations in total revenue, PMU isolates the underlying composition of product-level risk. My PMU measure offers a richer view of firm-level uncertainty rooted in product-market dynamics that can be applied to both public and private firms, a feature that existing measures lack.

I show that, in response to higher firm-level product-market uncertainty, early-stage firms significantly increase both product entry and exit, thereby shifting their portfolios toward newer products. The option-like nature of early-stage product strategies, where small bets can yield large returns, makes this churn a rational response to uncertainty, as firms seek to explore upside opportunities while shedding underperforming products. Late-stage firms, by contrast, reduce both entry and exit, consistent with a strategy of consolidation. For these firms, uncertainty discourages costly adjustments to established portfolios, making stability more attractive than reoptimization. These results are consistent with the impact of uncertainty on investment, underscoring the complementary nature of firms' financial and strategic decisions.

Overall, my findings indicate that product life cycle heterogeneity plays an important role in the transmission of uncertainty. My paper is the first to examine how uncertainty affects firms' product portfolios and to show that firms at different stages in the prod-

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[2] Because my product-level analysis includes both private and public companies, I cannot use option-implied volatility.

uct life cycle respond differently to increases in uncertainty, and that this matters for understanding the aggregate implications of uncertainty for the economy.

The paper is organized as follows. Section 2 reviews the related literature. Section 3 discusses the theoretical framework. Section 4 presents the investment and innovation analysis, Section 5 documents evidence on product market outcomes, and Section 6 concludes.

2. Related Literature

This paper contributes to the corporate finance literature in several ways. A sizable literature has documented a negative relationship between uncertainty and investment (Bloom, Bond, and Van Reenen, 2007; Julio and Yook, 2012; Caggese, 2012; Gulen and Ion, 2016; Bhattacharya, Hsu, Tian, and Xu, 2017; Kim and Kung, 2017; Cong and Howell, 2021; Kermani and Ma, 2023; Kumar, Gorodnichenko, and Coibion, 2023; Campello, Kankanhalli, and Kim, 2024; Alfaro, Bloom, and Lin, 2024). Notable exceptions are Lin, Schmid, and Weisbach (2025), who focuses on the electricity industry to show that uncertainty about future electricity demand increases investment in plants with flexible production technologies while depressing investment in non-flexible ones, and Grigoris and Segal (2025), who shows that the impact of uncertainty shocks on firm-level investment depends on their origin in supply chains.

I contribute to this literature by providing the first evidence that the overall sensitivity of investment to uncertainty does not depend only on asset flexibility, investment type or origin in supply chains. My findings reveal that the effect of economic uncertainty on firms' investment policies varies across firms' product life cycles—early-stage firms increase both physical and intangible investment, while late-stage firms reduce it. This distinction provides novel implications: the expansionary behavior of early-stage firms offsets a substantial share of the decline in investment that would arise if all firms behaved like late-stage firms.

The literature on the relationship between uncertainty and innovation is replete with mixed evidence. Stein and Stone (2013), Atanassov, Julio, and Leng (2024) and Campello, Cortes, d'Almeida, and Kankanhalli (2022) show that U.S firms increase R&D in response to higher uncertainty, consistent with the growth option theory. In contrast, Alfaro, Bloom, and Lin (2024) find that in response to uncertainty shocks, firms cut intangible investment. Bhattacharya, Hsu, Tian, and Xu (2017) show that higher uncertainty around national elections reduces firm patenting. Caggese (2012) finds that an increase in uncertainty has a large negative effect on the risky innovation of entrepreneurial firms. Coiculescu, Izhakian, and Ravid (2023) argue that firms facing high ambiguity decrease and delay both R&D and patents, but riskier firms invest more in R&D, but they also file fewer patents.

The different findings above can, in part, be explained by analyzing firms at different stages of their product life cycle. Atanassov, Julio, and Leng (2024) show that political uncertainty affects R&D only for high-tech and high-growth firms, which are more likely to be in the early stages of their product life cycle. Coiculescu, Izhakian, and Ravid (2023) reach similar conclusions, showing that higher risk is associated with greater R&D among high-tech firms; however, no effect is found for patents. In contrast, Alfaro, Bloom, and Lin (2024) focus on public U.S. firms and show that the average impact of uncertainty on intangible investment is negative. Caggese (2012) uses a sample of Italian manufacturing firms with an average age of 23 years that are typically in later stages to show that higher uncertainty decreases innovation.

I reconcile the mixed findings in the literature by showing that firms' responses to uncertainty depend on their product life cycle stage. Early-stage firms increase innovation inputs (R&D), outputs (patents), and capital expenditures when uncertainty rises, while late-stage firms cut investment, acquisitions, and innovation, and increase savings. These patterns hold across multiple outcomes and are not driven by any single investment type. The results are robust to various uncertainty measures, firm-level controls, and fixed effects that absorb industry-time shocks, allowing identification from within-industry variation across firms.

My work also relates to the product markets literature. Argente, Lee, and Moreira (2018) document a decline in product reallocation during the Great Recession. Hoberg and Maksimovic (2022) develop a novel 10-K text-based model of product life cycles and show that conditioning on the life cycle substantially improves the power of q to explain investment and reveals a natural ordering of investments over the life cycle. Hajda and Nikolov (2022) document how product life cycle affects investment and financing by estimating an industry equilibrium model that embeds product portfolio characteristics. Chen, Hoberg, and Maksimovic (2023) find that the product life cycle impacts disclosure policies. Argente, Lee, and Moreira (2024) show that the sales of individual products decline at a steady pace over most of their life cycles, mostly because the appeal of products declines with age. None of these papers study the relationship between uncertainty and product markets. I use granular product-level data to construct a novel firm-level measure of product market uncertainty and show that uncertainty affects product market outcomes differently depending on the product life cycle stage.

3. Theoretical Framework

I develop a real-options model to study the impact of uncertainty on firm investment. This model integrates three building blocks from the investment literature but applies them in a life-cycle-dependent setting. First, following Bar-Ilan and Strange (1996), growth-option projects are modeled as multi-stage R&D with investment lags: firms commit resources at $t = 0$ and receive informative signals before deciding on continuation, allowing abandonment. Second, consistent with Bernanke (1983), mature projects are irreversible, generating an option to delay that makes these investments decline in uncertainty. Third, uncertainty enters strictly as a mean-preserving spread, in the spirit of Campello and Kankanhalli (2022), affecting only payoff dispersion and not expected levels. The novel contribution is that these three elements interact with differences in opportunity sets and scalability across the product life cycle: early-stage firms hold many scalable growth options that benefit from uncertainty and complementary capacity, while late-stage firms predominantly face unscalable, irreversible projects, making uncertainty contractionary.

3.1 Model Setup

Environment and Timing. Time is discrete, $t \in \{0, 1, 2\}$, and there is no discounting. Firms maximize expected firm value at $t = 0$; option values arise solely from the timing of information arrival and irreversibility. At $t = 0$, the firm chooses which projects to initiate and how much capacity to install. At $t = 1$, the firm receives information about exploratory R&D projects and decides whether to continue or abandon them; it may also initiate projects that were optimally delayed. At $t = 2$, all remaining projects generate payoffs.

Each firm belongs to one of two product life-cycle stages, $s \in \{E, L\}$, where E denotes early-stage firms and L denotes late-stage firms. The life-cycle stage index captures the structure of the firm's investment opportunity set and the strength of complementarities between capacity and growth. Uncertainty is summarized by a scalar $\sigma \geq 0$, which indexes a family of mean-preserving spreads (MPS) for all payoff-relevant random variables. An increase in σ raises payoff dispersion without affecting expected values.

Project Types and Opportunity Sets. A firm can invest in three types of projects. Exploratory (growth-option) R&D projects, indexed by $j = \text{exp}$, are multi-stage, risky projects with an abandonment option and scalability through innovative capacity. Incremental (process-improvement) R&D projects, indexed by $j = \text{inc}$, comprise small-scale innovations in existing lines and behave like mature capital investment with an option to delay. Finally, mature (fixed-capital) projects, indexed by $j = M$, are traditional investments in existing product lines, characterized by costly reversibility and an option to delay.

A stage-s firm has access to a continuum of potential projects. The total mass of R&D-type opportunities (exploratory plus incremental) is given by $R_s \geq 0$, and the total mass of mature opportunities is $N_s \geq 0$. Thus, the share of R&D-type projects is $\theta_s \equiv \frac{R_s}{R_s+N_s}$. Consistent with Hoberg and Maksimovic (2022), I assume that early-stage firms have opportunity sets tilted toward R&D-type opportunities, $\theta_E > \theta_L$.

The firm chooses the measures of projects initiated at $t = 0$, $(x^{\text{exp}}_{G,s}, x^{\text{inc}}_{G,s}, x_{M,s})$, subject to

$$0 \leq x^{\text{exp}}_{G,s} + x^{\text{inc}}_{G,s} \leq R_s, \qquad 0 \leq x_{M,s} \leq N_s.$$

where the total R&D is $x_{G,s} \equiv x^{\text{exp}}_{G,s} + x^{\text{inc}}_{G,s}$.

Project Productivity. Potential projects differ in their expected productivity. Within each project type j and life-cycle stage s, projects are indexed by the mean μ of a project's cash-flow distribution, which does not affect its dispersion. For each (j, s),

$$\mu \sim F_{j,s}(\mu), \quad \mu \in [\underline{\mu}_{j,s}, \overline{\mu}_{j,s}],$$

with density $f_{j,s}(\mu)$. The distributions $\{F_{j,s}\}$ describe the quality composition of the firm's opportunity set. Project values are strictly increasing in μ for all types and stages. For early-stage firms ($s = E$), exploratory R&D projects are more productive than incremental R&D projects in the sense of first-order stochastic dominance:

$$F_{\text{exp},E}(\mu) \leq F_{\text{inc},E}(\mu) \quad \text{for all } \mu,$$

with strict inequality on a set of positive measure. For late-stage firms ($s = L$), incremental R&D projects first-order stochastically dominate exploratory R&D projects:

$$F_{\text{inc},L}(\mu) \leq F_{\text{exp},L}(\mu) \quad \text{for all } \mu,$$

with strict inequality on a set of positive measure. This ensures that early-stage firms are relatively rich in high-quality growth options, while late-stage firms primarily face incremental innovation opportunities.

To ensure unique optima and well-defined comparative statics, I assume that for each project type j and life-cycle stage s, the productivity distribution $F_{j,s}(\mu)$ satisfies the Increasing Hazard Rate (IHR) property. This guarantees that extensive-margin implementation is characterized by a unique productivity cutoff $\mu^*_{j,s}(\sigma)$. For multi-stage projects (and any delayed investment decision based on realized signals or payoffs), I assume an additive noise structure with a log-concave density (e.g., normal), which implies the monotone likelihood ratio property. As a result, continuation and implementation decisions are characterized by threshold rules and the distribution of productivity among selected projects satisfies conditional first-order stochastic dominance.

Payoff Processes. If initiated, a mature project with productivity μ yields

$$v_t(\mu) = \mu\bar{v}_t + \varepsilon_t, \qquad \mathbb{E}[\varepsilon_t] = 0, \qquad \text{Var}(\varepsilon_t) = \sigma_v^2(\sigma), \quad \text{for } t = 1, 2.$$

An incremental R&D project yields

$$r_t(\mu) = \mu\bar{r}_t + \zeta_t, \qquad \mathbb{E}[\zeta_t] = 0, \qquad \text{Var}(\zeta_t) = \sigma_r^2(\sigma), \quad \text{for } t = 1, 2.$$

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An exploratory R&D project initiated at $t = 0$ generates a signal at $t = 1$,

$$u_1(\mu) = \mu + \eta_1,$$

after which the firm decides whether to abandon or continue the project by paying a continuation cost $d > 0$. If continued, the project yields

$$u_2(\mu) = u_1(\mu) + \eta_2, \quad \text{at } t = 2.$$

The joint distribution of (u_1, u_2) is an MPS family indexed by σ. The additive signal structure, together with log-concavity of the noise terms, ensures the monotone likelihood ratio property, so higher realized signals correspond to stochastically higher posterior productivity.

Capacity and Costs. At $t = 0$ the firm chooses innovative capacity $x_{IC,s} \geq 0$. If an exploratory project is continued, its payoff is scaled by

$$g_s(x_{IC,s}) = (x_{IC,s})^{\gamma_s}, \qquad \gamma_s > 0.$$

Here parameter γ_s captures complementarities between capacity and growth options. I assume innovative capacity is strongly complementary with growth options for early-stage firms ($\gamma_E > 1$) and only weakly complementary for late-stage firms (I assume $\gamma_L \approx 0$ and interpret γ_L as small).

Each mature project requires one unit of mature capacity, so $x_{M,s}$ also represents committed mature capacity. Therefore, total capacity, or total Capex is defined as

$$I_s^K(\sigma) \equiv \underbrace{x_{IC,s}(\sigma)}_{\text{Innovative Capacity}} + \underbrace{x_{M,s}(\sigma)}_{\text{Mature Capacity}}$$

Total costs are

$$C_s = c_g x_{IC,s} + \frac{\alpha_{IC}}{2} x_{IC,s}^2 + \frac{\alpha_{\exp}}{2}(x_{G,s}^{\exp})^2 + \frac{\alpha_{\text{inc}}}{2}(x_{G,s}^{\text{inc}})^2 + \frac{\alpha_M}{2} x_{M,s}^2, \tag{1}$$

with per-project initiation costs $k_R^{\exp}$, k_R^{inc}, and c_m.

3.2 Firm Objective and Predictions

Given uncertainty σ and life-cycle stage $s \in \{E, L\}$, a firm chooses the measures of projects initiated at $t = 0$, exploratory R&D $x_{G,s}^{\exp}$, incremental R&D $x_{G,s}^{\text{inc}}$, and mature projects $x_{M,s}$, as well as innovative capacity $x_{IC,s}$, to maximize expected firm value at $t = 0$. Optimal investment is characterized by type- and stage-specific productivity cutoffs.[3] Appendix A derives these cutoffs and shows that a firm's problem can be written in terms of the value of the marginal implemented project of each type.

Let $V_M(\sigma)$ denote the value of the marginal mature project, $V_G^{\text{inc}}(\sigma)$ the value of the marginal incremental R&D project, and $V_G^{\exp}(\sigma; x_{IC,s})$ the value of the marginal exploratory project, all evaluated at the endogenous productivity cutoffs. The firm's objective function is

$$V_0^s(\sigma) = \max_{x_{G,s}^{\exp}, x_{G,s}^{\text{inc}}, x_{M,s}, x_{IC,s} \geq 0} \left\{ x_{G,s}^{\exp} V_G^{\exp}(\sigma; x_{IC,s}) + x_{G,s}^{\text{inc}} V_G^{\text{inc}}(\sigma) + x_{M,s} V_M(\sigma) - C_s \right\}, \tag{2}$$

where C_s is the total cost function defined in Equation (1).

A firm's optimal choices are characterized by standard first-order conditions that I relegate to Appendix A. Here, I summarize the key comparative statics with respect to uncertainty σ and explain the economic mechanisms that drive them.

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[3] I assume the implementation cost parameters α_j are sufficiently large relative to the mass of opportunities R_s and N_s that the constraints do not bind. This ensures that optimal investment is characterized by unique interior cutoffs, and uncertainty operates through the extensive margin of project selection.

Mature projects. For mature projects, a firm has an option to delay investment until $t = 1$. Higher uncertainty increases the value of waiting but does not affect the expected payoff from immediate investment. As a result, the productivity cutoff for mature projects rises with uncertainty, causing the measure of mature projects initiated at $t = 0$ to decline:

$$\frac{\partial x_{M,s}}{\partial \sigma} < 0.$$

This option-to-delay mechanism operates for firms at all life-cycle stages.

Incremental R&D projects. Incremental R&D projects are irreversible once undertaken but can be postponed. As with mature projects, higher uncertainty raises the value of waiting, increasing the productivity cutoff and reducing the measure of incremental R&D projects initiated at $t = 0$:

$$\frac{\partial x_{G,s}^{\text{inc}}}{\partial \sigma} < 0.$$

Exploratory R&D projects. Exploratory R&D projects feature an abandonment option and convex payoffs. After observing interim information, a firm can abandon poorly-performing projects, limiting downside losses, while successful projects generate large upside payoffs. Higher uncertainty increases the likelihood of such upside outcomes, lowering the productivity cutoff and increasing exploratory R&D:

$$\frac{\partial x_{G,s}^{\text{exp}}}{\partial \sigma} > 0.$$

Innovative capacity. Innovative capacity only affects exploratory projects and it scales their payoffs nonlinearly. When the complementarity parameter $\gamma_s > 1$, the marginal value of innovative capacity is increasing in uncertainty, implying:

$$\frac{\partial x_{IC,E}}{\partial \sigma} > 0.$$

When this complementarity is weak, the response of innovative capacity to uncertainty is correspondingly limited. These optimality conditions imply that uncertainty reallocates investment across project types in a way that depends on a firm's position in the product life cycle. The following empirical predictions obtain:

Prediction 1 (Early-stage firms). An increase in uncertainty σ raises both R&D investment and total Capex:

$$\frac{\partial x_{G,E}}{\partial \sigma} > 0, \qquad \frac{\partial I_E^K}{\partial \sigma} > 0.$$

For early-stage firms ($s = E$), the opportunity set is tilted toward exploratory R&D-type projects (θ_E high), and investment in innovative capacity is strongly complementary with R&D ($\gamma_E > 1$). Moreover, because the relative mass of mature projects N_E is small when θ_E is high, the option-to-delay channel for mature investments is weak in quantitative terms. Therefore, an increase in uncertainty σ raises both R&D investment and total Capex.

Prediction 2 (Late-stage firms). Higher uncertainty σ reduces total Capex and has a weak or negative effect on overall R&D.

$$\frac{\partial x_{M,L}}{\partial \sigma} < 0, \qquad \frac{\partial I_L^K}{\partial \sigma} < 0, \qquad \frac{\partial x_{G,L}}{\partial \sigma} \lesssim 0.$$

For late-stage firms ($s = L$), the opportunity set is dominated by mature projects (θ_L low), growth-capacity complementarity is weak ($\gamma_L \approx 0$), and R&D is largely incremental. An increase in uncertainty σ reduces the investment in mature capacity (the option-to-delay effect) and incremental R&D, while exerting only a weak positive effect on the few remaining exploratory projects. As a result, total Capex and overall R&D respond weakly or negatively.

In sum, uncertainty is expansionary for investment when firms hold many scalable growth options and can deploy complementary capacity, but contractionary when firms' portfolios are dominated by mature projects and incremental R&D with an option to delay (late-stage). Differences in the composition of projects and the strength of capacity–growth complementarities over the product life cycle therefore generate opposite investment responses to uncertainty across firms.

The core investment predictions established above determine the firm's productive capacity in response to uncertainty. However, these inputs must be channeled into observable strategic outputs to validate the theoretical mechanism. I thus derive additional predictions regarding innovation output and product market strategy. For early-stage firms, the increased investment is necessary to fund a strategy of high experimentation (churn) that maximizes the value of the option to scale. For late-stage firms, the reduced investment necessitates a strategy of stability to protect existing market share and cash flows. These additional predictions confirm that the differential allocation of capital across the product life cycle is directed toward the predicted optimal strategic response.

Prediction 3. The expansionary investment response facilitates a strategy of market experimentation to exploit high-return growth opportunities. As a result, the effects of increased uncertainty are given by:

$$\frac{\partial(\text{Innovation Output})}{\partial\sigma} > 0 \quad \text{and} \quad \frac{\partial(\text{Product Entry})}{\partial\sigma} > 0, \qquad \frac{\partial(\text{Product Exit})}{\partial\sigma} > 0.$$

Prediction 4. The contractionary investment response reflects a defense of established stability by minimizing costly market adjustments. As a result, the effects of increased uncertainty are given by:

$$\frac{\partial(\text{Innovation Output})}{\partial\sigma} < 0 \quad \text{and} \quad \frac{\partial(\text{Product Entry})}{\partial\sigma} < 0, \qquad \frac{\partial(\text{Product Exit})}{\partial\sigma} < 0.$$

4. Investment and Innovation Outcomes

4.1 Data

I employ a comprehensive dataset covering the 1997-2019 period. I obtain data on firm characteristics from COMPUSTAT Fundamentals Annual. Stock returns are from CRSP, option-implied volatility is from OptionMetrics, patents are from USPTO, Kogan, Papanikolaou, Seru, and Stoffman (2017) and Ganglmair, Robinson, and Seeligson (2022), online job posts are from Burning Glass and Bloom, Hassan, Kalyani, Lerner, and Tahoun (2021), and firms' product life stage data is from Hoberg and Maksimovic (2022). Following the literature, I exclude financial firms, regulated utilities, and government. I require firms to provide valid and positive information on their total assets and sales, and exclude firms with negative capital expenditures (CAPX) and R&D. Panel (A) in Table 1 provides the summary statistics for the basic firm characteristics in the sample. Section B in the Appendix gives definitions of firm-level variables.

4.1.1 Measuring Product Life Cycles

I use firm's product life cycle data from Hoberg and Maksimovic (2022), which develop a novel 10-K text-based model of product life cycles by defining a four-stage product life cycle: product innovation (Life1), process innovation (Life2), maturity (Life3), and decline (Life4). Life1 firms intensively discuss an "explanation of material product research and development to be performed during the period covered". Regarding process innovation, they require the firm to disclose its results from operations, of which discussions of the costs of production are a significant component. A firm in the third maturity stage is characterized by discussions of continuation and market share but without reference to product or process innovation. Finally, a firm in the fourth stage discusses obsolescence and product discontinuation.

Using "Chained Context Discovery," Hoberg and Maksimovic (2022) compute a four-element vector for each firm-year, with weights summing to one. This captures multi-product firms' simultaneous exposure to different stages. For example, a firm with vector {0.6, 0.3, 0.1, 0} is earlier in its life cycle than a firm with weights {0.1, 0.3, 0.3, 0.3}. Panel A of Figure 1 plots life stage trends over time, and Figure 2 illustrates life cycle profiles for Johnson & Johnson and Amazon, showing substantial heterogeneity in firm trajectories. Table 2 shows the correlation of firm basic characteristics with each life stage variable. Early-stage firms are smaller, exhibit higher Tobin's Q, hold more cash, and invest heavily in R&D.

To analyze uncertainty's effect by life stage, I focus on the Life1 share—denoted as *Early Stage*. Early-stage firms, which face investment lags and portfolio composed of growth-options projects, may benefit from uncertainty due to valuable growth options: uncertainty increases the upside of innovation while limiting downside risks. Consistent with Hoberg and Maksimovic (2022), I show in Appendix C that the main results do not hold when firm age is used as a proxy for early-stage.

4.1.2 Measuring Uncertainty

I use derivatives market data to construct forward-looking measures of firm-level uncertainty. My main proxy is firm-level option-implied volatility, calculated as the 12-month average of daily implied volatility, where each day's value is the average of forward 365-day at-the-money (ATM) call and put options. This measure captures investors' expectations of the distribution of firm-specific returns and thus reflects firm-specific uncertainty.

To support and complement my analysis, I use realized annual volatility from CRSP stock returns as a firm-level measure of uncertainty and additional aggregate uncertainty proxies: the VIX (from Bloomberg), and three common components—financial (FIN), real (REAL), and macroeconomic (MACRO) uncertainty—from Jurado, Ludvigson, and Ng (2015).

4.2 Empirical Strategy

A key concern when estimating the effect of uncertainty on investment is that firm-level uncertainty may be correlated with unobserved factors that also affect investment. To address this endogeneity, I use an instrumentation strategy following Alfaro, Bloom, and Lin (2024), which exploits firms' differential exposure to aggregate volatility shocks in energy, currency, and policy. The instrument provides exogenous variation in firm-level uncertainty, without capturing firm-specific shocks or expected gains/losses.

For example, firms may differ in their sensitivity to oil price levels—some positively, some negatively, and others not at all—yet all are non-directionally exposed to oil price uncertainty. By controlling for exposure to oil price *levels*, I can identify variation in firm-level volatility driven by second-moment shocks. This distinction is crucial, as price changes often coincide with increases in volatility, making it important to separate level effects from uncertainty effects.

The first step to constructing the instruments is to estimate the sensitivities to energy, currencies, and policy at the industry level by regressing firm daily stock returns on the price growth of energy, 7 currencies (Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona), and changes in daily policy uncertainty. The sensitivity for firm i in industry j is estimated as follows:

$$r_{i,t} = \alpha_j + \Sigma_k \text{sensitivity}_j^k \times r_t^k + \epsilon_{i,t}, \tag{3}$$

where $r_{i,t}$ is the daily risk-adjusted return on firm i and r_t^k is the change in the price of commodity k.[4] The daily risk-adjusted returns are the residuals of firm-level regressions of daily CRSP stock returns on the four-factor asset pricing model (CRSP value-weighted index in excess of the risk-free rate, the book-to-market factor, the size factor, and the momentum factor). Adjusting firm-level returns for aggregate risk addresses concerns over whether the sensitivities to energy, currencies, and policy are capturing exposures to common risk factors.

Then, for the 9 aggregate price shocks (oil, 7 currencies, and policy), the absolute value of the time-varying sensitivities is multiplied by shocks to the realized volatilities of the aggregate variables. This provides 9 instruments for lagged firm-level uncertainty. Importantly, the sensitivities are lagged by three years, such that they pre-date both the outcome and control variables. As a result, the instruments are the 3-year lagged cross-industry non-directional exposure times the lagged change in volatility for oil prices, 7 leading currencies, and policy uncertainty (see Alfaro, Bloom, and Lin (2024) for details). Specifically, the instruments are defined as:

$$Instruments_{i,t-1} = |\text{sensitivity}_{j,t-3}^{k}| \times \Delta\sigma_{t-1}^{k}. \tag{4}$$

The volatilities of oil and the 7 currencies employed are the 252-day standard deviation of daily returns on crude oil prices (West Texas Intermediate (WTI) oil price data) and 252-day standard deviation of daily changes in bilateral exchange rates against the US Dollar (foreign currency units per 1USD data). The 252-day average of trading-day US economic policy uncertainty (EPU) from Baker, Bloom, and Davis (2016) is used for economic policy uncertainty.

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[4] The sensitivities are estimated at the industry level 2-digit SIC code.

The empirical analysis is based on the estimation of the following specification:

$$\begin{aligned} y_{i,t} = \alpha_i + \theta_t + \beta_1 \times Uncertainty_{i,t-1} + \beta_2 \times Early\_Stage_{i,t-2} \\ + \beta_3 \times Uncertainty_{i,t-1} \times Early\_Stage_{i,t-2} + \gamma' X_{i,t-1} + \epsilon_{it}, \end{aligned} \tag{5}$$

where $y_{i,t}$ is an outcome variable for firm i in time t, $Early\_Stage$ is the Life1 variable lagged by two years to avoid endogeneity issues, *Uncertainty* is the instrumented option-implied volatility, and α_i and θ_t are firm and time fixed effects, respectively. $X_{i,t-1}$ is a vector of firm controls, which includes size, Tobin's Q, book leverage, cash flows, age, and the stock return of the firm (measured as firms' 12-month compounded return from CRSP). Importantly, I also include the first-moment effects of each of the 9 instruments ($\text{sensitivity}^k_{j,t-3} \times r^k_{t-1}$) to disentangle the second moment effects from correlated first moment effects. These are the annual exposure of firms to aggregate price movements (i.e., returns rather than the volatility of each instrument). In some specifications, I also interact the *Uncertainty* variable with all controls and the results are unchanged. Finally, standard errors are robust and clustered at the industry level (2-digit SIC code).

In this specification, β_1 captures the effect of uncertainty on late-stage firms (those with $Early\_Stage = 0$), while β_3 measures how this effect differs for early-stage firms. Thus, the effect of uncertainty on early-stage firms is given by $\beta_1 + \beta_3$. If β_1 is negative and β_3 is positive, the overall effect for early-stage firms can turn positive whenever the mitigating effect of β_3 outweighs the negative baseline effect of β_1. This framework allows me to test directly whether early-stage firms respond differently to uncertainty than late-stage firms.

4.2.1 Instrument Validity

A valid instrument requires instrument exogeneity (exclusion restriction) and relevance. In Appendix E, I show the 1st stage F-tests of excluded instruments, which indicates that the relevance condition is well satisfied jointly by the instruments. The exclusion restriction requires (1) the instruments to not be correlated with firm-specific unobservables that affect the outcome variable and are correlated with uncertainty; and (2) the instruments to have no direct effect on the outcome variable.

One concern with my identification strategy is that changes in aggregate volatility may influence investment through channels other than firm-level uncertainty. In particular, aggregate volatility could alter financing conditions directly, creating an alternative pathway that does not operate through uncertainty. Consider the following example. Airlines often rely on derivative contracts to hedge jet fuel expenses, while retailers hedge very little. If aggregate oil price volatility rises, the cost of hedging fuel may increase sharply for airlines, restricting their effective financing capacity even if their firm-specific uncertainty does not change. In this case, the unobservable hedging-cost shock occurs contemporaneously with the change in aggregate volatility and could bias the estimates if it were correlated with the instrument.

The instrument combines changes in aggregate volatility at time t, whether in oil, exchange rates, or economic policy uncertainty (EPU), with industry exposures estimated from rolling windows that end at $t-2$. These exposures are lagged, predetermined statistical measures of historical co-movement with oil, currency, or policy, not contemporaneous indicators of hedging intensity. An increase in aggregate volatility can certainly raise hedging costs at time t, but this would threaten the exclusion restriction only if those contemporaneous, unobservable hedging-cost shocks happened to scale with the lagged exposures used in the instrument. For example, if hedging costs in an industry with a beta of 2.0 rose about four times more than in an industry with a beta of 0.5 in response to higher volatility. This proportionality is implausible. First, I control directly for first-moment price changes, which already capture hedging costs that move with the level of oil, exchange rates, or policy. Second, hedging costs today are determined by current market conditions, not by regression-based betas constructed from historical return data ending two years earlier. Thus, while changes in aggregate volatility may raise hedging costs broadly, it is hard to see them doing so in a way that maps closely into the lagged exposures that form the basis of the instrument.

Another concern with the identification strategy relates to the potential endogeneity of $Early\_Stage_{i,t-2}$. First, this variable is lagged by two years, ensuring that it predates both the uncertainty measure and the control variables. Second, my focus is on the interaction between $Early\_Stage_{i,t-2}$ and uncertainty. For endogeneity to arise, there would need to be unobservable firm-specific shocks that simultaneously influence the early-stage variable at $t-2$ and the outcome variable at time t, while remaining orthogonal to the uncertainty measure. Such shocks would have to be unusually persistent, affecting firm behavior across multiple periods, substantial enough to shape investment or innovation outcomes, yet unrelated to the firm's perceived risk or macroeconomic conditions. This seems unlikely. Moreover, as Table 2 shows, the $Early\_Stage$ variable is highly persistent over time, indicating that a firm's life cycle exposure is stable and that transitions through the cycle occur gradually rather than as immediate responses to short-term shocks. Finally, to further reduce the risk that the interaction term is capturing spurious correlations, I control for firm and time fixed effects, a rich set of lagged firm-level controls, and first-moment exposures to each of the instruments (directional exposures). Overall, these features strengthen the validity of the identification of heterogeneous effects of uncertainty across product life cycle stages.

4.3 Main Results

This section examines the impact of uncertainty on firms' decisions. Subsection 4.3.1 analyzes its effect on investment policies, while Subsection 4.3.2 presents the aggregate investment implications. Subsection 4.3.3 discusses the effect of uncertainty on innovation. The online Appendix provides additional results (e.g., hiring decisions, financing policies, and competition), strengthens the external validity of my findings by examining the impact of uncertainty on VC-backed firms, and reports robustness checks.

4.3.1 Investment Outcomes

I begin by analyzing the effect of uncertainty on intangible investment. Table 3 presents the findings. Early-stage firms significantly increase intangible investment, while late-stage firms reduce it. A one standard deviation increase in uncertainty (0.215, or a 21.5% increase in option-implied volatility) raises early-stage firms' R&D, and intangible investment rate by 4.6 and 2.1 percentage points, respectively. These magnitudes are economically significant. For instance, the increase in the intangible investment rate corresponds to an 11% rise relative to the mean. In contrast, the same increase in uncertainty leads late-stage firms to reduce intangible investment by approximately 6.4% relative to the mean.

Table 3 also reports results for physical investment. In response to a one standard deviation increase in uncertainty, early-stage firms increase their capital expenditures by about 1.0 percentage point. Notably, this effect is much smaller than the increase in R&D spending. This pattern reflects the fact that capital expenditures are costlier to reverse, which makes the associated growth option less valuable under uncertainty.

The positive effect of uncertainty on capital expenditures for early-stage firms has two important implications. First, it reinforces that heterogeneity in the impact of uncertainty is not simply about the scale of investment (whether in CAPX or R&D). Second, it highlights the role of uncertainty in shaping capital investment in innovative capacity (IC). According to Kumar and Li (2016), IC investments include the construction of long-range research facilities, the purchase of R&D equipment with alternative future uses, and the acquisition of patents. These investments enhance a firm's innovation capacity but are often recorded under capital expenditures and/or total assets rather than R&D. Since R&D is the most widely used proxy for innovation in the literature, it is reasonable to interpret the capital investment of R&D-active firms (such as early-stage firms) as a proxy for IC investment.

For late-stage firms, the value of the growth option diminishes substantially with uncertainty. As a result, they have stronger incentives to adopt a "wait-and-see" approach to investment. Consistent with this mechanism, I find that a one standard deviation increase in uncertainty leads to a significant reduction in capital expenditures by 5.5 percentage points. I also document a drop in acquisitions, consistent with the fact that such investments are even costlier to reverse.

Overall, these findings underscore the importance of the product life cycle in shaping firms' responses to uncertainty. Early-stage firms hold many scalable growth options and can deploy complementary capacity, giving them an option-like payoff structure: they can continue if future conditions are favorable or abandon if not. This option value makes uncertainty positively related to innovation inputs. By contrast, late-stage firms' portfolios are dominated by mature projects, for which the value of experimentation is lower. Consequently, uncertainty discourages further investment, producing a negative relationship between uncertainty and innovation inputs.

4.3.2 Aggregate Impacts

Given the contrasting responses of early- and late-stage firms, the next natural question is how much early-stage firms offset the negative impact of uncertainty on aggregate investment. To investigate this, I implement a back-of-the-envelope calculation to estimate the heterogeneous aggregate impact of uncertainty. First, I use the estimated coefficients from Equation (5) to obtain the total effect of a one standard deviation increase in instrumented option-implied volatility on these firms. Second, I calculate the change in the ratios of CAPX/Assets and R&D/Assets following the increase. Third, I multiply these changes in ratios by the average value of total assets to obtain the changes in CAPX and R&D in dollar terms. Finally, I aggregate the total changes in CAPX and R&D to estimate the overall effect in millions of dollars and multiply this by the number of firms.

Table 4 summarizes the results. I document that, in dollar terms, the increase in CAPX and R&D for the average early-stage firm is approximately \$0.777 million and \$22.757 million, respectively. The decreases in CAPX and R&D for the average late-stage firm are approximately \$16.635 million and \$2.485 million, respectively. Figure 3 plots the extent to which early-stage firms attenuate the total negative impact of uncertainty on investment, along with the share of early-stage firms in my sample. I show that the positive response of early-stage firms offsets about 27.2% of the total negative impact that would have occurred if all firms responded like late-stage firms. These findings suggest that the composition of firms in the economy can significantly influence the aggregate sensitivity of investment to uncertainty.

4.3.3 Innovation

I show that the positive effect of uncertainty on investment translates into greater innovation for early-stage firms. Table 5 shows that a one standard deviation increase in uncertainty raises the probability of filing a patent by 4.57 percentage points, representing a 16.24% increase relative to the mean. Moreover, following increases in uncertainty, the number of patents filed by early-stage firms rises by approximately 1.3 percentage points after three years. In contrast, later-stage firms reduce their patent filings.[5]

I also examine the effect of uncertainty on product patents, as early-stage firms are in the product innovation stage and their innovation is therefore expected to be concentrated in product patents. I define product patents as patents in which more than 50% of the claims are product claims, following the categorization in Ganglmair, Robinson, and Seeligson (2022). Table 5 confirms this conjecture: in response to a one standard deviation increase in uncertainty, early-stage firms significantly increase their product patents.

Next, I construct the variable *otherpatents*, defined as the number of patents not classified as product patents. I then estimate the effect of uncertainty on *(productpatent* –

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[5] Both innovation output measures are evaluated three years after the increase in uncertainty, capturing the typical lag between initiating an R&D project and filing a patent.

otherpatents), a dummy variable equal to one when the number of product patents exceeds the number of other patents. The goal is to test whether product patents increase relative to other types of patents (such as process patents) for early-stage firms when uncertainty rises. Table 5 reports the results: in response to higher uncertainty, product patents significantly increase relative to other patents only for early-stage firms, indicating that their innovation is heavily concentrated in product development.

4.4 Uncertainty and Irreversibility

Do some early-stage firms, for which the irreversibility of investment is particularly high, react negatively to increases in uncertainty? To analyze this question, I use the measure of asset redeployability from Kim and Kung (2017). The idea is that more redeployable assets exhibit higher recovery rates and are traded more actively in secondary markets. Therefore, corporate investment should decrease relatively more for firms with less redeployable assets, because the incentive to delay investment is stronger when liquidating capital is more costly.

As a first-step analysis, I sort firms into two groups each year based on their redeployability values, creating the dummy variable IRR, which equals one if a firm's asset redeployability is below the median and zero otherwise. I then estimate Equation (5), including the interaction term between uncertainty and IRR. Table 6 shows that the interaction between early stage and uncertainty remains unchanged after controlling for redeployability. I also find that, in response to higher uncertainty, firms with low redeployability significantly reduce their investment by more than other firms, consistent with the idea that firms' investment responses to uncertainty are more pronounced when the cost of reversing investment decisions is higher.

Next, I examine whether early-stage firms for which investment irreversibility is particularly high react negatively to increases in uncertainty. To do this, I employ a triple-interaction approach, interacting Uncertainty × Early Stage with IRR. The results are presented in Table 6 (column 3). I find that while early-stage firms with low irreversibility significantly increase investment in R&D, the positive effect of uncertainty on R&D remains positive but is significantly attenuated for early-stage firms with high irreversibility. These findings suggest that irreversibility plays an important role in the transmission of uncertainty across firms over the product life cycle and partially offsets the positive effect of more valuable abandonment options for early-stage firms.

4.5 Uncertainty and Financing Constraints

There is evidence that financing constraints play a significant role in the transmission of uncertainty to the corporate sector. For example, Favara, Gao, and Giannetti (2021) show that access to debt markets helps mitigate the negative effects of uncertainty on corporate financial decisions. Similarly, Alfaro, Bloom, and Lin (2024) find that uncertainty shocks reduce firm investment, and that this effect is amplified by financing constraints. This section explores the following question: What happens when early-stage firms face financing constraints?

To study the impact of uncertainty on financially constrained firms in the early stage of the product life cycle, I use a text-based measure of financial constraints to identify constrained firms. This measure, developed by Hoberg and Maksimovic (2015) and extended by Linn and Weagley (2024), defines a firm as constrained if it reports in its 10-K filing that investment is delayed due to liquidity issues. To remain agnostic about the source of the constraint, I define a firm as constrained in a given year if it is classified in the top tercile of both the equity- and debt-constraint measures. I then estimate Equation (5) by adding an interaction term between Uncertainty × Early Stage and the financial constraint dummy (FC).

Table 7 presents the results. I find that while unconstrained early-stage firms significantly increase investment in R&D, the positive effect of uncertainty on R&D is significantly attenuated for early-stage firms facing financing constraints. Overall, these findings are consistent with the idea that greater difficulty in accessing equity and debt markets reduces the positive effects of uncertainty and underscores the important role of financing constraints in the transmission of uncertainty to early-stage firms.

5. Product Market Outcomes

Having established how uncertainty shapes firms' investment and innovation, I now turn to product market outcomes. Investment decisions determine the resources and incentives available for product development, launch, and discontinuation. Therefore, firms' differing investment responses to uncertainty should naturally translate into distinct product market strategies. Understanding these dynamics is thus essential for assessing the full impact of uncertainty on firm behavior.

5.1 Data

The product data come from the retail scanner data (also referred to as RMS data) provided by the Kilts Data Center at the University of Chicago Booth School of Business. This data consist of weekly pricing, volume, and store merchandising information generated by participating retail point-of-sale systems across all U.S. markets. My sample period spans January 2006 to December 2019.

Figure 4 illustrates the product portfolio hierarchy in the NielsenIQ Retail Scanner Data. Firms' products are categorized into departments, groups, modules, and products (UPC). In my analysis, a product is defined at the UPC level—the most granular category—which can be linked to a specific product variety. As discussed in Hajda and Nikolov (2022), using a broader definition of a product would largely overlook important product-level dynamics. I conduct my analysis at the quarterly level, and for each product-quarter, I define revenue as the total sales across all stores and weeks within that quarter.

To link firms with products, I use data from GS1 U.S. Data Hub, the official source of UPCs. To obtain a UPC, firms must first acquire a GS1 company prefix, a five- to ten-digit number that identifies the firm and its products. This structure allows me to conduct the analysis at the parent-company level. Following Argente, Lee, and Moreira (2018, 2024), I use the list of prefixes issued by GS1 to match approximately 80% of all UPCs in the NielsenIQ data to firms. Matching firms to products enables me to compute each firm's product portfolio, identify the sales of every product within the portfolio, and aggregate these sales at the firm level.

Table 8 reports descriptive statistics for firms and products in the NielsenIQ sample. Panel A shows that firms maintain an average of 19 products in their portfolios. The average product portfolio age is 0.448, indicating that, on average, firms hold relatively young product portfolios. The mean firm generates approximately $893,000 in sales. Panel B provides statistics at the product level. The average product generates about $91,000 in quarterly sales. The sample comprises 22,320 firms and 568,698 unique products, providing a rich setting to analyze product portfolio dynamics.

5.2 Measuring Product Life Cycle

Following Hajda and Nikolov (2022), I measure product portfolio age as the weighted share of old products, whose age exceeds half of their lifespan, in the product portfolio, where the weights correspond to product-specific revenue:[6]

$$age_{i,t} = \frac{\text{weighted \# of products with age exceeding 50\% of lifespan (it)}}{\text{total \# of products (it)}}$$

Intuitively, $age_{i,t}$ captures the percentage of old products in a firm's portfolio. On average, firms in my sample have 44.8% of old products, as reported in Panel A of Table 8. Product portfolio age varies substantially, with a standard deviation of

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[6] I exclude first and last years of the data when computing the measure to make sure that product portfolio age is correctly captured.

0.350. This variation is important as it highlights that many firms have portfolios composed entirely of either new or old products.

To identify firms in the early stages of their product life cycles, I construct the *Early_Stage* variable through a two-step process. First, I define $(1 - age_{i,t})$ as the percentage of new products in a firm's portfolio. A higher value of $(1 - age_{i,t})$ indicates a larger share of new products and, therefore, that the firm is at an earlier stage of the product life cycle. Second, I sort firms each quarter into two groups based on the distribution of $(1 - age_{i,t})$. The *Early_Stage* variable is then defined as a dummy equal to one if a firm has a sufficiently high share of new products in its portfolio. Figure 5 shows that the average early-stage firm has 14.1% of old products, whereas the average late-stage firm has 64.5%.

5.3 Product-Market Uncertainty (PMU)

A key challenge in estimating the impact of uncertainty on product-market outcomes is the lack of firm-level uncertainty measures. Because the product-level analysis includes both private and public companies, option-implied volatility cannot be used. A common alternative is to rely on aggregate measures of uncertainty (e.g., the EPU index). Although such indices capture economy-wide shocks, they do not reflect the idiosyncratic volatility inherent in a firm's own product portfolio. This limitation is particularly important when analyzing how responses to uncertainty vary across the product life cycle, since aggregate measures cannot disentangle whether observed firm behavior is driven by strategic exposure to volatile product markets or by broader macroeconomic conditions. In addition, aggregate measures are often highly correlated with first-moment shocks at the economy-wide level, making it difficult to isolate the causal effect of uncertainty on firm decisions.

To address this, I construct a novel firm-level measure of product-market uncertainty (PMU) that leverages highly granular product-level sales data. Specifically, I compute the four-quarter rolling standard deviation of log sales growth for each product (UPC) within a firm's portfolio. These product-level volatilities are then aggregated to the firm level using revenue shares as weights, ensuring that the measure reflects the relative importance of each product in the firm's operations. This approach captures the extent of uncertainty that firms face in their product markets, while preserving within-firm heterogeneity across products. Panel C of Table 8 provides the summary statistics of PMU.

The PMU measure offers several key advantages relative to existing proxies. First, it disentangles portfolio composition from aggregate performance. While cash flow volatility reflects total firm performance, PMU isolates the volatility of individual products, offering a more precise view of the firm's exposure to product-market risk. Second, PMU reduces contamination from firm-wide shocks by relying on product-level sales dynamics, which helps filter out transitory noise that affects aggregate volatility. Third, PMU highlights the firm's strategic exposure to inherently volatile product markets, a dimension shaped by longer-term positioning and product strategies rather than short-term realized shocks. Finally, the measure provides a more granular lens on uncertainty by exploiting product-level heterogeneity, allowing me to capture within-firm differences in risk exposure that traditional firm-level volatility measures overlook.

One concern in measuring PMU is distinguishing second-moment effects from first-moment dynamics. I address this by directly controlling for first-moment variables such as product sales growth and levels, thereby ensuring that the measure primarily reflects volatility rather than mean performance. Another limitation is that PMU is based on realized sales volatility and may therefore not fully capture forward-looking perceptions of risk. Nevertheless, realized volatility measures, such as stock return or cash flow volatility, are widely used in the corporate finance literature to study uncertainty, lending credibility to this approach. In fact, I show that the impacts on investment and innovation remain very similar when using realized annual volatility from CRSP stock returns as a firm-level measure of uncertainty, rather than option-implied volatility.

I validate the PMU by aggregating it across firms and conducting two exercises. First, I examine its correlation with common aggregate proxies of uncertainty used in the literature. Table 9 shows that PMU is positively correlated with these measures, but the correlations are not strong, suggesting that PMU captures something unique. Second, I plot PMU against GDP growth in Figure 6, which reveals a negative correlation, indicating that PMU is countercyclical. These validation exercises provide evidence that PMU is both distinct from existing proxies and economically meaningful, making it a useful firm-level measure of uncertainty.

5.4 Empirical Strategy

I use the firm-level PMU to study whether firms adjust product entry and exit differently depending on their life cycle stage. Following Argente, Lee, and Moreira (2018, 2024), the entry rate is defined as the number of new products introduced in period t as a share of the total number of products in period t. The exit rate is defined as the number of products that exited in period t (i.e., the last time a transaction is observed is in $t-1$) as a share of the total number of products in period $t-1$.

I then estimate the following specification:

$$\begin{aligned} y_{i,t+h} = \alpha_i + \theta_t + \psi_q + \beta_1 \times PMU_{i,t} + \beta_2 \times Early\_Stage_{i,t-4} \\ + \beta_3 \times PMU_{i,t} \times Early\_Stage_{i,t-4} + \gamma' X_{i,t-1} + \epsilon_{it} \end{aligned} \tag{6}$$

where $y_{i,t+h}$ is an outcome variable for firm i in quarter t for $h = 16$ (i.e., four years ahead).[7] $Early\_Stage$ is a dummy equal to one if a firm has a sufficiently high share of new products in its portfolio, as defined in Section 5.2. I lag $Early\_Stage$ by one year (four quarters) to avoid endogeneity issues and to capture firms' ex-ante life stage. PMU is the

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[7] Given that I observe the impact on patents after three years, and evidence from Argente, Baslandze, Hanley, and Moreira (2020) suggests a positive association between patents and product introduction after one year, I investigate the outcome variable four years ahead.

firm-level product-market uncertainty, and α_i, θ_t, and ψ_q are firm, time, and quarter fixed effects, respectively. Including quarter fixed effect allows me to control for within-year seasonal patterns (systematic differences between Q1, Q2, Q3, and Q4 across all years). $X_{i,t-1}$ is a vector of firm controls, which includes the average log of revenues and the average sales growth over the previous four quarters. Importantly, by including these controls, I directly account for first-moment effects, thereby ensuring that PMU captures second-moment variation. In some specifications, I also include macroeconomic controls such as GDP growth, industrial production, CPI, and the employment ratio. Finally, standard errors are clustered at the firm level and are robust to heteroskedasticity.

5.5 Main Results

I begin by analyzing the impact of uncertainty on the product entry. Table 10 reports the results. I find that, in response to an increase in PMU, early-stage firms significantly increase product entry. The magnitudes are economically meaningful. For example, a two–standard deviation increase in PMU raises product entry among early-stage firms by 1.7%. In contrast, late-stage firms significantly reduce product entry by 3.9%. The positive impact of uncertainty on product entry among early-stage firms is consistent with the investment and innovation results documented earlier. Higher investment and greater patenting activity in response to uncertainty may translate into more product launches, highlighting the complementarity between R&D, innovation, and product-market strategies at early stages of the life cycle.[8]

I then turn to product exit to assess whether firms also adjust their portfolios by discontinuing products. Again, I find contrasting results between firms at early and late stages of the product life cycle. Table 11 shows that, in response to a two–standard deviation increase in PMU, early-stage firms increase product exit by 1.4%, whereas late-

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[8] Argente, Baslandze, Hanley, and Moreira (2020) shows that the degree of association between patent and product introduction is positive and larger for smaller firms.

stage firms decrease product exit by 4.6%. These findings are robust to the inclusion of firm and time fixed effects as well as first-moment controls. The increase in product exit among early-stage firms is consistent with an experimentation strategy: firms respond to uncertainty by also pruning underperforming products.

Given these opposing dynamics, one would expect early-stage firms to exhibit greater product reallocation—actively reshaping their portfolios through simultaneous entry and exit—while late-stage firms show reduced reallocation, consistent with stability and consolidation. I examine this prediction directly by analyzing the overall change in the portfolio of products, captured by the sum of the entry and exit rates. Table 12 shows that product reallocation increases among early-stage firms but decreases among late-stage firms in response to higher PMU. For early-stage firms, higher uncertainty stimulates both product entry and exit, leading to greater portfolio churn and experimentation. This pattern reflects an active reallocation of resources across products, as firms introduce new offerings while pruning weaker ones. In contrast, late-stage firms reduce both entry and exit, resulting in lower reallocation. This behavior is consistent with consolidation around established products and a more cautious, wait-and-see approach under uncertainty.

6. Conclusion

This paper shows that a firm's stage in the product life cycle plays a critical role in shaping how it responds to higher uncertainty. I provide comprehensive and novel evidence that early-stage firms increase investment and innovation in response to higher uncertainty, while later-stage firms become more conservative, cutting back on both investment and innovation outputs. These patterns are robust across firm-level outcomes and are confirmed in aggregate analysis, which shows that the expansionary responses of early-stage firms offset a sizable share of the decline in investment that would occur if all firms behaved like late-stage firms.

Extending the analysis to product markets, I introduce a novel firm-level measure of product-market uncertainty and show that early-stage firms actively reoptimize their product portfolios through increased entry and exit, whereas late-stage firms consolidate around existing offerings. Overall, these findings reconcile mixed results in the literature by highlighting that uncertainty does not have a uniform effect across firms. Instead, firms' responses depend systematically on their product life cycle stage, an insight with important implications for corporate decision-making, macroeconomic modeling, and policy design in times of uncertainty.

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Table 1. Summary Statistics: Firm Characteristics

Panel A: Overall Sample

	Obs	Mean	Median	Std. Dev.
R&D/Assets	141,841	0.095	0.00	0.254
SG&A/Assets	127,035	0.212	0.08	0.586
Investment	140,854	0.081	0.03	0.149
Disinvestment	112,836	0.009	0.00	0.032
Log(Employees)	135,925	1.038	0.48	1.239
Log(Cash)	156,802	2.536	2.79	2.954
Q	140,107	1.885	1.57	0.978
Size	161,277	4.856	4.94	2.883
Book Leverage	160,736	0.383	0.18	0.948
Cash/Assets	161,222	0.225	0.11	0.259
Cash Flow	141,400	-0.340	0.08	1.875
Age	204,377	12.99	10.0	11.70
Stock Return	84,039	0.137	0.05	0.649
Stock return Volatility	84,039	0.560	0.45	0.358
INFLEX	129,535	2.940	0.97	8.541

Panel B: Early-Stage Firms

	Obs	Mean	Median	Std. Dev.
R&D/Assets	17,539	0.265	0.13	0.369
SG&A/Assets	13,812	0.344	0.14	0.735
Investment	17,442	0.041	0.01	0.087
Disinvestment	14,999	0.005	0.00	0.025
Log(Employees)	17,188	0.523	0.13	0.896
Log(Cash)	17,427	2.733	3.17	2.959
Q	16,933	2.400	2.53	0.982
Size	17,609	4.068	4.15	2.741
Book Leverage	17,519	0.446	0.07	1.284
Cash/Assets	17,607	0.411	0.36	0.302
Cash Flow	17,482	-0.730	-0.10	2.344
Age	20,254	12.98	10.0	9.519
Stock Return	12,801	0.173	0.01	0.833
Stock return Volatility	12,801	0.692	0.60	0.395
INFLEX	13,733	4.963	1.49	11.58

This table provides summary statistics for basic firm characteristics. The sample covers the years 1997 to 2019. Panel (A) reports the summary statistics in the overall sample. Panel (B) reports the summary statistics for early-stage firms (life1 is greater than all other life stages).

Table 2. Pearson correlation coefficients and Persistence Statistics

Panel A	R&D/Assets	CAPX/Assets	Tobin's Q	Size	Cash/Assets	Age
Product Stage (Life1)	0.4588	-0.1012	0.0949	-0.2208	0.4952	-0.2337
Process Stage (Life2)	-0.2623	0.1855	-0.0704	0.1453	-0.2864	0.1218
Mature Stage (Life3)	-0.1001	-0.0770	0.0024	0.0404	-0.1259	0.0057
Declining Stage (Life4)	-0.0930	-0.0965	-0.0198	0.0171	-0.0675	0.1375

Panel B	Product Stage (Life1)	Process Stage (Life2)	Mature Stage (Life3)	Declining Stage (Life4)
AR(1) coefficient	0.8614	0.8701	0.8293	0.7864

Panel A of this table provides pearson correlation coefficients for basic firm characteristics by product life cycle stage and Panel B provides autoregressive coefficients that are equal to the ordinary least squares (OLS) coefficient obtained when regressing each variable on its lagged value. The sample covers the years 1997 to 2019. Product Stage (Life1) measures the intensity of product innovation; Process Stage (Life2) measures the intensity of process innovation; Mature Stage (Life3) measures the intensity of stable and mature products; and Declining Stage (Life4) measures the intensity of product decline (discontinuation).

Table 3. Effect of Uncertainty on Investment Policies

	R&D/Assets	Intangible Investment	CAPX/Assets	Acquisitions
Uncertainty	-0.010	-0.012**	-0.055**	-0.0784**
	(0.006)	(0.005)	(0.026)	(0.039)
Uncertainty × Early Stage	0.056***	0.033**	0.065**	-0.0113
	(0.013)	(0.014)	(0.028)	(0.121)
Observations	29,507	27,099	29,396	28,006
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on investment policies. The dependent variables are R&D/Assets, intangible investment (R&D + 0.3 × SG&A, divided by intangible capital), CAPX/Assets and Acquisitions (a dummy equal to one if acquisition expenditures are greater than zero). Firm controls and IV first-moment controls are defined as in Section 4.2. Heteroskedasticity-robust standard errors, clustered at the industry level (SIC-2), are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Aggregate Effect in Response to a Increase in Uncertainty

	Early Stage Firms	Late Stage Firms
CAPX ($ millions)	0.777	-16.635
R&D ($ millions)	22.757	-2.485
Total Effect ($ millions)	23.534	-19.120
Aggregate Effect ($ millions)	28709.42	-105624.30

This table reports the economic magnitudes of the change in capital expenditures (CAPX) and R&D expenses in response to a one standard deviation increase in uncertainty (instrumented option implied volatility). Total Effect is the sum of effects on CAPX and R&D. Aggregate Effect is the Total Effect multiplied by the number of firms in each group.

Table 5. Effect of Uncertainty on Innovation

	Prob(Patent)	Patents Filed	Product Patents	Product - Other Patents
Uncertainty	-0.0383	-0.0046*	-0.0691	-0.0926*
	(0.0379)	(0.0027)	(0.0610)	(0.0518)
Uncertainty × Early Stage	0.0841*	0.0181**	0.1429***	0.1136***
	(0.0493)	(0.0082)	(0.0419)	(0.0445)
Observations	23,690	23,637	22,531	22,336
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on innovation. The dependent variables are Prob(Patent), a dummy equals one if the firm filed a patent, number of patents filed divided by lagged total assets, product patents (dummy variable that equals one when product patents are greater than zero), and product patents-other patents (dummy variable that equals one when the difference between product patents and other patents is greater than zero). Product patents are patents with over 50% of the claims being product claims, following the categorization in Ganglmair, Robinson, and Seeligson (2022). Other patents are patents that are not product patents. Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Effect of Uncertainty on Investment: Irreversibility and Product Life Stages

	R&D/Assets	R&D/Assets	R&D/Assets
Uncertainty	-0.010	-0.0063	-0.0165**
	(0.006)	(0.005)	(0.0082)
Uncertainty × Early Stage	0.056***	0.0481***	0.0641***
	(0.013)	(0.015)	(0.0187)
Uncertainty × IRR		-0.0067***	0.0066
		(0.002)	(0.004)
Uncertainty × Early Stage × IRR			-0.0442***
			(0.0117)
Observations	29,507	27,131	27,131
Firm Controls	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' investment using Equation (5). The dependent variable is R&D/Assets. IRR is a dummy variable , which is equal to one if a firm's asset redeployability is below the median, and zero otherwise (see Section 4.4 for details). Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Effect of Uncertainty on Investment: Financing Constraints and Product Life Stages

	R&D/Assets	R&D/Assets	R&D/Assets
Uncertainty	-0.010	-0.0119	-0.0150*
	(0.006)	(0.007)	(0.009)
Uncertainty × Early Stage	0.056***	0.0620***	0.0652***
	(0.013)	(0.0155)	(0.0161)
Uncertainty × FC		-0.0105*	0.0039
		(0.0061)	(0.0033)
Uncertainty × Early Stage × FC			-0.0682***
			(0.0183)
Observations	29,507	28,309	28,309
Firm Controls	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' investment using Equation (5). The dependent variable is R&D/Assets. FC is dummy equals to one if the firm is constrained in a given year. I define a firm as constrained in a given year if it is classified in the top tercile of both the equity- and debt-constraint measures. Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Firm and Product Summary Statistics

Panel A: Firms	**Mean**	**Median**	**25th Pctl**	**75th Pctl**
Number of Products	19	4	2	13
Product Portfolio Age	0.448	0.376	0.111	0.787
Sales (quarterly, US$1,000s)	892.8	11	0.7	118
Total Firms: 22,320				

Panel B: Products	**Mean**	**Median**	**25th Pctl**	**75th Pctl**
Sales (quarterly, US$1,000s)	91	1.2	0.07	17
Total Products: 568,698				

Panel C: Product-Market Uncertainty	**Mean**	**Median**	**25th Pctl**	**75th Pctl**
PMU	0.592	0.342	0.158	0.710

Panel A reports statistics at the firm level, including the number of products, product portfolio age, and quarterly sales. Panel B reports statistics at the product level, focusing on quarterly sales. Panel C reports the firm-level measure of product-market uncertainty. The sample covers 22,320 firms and 568,698 unique products.

Table 9. Correlation of PMU and Other Measures

	PMU	**EMV**	**VIX**	**FIN**	**REAL**
PMU					
EMV	0.2007				
VIX	0.1512	0.8275			
FIN	0.1184	0.7252	0.8354		
REAL	0.0194	0.5320	0.7113	0.8500	
MACRO	0.0774	0.6658	0.8122	0.8367	0.9091

This table reports pairwise correlations between Product-Market Uncertainty (PMU) and standard aggregate proxies of uncertainty, including EMV (Economic Policy Uncertainty based on news), VIX (implied stock market volatility), FIN (financial uncertainty), REAL (real uncertainty), and MACRO (macroeconomic uncertainty).

Table 10. Effect of Uncertainty on Product Entry

	Product Entry	Product Entry	Product Entry
PMU	-0.0015***	-0.0016***	-0.0014***
	(0.0005)	(0.0005)	(0.0005)
PMU × Early Stage	0.0023***	0.0023***	0.0020***
	(0.0006)	(0.0006)	(0.0005)
Observations	194,591	194,591	194,591
Macro Controls	Yes	Yes	No
1st moment controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Time FE	No	No	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on product entry. The dependent variable is Product Entry, defined as the number of new products introduced in period t as a share of the total number of products in period t. Firm Controls and 1st moment controls are defined as in Section 5.4. Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Effect of Uncertainty on Product Exit

	Product Exit	Product Exit	Product Exit
PMU	-0.0016***	-0.0014**	-0.0013**
	(0.0005)	(0.0005)	(0.0005)
PMU × Early Stage	0.0018**	0.0017**	0.0017**
	(0.0007)	(0.0007)	(0.0007)
Observations	191,155	191,155	191,155
Macro Controls	Yes	Yes	No
1st moment controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Time FE	No	No	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on product exit. The dependent variable is Product Exit, defined as the number of products that exited in period t (i.e., the last time a transaction is observed is in $t-1$) as a share of the total number of products in period $t-1$. Firm Controls and 1st moment controls are defined as in Section 5.4. Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

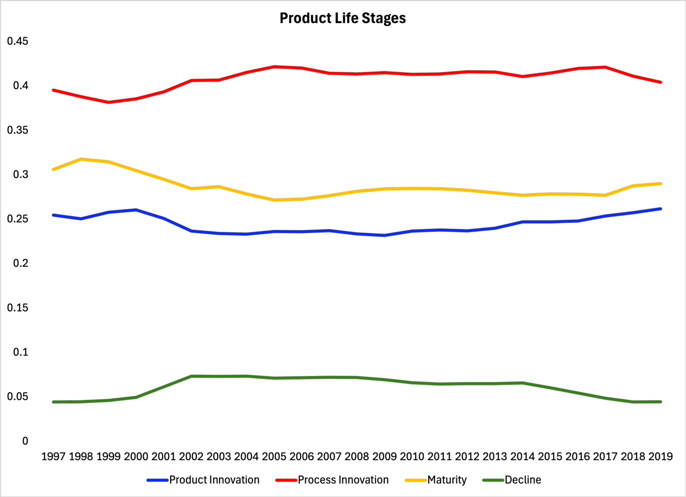
Table 12. Effect of Uncertainty on Product Reallocation

	Product Reallocation	Product Reallocation	Product Reallocation
PMU	-0.0027***	-0.0025***	-0.0022***
	(0.0007)	(0.0007)	(0.0007)
PMU × Early Stage	0.0037***	0.0036***	0.0033***
	(0.001)	(0.0010)	(0.0009)
Observations	191,155	191,155	191,155
Macro Controls	Yes	Yes	No
1st moment controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Time FE	No	No	Yes

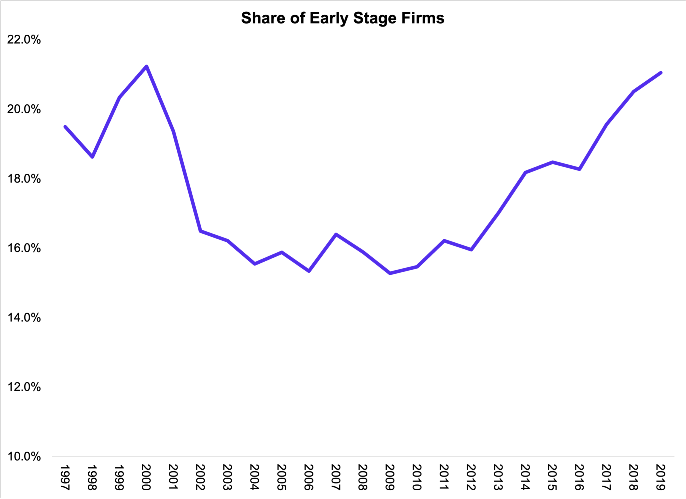
This table reports the coefficients of uncertainty and its interaction with Early Stage on product reallocation. The dependent variable is Product Rellocation, defined as the sum of product entry rate and product exit rate. Firm Controls and 1st moment controls are defined as in Section 5.4. Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Figure 1. Product Life Cycle Measures

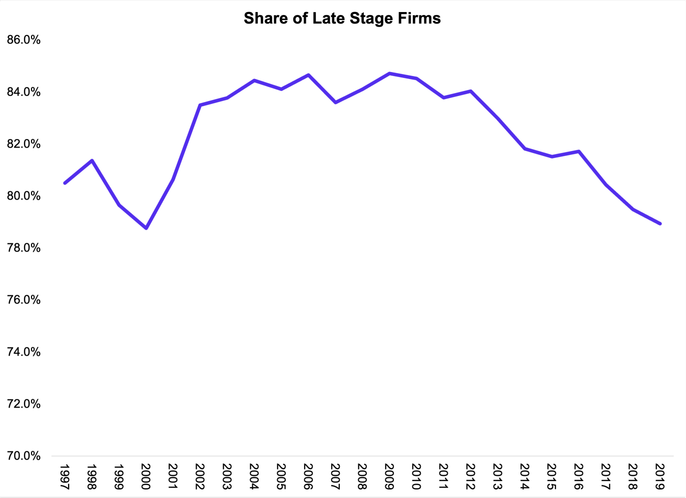
Panel A: Life Stages Over Time



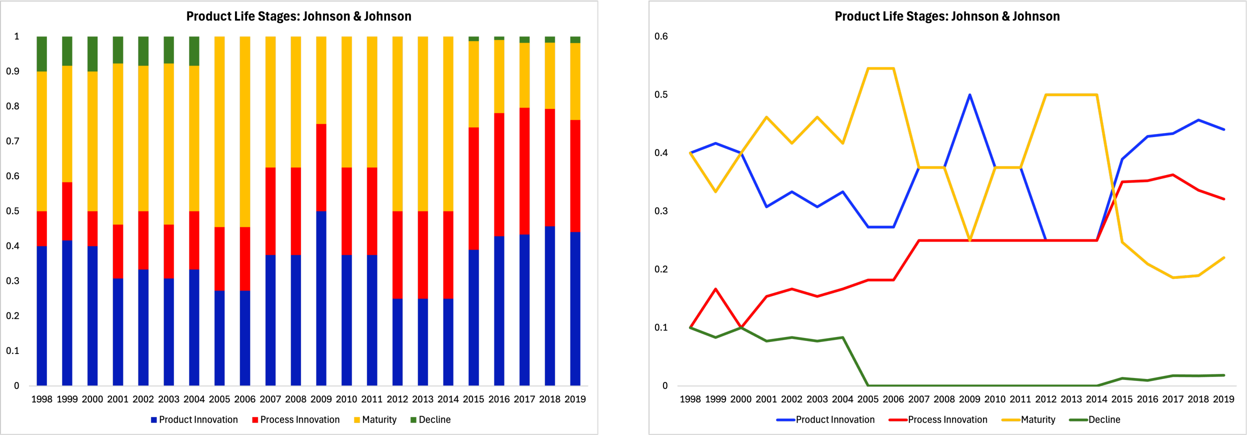
Panel B: Share of Early Stage Firms



Panel C: Share of Late Stage Firms

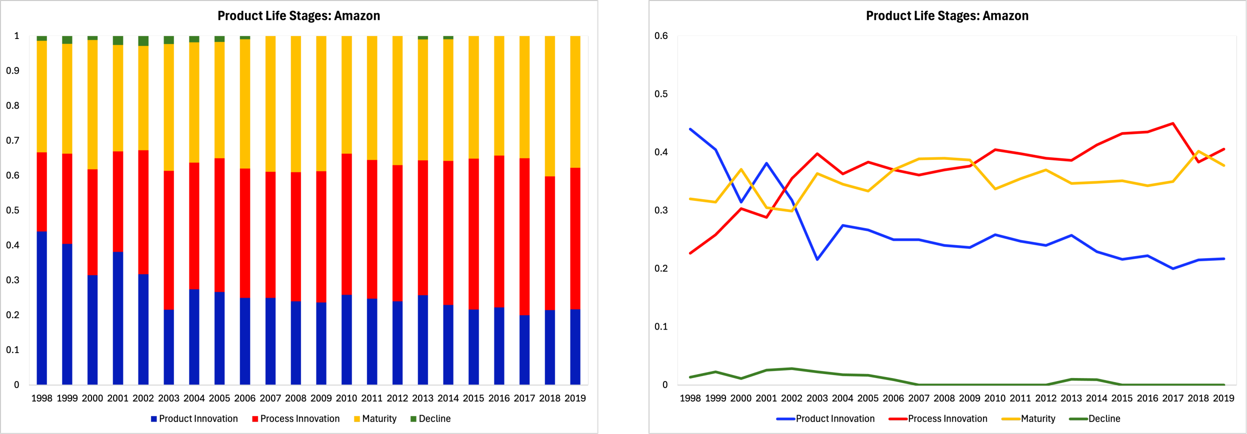


Panel A of this figure shows the average life stage variables over time. Product Stage (Life1) measures the intensity of product innovation; Process Stage (Life2) measures the intensity of process innovation; Mature Stage (Life3) measures the intensity of stable and mature products; and Declining Stage (Life4) measures the intensity of product decline (discontinuation). Panels B and C shows the share of early stage and late stage firms , respectively.



Panel A: Johnson & Johnson

Panel B: Johnson & Johnson

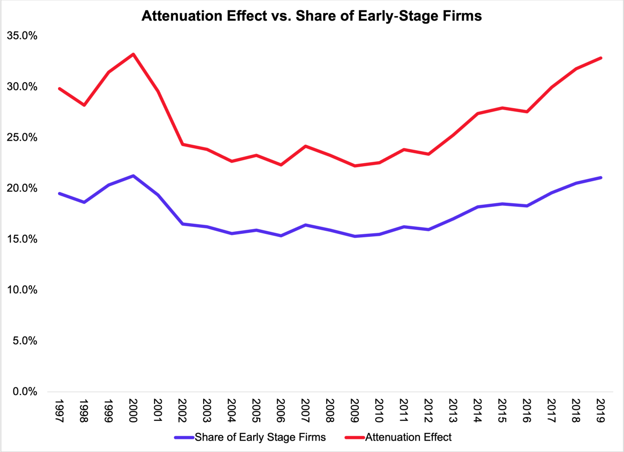


Panel C: Amazon

Panel D: Amazon

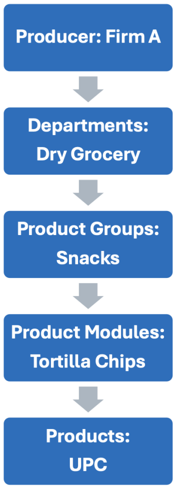
Figure 2. This figure shows the average life stage variables over time. Product Stage (Life1) measures the intensity of product innovation; Process Stage (Life2) measures the intensity of process innovation; Mature Stage (Life3) measures the intensity of stable and mature products; and Declining Stage (Life4) measures the intensity of product decline (discontinuation).

Figure 3. Aggregate Investment Implications



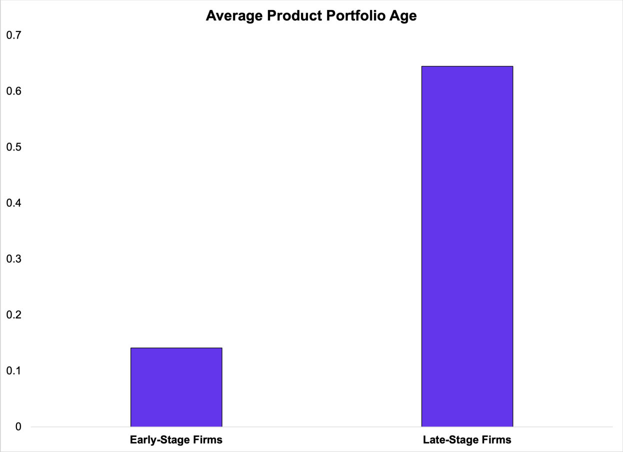
This figure plots the attenuation effect of uncertainty on aggregate investment (red) against the share of early-stage firms in the economy (blue) following the methodology in Section 4.3.2. The attenuation effect captures the extent to which early-stage firms offset the negative impact of uncertainty on aggregate investment.

Figure 4. Product Portfolio Hierarchy



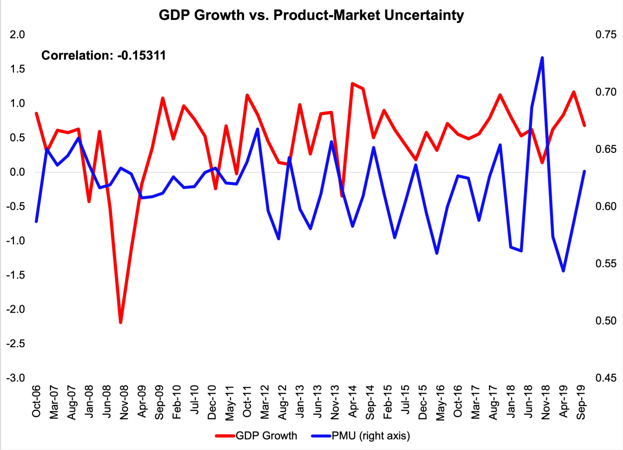
This figure plots the product portfolio hierarchy from the NielsenIQ Retail Scanner Data. Firms' products are categorized into departments, groups, modules, and products (UPC).

Figure 5. Product Portfolio Age



This figure plots the average product portfolio age for early- and late-stage firms. Product portfolio age is defined as the weighted share of old products, whose age exceeds half of their lifespan, in the product portfolio, where the weights correspond to product-specific revenue.

Figure 6. Product-Market Uncertainty and GDP Growth



This figure plots the aggregate PMU (red) against GDP growth (blue). Aggregate PMU is defined as the average of PMU across firms and GDP growth is the growth rate of real GDP from FRED.

Online Appendix for "Product Life Cycle Heterogeneity in the Transmission of Uncertainty"

A. Proofs and Derivations

This appendix provides the formal derivations and proofs for the results stated in Section 3. I derive project values, characterize optimal investment using productivity cutoffs, present the Kuhn–Tucker conditions of the firm's problem, and establish the comparative statics with respect to uncertainty σ. Throughout, uncertainty $\sigma \geq 0$ indexes mean-preserving spreads (MPS) of all payoff-relevant random variables.

A.1 Project Heterogeneity and Cutoff Representation

Within each project type $j \in \{\exp, \text{inc}, M\}$ and stage s, potential projects differ in expected productivity μ, distributed according to $F_{j,s}(\mu)$ on $[\underline{\mu}_{j,s}, \overline{\mu}_{j,s}]$ with density $f_{j,s}(\mu)$.

Lemma 1 (Monotonicity in productivity). *For all project types j and stages s, the $t = 0$ value of a project $V_j(\sigma, \mu)$ is strictly increasing in μ.*

Proof. In all payoff processes, μ enters additively and linearly in the mean of future cash flows and does not affect dispersion. As continuation and waiting payoffs are increasing in expected cash flows, project values inherit strict monotonicity in μ. □

With convex implementation costs, optimal investment can be represented by a productivity cutoff. For each project type j and stage s, there exists a cutoff $\mu^*_{j,s}(\sigma)$ such that all projects with $\mu \geq \mu^*_{j,s}(\sigma)$ are implemented at $t = 0$. The cutoff satisfies the marginal condition

$$V_j(\sigma, \mu^*_{j,s}(\sigma)) = \alpha_j \, x_{j,s}(\sigma), \tag{7}$$

together with the mapping between quantities and cutoffs:

$$x_{j,s}(\sigma) = \int_{\mu^*_{j,s}(\sigma)}^{\overline{\mu}_{j,s}} f_{j,s}(\mu)\, d\mu = 1 - F_{j,s}\Big(\mu^*_{j,s}(\sigma)\Big)\,. \tag{8}$$

Feasibility requires

$$0 \le x^{\text{exp}}_{G,s} + x^{\text{inc}}_{G,s} \le R_s, \qquad 0 \le x_{M,s} \le N_s,$$

where $(x_{\text{exp},s}, x_{\text{inc},s}, x_{M,s}) \equiv (x^{\text{exp}}_{G,s}, x^{\text{inc}}_{G,s}, x_{M,s})$. Therefore, the opportunity set parameters (R_s, N_s), and hence the share $\theta_s = \frac{R_s}{R_s+N_s}$, bound the quantitative importance of the mature margin in each life-cycle stage.

A.2 Firm Problem

For a firm in life-cycle stage $s \in \{E, L\}$, expected firm value at $t = 0$ is

$$\begin{aligned} V^s_0(\sigma) = \max_{x^{\text{exp}}_{G,s},\, x^{\text{inc}}_{G,s},\, x_{M,s},\, x_{IC,s} \ge 0} \Big\{ & x^{\text{exp}}_{G,s} V^{\text{exp}}_G(\sigma; x_{IC,s}) + x^{\text{inc}}_{G,s} V^{\text{inc}}_G(\sigma) + x_{M,s} V_M(\sigma) \\ & - c_g x_{IC,s} - \frac{\alpha_{IC}}{2} x^2_{IC,s} - \frac{\alpha_{\text{exp}}}{2}(x^{\text{exp}}_{G,s})^2 - \frac{\alpha_{\text{inc}}}{2}(x^{\text{inc}}_{G,s})^2 - \frac{\alpha_M}{2} x^2_{M,s} \Big\}. \end{aligned} \tag{9}$$

where $V_M(\sigma)$, $V^{\text{inc}}_G(\sigma)$, and $V^{\text{exp}}_G(\sigma; x_{IC,s})$ denote the values of the marginal implemented project of each type, evaluated at endogenous productivity cutoffs derived above.

The Kuhn–Tucker (KT) conditions for an optimum are listed below. Consistent with the interior solution assumption discussed in Section 3, I focus on the case where $x_{j,s} > 0$ and the capacity constraints are not binding, such that the marginal value of the implemented project exactly equals its marginal cost.

Exploratory R&D $x_{G,s}^{\exp}$.

$$\frac{\partial V_0^s}{\partial x_{G,s}^{\exp}} = V_G^{\exp}(\sigma; x_{IC,s}) - \alpha_{\exp} x_{G,s}^{\exp} \leq 0, \qquad x_{G,s}^{\exp} \geq 0, \qquad x_{G,s}^{\exp}\left(V_G^{\exp}(\sigma; x_{IC,s}) - \alpha_{\exp} x_{G,s}^{\exp}\right) = 0.$$

An interior solution ($x_{G,s}^{\exp} > 0$) requires

$$V_G^{\exp}(\sigma; x_{IC,s}) = \alpha_{\exp} x_{G,s}^{\exp}.$$

Incremental R&D $x_{G,s}^{\text{inc}}$.

$$\frac{\partial V_0^s}{\partial x_{G,s}^{\text{inc}}} = V_G^{\text{inc}}(\sigma) - \alpha_{\text{inc}} x_{G,s}^{\text{inc}} \leq 0, \qquad x_{G,s}^{\text{inc}} \geq 0, \qquad x_{G,s}^{\text{inc}}\left(V_G^{\text{inc}}(\sigma) - \alpha_{\text{inc}} x_{G,s}^{\text{inc}}\right) = 0.$$

An interior solution ($x_{G,s}^{\text{inc}} > 0$) requires

$$V_G^{\text{inc}}(\sigma) = \alpha_{\text{inc}} x_{G,s}^{\text{inc}}.$$

Mature projects $x_{M,s}$.

$$\frac{\partial V_0^s}{\partial x_{M,s}} = V_M(\sigma) - \alpha_M x_{M,s} \leq 0, \qquad x_{M,s} \geq 0, \qquad x_{M,s}\left(V_M(\sigma) - \alpha_M x_{M,s}\right) = 0.$$

An interior solution ($x_{M,s} > 0$) requires

$$V_M(\sigma) = \alpha_M x_{M,s}.$$

Innovative capacity $x_{IC,s}$.

$$\begin{aligned}\frac{\partial V_0^s}{\partial x_{IC,s}} =& x_{G,s}^{\exp} \frac{\partial V_G^{\exp}(\sigma; x_{IC,s})}{\partial x_{IC,s}} - c_g - \alpha_{IC} x_{IC,s} \leq 0, \quad x_{IC,s} \geq 0, \\ & x_{IC,s}\left(x_{G,s}^{\exp} \frac{\partial V_G^{\exp}(\sigma; x_{IC,s})}{\partial x_{IC,s}} - c_g - \alpha_{IC} x_{IC,s}\right) = 0.\end{aligned}$$

When $x_{IC,s} > 0$ and $x^{\text{exp}}_{G,s} > 0$ (the empirically relevant case for early-stage firms), the interior FOC is

$$c_g + \alpha_{IC} x_{IC,s} = x^{\text{exp}}_{G,s}(\sigma)\,\frac{\partial V^{\text{exp}}_{G}(\sigma; x_{IC,s})}{\partial x_{IC,s}}. \tag{10}$$

Equation (10) implicitly defines the optimal $x_{IC,s}(\sigma)$ for each stage s and level of uncertainty σ.

The FOCs imply that determining how uncertainty σ affects investment requires characterizing its effects on V_M, V^{exp}_G, and V^{inc}_G. Sections A.3–A.5 provide this analysis.

A.3 Mature Projects

Each mature project yields cash flows $v_1(\mu)$ and $v_2(\mu)$ at $t = 1$ and $t = 2$ if undertaken. These satisfy

$$v_t(\mu) = \mu\,\bar{v}_t + \varepsilon_t, \qquad \mathbb{E}[\varepsilon_t] = 0, \quad \text{Var}(\varepsilon_t) = \sigma^2_v(\sigma),$$

where $\sigma^2_v(\sigma)$ increases in σ and the distribution of $v_t(\mu)$ is a mean-preserving spread family in σ for each fixed μ. If the firm invests immediately at $t = 0$, the project value is

$$V^{\text{now}}_M(\sigma, \mu) = \mathbb{E}[v_1(\mu) + v_2(\mu)] - c_m = \mu(\bar{v}_1 + \bar{v}_2) - c_m, \tag{11}$$

which does not depend on σ. Alternatively, the firm can wait until $t = 1$ and observe $v_2(\mu)$, then decide whether to invest. If it invests at $t = 1$, it pays c_m and receives $v_2(\mu)$ at $t = 2$; if not, it receives 0. The $t = 0$ value of this option-to-delay strategy is

$$V^{\text{wait}}_M(\sigma, \mu) = \mathbb{E}\big[\max\{v_2(\mu) - c_m, 0\}\big]. \tag{12}$$

Lemma 2. *For any fixed μ, $V^{\text{wait}}_M(\sigma, \mu)$ is strictly increasing in σ.*

Proof. The payoff function $\max\{v_2(\mu) - c_m, 0\}$ is increasing and convex in $v_2(\mu)$. By assumption, $v_2(\mu; \sigma')$ is a mean-preserving spread of $v_2(\mu; \sigma)$ whenever $\sigma' > \sigma$. The combination of convexity and the MPS ordering implies, by Jensen's inequality and standard results on second-order stochastic dominance, that

$$\mathbb{E}[\max\{v_2(\mu; \sigma') - c_m, 0\}] > \mathbb{E}[\max\{v_2(\mu; \sigma) - c_m, 0\}],$$

so $V_M^{\text{wait}}(\sigma, \mu)$ is strictly increasing in σ. □

The $t = 0$ value of a mature project of productivity μ is

$$V_M(\sigma, \mu) = \max\{V_M^{\text{now}}(\sigma, \mu), V_M^{\text{wait}}(\sigma, \mu)\}. \tag{13}$$

Proposition 1. *The measure of mature projects undertaken at $t = 0$, $x_{M,s}(\sigma)$, is strictly decreasing in σ:*

$$\frac{\partial x_{M,s}}{\partial \sigma} < 0.$$

Proof. For each μ, Lemma 2 implies that the value of waiting $V_M^{\text{wait}}(\sigma, \mu)$ rises with σ while $V_M^{\text{now}}(\sigma, \mu)$ is unchanged. Thus, the net advantage of immediate investment ($V_M^{\text{now}} - V_M^{\text{wait}}$) shrinks as σ increases. With heterogeneous productivities, the marginal mature project at stage s is characterized by the cutoff $\mu^*_{M,s}(\sigma)$ solving

$$V_M(\sigma, \mu^*_{M,s}(\sigma)) = \alpha_M x_{M,s}(\sigma).$$

To maintain this optimality condition, which requires $V_M^{\text{now}}(\sigma, \mu^*) \geq V_M^{\text{wait}}(\sigma, \mu^*)$ for the marginal project, the shrinking net advantage of acting now causes the cutoff $\mu^*_{M,s}(\sigma)$ to rise. Because $x_{M,s}(\sigma)$ is the mass of projects with $\mu \geq \mu^*_{M,s}(\sigma)$, a higher cutoff implies a smaller mass, i.e, $\partial x_{M,s}/\partial \sigma < 0$. □

A.4 Incremental (Process-Improvement) R&D

Incremental R&D projects are modeled as small-scale investments in existing product lines. An incremental R&D project yields cash flows $r_1(\mu)$ and $r_2(\mu)$ at $t = 1$ and $t = 2$ if undertaken at $t = 0$:

$$r_t(\mu) = \mu\,\bar{r}_t + \zeta_t, \qquad \mathbb{E}[\zeta_t] = 0, \quad \mathrm{Var}(\zeta_t) = \sigma_r^2(\sigma),$$

where $\sigma_r^2(\sigma)$ increases in σ and the distribution of $r_t(\mu)$ is a mean-preserving spread family. If the firm invests immediately at $t = 0$, the project value is

$$V_G^{\text{inc,now}}(\sigma,\mu) = \mathbb{E}[r_1(\mu) + r_2(\mu)] - k_R^{\text{inc}} = \mu(\bar{r}_1 + \bar{r}_2) - k_R^{\text{inc}}, \tag{14}$$

which does not depend on σ.

As with mature projects, the firm can delay incremental R&D until $t = 1$ and invest only if $r_2(\mu)$ is sufficiently high. The value of this option to delay is

$$V_G^{\text{inc,wait}}(\sigma,\mu) = \mathbb{E}\big[\max\{r_2(\mu) - k_R^{\text{inc}}, 0\}\big]. \tag{15}$$

The payoff $\max\{r_2(\mu) - k_R^{\text{inc}}, 0\}$ is increasing and convex in $r_2(\mu)$, and $r_2(\mu)$ is an MPS family in σ. The same reasoning as in Lemma 2 yields:

Lemma 3. *For any fixed μ, $V_G^{inc,wait}(\sigma,\mu)$ is strictly increasing in σ.*

The $t = 0$ value of an incremental project is therefore

$$V_G^{\text{inc}}(\sigma,\mu) = \max\{V_G^{\text{inc,now}}(\sigma,\mu), V_G^{\text{inc,wait}}(\sigma,\mu)\}. \tag{16}$$

Proposition 2. *The measure of incremental R&D projects initiated at $t = 0$, $x_{G,s}^{inc}(\sigma)$, is strictly decreasing in σ:*

$$\frac{\partial x_{G,s}^{inc}}{\partial \sigma} < 0.$$

Proof. Define the net advantage of immediate incremental R&D, relative to waiting:

$$\Pi_G^{\text{inc,now}}(\sigma, \mu) \equiv V_G^{\text{inc,now}}(\sigma, \mu) - V_G^{\text{inc,wait}}(\sigma, \mu).$$

From (14) and Lemma 3, $\partial V_G^{\text{inc,now}}(\sigma, \mu)/\partial\sigma = 0$ and $\partial V_G^{\text{inc,wait}}(\sigma, \mu)/\partial\sigma > 0$, so the net advantage is strictly decreasing:

$$\frac{\partial \Pi_G^{\text{inc,now}}(\sigma, \mu)}{\partial \sigma} < 0.$$

Higher σ thus reduces the set of productivities μ for which immediate implementation at $t = 0$ is worthwhile relative to waiting. With convex implementation costs, the cutoff productivity $\mu^*_{\text{inc},s}(\sigma)$ must rise with σ to maintain the optimality condition, and the mass of projects with $\mu \geq \mu^*_{\text{inc},s}(\sigma)$ declines, i.e., $\partial x_{G,s}^{\text{inc}}/\partial\sigma < 0$. $\square$

A.5 Exploratory Growth-Option R&D and Innovative Capacity

Exploratory (growth-option) R&D projects have a multi-stage structure with an abandonment option and scalability via innovative capacity $x_{IC,s}$. At $t = 0$, initiating one project costs $k_R^{\text{exp}} > 0$. For an exploratory project of expected productivity μ, the interim signal at $t = 1$ is

$$u_1(\mu) = \mu + \eta_1, \qquad \mathbb{E}[\eta_1] = 0, \quad \text{Var}(\eta_1) = \sigma_u^2(\sigma),$$

which summarizes information about the project's prospects. Based on $u_1(\mu)$, the firm either abandons or continues the project. If it abandons, it pays no further costs and receives no payoff at $t = 2$. If it continues, it pays a continuation cost $d > 0$ at $t = 1$.

At $t = 2$, conditional on continuation, the project yields a final payoff

$$u_2(\mu) = u_1(\mu) + \eta_2, \qquad \mathbb{E}[\eta_2] = 0, \quad \text{Var}(\eta_2) = \sigma_u^2(\sigma),$$

and the pair $(u_1(\mu), u_2(\mu))$ is drawn from a joint distribution indexed by σ that is a mean-preserving spread family.

Innovative capacity $x_{IC,s}$ scales the payoff of a continued project:

$$\pi_2^G(\mu) = u_2(\mu)\,(x_{IC,s})^{\gamma_s}, \qquad \gamma_s > 0.$$

where parameter γ_s captures complementarity between capacity and growth options. Given $(x_{IC,s}, \sigma)$, the firm follows a threshold rule at $t = 1$: there exists a cutoff $\bar{u}_1^*(x_{IC,s}, \sigma)$ such that projects with $u_1(\mu) \geq \bar{u}_1^*$ are continued and projects with $u_1(\mu) < \bar{u}_1^*$ are abandoned. The continuation cutoff $\bar{u}_1^*$ is implicitly defined by the condition that the expected $t = 2$ payoff exactly covers the continuation cost d:

$$\mathbb{E}_{u_2(\mu)|\bar{u}_1^*}\big[u_2(\mu)(x_{IC,s})^{\gamma_s}\big] = d.$$

For a project of productivity μ, the $t = 0$ value is

$$V_G^{\exp}(\sigma, \mu; x_{IC,s}) = -k_R^{\exp} + \mathbb{E}_{u_1(\mu)}\Big[\max\Big\{\mathbb{E}_{u_2(\mu)|u_1(\mu)}\big[u_2(\mu)(x_{IC,s})^{\gamma_s}\big] - d\ ,\ 0\Big\}\Big]. \tag{17}$$

Lemma 4. *For any $x_{IC,s} > 0$, $\gamma_s > 0$, and fixed μ, $V_G^{exp}(\sigma, \mu; x_{IC,s})$ is strictly increasing in σ.*

Proof. Define the continuation payoff conditional on $(u_1(\mu), u_2(\mu))$:

$$\Phi(u_1(\mu), u_2(\mu); x_{IC,s}) \equiv \max\big\{u_2(\mu)(x_{IC,s})^{\gamma_s} - d, 0\big\}.$$

For any fixed $x_{IC,s}$ and $\gamma_s > 0$, Φ is increasing and convex in $u_2(\mu)$. Let

$$h(u_1(\mu); \sigma, x_{IC,s}) \equiv \mathbb{E}_{u_2(\mu)|u_1(\mu)}[\Phi(u_1(\mu), u_2(\mu); x_{IC,s})].$$

Because $(u_1(\mu), u_2(\mu))$ is a mean-preserving spread family in σ and Φ is convex in $u_2(\mu)$, $h(u_1(\mu); \sigma, x_{IC,s})$ is increasing in σ for each $u_1(\mu)$. Taking the outer expectation over $u_1(\mu)$

and subtracting the initiation cost k_R^{exp} preserves this monotonicity, so $V_G^{\text{exp}}(\sigma, \mu; x_{IC,s})$ is strictly increasing in σ. □

Lemma 5. *For any $\gamma_s > 1$ and fixed μ, the marginal value of innovative capacity,*

$$\frac{\partial V_G^{exp}(\sigma, \mu; x_{IC,s})}{\partial x_{IC,s}},$$

is increasing in σ.

Proof. Under standard regularity condition (differentiation under the expectation sign), differentiate (17) with respect to $x_{IC,s}$. Inside the $\max\{\cdot, 0\}$ operator, the relevant term is $\mathbb{E}_{u_2(\mu)|u_1(\mu)}[u_2(\mu)(x_{IC,s})^{\gamma_s}]$. When the project is continued, the derivative with respect to $x_{IC,s}$ is

$$\gamma_s (x_{IC,s})^{\gamma_s - 1}\, \mathbb{E}_{u_2(\mu)|u_1(\mu)}[u_2(\mu)].$$

Thus, up to the continuation indicator,

$$\frac{\partial V_G^{\text{exp}}(\sigma, \mu; x_{IC,s})}{\partial x_{IC,s}} = \mathbb{E}\Big[\mathbf{1}\{\text{continuation at } t = 1\} \cdot \gamma_s (x_{IC,s})^{\gamma_s - 1} u_2(\mu)\Big].$$

When $\gamma_s > 1$, $(x_{IC,s})^{\gamma_s - 1}$ is increasing in $x_{IC,s}$, and the continuation payoff is more strongly convex in $u_2(\mu)$ than when $\gamma_s \leq 1$. A mean-preserving spread in $(u_1(\mu), u_2(\mu))$ shifts probability mass toward high-$u_2(\mu)$ states and, through the continuation rule, toward states in which the project is more likely to be continued and $u_2(\mu)$ is large. As in Lemma 4, the MPS plus convexity argument implies that the expectation of this marginal payoff is increasing in σ, so $\partial V_G^{\text{exp}} / \partial x_{IC,s}$ is increasing in σ. □

In the extensive-margin interpretation, Lemma 4 implies that for each μ, higher σ raises $V_G^{\text{exp}}(\sigma, \mu; x_{IC,s})$. Therefore the set of exploratory projects with non-negative NPV at $t = 0$ expands with σ, i.e.,

$$\frac{\partial x_{G,s}^{\text{exp}}}{\partial \sigma} > 0.$$

A.6 Comparative Statics and Proof of Predictions

From Propositions 1 and 2 and Lemma 4, we have:

$$\frac{\partial x_{M,s}}{\partial \sigma} < 0, \qquad \frac{\partial x_{G,s}^{\text{inc}}}{\partial \sigma} < 0, \qquad \frac{\partial x_{G,s}^{\text{exp}}}{\partial \sigma} > 0.$$

I now characterize how $x_{IC,s}(\sigma)$ responds to σ for early- and late-stage firms.

Lemma 6. *For early-stage firms ($s = E$) with strong capacity–growth complementarity ($\gamma_E > 1$) and a positive exploratory R&D scale ($x_{G,E}^{\text{exp}} > 0$), the optimal innovative capacity is increasing in uncertainty:*

$$\frac{\partial x_{IC,E}}{\partial \sigma} > 0.$$

Proof. For $s = E$, the interior FOC (10) is

$$c_g + \alpha_{IC} x_{IC,E} = x_{G,E}^{\text{exp}}(\sigma)\, \frac{\partial V_G^{\text{exp}}(\sigma; x_{IC,E})}{\partial x_{IC,E}}.$$

Fix $x_{IC,E}$ and increase σ. By Lemma 4, $V_G^{\text{exp}}(\sigma, \mu; x_{IC,E})$ rises for all μ, so the extensive margin of exploratory projects expands and $x_{G,E}^{\text{exp}}(\sigma)$ increases. By Lemma 5, the marginal value $\partial V_G^{\text{exp}}(\sigma; x_{IC,E}) / \partial x_{IC,E}$ also increases with σ when $\gamma_E > 1$. Thus the right-hand side

$$x_{G,E}^{\text{exp}}(\sigma)\, \frac{\partial V_G^{\text{exp}}(\sigma; x_{IC,E})}{\partial x_{IC,E}}$$

is increasing in σ for any fixed $x_{IC,E}$, while the left-hand side $c_g + \alpha_{IC} x_{IC,E}$ does not depend on σ. To restore the equality as σ rises, the firm must increase $x_{IC,E}(\sigma)$ so that the higher convex cost offsets the higher marginal benefit. Under standard regularity (monotonicity of the RHS in $x_{IC,E}$ for early-stage firms), the implicit function theorem then implies $\partial x_{IC,E} / \partial \sigma > 0$ at the interior solution. □

For late-stage firms with $\gamma_L \approx 0$, $V_G^{\text{exp}}(\sigma; x_{IC,L})$ depends only weakly on $x_{IC,L}$, and the marginal value of $x_{IC,L}$ is almost flat in σ, so any $\partial x_{IC,L} / \partial \sigma$ is weak.

Proof of Prediction 1 (Early-stage). We have

$$\frac{\partial x_{G,E}}{\partial \sigma} = \frac{\partial x_{G,E}^{\mathrm{exp}}}{\partial \sigma} + \frac{\partial x_{G,E}^{\mathrm{inc}}}{\partial \sigma},$$

where $\partial x_{G,E}^{\mathrm{exp}}/\partial \sigma > 0$ and $\partial x_{G,E}^{\mathrm{inc}}/\partial \sigma < 0$. Given the exogenous productivity assumption that ensures exploratory R&D dominates the optimal mix for early-stage firms ($s = E$), the opportunity set is tilted toward R&D-type projects (θ_E high and N_E small), and complementarity between innovative capacity and R&D is strong ($\gamma_E > 1$), so the positive exploratory term dominates the negative incremental term, yielding

$$\frac{\partial x_{G,E}}{\partial \sigma} > 0.$$

Second, total Capex at stage E is

$$I_E^K(\sigma) = x_{IC,E}(\sigma) + x_{M,E}(\sigma).$$

By Lemma 6, $\partial x_{IC,E}/\partial \sigma > 0$. By Proposition 1, $\partial x_{M,E}/\partial \sigma < 0$. For early-stage firms, the mass of mature opportunities N_E is small, so the magnitude of the option-to-delay effect on mature projects, $|\partial x_{M,E}/\partial \sigma|$, is quantitatively limited relative to the expansion in innovative capacity. Hence

$$\frac{\partial I_E^K}{\partial \sigma} = \frac{\partial x_{IC,E}}{\partial \sigma} + \frac{\partial x_{M,E}}{\partial \sigma} > 0.$$

Thus, for early-stage firms,

$$\frac{\partial x_{G,E}}{\partial \sigma} > 0, \qquad \frac{\partial I_E^K}{\partial \sigma} > 0,$$

as stated in Prediction 1. □

Proof of Prediction 2 (Late-stage). We have:

$$\frac{\partial x_{G,L}}{\partial \sigma} = \frac{\partial x^{\text{exp}}_{G,L}}{\partial \sigma} + \frac{\partial x^{\text{inc}}_{G,L}}{\partial \sigma}.$$

where $\partial x^{\text{exp}}_{G,L}/\partial \sigma > 0$ and $\partial x^{\text{inc}}_{G,L}/\partial \sigma < 0$. Given the the exogenous productivity assumption that ensures incremental R&D dominates the optimal mix for late-stage firms ($s = L$), the opportunity set is dominated by mature projects (θ_L low and N_L large), and growth-capacity complementarity is weak ($\gamma_L \approx 0$). Hence the negative incremental component dominates the positive exploratory component, yielding

$$\frac{\partial x_{G,L}}{\partial \sigma} \lesssim 0.$$

Second, total Capex at stage L is

$$I^K_L(\sigma) = x_{IC,L}(\sigma) + x_{M,L}(\sigma).$$

Because $\gamma_L \approx 0$, the marginal value of $x_{IC,L}$ is almost independent of σ, so any response $\partial x_{IC,L}/\partial \sigma$ is weak. By contrast, mature projects and incremental R&D are strongly subject to the option-to-delay effect (Propositions 1 and 2), which shifts investment out of $t = 0$ as σ rises. Therefore,

$$\frac{\partial x_{M,L}}{\partial \sigma} < 0 \quad \text{and} \quad \frac{\partial x_{IC,L}}{\partial \sigma} \approx 0,$$

so

$$\frac{\partial I^K_L}{\partial \sigma} = \frac{\partial x_{IC,L}}{\partial \sigma} + \frac{\partial x_{M,L}}{\partial \sigma} < 0.$$

Together, these results imply that for late-stage firms,

$$\frac{\partial x_{M,L}}{\partial \sigma} < 0, \qquad \frac{\partial I^K_L}{\partial \sigma} < 0, \qquad \frac{\partial x_{G,L}}{\partial \sigma} \lesssim 0,$$

as stated in Prediction 2. $\square$

B. Firm-level Variables

This section describes the definition of firm-level variables. *Investment* is annual capital expenditures (COMPUSTAT's capx) divided by lagged total assets (COMPUSTAT's at). *R&D* is annual R&D (COMPUSTAT's xrd). I follow the literature and set missing values of R&D equals to zero. *SG&A* is annual 0.3 × COMPUSTAT's xsga. *Disinvestment* is sale of property (COMPUSTAT's sppe) divided by PPE (COMPUSTAT's ppegt). Employee is the number of employees (COMPUSTAT's emp). *Working Capital* is the sum of inventories (COMPUSTAT's invt) and receivables (COMPUSTAT's rect) divided by lagged total assets. *Cash flow* represents the ratio of operating income before depreciation (COMPUSTAT's oibdp) to the lag of total assets. *Size* is given by the logarithm of total assets. *Cash holdings* are measured as the ratio of cash and short-term investments (COMPUSTAT's che) to total assets. *Total debt* is long-term debt (COMPUSTAT's dltt) plus debt in Current Liabilities (COMPUSTAT's dlc). *Book leverage* denotes the ratio of total debt to total assets. Q is defined as the ratio of total assets plus market capitalization minus common equity minus deferred taxes and investment tax credit (at + prcc×csho - ceq -txditc) to total assets (at). *Age* is the number of years since a firm first appears in Compustat. *Annual realized volatility* is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP, and annualized by multiplying by $\sqrt{252}$. *Annual implied volatility* is the 12-month average of firms' daily option-implied volatility, where the daily observations are the simple average of forward 365-day-horizon at-the-money (ATM) call and put options.

C. The Role of Age

One concern is that early-stage firms are negatively correlated with firm age and, as a result, my findings may simply reflect firm age effects rather than product life-cycle heterogeneity. I address this concern by re-estimating my main specifications while including an interaction between firm age and uncertainty, keeping the same set of controls. Table J.10 shows that the results remain unchanged.

I next test whether the heterogeneous investment response can be obtained without using the product life-cycle measure. Specifically, I examine whether specifications based solely on firm age can generate differential responses to uncertainty across firms. Table J.1 shows that the results do not hold when firm age is used as a proxy for early-stage status. These findings confirm the robustness of my main results and are consistent with Hoberg and Maksimovic (2022), who argue that older firms may exhibit high Life1 exposure due to shocks or the introduction of new products. Focusing on the product life cycle rather than the firm's age allows me to capture whether firms' portfolios are tilted toward exploratory projects and scalable opportunities, the core mechanism driving the positive investment response among early-stage firms.

D. Competition and Uncertainty

One concern with my findings is that early-stage firms tend to operate in more competitive markets, and as a result, the results may simply reflect the effects of market competition rather than firm life-cycle dynamics. I address this concern by using the product-market fluidity measure from Hoberg, Phillips, and Prabhala (2014) as a proxy for competition. This measure captures the extent to which other firms in related markets change their product offerings in the current year relative to the previous year. Higher fluidity indicates that potential rivals are more agile and innovative in the product space, suggesting that firms operating in more fluid markets face greater competitive threats. I re-estimate my main specification by including an interaction between competition, a dummy variable equal to one if the product-market fluidity measure is above the annual median, and uncertainty, while maintaining the same set of controls. Table J.2 confirms that the results are robust to controlling for competition.

I next study the interaction between uncertainty, product-market competition, and investment. In a real-options framework, Gu (2016) shows that R&D-intensive firms in competitive industries exhibit more option-like payoffs. If competition amplifies the convexity of cash flows from innovative projects, then uncertainty shocks should exert a stronger effect on the value of these growth options in competitive markets. This reasoning leads to the hypothesis that early-stage firms operating in more competitive product markets increase investment by more in response to higher uncertainty. This is exactly what I find. Column (3) of Table J.2 shows that increases in uncertainty significantly raise R&D investment among early-stage firms, and that this effect is amplified for firms operating in more fluid markets. These results provide novel insights into how competition and firms' product life-cycle stages jointly shape the transmission of uncertainty to corporate investment.

E. IV First-Stage

I implement the identification strategy discussed in Section 4.2 using an instrumental variable (IV) approach. I use the following first-stage specification to implement this analysis:

$$\begin{aligned} Uncertainty_{i,t-1} = {} & \alpha_i + \theta_t + \beta' \; Instruments_{i,t-1} + \mu \; Early\_Stage_{i,t-2} \\ & + \eta' \; Instruments_{i,t-1} \times Early\_Stage_{i,t-2} + \gamma' \; X_{i,t-1} + \epsilon_{it} \end{aligned} \tag{18}$$

where *Instruments* are the 9 instruments (oil prices, 7 leading currencies, and policy uncertainty) and $X_{i,t-1}$ is the same vector of firm-controls as in Equation (5). Table J.3 shows the 2SLS first-stage results for R&D. The F-statistics of 33.42 indicate a well-identified first-stage relevance condition, and the Hansen-Sargan over-identification test does not reject the validity of the instruments, since the p-value of the J statistic is 0.177. As a result, it fails to reject the null that the instruments are exogenous. Overall, Table J.3 confirms the well-satisfied relevance and exclusion restrictions for the set of 9 instruments for uncertainty.

F. Financing Policies

Hoberg and Maksimovic (2022) document a strong association between early-stage firms and equity financing, and between later-stage firms and debt financing. Building on this insight, I examine how uncertainty affects firms' financing decisions. I define *net equity issuance* as Compustat's *SSTK* minus *PRSTKC*, divided by lagged assets, and *net debt issuance* as *DLTIS* minus *DLTR*, also scaled by lagged assets. Table J.4 presents the results. Following a one standard deviation increase in uncertainty, early-stage firms significantly increase equity issuance, while later-stage firms reduce debt issuance, highlighting a sharp contrast in how firms adjust their financing strategies in response to uncertainty.

I next study the impact of uncertainty on firms' savings. Acharya, Almeida, and Campello (2013) show that in times of heightened aggregate volatility, firms with higher market exposure are likely to increase liquid asset holdings for precautionary reasons. As a result, I expect firms to increase their cash savings in response to higher uncertainty. However, this effect should be attenuated for early-stage firms as they are more risk-taking and are reacting by increasing their investments. Table J.4 strongly supports my predictions. While firms in later stages of their product life cycle increase their savings by 46.5% in response to higher uncertainty, early-stage firms increase it by approximately 18.4%.

G. Uncertainty and VC Investment

I strengthen the external validity of my results by testing whether VCs reallocate their investments in response to higher economic uncertainty. Early-stage startups are typically in the product development phase and benefit most from the growth-option value of uncertainty, whereas late-stage startups are closer to commercialization and face higher sunk costs. Therefore, I examine whether higher uncertainty increases VC investment in early-stage startups while decreasing investment in late-stage startups.

Although late-stage startups are younger and more innovation-oriented than the early-stage Compustat firms in my baseline analysis, the relative distinction between early and late stages remains meaningful in the VC setting. Moreover, because VC funds operate with committed capital that must be deployed, investors typically reallocate capital across stages. This institutional feature reinforces the underlying mechanism: under higher uncertainty, VCs shift investment toward early-stage, growth-option-intensive firms while reducing commitments to late-stage startups.

The first challenge to empirically test this channel is the lack of proxy for uncertainty at the firm-level for startups. I address this by performing a principal component analysis (PCA) on five aggregate proxies: the CBOE Volatility Index (VIX), common financial uncertainty (FIN), common real uncertainty (REAL), common macroeconomic uncertainty (MACRO) from Jurado, Ludvigson, and Ng (2015), and equity market volatility (EMV) from Baker, Bloom, Davis, and Kost (2019). The advantage of this approach is that it condenses the information from these proxies into a smaller set of variables, while remaining agnostic about the specific source of uncertainty. Table J.5 collects the results from the principal component analysis. Panel A shows the slope coefficients of each uncertainty proxy on the first five principal components (PC1 to PC5), and Panel B displays the associated diagnostic statistics. The findings suggest that the first principal component explains about 77% of the variation in the uncertainty proxies and the first two in combination explain about 97%.

The second challenge is the lack of detailed deal-level data on VC investment. I overcome this challenge by constructing a granular dataset of VC deals from 1990 to 2023, covering 30,805 unique firms. The data include information on financing stage, deal volume, general partners (GPs), and firm industry. Following Preqin's classification, I categorize firm stages as follows: Early Stage (seed, angel, grant, series A), and Late Stage (series B and C).

I then estimate the following equation for each of these two stages:

$$y_{i,t} = \beta_1 \, Uncertainty_{t-1} + \gamma \, X_{t-1} + \alpha_i + \epsilon_{i,t}, \tag{19}$$

where $y_{i,t}$ is the outcome variable (the log of deal financing size and the log of the number of VC investments) at time t. $Uncertainty_{t-1}$ refers to the first principal component of the uncertainty measure described above. X_{t-1} is a vector of controls that includes the lagged CPI, industrial production, GDP growth, and the Excess Bond Premium. α_i represents firm fixed effects, and standard errors are robust and clustered at the firm level.

Table J.6 presents the results. In response to higher uncertainty, there is a significant increase in VC investments for early-stage startups, while investments decrease for late-stage startups. Specifically, a one-standard-deviation increase in uncertainty leads to a 2.87% increase in VC investments for early-stage startups and a 5.7% decrease for late-stage startups, both relative to their respective means. I confirm these findings by showing a consistent effect on early-stage startups when the log of the number of investments is used as the outcome variable. This alternative specification reinforces the robustness of the observed relationship between uncertainty and VC investment across different stages.

Overall, the evidence from VC-backed firms reinforces my baseline results. Consistent with the growth-option channel, higher uncertainty induces a reallocation of capital toward early-stage startups, where the potential upside of product development dominates, and away from late-stage startups, where sunk costs and commercialization risks are more salient. This pattern highlights that the life-cycle distinction in firm responses to uncertainty is not unique to Compustat firms but extends to the VC setting, where investment decisions are shaped by the need to deploy committed capital. The fact that VCs actively reallocate across stages under uncertainty provides direct support for the mechanism underlying my findings: uncertainty amplifies the value of growth options while discouraging irreversible commitments, leading to heterogeneous investment dynamics across the product life cycle.

H. Hiring Decisions

Previous literature has shown that firms with skill-intensive operations can have incentives to increase their skilled workforce in an environment with greater uncertainty, but uncertainty is not associated with increases in the high-skilled or low-skilled workforce of plants that are not skill intensive (Carvalho, 2024). Consistent with the fact that early-stage firms are both R&D-intensive and likely more skill intensive, I expect these firms to significantly increase hiring in response to higher uncertainty, while later-stage firms reduce it.

To study the impact of uncertainty on firms' hiring decisions, I use data from Bloom, Hassan, Kalyani, Lerner, and Tahoun (2021), which collects roughly 200 million job postings from Burning Glass (BG). BG aggregates online job postings from online job boards (such as indeed.com), employer websites, and other sources into a de-duplicated database. The data is available only from 2010-2019.[9] I then estimate the effect of uncertainty on the number of job postings using Equation (21).

Table J.7 shows that in response to higher uncertainty, firms in later stages of their product life cycle significantly decrease their number of online job postings. In contrast, early-stage firms increase their number of online job postings, suggesting they are trying to hire more workers. I then turn to study the effect of uncertainty on the number of tech job postings. Following Bloom, Hassan, Kalyani, Lerner, and Tahoun (2021), the number of tech job postings is defined as job postings that mention a new technology (see Bloom, Hassan, Kalyani, Lerner, and Tahoun (2021) for details). Table J.7 collects the results. I find that early-stage firms significantly increase the number of "tech hiring" in response to higher uncertainty.

Overall, these results are consistent with the findings for investment and innovation. In response to higher uncertainty, the growth option becomes more valuable for these firms, and they increase R&D expenses and the number of patents (especially product patents). As these firms are likely working with new technologies, they increase their number of online tech job postings to try to hire more workers.

I. "Good" and "Bad" Uncertainty

Segal, Shaliastovich, and Yaron (2015) decompose aggregate uncertainty into "good" and "bad" volatility components, associated with positive and negative innovations to macroeconomic growth, and find that "good" uncertainty predicts an increase in future economic activity, such as consumption and output, while "bad" uncertainty forecasts a decline in economic growth and depresses asset prices. A natural and logical question is how early-stage and later-stage firms respond differently to good and bad uncertainty. For example, growth options may be more likely to trigger investment in response to

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[9] The available sample period is only nine years; therefore, I use aggregate measures of uncertainty for this analysis to increase the number of observations.

good uncertainty, whereas later-stage firms may be more likely to cutting back on the expansion of assets-in-place in response to bad uncertainty.

To analyze this question, I follow the methodology in Segal, Shaliastovich, and Yaron (2015) and use the ex ante predictable components of the positive and negative realized semivariances of earnings growth rate as the respective proxies for good and bad uncertainty. The positive (negative) semivariance captures the volatility component that is associated with the positive (negative) part of the total variation of earnings growth, and its predictive component corresponds to the concept for good (bad) uncertainty.[10]

After obtaining the proxies for good (Vg) and bad (Vb) uncertainty, I estimate the following equation:

$$\begin{aligned} y_{i,t} = \alpha_i &+ \beta_1 \times Vg_{t-1} + \beta_2 \times Vb_{t-1} + \beta_3 \times Early\_Stage_{i,t-2} \\ &+ \beta_4 \times Vg_{t-1} \times Early\_Stage_{i,t-2} + \beta_5 \times Vb_{t-1} \times Early\_Stage_{i,t-2} \\ &+ Controls + \epsilon_{it} \end{aligned} \tag{20}$$

where $y_{i,t}$ is an outcome variable for firm i in time t, $Early\_Stage$ is the Life1 variable lagged by two years to avoid endogeneity issues (see Subsection 4.1.1), and α_i is firm fixed effects. The vector of controls includes size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include real GDP Growth measured as the log growth of real GDP, and the interaction of this variable with $Early\_Stage$ to control for cyclicality (business cycles effects). Standard errors are robust and clustered at the firm level.

Table J.8 presents the results. I show that early-stage firms increase R&D in response to both "good" and "bad" uncertainty. However, the economic magnitudes are larger in response to higher "good" uncertainty. For instance, early-stage firms increase their R&D more in response to "good" uncertainty than to "bad" uncertainty, with the effect under good uncertainty being more than twice as large. In contrast, I find that later-

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[10] See Segal, Shaliastovich, and Yaron (2015) for details.

stage firms reduce investment in response to both "good" and "bad" uncertainty. This suggests that, for mature firms, any increase in uncertainty leads to precautionary cutbacks. These firms face fewer growth options and more irreversible investments (e.g., capacity expansion, acquisitions), which are riskier under any uncertainty.

J. Additional Results and Robustness

This section provides additional results and robustness checks.

Additional firm-level uncertainty. In addition to option implied volatility, I use realized annual volatility from CRSP stock returns as a firm-level measure of uncertainty. Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP (variable RET) and annualized by multiplying by $\sqrt{252}$ (a year typically spans 252 trading days). Table J.9 shows qualitatively similar findings.

Controls and Uncertainty. In my baseline specification, I control for size, Tobin's Q, book leverage, cash flows, age, and the stock return of the firm (measured as the firm's 12-month compounded return from CRSP). Given potential concerns that the early-stage variable may be correlated with these characteristics, I re-estimate the baseline specification by interacting these controls with uncertainty. Table J.10 shows that the coefficient on the interaction between Uncertainty × Early Stage remains positive and very similar to the baseline results.

Table J.10 also shows that the different responses of firms across the product life cycle are not entirely driven by differences in Tobin's Q. Firm product life cycle stages capture differences in the type, timing, and maturity of investment, rather than just differences in market valuation. In contrast, Tobin's Q is a valuation-based measure that compares the market value of a firm to the replacement cost of its assets, providing a signal about the profitability of marginal investment opportunities. However, Q does not distinguish between firms at different stages of development or account for the nature of their investment activities. In fact, I find that the coefficient on the interaction between Uncertainty × Q is also positive and statistically significant, but its magnitude is much smaller than that of the interaction between Uncertainty × Early Stage. These findings highlight the unique role of product life cycle stages in the transmission of uncertainty.

Non-Linearities. One important step in the identification strategy is to identify exogenous variation in firm-level volatility that is orthogonal to the endogenous components driving firm-level volatility shocks. As a result, I include in the main specification the variable $1st\_Moment$, which are the first moment effects of each of the 9 instruments. Still, one may be concerned that this is not appropriately measuring uncertainty for early-stage firms as non-linearities in the upside may be especially important for these firms. To address this issue, I construct additional controls, $1st\_Moment^2$, and estimate Equation (5) controlling for both $1st\_Moment$ and $1st\_Moment^2$ (interacted with the life stage variable as well). Table J.11 shows the main results are qualitatively the same.

The Average Impact of Uncertainty. Although my main analysis focuses on the heterogeneous impact of uncertainty across firms, I also investigate the average effect of uncertainty on firm investment. Table J.12 presents the results. Consistent with Alfaro, Bloom, and Lin (2024), I find that, in response to higher uncertainty, firms reduce, on average, intangible investment, Capex, and acquisitions.

Controlling for other stages. To address potential correlations between the early stage and other stages, I estimate Equation (5) controlling for all the stages (life2, life3, and life4). Table J.13 shows that the results are qualitatively the same.

Aggregate Uncertainty Measures. Measuring uncertainty is always a challenge. I support and complement my analysis by using a comprehensive set of uncertainty proxies. Specifically, I use the CBOE volatility index (VIX), common financial uncertainty (FIN), common real uncertainty (REAL), and common macroeconomic uncertainty (MACRO) from Jurado, Ludvigson, and Ng (2015), and estimate the following specification:

$$\begin{aligned} y_{i,t} = \alpha_i + \beta_1 \times Uncertainty_{t-1} + \beta_2 \times Early\_Stage_{i,t-2} \\ + \beta_3 \times Uncertainty_{t-1} \times Early\_Stage_{i,t-2} + \gamma' X_{i,t-1} + \theta' Z_{t-1} + \epsilon_{it} \end{aligned} \tag{21}$$

where $y_{i,t}$ is an outcome variable for firm i in time t, $Early\_Stage$ is the Life1 variable lagged by two years to avoid endogeneity issues (see Subsection 4.1.1), $Uncertainty$ is one of the uncertainty proxies described above, and α_i is firm fixed effects. $X_{i,t-1}$ is a vector of firm controls, which includes size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include a vector of macro controls which includes real GDP Growth measured as the log growth of real GDP, Inflation Rate measured as the log difference in GDP deflator, Real Federal Funds Rate measured as the difference between Effective Federal Funds Rate and Inflation Rate, and Credit Spread (Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity). Standard errors are robust and clustered at the firm level.

Tables J.14 and J.16 present the findings. Regardless of the uncertainty measure used, the results consistently show that early-stage firms increase both innovation input and output in response to higher uncertainty, while later-stage firms reduce them. Tables J.15 and J.17 demonstrate that these results are robust to the inclusion of industry × time fixed effects. This is important, as it absorbs all variation common to firms within the same industry and time period. As a result, identification relies on within-industry, cross-firm variation in how uncertainty interacts with firm characteristics, effectively controlling for industry-specific shocks in each period.

Dynamics of Investment. Previous research has shown that the effects of uncertainty shocks on firms' investment are temporary (Bloom, 2009). Intuitively, firms react by delaying, rather than permanently canceling, their investment plans when faced with greater uncertainty. As a result, I study the dynamics of investment estimating a modified version of Equation (5) in which I regress leads of investment on uncertainty, along with the same set of control variables and fixed effects as before. I consider leads of up to three years ahead for both outcome variables.

Table J.18 presents the results. Panel A shows that the effect of uncertainty on R&D for early-stage firms diminishes over time: after three years, the effect is only half as large as it was after one year. Panel B indicates that the effect on physical investment is more transitory, appearing only in the first year. At the same time, the increases in investment are not fully offset by subsequent declines, suggesting that uncertainty has longer-term implications for early-stage firms' capital accumulation.

Missing R&D. In my main analysis, I set missing values of R&D equal to zero. One concern is that early-stage firms may have a differential tendency to report R&D strategically compared to late-stage firms, particularly during periods of higher uncertainty. This could introduce non-classical measurement error in the outcome variable, which may bias estimates. I address this concern by estimating the effect of uncertainty on firms' R&D expenses without setting missing values equal to zero. Table J.19 shows that the main results are virtually unchanged. In response to higher uncertainty, early-stage firms significantly increase their R&D expenses.

Appendix Table J.1. Effect of Uncertainty on Investment Policies

	R&D/Assets	Intangible Investment	CAPX/Assets	Acquisitions
Uncertainty	-0.0014	-0.0078*	-0.0729*	-0.0513
	(0.0073)	(0.0046)	(0.0396)	(0.0418)
Uncertainty × Young	0.0080	0.0065**	0.0140	-0.0157
	(0.0066)	(0.0026)	(0.0109)	(0.0283)
Observations	29,662	27,249	29,550	29,146
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on investment policies. The dependent variables are R&D/Assets, intangible investment (R&D + 0.3 × SG&A, divided by intangible capital), CAPX/Assets and Acquisitions (a dummy equal to one if acquisition expenditures are greater than zero). Young is a dummy variable equal to one if the firm is young (i.e., below the median in terms of age). Firm controls and IV first-moment controls are defined as in Section 4.2. Heteroskedasticity-robust standard errors, clustered at the industry level (SIC-2), are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.2. Effect of Uncertainty on Investment: Competition and Product Life Stages

	R&D/Assets	R&D/Assets	R&D/Assets
Uncertainty	-0.010	-0.0092*	-0.0048
	(0.006)	(0.0048)	(0.0048)
Uncertainty × Early Stage	0.056***	0.0580***	0.0388***
	(0.013)	(0.0146)	(0.0160)
Uncertainty × Competition		-0.0013	-0.0116**
		(0.0026)	(0.0050)
Uncertainty × Early Stage × Competition			0.0400**
			(0.0159)
Observations	29,507	29,336	29,336
Firm Controls	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' investment using Equation (5). The dependent variable is R&D/Assets. Competition is a dummy variable that equals one if the product market fluidity measure is above the median in a given year. Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.3. 2SLS 1st stage results: R&D expenses

	$Uncertainty_{t-1}$
CAD IV	-1.512**
	(0.673)
EURO IV	0.180
	(0.406)
JPY IV	0.596
	(0.611)
AUD IV	-0.995**
	(0.465)
SEK IV	2.454***
	(0.622)
CHF IV	-0.458
	(0.321)
GBP IV	1.391
	(0.861)
OIL IV	1.405*
	(0.768)
EPU IV	2.135*
	(1.30)
CAD IV × Early Stage	0.278
	(1.889)
EURO IV × Early Stage	3.675**
	(1.483)
JPY IV × Early Stage	-2.408
	(1.607)
AUD IV × Early Stage	5.815***
	(1.439)
SEK IV × Early Stage	-9.836***
	(1.759)
CHF IV × Early Stage	0.952
	(1.175)
GBP IV × Early Stage	-2.252
	(3.210)
OIL IV × Early Stage	3.746
	(6.153)
EPU IV × Early Stage	3.233
	(4.023)
Observations	29,502
Firm Controls	Yes
IV 1st moment controls	Yes
Firm FE	Yes
Year FE	Yes
1st stage F-test	33.42
p-val Sargan-Hansen J-test	0.177

This reports the first stage regression results of the excluded instruments used in the 2SLS firm-level R&D regressions estimated using Equation (18). Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.4. Effect of Uncertainty on Financing Policies

	Equity Issuance	Debt Issuance	Cash Holdings
Uncertainty	0.005	-0.039**	0.465***
	(0.036)	(0.018)	(0.099)
Uncertainty × Early Stage	0.116**	-0.005	-0.281**
	(0.047)	(0.048)	(0.142)
Observations	26,680	28,258	29,433
Firm Controls	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' financing policies. The dependent variables are net equity issuance, net debt issuance, and cash holdings. Net equity issuance is defined as Compustat's *SSTK* minus *PRSTKC*, divided by lagged assets, net debt issuance is defined as *DLTIS* minus *DLTR*, also scaled by lagged assets, and cash holdings is the log of cash (Compustat's *che*). Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.5. Aggregate Measures of Uncertainty

	Panel A: Principal Components Loadings				
	PC1	PC2	PC3	PC4	PC5
MACRO	0.4784	-0.3337	0.2147	0.0906	-0.7781
VIX	0.4930	0.2294	-0.2714	-0.7932	0.0375
FIN	0.4948	0.0799	-0.6424	0.5579	0.1576
REAL	0.4113	-0.5677	0.3838	-0.0114	0.6010
EMV	0.3377	0.7123	0.5659	0.2263	0.0846
	Panel B: Principal Component Diagnostics				
Eigenvalue	3.83	1.02	0.12	0.006	0.002
Explained Variation	0.7672	0.2056	0.0253	0.0013	0.0005

This table reports the results from a principal component analysis (PCA) run on five uncertainty measures. Panel A provides the slope coefficients of the five uncertainty measures on the first five principal components (PC1 to PC5) and Panel B reports diagnostic statistics derived from that analysis. I use five measures of uncertainty: the CBOE Volatility Index (VIX), common financial uncertainty (FIN), common real uncertainty (REAL), common macroeconomic uncertainty (MACRO) from Jurado, Ludvigson, and Ng (2015), and equity market volatility (EMV) from Baker, Bloom, Davis, and Kost (2019).

Appendix Table J.6. Effect of Uncertainty on VC Investment

	Deal Financing Size		Number of Investments	
	Early-Stage	Late-Stage	Early-Stage	Late-Stage
Uncertainty	0.00906**	-0.0280***	0.00452**	-0.00417
	(0.00427)	(0.00969)	(0.00201)	(0.00297)
Observations	134,592	81,172	134,592	81,172
Firm FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes

This table reports the coefficients of the regression of uncertainty on VC investment. The dependent variables are the log of the volume size of the VC investment and the log of the number of VC investment (deals). I estimate Equation (19) for each financing stage. Following Preqin's classification, I define the following stages: Early-stage (series A, seed, angel, grant), and Late Stage (series B and series C). Macro Controls are defined as in Section G. Uncertainty is the first principal component from the five common uncertainty measures drawn from prior studies. Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.7. Effect of Uncertainty on the number of Job Posts

	log(Number of job posts)	log(Number of job posts)	log(Number of tech job posts)	log(Number of tech job posts)
Uncertainty	-0.1294***		-0.0966***	
	(0.0170)		(0.0207)	
Uncertainty × Early Stage	0.2031***	0.1712***	0.1772***	0.1752***
	(0.0410)	(0.0465)	(0.0473)	(0.0576)
Observations	23,551	23,338	23,551	23,338
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	No	Yes	No	Yes
Macro Controls	Yes	No	Yes	No

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' number of job posts using Equation (5). The dependent variable is the log of the number of jobs posts and the log of the number of tech job posts (see Subsection H). The controls are size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include a vector of macro controls which includes real GDP Growth measured as the log growth of real GDP, Inflation Rate measured as the log difference in GDP deflator, Real Federal Funds Rate measured as the difference between Effective Federal Funds Rate and Inflation Rate, and Credit Spread (Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity). Uncertainty is the first principal component from the five common uncertainty measures drawn from prior studies. Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.8. "Good" and "Bad" Uncertainty

	R&D/Assets		
	(1)	(2)	(3)
Bad Uncertainty	-0.0034***		-0.0021**
	(0.0009)		(0.0009)
Bad Uncertainty × Early Stage	0.0142***		0.0080*
	(0.0045)		(0.0047)
Good Uncertainty		-0.0049***	-0.0032**
		(0.0013)	(0.0012)
Good Uncertainty × Early Stage		0.0225***	0.0161**
		(0.0065)	(0.0067)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' R&D expenses. I decompose aggregate uncertainty into "good" and "bad" volatility components using the methodology in Segal, Shaliastovich, and Yaron (2015) (see Subsection I). The dependent variable is R&D/Assets. The vector of controls includes size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include real GDP Growth measured as the log growth of real GDP, and the interaction of this variable with Early Stage to control for cyclicality (business cycles effects). Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.9. Effect of Uncertainty on Innovation Input and Output: Realized Volatility as Firm-level Uncertainty

	R&D/Assets	Intangible Investment	Prob(Patent)	Patents Filed
Uncertainty	-0.0071***	-0.0103***	-0.0066	-0.0014
	(0.0023)	(0.0035)	(0.0150)	(0.0012)
Uncertainty × Early Stage	0.0146***	0.0147*	0.0979***	0.0093***
	(0.0052)	(0.0080)	(0.0309)	(0.0024)
Observations	50,655	46,695	40,781	40,691
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on investment and innovation. The dependent variables are R&D/Assets, Intangible Investment (R&D + 0.3 × SG&A divided by intangible capital), Prob(Patent) and number of patents filed divided by lagged total assets. Prob(Fill Patent) is a dummy equals one if the firm filed a patent and number of patents filed is the number of patents filed. I proxy for firm-level uncertainty using the realized annual volatility from CRSP stock returns. Annual realized volatility is the 12-month standard deviation of firms' cum-dividend daily stock returns from CRSP (variable RET) and annualized by multiplying by $\sqrt{252}$ (a year typically spans 252 trading days). Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.10. Uncertainty and the Interaction with Controls

	R&D/Assets	R&D/Assets	R&D/Assets	R&D/Assets	R&D/Assets	R&D/Assets
Uncertainty	-0.0001	-0.0175	-0.0098*	0.0032	-0.0033	0.0072
	(0.0063)	(0.0120)	(0.0054)	(0.0120)	(0.0034)	(0.0078)
Uncertainty × Early Stage	0.0513***	0.0468***	0.0540***	0.0373***	0.0485***	0.0321***
	(0.0115)	(0.0122)	(0.0112)	(0.0106)	(0.0103)	(0.0110)
Uncertainty × logAge	-0.0035					
	(0.0029)					
Uncertainty × Q		0.0033**				
		(0.0013)				
Uncertainty × BookLev			-0.0062			
			(0.0124)			
Uncertainty × CashFlow				-0.0333		
				(0.0262)		
Uncertainty × Realized_Return					-0.0009	
					(0.0016)	
Uncertainty × Size						-0.0024**
						(0.0011)
Observations	29,512	29,077	29,462	28,164	27,696	29,512
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' R&D expenses using Equation (5). The dependent variable is R&D/Assets. Firm Controls and IV 1st moment controls are defined as in Section 4.2. I also control for size, Tobin's Q, book leverage, cash flows, age, the stock return of the firm (measured as firm' 12-month compounded return from CRSP) and their interactions with Uncertainty. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.11. Effect of Uncertainty on Investment and Innovation: Controlling for non linearities

	R&D/Assets	Intangible Investment	Prob(Patent)	Patents Filed
Uncertainty	-0.0107	-0.0135**	-0.0937***	-0.0092**
	(0.0069)	(0.0069)	(0.0345)	(0.0029)
Uncertainty × Early Stage	0.0758***	0.0296**	0.1193*	0.0299***
	(0.0194)	(0.0147)	(0.0627)	(0.0065)
Observations	29,502	27,099	23,687	23,635
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes
$1st\_Moment \times EarlyStage$	Yes	Yes	Yes	Yes
$1st\_Moment^2 \times EarlyStage$	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on investment and innovation. The dependent variables are R&D/Assets, Intangible Investment (R&D + 0.3 × SG&A divided by intangible capital), Prob(Patent) and number of patents filed divided by lagged total assets. Prob(Fill Patent) is a dummy equals one if the firm filed a patent and number of patents filed is the number of patents filed. Firm Controls and IV 1st moment controls are defined as in Section 4.2. I also control for $1st\_Moment^2$ (interacted with Early Stage). Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.12. Effect of Uncertainty on Investment Policies

	R&D/Assets	Intangible Investment	CAPX/Assets	Acquisitions
Uncertainty	0.0106	-0.0143**	-0.0837**	-0.0743**
	(0.0073)	(0.0056)	(0.0359)	(0.0356)
Observations	33,389	30,736	33,244	32,854
IV 1st moment controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty on investment policies. The dependent variables are R&D/Assets, intangible investment (R&D + 0.3 × SG&A, divided by intangible capital), CAPX/Assets and Acquisitions (a dummy equal to one if acquisition expenditures are greater than zero). Firm controls and IV first-moment controls are defined as in Section 4.2. Heteroskedasticity-robust standard errors, clustered at the industry level (SIC-2), are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.13. Effect of Uncertainty on Innovation Input: Controlling for other stages

	R&D/Assets	R&D/Assets	R&D/Assets	R&D/Assets
Uncertainty	-0.0058	-0.0125*	-0.0080	-0.0204
	(0.0093)	(0.0073)	(0.0057)	(0.0191)
Uncertainty × Life1	0.0503***	0.0535***	0.0550***	0.0619**
	(0.0145)	(0.0125)	(0.0119)	(0.0237)
Uncertainty × Life2	-0.0052			0.0097
	(0.0074)			(0.0154)
Uncertainty × Life3		0.0112		0.0211
		(0.0083)		(0.0178)
Uncertainty × Life4			-0.0131	
			(0.0166)	
Observations	29,511	29,511	29,511	29,511
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' R&D expenses using Equation (5). The dependent variable is R&D/Assets. Firm Controls and IV 1st moment controls are defined as in Section 4.2. I also control for the other stages (life2, life3 and life4) and their interactions with uncertainty. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.14. Effect of Aggregate Uncertainty on R&D Expenses

	R&D/Assets			
	VIX	FIN	MACRO	REAL
Uncertainty	-0.257***	-0.475***	-1.306***	-1.103***
	(0.029)	(0.047)	(0.178)	(0.187)
Uncertainty × Early Stage	0.317***	0.599***	3.244***	3.725***
	(0.122)	(0.188)	(0.852)	(0.917)
Observations	80,856	80,856	80,856	80,856
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' R&D expenses using aggregate uncertainty proxies. The dependent variable is R&D/Assets. The controls are size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include a vector of macro controls which includes real GDP Growth measured as the log growth of real GDP, Inflation Rate measured as the log difference in GDP deflator, Real Federal Funds Rate measured as the difference between Effective Federal Funds Rate and Inflation Rate, and Credit Spread (Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity). VIX is the CBOE volatility index, common financial uncertainty (FIN), common real uncertainty (REAL) and common macroeconomic uncertainty (MACRO) are from Jurado, Ludvigson, and Ng (2015). Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.15. Effect of Aggregate Uncertainty on R&D Expenses: Industry-Time FE

	R&D/Assets			
	VIX	FIN	MACRO	REAL
Uncertainty × Early Stage	0.234*	0.481***	2.824***	3.196***
	(0.123)	(0.186)	(0.834)	(0.900)
Observations	80,856	80,856	80,856	80,856
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' R&D expenses using aggregate uncertainty proxies. The dependent variable is R&D/Assets. The controls are size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include a vector of macro controls which includes real GDP Growth measured as the log growth of real GDP, Inflation Rate measured as the log difference in GDP deflator, Real Federal Funds Rate measured as the difference between Effective Federal Funds Rate and Inflation Rate, and Credit Spread (Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity). VIX is the CBOE volatility index, common financial uncertainty (FIN), common real uncertainty (REAL) and common macroeconomic uncertainty (MACRO) are from Jurado, Ludvigson, and Ng (2015). Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.16. Effect of Aggregate Uncertainty on Patents

	Patents Filed			
	VIX	FIN	MACRO	REAL
Uncertainty	-0.0591***	-0.0820***	-0.2982***	-0.2833***
	(0.0082)	(0.0134)	(0.0439)	(0.0453)
Uncertainty × Early Stage	0.2393***	0.3847***	1.500***	1.425***
	(0.0277)	(0.0428)	(0.1834)	(0.2093)
Observations	63,263	63,263	63,263	63,263
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' innovation using aggregate uncertainty proxies. The dependent variable is the number of patents filed divided by lagged total assets. The controls are size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include a vector of macro controls which includes real GDP Growth measured as the log growth of real GDP, Inflation Rate measured as the log difference in GDP deflator, Real Federal Funds Rate measured as the difference between Effective Federal Funds Rate and Inflation Rate, and Credit Spread (Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity). VIX is the log of the CBOE volatility index, common financial uncertainty (FIN), common real uncertainty (REAL) and common macroeconomic uncertainty (MACRO) are the log values of the uncertainty indexes from Jurado, Ludvigson, and Ng (2015). Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.17. Effect of Aggregate Uncertainty on Patents: Industry-Time FE

	Patents Filed			
	VIX	FIN	MACRO	REAL
Uncertainty × Early Stage	0.2268***	0.3601***	1.424***	1.357***
	(0.0281)	(0.0434)	(0.1870)	(0.2130)
Observations	63,208	63,208	63,208	63,208
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on firms' innovation using aggregate uncertainty proxies . The dependent variable is the number of patents filed divided by lagged total assets. The controls are size, Tobin's Q, book leverage, cash flows, age, and cash holdings. I also include a vector of macro controls which includes real GDP Growth measured as the log growth of real GDP, Inflation Rate measured as the log difference in GDP deflator, Real Federal Funds Rate measured as the difference between Effective Federal Funds Rate and Inflation Rate, and Credit Spread (Corporate Bond Yield Relative to Yield on 10-Year Treasury Constant Maturity). VIX is the log of the CBOE volatility index, common financial uncertainty (FIN), common real uncertainty (REAL) and common macroeconomic uncertainty (MACRO) are the log values of the uncertainty indexes from Jurado, Ludvigson, and Ng (2015). Standard errors heteroskedasticity robust and clustered at the firm level are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.18. Uncertainty and Investment Dynamics

	Panel A: R&D/Assets		
	One-Year Ahead	Two-Year Ahead	Three-Year Ahead
Uncertainty × Early Stage	0.056*** (0.013)	0.046*** (0.015)	0.027*** (0.006)
	Panel B: CAPX/Assets		
	One-Year Ahead	Two-Year Ahead	Three-Year Ahead
Uncertainty × Early Stage	0.065** (0.028)	-0.001 (0.020)	-0.007 (0.010)
Firm Controls	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on the dynamics of investment over time. I estimate a modified version of Equation (5) in which I regress leads of R&D and CAPX on uncertainty and its interaction with the early stage variable, along with the same set of control variables and fixed effects as in Equation (5). I consider leads of up to three years ahead for both outcome variables. Firm Controls and IV 1st moment controls are defined as in Section 4.2. Standard errors heteroskedasticity robust and clustered at the industry level (SIC-2) are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table J.19. Effect of Uncertainty on R&D: missing values not equals to zero

	R&D/Assets
Uncertainty	-0.022 (0.015)
Uncertainty × Early Stage	0.054*** (0.011)
Observations	19,654
Firm Controls	Yes
IV 1st moment controls	Yes
Firm FE	Yes
Year FE	Yes

This table reports the coefficients of uncertainty and its interaction with Early Stage on investment policies. The dependent variables is R&D/Assets. Missing values of R&D are not set equals to zero. Firm controls and IV first-moment controls are defined as in Section 4.2. Heteroskedasticity-robust standard errors, clustered at the industry level (SIC-2), are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.