Product Life Cycle Heterogeneity in the Transmission of Uncertainty*

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Abstract

Research on the effects of economic uncertainty has traditionally sought to establish whether uncertainty hurts or boosts corporate investment. This paper proposes that both outcomes emerge in the data, and that which one obtains depends on a firm's stage in the product life cycle. To formalize this argument, I develop a real-options model in which firms allocate resources across exploratory R&D, incremental R&D, and mature capital, and in which life-cycle stages differ in the composition of opportunity sets and in the complementarity between innovative capacity and growth options. I use text-based life-cycle measures from 10-K filings to classify firms according to life-cycle stage. I then examine the impact of uncertainty on firm-level investment and innovation using option-implied volatility instrumented with industry exposure to aggregate volatility shocks, which isolates second-moment variation from correlated first-moment effects. When uncertainty rises, early-stage firms raise capital expenditures and (especially) R&D, and product patenting, while late-stage firms cut them. Structural estimation of the model shows that early-stage expansion offsets roughly one fifth of the investment contraction among late-stage firms, an offset that has grown as the economy has become more innovation-intensive. Finally, I trace responses into product markets using individual product-level data from NielsenIQ's Retail Scanner. I create a new firm-level measure of product-market uncertainty by calculating the within-quarter standard deviation of weekly log revenue growth for each product, then aggregate it to the firm level and use a novel instrument based on product-portfolio exposure to aggregate volatility. I find that early-stage firms increase product entry and shift toward unfamiliar categories; late-stage firms consolidate.

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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 portfolio adjustments, decisions that are central to firms' growth trajectories and competitive dynamics.

This paper shows that the research on corporate decision-making under uncertainty misses key nuances by focusing only on whether uncertainty hurts or boosts firms' investment, innovation, and product-market outcomes: both outcomes obtain in the data. I establish 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.

I provide novel evidence 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, shifting their portfolios toward newer products, while late-stage firms retrench and prioritize portfolio stability. These heterogeneous responses help reconcile prior conflicting findings in the literature. They also have important aggregate implications: the expansionary behavior of early-stage firms offsets a sizable share of the investment contraction among late-stage firms.

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 firm-level option-implied volatility, instrumented with industries' predetermined exposure to aggregate

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

volatility shocks in oil, currencies, and economic policy. The identifying variation is thus the differential incidence of common uncertainty shocks across industries, which is orthogonal to the firm's own investment and innovation choices and allows me to disentangle 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 find 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 smaller increase in capital expenditures than in R&D expenses is consistent with capital expenditures being a type of investment that is more costly to reverse, making the associated growth option less valuable. In contrast, firms in later product life cycle stages reduce R&D and capital expenditures by 1 and 5.5 percentage points, respectively, in response to a one standard deviation increase in 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 two years, a one standard deviation increase in uncertainty increases both the probability of filing a patent and the number of patents filed by 4.6 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 their position in the product innovation stage, where innovation naturally concentrates in product patents. The opposite holds for later-stage firms, highlighting the important role of the product cycle in transmitting uncertainty to firms' innovation.

I also show how uncertainty affects 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 the overall composition of product 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 uncertainty. The high-frequency nature of my data allows me to compute the within-quarter standard deviation of weekly log revenue growth for each product. I 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, this measure isolates the underlying composition of product-level risk. My new 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.

To address the endogeneity of estimating the effect of uncertainty on product market outcomes, I develop a novel instrumental variable strategy that adapts the approach in Alfaro, Bloom, and Lin (2024) to the product-market setting. The identification strategy exploits firms' differential product portfolio exposure to aggregate volatility shocks. Specifically, I estimate each firm's revenue sensitivity to nine aggregate price series—oil, seven major currencies, and economic policy uncertainty—at the product-group level, and interact the absolute value of these sensitivities with changes in the corresponding aggregate volatilities. The resulting instruments isolate exogenous variation in firm-level uncertainty driven by the interaction of predetermined portfolio exposures with aggregate second-moment shocks, while controlling directly for first-moment effects.

I find that, in response to higher uncertainty, early-stage firms significantly increase net product entry, thereby shifting their portfolios toward newer products. I decompose product innovation along margins of increasing novelty and find that uncertainty shifts the composition of early-stage firms' innovation toward exploration: early-stage firms are significantly more likely to introduce new products in unfamiliar product categories rather than in established ones. The option-like nature of early-stage product strategies, where small bets can yield large returns, makes this a rational response to uncertainty, as firms seek to explore upside opportunities. Late-stage firms, by contrast, reduce net product entry, 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

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

with the impact of uncertainty on investment, underscoring the complementary nature of firms' financial and strategic decisions.

To understand these empirical 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.

To quantify the importance of product life cycle heterogeneity in the transmission of uncertainty, I estimate the structural parameters of the model by matching a set of model-implied moments to their empirical counterparts. The model fits the data well, reproducing the correct sign and approximate magnitude of all types of investment. Moreover, the estimates suggest that early-stage expansion offsets roughly one fifth of the total investment contraction among late-stage firms, confirming that the growth option channel is quantitatively significant.

I conduct several counterfactual experiments. First, I show that shutting down the growth option channel makes all firms contractionary, recovering the standard result in the real options literature (Bloom, 2009). Second, I find that the aggregate investment response to higher economic uncertainty turns positive when early-stage firms constitute more than 54% of the economy, a threshold far from the current 18% but informative about secular trends toward innovation-intensive industries. Third, I find that the offset has grown substantially over the past two decades as the economy has shifted toward more early-stage firms, suggesting that the aggregate investment response to uncertainty has become less contractionary over time. Overall, my findings establish that product life-cycle heterogeneity plays a central role in how uncertainty transmits to corporate investment and product markets, reconciling conflicting findings in the literature and showing that the aggregate investment response to uncertainty depends on—and evolves with—the economy's life-cycle composition.

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, Section 6 examines the quantitative implications of the model, and Section 7 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 (Leahy and Whited, 1996; 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). Exceptions are Lin, Schmid, and Weisbach (2025), who focus on the electricity industry and find 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 show 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 effect of 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 has novel implications: early-stage firms are the economy's engine of innovation and growth, so whether uncertainty suppresses or stimulates their invest-

ment determines the aggregate consequences of uncertainty shocks. Moreover, because early- and late-stage firms respond in opposite directions, treating firms as homogeneous misstates the aggregate effects of uncertainty and overlooks how those effects change as the economy becomes more innovation-intensive. Quantitatively, a structural estimation of the model shows that early-stage expansion offsets roughly one fifth of the total investment contraction among 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. Crouzet and Eberly (2026) document that aggregate R&D investment is far less cyclical than investment in equipment and structures, and attribute this to the fact that R&D uncertainty is resolved by investing rather than by waiting. 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, while riskier firms invest more in R&D but file fewer patents.

My paper shows how these different findings above can, in part, be explained by the fact that they analyze 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 find 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 and finds that higher uncertainty decreases innovation.

I reconcile these mixed findings 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) find 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 uncertainty and show that uncertainty affects product market outcomes differently depending on the product life cycle stage. In particular, my paper is the first to examine how uncertainty affects firms' product portfolios.

3. Theoretical Framework

This section develops the economic intuition for why firms at different stages of the product life cycle respond differently to uncertainty. I describe the key channels through which uncertainty affects investment, explain how the composition of a firm's opportunity set determines which channel dominates, and derive four empirical predictions. I develop a formal real-options model that generates these predictions in Section 6, where I also structurally estimate the model and examine its quantitative implications.

Consider a firm that can invest in different types of projects. Some projects are *exploratory*: they involve multi-stage R&D with an option to abandon after receiving an interim signal about quality. Others are *incremental* R&D or *mature capital* investments: they are largely irreversible and can be delayed until more information arrives. The firm also chooses how much to invest in *innovative capacity*—infrastructure, equipment, and organizational capabilities that amplify the returns of successful exploratory projects.

Uncertainty enters as a mean-preserving spread in project payoffs: higher uncertainty increases the dispersion of outcomes without changing their mean. This is a standard formulation in the real-options literature and ensures that the effects I identify are driven by second-moment variation rather than changes in expected profitability.

The distinction between early-stage and late-stage firms lies in two dimensions:

Opportunity-set composition. Early-stage firms hold portfolios tilted toward exploratory, growth-option projects, while late-stage firms hold portfolios tilted toward mature, irreversible projects. This is consistent with the empirical evidence in Hoberg and Maksimovic (2022), who show that early-stage firms are concentrated in product innovation and late-stage firms in mature and declining product lines.

Scalability of growth options. Early-stage firms benefit from strong complementarities between innovative capacity and exploratory R&D: investing in capacity (e.g., research facilities, patent portfolios) amplifies the payoffs of successful exploratory projects. For late-stage firms, whose product lines are mature, this complementarity is weak or absent—innovative capacity has little to amplify.

Three distinct channels determine how uncertainty affects a firm's investment:

The abandonment option (exploratory R&D). Exploratory R&D projects are multi-stage: a firm commits resources upfront, receives an informative signal about project quality, and then decides whether to continue or abandon. This creates a call-option-like payoff structure—the firm captures the upside from successful projects while limiting downside losses by abandoning failures. Because the payoff from this structure is convex in the underlying uncertainty, a mean-preserving spread in outcomes raises the expected value of exploratory projects. Higher uncertainty therefore *increases* the incentive to initiate exploratory R&D. This mechanism follows the logic of growth-option models in the tradition of Bar-Ilan and Strange (1996).

The scalability channel (innovative capacity). When exploratory R&D becomes more valuable under uncertainty, so does the infrastructure that amplifies its returns. For early-stage firms with strong complementarities between capacity and exploration, this creates a positive feedback loop: higher uncertainty raises the value of exploratory projects, which raises the marginal product of innovative capacity, which further amplifies exploratory returns. This feedback loop means that early-stage firms increase not only R&D but also physical investment (recorded as capital expenditures) in response to uncertainty. The strength of this channel depends on the degree of complementarity between innovative capacity and growth options—a parameter I estimate structurally in Section 6.

The option to delay (mature and incremental projects). When a project is largely irreversible, uncertainty raises the value of waiting for more information before committing resources. This is the classic option-to-delay mechanism of Bernanke (1983): higher uncertainty increases the value of the "wait-and-see" option, raising the hurdle for immediate investment. Both mature capital projects and incremental (process-improvement)

R&D are subject to this channel, as they involve sunk costs and can be postponed. Higher uncertainty therefore *decreases* investment in these project types.

Every firm is simultaneously exposed to all three channels. What determines the net effect of uncertainty on a firm's total investment is the *composition* of its opportunity set and the *strength* of the scalability channel. For early-stage firms, the opportunity set is rich in exploratory projects and the complementarity between innovative capacity and growth options is strong. Therefore, the expansion in exploratory R&D and innovative capacity more than offsets the contraction in incremental R&D and mature capital. As a result, both total R&D and total capital expenditures rise with uncertainty. For late-stage firms, the opportunity set is concentrated in mature and incremental projects, and the scalability channel is effectively shut down (there are few growth options for innovative capacity to amplify). As a result, the contraction in mature capital and incremental R&D drives the overall response. Both total R&D and total capital expenditures fall with uncertainty.

An alternative mechanism through which uncertainty can raise investment is the Oi-Abel-Hartman effect (Oi, 1961; Abel, 1983; Hartman, 1972): when firms can adjust inputs after observing shocks, the profit function is convex in prices, so a mean-preserving spread raises expected profits and stimulates investment. This channel is distinct from the growth-option mechanism I propose, and two features of the data allow me to distinguish between them.

First, the Oi-Abel-Hartman effect operates through ex-post flexibility—it predicts that firms with *greater* ability to adjust inputs should benefit more from uncertainty. However, early-stage firms are typically *less* flexible: they are more R&D-intensive and hold more specific assets. I use the INFLEX measure of Gu, Hackbarth, and Johnson (2018) to show in Table 1 that early-stage firms exhibit significantly higher inflexibility than late-stage firms. If profit-function convexity were the dominant channel, it should favor late-stage firms with established, adjustable operations—the opposite of what I find.

Second, the Oi-Abel-Hartman effect is primarily a long-run phenomenon that requires firms to fully adjust their factor mix after observing shocks. As Bloom (2014) argues, in the short run, adjustment costs and investment lumpiness prevent firms from freely reoptimizing inputs, so the option-to-delay channel dominates. The investment responses I document are concentrated in the first one to three years following an increase in uncertainty, a horizon over which the growth-option and option-to-delay channels are most operative and the Oi-Abel-Hartman channel is weakest.

The channels discussed above, combined with life-cycle heterogeneity in opportunity sets and complementarities, generate four predictions that I take to the data:

Prediction 1 (Early-stage firms: investment expands). When uncertainty increases, early-stage firms raise both R&D spending and capital expenditures. The abandonment option makes exploratory R&D more valuable, and the scalability channel makes innovative capacity (a component of Capex) more valuable. These expansionary forces dominate the option-to-delay channel for the firm's (relatively few) mature and incremental projects.

Prediction 2 (Late-stage firms: investment contracts). When uncertainty increases, late-stage firms reduce both R&D spending and capital expenditures. The option-to-delay channel dominates because the firm's portfolio is concentrated in irreversible, mature projects, and the scalability channel is inoperative.

Prediction 3 (Early-stage firms: innovation and product experimentation increase). The expansionary investment response of early-stage firms should translate into greater innovation output (e.g., patent filings, particularly product patents) and increased product-market experimentation, reflected in higher rates of net product entry. Moreover, this experimentation should be directed toward *exploration*: early-stage firms should not only introduce more products but also shift the composition of their innovation toward unfamiliar product categories, consistent with elevated uncertainty raising the option value of exploring new markets. Intuitively, early-stage firms respond to uncertainty by placing more "bets"—and placing them in new territory—a strategy that maximizes the value of their growth options.

Prediction 4 (Late-stage firms: consolidation and stability). The contractionary investment response of late-stage firms should manifest as reduced innovation output and lower product entry rates. Facing fewer growth options, late-stage firms respond to uncertainty by scaling back product introduction without altering its composition—they consolidate around their established product portfolios rather than experimenting with new offerings.

Predictions 1 and 2 are derived formally from the real-options model in Section 6. Predictions 3 and 4 are qualitative corollaries: they follow from the logic that firms' product-market strategies are complementary to their investment decisions. I test all four predictions empirically in Sections 4 and 5.

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 are 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 C in the Appendix gives definitions of firm-level variables.

4.1.1 Measuring Product Life Cycles

I use firms' product life cycle data from Hoberg and Maksimovic (2022). They 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. Panel (C) in Table 1 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 hold portfolios composed of growth-option 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 D that the main results do not hold when firm age is used as a proxy for early-stage status.

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:

$$r_{i,t} = \alpha_j + \sum_k \text{sensitivity}_j^k \times r_t^k + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the daily risk-adjusted return on firm i and r_t^k is the change in the price of aggregate variable k.[3] 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, book-to-market factor, size factor, and momentum factor).

I estimate the sensitivities from pooled firm-day observations within an industry rather than from an industry portfolio return; the pooled regression uses the full cross-section of firm-days and is more precise. I estimate sensitivities at the industry rather than the firm level for two reasons. Firm-level rolling regressions with nine aggregate regressors are noisy, particularly for small and young firms, which would weaken the first stage precisely for the early-stage firms of interest. More importantly, firm-level sensitivities can reflect firm choices—hedging policies, product mix, or geographic footprint—that may be correlated with the firm's investment plans, whereas industry-level exposures are more plausibly predetermined with respect to individual firm decisions. Finally, I use risk-adjusted returns because oil, currency, and policy-uncertainty returns are correlated with the market factor. With raw returns, the estimated sensitivities would partly reflect market beta scaled by the correlation between the market and variable k, so that $|\text{sensitivity}_j^k|$ would rank industries by their exposure to aggregate volatility in general rather than to variable k specifically. Risk adjustment isolates each industry's incremental exposure to a given aggregate variable, which is what the shift-share logic of the instrument requires.

Then, for the nine aggregate price shocks (oil, seven 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 nine 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, seven leading currencies, and policy uncertainty (see Alfaro, Bloom, and

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

Lin (2024) for details). Specifically, the instruments are defined as:

$$Instrument^{k}_{i,t-1} = |\text{sensitivity}^{k}_{j,t-3}| \times \Delta\sigma^{k}_{t-1}. \tag{2}$$

The volatilities of oil and the seven 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.

The instruments combine an aggregate second-moment shock, $\Delta\sigma^{k}_{t-1}$, that is common to all firms, with a predetermined industry-level exposure, $|\text{sensitivity}^{k}_{j,t-3}|$. Because time fixed effects absorb the common component of each shock, the identifying variation is the *differential* transmission of aggregate volatility shocks across industries with different exposures to oil, currencies, and policy. The identified variation is therefore neither purely idiosyncratic firm-level uncertainty nor a purely common shock: it is the heterogeneous incidence of common uncertainty shocks. This is the relevant object for the aggregate questions in Section 6, which ask how aggregate investment responds when economy-wide uncertainty rises and firms differ in their life-cycle stage. The endogenous variable, option-implied volatility, is measured at the firm level, but the exogenous component I isolate varies at the industry level (and, through the interaction with *Early_Stage*, across firms within an industry). Appendix L shows that the results are robust to SIC 1-digit $\times$ year fixed effects, which absorb broad industry-time shocks, and Table L.19 confirms the same heterogeneity when uncertainty is measured with common aggregate proxies, indicating that the life-cycle heterogeneity operates for common shocks and not only for their differential industry incidence.

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

$$\begin{aligned} y_{i,t} = \alpha_i + \theta_t + \beta_1 \times Uncertainty_{i,t-1} + \beta_2 \times Early_Stage_{i,t-2} \\ + \beta_3 \times Uncertainty_{i,t-1} \times Early_Stage_{i,t-2} + \gamma' X_{i,t-1} + \epsilon_{it}, \end{aligned} \tag{3}$$

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 re-

turn from CRSP).[4] Importantly, I also include the first-moment effects of each of the 9 instruments (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) as in Alfaro, Bloom, and Lin (2024).[5]

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 F, 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 not to 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.

[4] To address potential concerns about bad controls, I re-estimate the main specification without firm-level controls (other than fixed effects) and obtain similar results. Results are available upon request.

[5] Results are unchanged with two-way clustering by industry and year.

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 two years before the volatility change. 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. This would require, for example, that hedging costs in an industry with a beta of 2.0 rise roughly four times more than in an industry with a beta of 0.5 in response to the same increase in volatility. Such 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 Panel (D) in Table 1 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 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 2 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 rates 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 2 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 is consistent with 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. Because 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 Innovation

I show that the positive effect of uncertainty on investment translates into greater innovation for early-stage firms. Table 3 shows that a one standard deviation increase in uncertainty raises the probability of filing a patent by 4.58 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 two years. In contrast, later-stage firms reduce their patent filings.[6]

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 3 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 – 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 3 reports the results: in response to higher uncertainty, product

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

patents significantly increase relative to other patents only for early-stage firms, indicating that their innovation is heavily concentrated in product development.

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 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. These 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 3 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 Hajda and Nikolov (2022) discuss, 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. I also exclude private-label products, whose UPC codes are scrambled by Nielsen across periods. 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 to the firm level.

Table 4 reports descriptive statistics for firms and products in the NielsenIQ sample. Panel A shows that firms maintain an average of 26 products in their portfolios. The average product portfolio age is 0.378, indicating that, on average, firms hold relatively young product portfolios. The mean firm generates approximately $2.3 million in quarterly sales. Panel B provides statistics at the product level. The average product generates about $90,000 in quarterly sales. The sample comprises 45,575 firms and 1,914,067 unique products, providing a rich setting to analyze product portfolio dynamics.

The consumer goods sector is a natural setting for the exploratory growth options that feature in the model, for two reasons. First, the growth option in the model is a project that can be initiated at small scale, evaluated against an interim signal, and abandoned or scaled accordingly. In the scanner data, this is a new UPC: launch costs are modest, market feedback arrives within quarters, and products that fail to gain traction are withdrawn. The sample contains 1.9 million unique products and substantial churn (Argente, Lee, and Moreira, 2018), and Argente, Baslandze, Hanley, and Moreira (2020) document a direct link between patenting and product introduction in these data. Product experimentation is therefore the empirical counterpart of exploratory investment, and the composition of entry across familiar and unfamiliar product categories (Section 5.5) is the empirical counterpart of exploration. Second, consumer goods is not an innovation-intensive sector by conventional measures such as R&D intensity, so it constitutes a demanding test: if growth-option behavior under uncertainty is detectable here, it is likely to be at least as strong in more R&D-intensive industries. The setting also offers something those industries cannot—direct observation of the product portfolio itself, for public and private firms alike.

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:[7]

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

Intuitively, $age_{i,t}$ captures the percentage of old products in a firm's portfolio. On average, firms in my sample have 37.8% of old products, as reported in Panel A

[7] A product's lifespan is the time between its introduction and its withdrawal. I exclude the first and last years of the data when computing the measure to make sure that product portfolio age is correctly captured.

of Table 4. Product portfolio age varies substantially, with a standard deviation of 0.358. 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, implying 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's share of new products, $(1 - age_{i,t})$, is above the cross-sectional median in quarter t. Figure 4 shows that the average early-stage firm has 12.7% of old products, whereas the average late-stage firm has 67.9%.

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, for each product (UPC) within a firm's portfolio, I compute weekly log revenue growth and then take the within-quarter standard deviation of these weekly growth rates. This yields a contemporaneous, realized measure of product-level volatility each quarter that does not rely on any past data—it is constructed entirely from within-quarter variation. These product-level volatilities are then aggregated to

the firm level using revenue shares as weights:

$$PMU_{i,t} = \sum_{j \in \mathcal{J}_{i,t}} w_{j,t} \cdot \sigma_{j,t}$$

where $w_{j,t}$ is product j's share of firm i's total revenue in quarter t, and $\sigma_{j,t}$ is the within-quarter standard deviation of weekly log revenue growth for product j. This weighting ensures that the measure reflects the relative importance of each product in the firm's operations, thereby capturing the extent of uncertainty that firms face in their product markets, while preserving within-firm heterogeneity across products. Figure 5 shows the cross-sectional distribution of PMU averaged within firm, and Panel C of Table 4 reports summary statistics at the firm-quarter level; both indicate substantial product-level sales volatility across firms.

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 may not fully capture forward-looking perceptions of risk. However, the use of high-frequency weekly data within each quarter distinguishes PMU from traditional measures of firm-level sales or cash flow volatility, which typically require multi-year rolling windows of quarterly or annual observations. Because I observe weekly sales observations per product-quarter, I can construct a realized volatility measure at the quarterly frequency without relying on lagged data. This approach is analogous to how realized stock return volatility is computed from high-frequency intraday or daily returns, but applied to the product-market setting. Realized volatility measures, such as stock return 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 estimating the effect of uncertainty on standard outcome variables in the corporate finance literature. Figure 6 shows the impact of PMU on CAPX, R&D, Cash holdings and Number of Employees. In line with the literature, I find that higher uncertainty leads to lower investment, higher cash holdings and a lower number of employees. This validation exercise provides evidence that PMU is economically meaningful, making it a useful firm-level measure of uncertainty.

5.4 Empirical Strategy

A key concern when estimating the effect of PMU on product market outcomes is that firm-level uncertainty may be correlated with unobserved factors that also affect product entry and exit. For example, firms experiencing demand shocks may simultaneously exhibit higher product-level volatility and adjust their portfolios, creating a spurious correlation between PMU and product market outcomes. To address this endogeneity, I develop a novel instrumental variable strategy that adapts the approach in Alfaro, Bloom, and Lin (2024) to the product-market setting. The identification strategy exploits the fact that firms' product portfolios have differential revenue exposure to aggregate price shocks in energy, currencies, and economic policy. Crucially, the instruments isolate second-moment (volatility) variation in these aggregate prices, while first-moment (level) effects are controlled for directly.

5.4.1 Instrument Construction

While Alfaro, Bloom, and Lin (2024) exploit heterogeneous stock-return sensitivities to aggregate volatility shocks to instrument for firm-level uncertainty, their approach requires publicly traded firms. I develop a novel alternative that instead estimates *product-revenue* sensitivities, exploiting the granularity of the NielsenIQ scanner data. This adaptation has the key advantage of applying to both public and private firms, substantially expanding the scope of analysis.

Step 1: Product-group revenue betas. I begin by estimating the sensitivity of product-group revenue to aggregate price shocks. For each product group g, I estimate rolling

regressions of weekly log revenue growth on nine aggregate returns:

$$\Delta \ln Rev_{g,w} = \alpha_g + \sum_{k=1}^{9} \beta_g^k \cdot r_w^k + \varepsilon_{g,w} \tag{4}$$

where $\Delta \ln Rev_{g,w}$ is the weekly log revenue growth for product group g in week w, and r_w^k denotes the weekly return on aggregate variable k. The nine aggregate variables are: oil prices, seven leading currencies (Euro, Canadian Dollar, Japanese Yen, British Pound, Swiss Franc, Australian Dollar, and Swedish Krona), and changes in economic policy uncertainty. The rolling window spans 156 weeks (approximately three years), with a minimum of 104 weeks required for estimation.[8]

Estimating sensitivities at the product-group level, rather than at the firm level, is a deliberate design choice. Because product groups are defined by NielsenIQ's classification and are common across firms, group-level betas are not contaminated by firm-specific shocks that might simultaneously drive both the sensitivity estimates and the firm's product-market decisions. The rolling betas are collapsed to annual frequency by retaining the end-of-year estimate for each product group.

Figure 7 plots the cross-group distribution of product-revenue betas for three representative aggregate variables: oil, the average across seven currencies, and economic policy uncertainty. The distributions exhibit substantial heterogeneity, confirming that product groups differ meaningfully in their exposure to aggregate price risks. Figure 8 shows the product groups with the largest absolute exposure to each aggregate variable, revealing economically intuitive patterns. For example, perishable food categories such as unprocessed meat and frozen goods exhibit the largest oil betas, consistent with their dependence on energy-intensive supply chains, while electronics and baked goods show the highest sensitivity to currency fluctuations, and discretionary categories such as electronics, housewares, and stationery are the most exposed to economic policy uncertainty.

Step 2: Firm-level weighted-average betas. I aggregate the product-group betas to the firm level using revenue shares as weights. Specifically, firm i's sensitivity to aggregate variable k in year t is:

$$\beta_{i,t}^k = \sum_{g \in \mathcal{G}_{i,t}} \omega_{i,t}^g \cdot \beta_{g,t}^k \tag{5}$$

[8]The 156-week rolling window yields approximately 156 observations per regression, which compares favorably to the roughly 60 monthly observations in the five-year rolling windows used by Alfaro, Bloom, and Lin (2024).

where $\omega_{i,t}^{g}$ is the share of firm i's total revenue derived from product group g in year t, and $\beta_{g,t}^{k}$ is the estimated sensitivity of product group g to aggregate variable k. This revenue-weighted aggregation captures the fact that firms operating across multiple product groups inherit a portfolio of aggregate exposures, with more important product lines receiving greater weight.

Step 3: Instrument definition. The instruments interact the firm's predetermined, non-directional exposure to each aggregate variable with the recent change in that variable's volatility. Formally, the instrument for aggregate variable k is:

$$z_{i,t-1}^{k} = |\beta_{i,t-4Q}^{k}| \times \Delta\sigma_{t-1Q}^{k}, \tag{6}$$

where $|\beta_{i,t-4Q}^{k}|$ is the absolute value of firm i's revenue sensitivity to variable k, lagged by four quarters to ensure pre-determination, and $\Delta\sigma_{t-1Q}^{k}$ is the change in the realized volatility of aggregate variable k in the previous quarter. The absolute value captures the non-directional nature of exposure: firms with large positive or negative sensitivities to, say, oil prices are both exposed to increases in oil price uncertainty, regardless of the direction of their exposure. The four-quarter lag on the sensitivities ensures that they pre-date both the outcome and control variables, reducing concerns that contemporaneous shocks drive both the instruments and the outcome.

This construction yields nine instruments for PMU and, by interacting with the *Early_Stage* dummy, nine additional instruments for $PMU \times Early_Stage$, for a total of 18 instruments. The first-moment counterparts—the directional exposures $\beta_{i,t-4Q}^{k} \times r_{t-1Q}^{k}$—are included as controls in all specifications to absorb level effects of aggregate price movements on firm revenues.

5.4.2 Empirical Specification

Following Argente, Lee, and Moreira (2018), 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. Net product entry is defined as the difference between the entry rate and the exit rate.

I estimate the following specification by two-stage least squares (2SLS):

$$\begin{aligned} y_{i,t+h} = \alpha_i + \theta_t + \beta_1 \times \widehat{PMU}_{i,t-1} + \beta_2 \times Early_Stage_{i,t-2} \\ + \beta_3 \times \widehat{PMU}_{i,t-1} \times Early_Stage_{i,t-2} + \gamma' X_{i,t-1} + \epsilon_{it} \end{aligned} \tag{7}$$

where $y_{i,t+h}$ is an outcome variable for firm i in quarter $t+h$, with $h = 12$ quarters (three years ahead).[9] $\widehat{PMU}_{i,t-1}$ is the instrumented product-market uncertainty, lagged by one quarter. *Early_Stage* is a dummy equal to one if a firm is in the early stage, lagged by two quarters to capture firms' ex-ante life stage and avoid endogeneity. α_i and θ_t are firm and year-quarter fixed effects, respectively. $X_{i,t-1}$ is a vector of controls that includes lagged log revenue, lagged revenue growth, and the 18 first-moment controls described above. The first-moment controls directly account for level effects, ensuring that PMU captures second-moment variation. Standard errors are clustered at the firm level and are robust to heteroskedasticity.

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. The total effect for early-stage firms is $\beta_1 + \beta_3$. In Appendix G, I show F-statistics for the excluded instruments, indicating that the instruments are jointly relevant for predicting firm-level PMU.

A natural concern is that a life-cycle measure based on the age of the firm's products is mechanically related to product entry: a firm that recently introduced products has, by construction, a younger portfolio, and entry is persistent. However, the coefficient of interest is on the interaction of *Early_Stage* with instrumented PMU. For the mechanical channel to contaminate this coefficient, portfolio age would have to be related not to how much a firm enters, but to how much a firm's entry responds to exogenous shocks to aggregate volatility transmitted through its predetermined product-group exposures. Nothing in the construction of the age measure generates such a relation: the fact that a firm launched products in the recent past says nothing about whether its future entry co-moves with oil, currency, or policy volatility shocks. Three further features of the design reinforce this argument. First, the classification is lagged two quarters and the outcome is measured twelve quarters ahead, so the products that define the firm's stage are not the products whose entry is the outcome. Second, I control for the lagged outcome, which absorbs persistence in entry directly; the interaction coefficient is essentially unchanged. Third, the composition results in Table 6 cannot be produced by a mechanical relation between portfolio age and the volume of entry, since that relation has no implication for whether new products are directed toward familiar or unfamiliar product categories.

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

5.5 Main Results

5.5.1 Product Entry

I begin by analyzing the impact of uncertainty on product entry. Table 5 reports the 2SLS results. I find that, in response to an increase in PMU, early-stage firms significantly increase product entry, while late-stage firms reduce it. The coefficient on PMU is -0.108, indicating that for late-stage firms, a one-unit increase in instrumented PMU leads to a 10.8 percentage point decline in the product entry rate three years later. The interaction term $PMU \times Early_Stage$ is $+0.200$, implying that the total effect for early-stage firms is $-0.108 + 0.200 = +0.092$—a significant increase of 9.2 percentage points in product entry. These results are robust to the inclusion of the lagged dependent variable as an additional control (column 2), which accounts for persistence in entry rates. The coefficient on the interaction term remains positive and statistically significant at $+0.189$.

These magnitudes are economically meaningful. The contrasting responses across life-cycle stages highlight the complementarity between R&D, innovation, and product-market strategies at different stages of the life cycle. 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 translate into more product launches.[10] In contrast, late-stage firms respond to uncertainty by reducing product launches, consistent with the "wait-and-see" behavior documented for their investment decisions.

5.5.2 Net Product Entry

I now examine the effect of uncertainty on net product entry, which captures the net change in a firm's product portfolio by combining entry and exit dynamics. Table 5 shows that the results are qualitatively similar. The coefficient on PMU is -0.127, and the interaction with $Early_Stage$ is $+0.200$. For early-stage firms, the total effect on net product entry is positive ($-0.127 + 0.200 = +0.073$), indicating that these firms expand their portfolios in response to higher uncertainty. For late-stage firms, the negative coefficient implies portfolio contraction.

These findings are consistent with the predictions of the model. Early-stage firms respond to uncertainty by actively reshaping their portfolios—introducing new products at a faster rate than they discontinue existing ones—consistent with the option-like nature of early-stage product strategies, where small bets can yield large returns. Late-stage

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

firms, by contrast, reduce net product entry, consistent with a strategy of consolidation in which uncertainty discourages costly adjustments to established portfolios, making stability more attractive than reoptimization. These results are robust to the inclusion of lagged net product entry as a control (column 4), confirming that the findings are not driven by persistence in product portfolio dynamics.

5.5.3 Product Innovation Composition

The preceding results establish that early- and late-stage firms respond differently to uncertainty in the *quantity* of product entry. I now ask whether uncertainty also shapes the *composition* of product innovation—that is, whether new products are introduced in familiar or unfamiliar product categories.

Following Granja and Moreira (2023), I classify each new product introduction along two margins of increasing novelty, defined using the NielsenIQ product hierarchy. *Old-line entry* occurs when a firm introduces a new UPC within a product module in which it was already active in the preceding quarter; this represents incremental innovation within existing product categories. *New-line entry* occurs when a firm introduces a new UPC in a product module that is new to the firm, representing exploratory entry into unfamiliar product categories. For each margin, I construct an indicator variable equal to one if the firm undertakes that type of entry in any of the next 12 quarters, and estimate equation (7) using 2SLS. I also construct an *exploration tilt* indicator equal to one if the firm's new-line entry count exceeds its old-line entry count in any of the next 12 quarters, directly capturing whether the composition of innovation shifts toward exploration.

Table 6 reports the results. For old-line entry (column 1), the coefficient on PMU is -0.261 (significant at the 5% level) and the interaction $PMU \times Early_Stage$ is $+0.264$ (also significant at the 5% level). The net effect for early-stage firms is essentially zero ($-0.261 + 0.264 = +0.003$), indicating that early-stage firms maintain their rate of product introduction in existing product categories even as late-stage firms significantly cut back. This pattern is consistent with late-stage firms adopting a "wait-and-see" posture by freezing product refreshes in their established lines, while early-stage firms sustain incremental innovation.

For new-line entry (column 2), the interaction term $PMU \times Early_Stage$ is $+0.316$ (significant at the 5% level), while the coefficient on PMU alone is -0.208 (significant at the 10% level). The total effect for early-stage firms is positive ($-0.208 + 0.316 = +0.108$), meaning that early-stage firms facing higher uncertainty are *more likely* to enter entirely new product modules. This result provides direct evidence that uncertainty stimulates exploratory product innovation among early-stage firms, consistent with the growth-

options mechanism: when there is more uncertainty, the option value of experimenting with new product categories rises, and early-stage firms—whose portfolios are still being shaped—are best positioned to exploit these opportunities.

Column 3 directly tests whether uncertainty shifts the *composition* of innovation toward exploration. The interaction term $PMU \times Early_Stage$ is $+0.446$ (significant at the 1% level). The total effect for early-stage firms is $-0.063 + 0.446 = +0.383$, indicating that uncertainty substantially increases the probability that early-stage firms introduce more new products in unfamiliar product categories than in familiar ones. For late-stage firms, the coefficient on PMU is small and statistically insignificant (-0.063), consistent with uncertainty triggering a uniform reduction in product introduction without altering its composition.

These results reveal that uncertainty does not only affect the volume of product introduction; it also shifts its composition. With increased uncertainty, late-stage firms uniformly scale back product introduction across both familiar and unfamiliar categories, leaving the mix unchanged. Early-stage firms, by contrast, actively redirect their innovation toward exploratory product categories. This compositional shift sharpens the earlier finding that early-stage firms increase product entry: the additional products represent expansion into new territory—consistent with the higher option value of exploration when uncertainty elevates the potential upside of unfamiliar markets.

Overall, the product market evidence reinforces the investment and innovation results: uncertainty amplifies the value of growth options for early-stage firms while triggering retrenchment for late-stage firms. The entry and net entry results show that early-stage firms expand their portfolios under uncertainty, while the innovation composition results reveal that this expansion is driven by a deliberate shift toward exploratory entry into new product categories. The complementary nature of firms' financial and strategic decisions underscores the pervasive role of the product life cycle in shaping how uncertainty transmits to corporate behavior.

6. Model and Quantitative Analysis

This section presents the formal real-options model that underlies the intuition developed in Section 3, structurally estimates its parameters, and examines the quantitative implications of product life-cycle heterogeneity for investment under uncertainty. The model combines three building blocks from the investment literature in a product life-cycle–dependent setting. 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 continuing or abandoning. Following Bernanke (1983), mature projects are irreversible and therefore subject to an option to delay that makes investment decline in uncertainty. Following Campello and Kankanhalli (2022), uncertainty enters as a mean-preserving spread (MPS), affecting only payoff dispersion and not expected levels. The novel contribution is the interaction of these three elements with life-cycle heterogeneity in *opportunity sets* and in the *scalability* of growth options. Early-stage firms hold many scalable growth options whose value is amplified by complementary innovative capacity; late-stage firms predominantly face unscalable, irreversible projects whose option value to wait is dominant.

6.1 Model Setup

Environment and timing. Time is discrete, $t \in \{0, 1, 2\}$. The discount factor is set to $\beta = 1$.[11] Option value arises solely from the timing of information arrival and irreversibility. Firms maximize expected firm value at $t = 0$. At $t = 0$, the firm chooses which projects to initiate and how much innovative capacity to install. At $t = 1$, the firm receives information about exploratory R&D projects and decides whether to continue or abandon; projects that can be delayed (mature and incremental) may also be initiated at $t = 1$. At $t = 2$, all remaining projects generate payoffs.

Life-cycle stage. Each firm belongs to one of two stages, $s \in \{E, L\}$, where E denotes early-stage and L denotes late-stage. The stage indexes the *composition* of the firm's opportunity set and the *strength of complementarity* between innovative capacity and growth options (described below).

Uncertainty. A scalar $\sigma \geq 0$ indexes the MPS family of all payoff-relevant shocks. Formally, fix zero-mean reference distributions G_ε, G_ζ, and G_η on $\mathbb{R}$ and set $\varepsilon_t = \sigma\tilde{\varepsilon}_t$, $\zeta_t = \sigma\tilde{\zeta}_t$, $\eta_t = \sigma\tilde{\eta}_t$ with $(\tilde{\varepsilon}_t, \tilde{\zeta}_t, \tilde{\eta}_t) \sim G_\varepsilon \otimes G_\zeta \otimes G_\eta$. By construction the induced family is indexed by σ in the convex (Rothschild–Stiglitz) order, with fixed means and variance σ^2 times the reference variance. An increase in σ thus raises payoff dispersion without changing any conditional mean.

Project types and opportunity sets. A firm can invest in three project types. (i) *Exploratory* (growth-option) R&D projects, $j = \text{exp}$, are multi-stage, risky projects with an

[11] With three periods and annual calibration, discounting at realistic rates ($\beta \approx 0.95$) would scale all continuation values by at most $0.95^2 \approx 0.90$, a uniform rescaling that does not alter the comparative statics with respect to σ. I set $\beta = 1$ for transparency; all results are invariant to $\beta \in [0.90, 1.00]$.

abandonment option and payoffs that are scaled by innovative capacity. (ii) *Incremental* R&D projects, $j = \text{inc}$, are small-scale innovations in existing lines and, like mature capital, carry an option to delay. (iii) *Mature* projects, $j = M$, are traditional fixed-capital investments, also subject to an option to delay.

A stage-s firm draws potential projects from a continuum. The total mass of R&D-type opportunities (exploratory plus incremental) is R_s, and the total mass of mature opportunities is N_s. The R&D share is $\theta_s \equiv R_s/(R_s + N_s)$. Consistent with Hoberg and Maksimovic (2022), I assume early-stage firms hold opportunity sets tilted toward R&D-type projects, $\theta_E > \theta_L$.

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

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

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

Project productivity. Within each project type j and stage s, projects are indexed by a mean parameter μ,

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

with density $f_{j,s}$. The across-stage FOSD orderings discipline the opportunity sets: early-stage firms have better exploratory opportunities than late-stage firms; late-stage firms have better mature opportunities than early-stage firms. Each $F_{j,s}$ satisfies the increasing hazard-rate (IHR) property, ensuring unique productivity cutoffs $\mu^*_{j,s}(\sigma)$.

The extensive-margin problem—choosing which projects clear the cutoff $\mu^*_{j,s}$—is equivalent, to first order around the interior optimum, to a smooth investment problem with quadratic adjustment costs $\frac{\alpha_{j,s}}{2} x^2_{j,s}$ (derivation in Appendix A). The adjustment-cost parameter is pinned down by the density of projects at the cutoff:

$$\alpha_{j,s} \propto \frac{1}{f_{j,s}(\mu^*_{j,s})}. \tag{8}$$

The intuition is straightforward: when many marginal projects sit near the cutoff (high $f_{j,s}(\mu^*_{j,s})$), small changes in the hurdle bring in many additional projects, so investment is cheap to scale and $\alpha_{j,s}$ is low. When the cutoff lies in a thin part of the distribution, expanding investment requires reaching deeper into the project pool, and $\alpha_{j,s}$ is correspondingly high. In this way, $\alpha_{j,s}$ summarizes the entire opportunity set $F_{j,s}$ (and population size N_s or R_s) through a single sufficient statistic. For the remainder of this section

I work directly with $\alpha_{j,s}$. I impose the following FOSD orderings of opportunity sets:

$$\alpha_{\text{exp},E} < \alpha_{\text{exp},L}, \qquad \alpha_{M,E} > \alpha_{M,L}.$$

The first ordering reflects the richer exploratory opportunity set available to early-stage firms; the second reflects the richer mature-project opportunity set of late-stage firms. The ordering of $\alpha_{\text{inc},E}$ and $\alpha_{\text{inc},L}$ is left unrestricted: in principle, either stage could have a richer set of incremental projects, and the model's comparative-statics predictions hold regardless of the sign of $\alpha_{\text{inc},E} - \alpha_{\text{inc},L}$.[12]

Payoff processes. A *mature* project with productivity μ yields $v_t(\mu) = \mu\bar{v}_t + \varepsilon_t$ at $t = 1, 2$. An *incremental* R&D project yields $r_t(\mu) = \mu\bar{r}_t + \zeta_t$ at $t = 1, 2$. An *exploratory* R&D project initiated at $t = 0$ generates an interim signal at $t = 1$, $u_1(\mu) = \mu + \eta_1$; after observing $u_1(\mu)$ the firm pays a continuation cost $d > 0$ to receive $u_2(\mu) = u_1(\mu) + \eta_2$ at $t = 2$, or abandons for zero payoff. Because η_2 is zero-mean and independent of u_1, $\mathbb{E}[u_2(\mu) \mid u_1(\mu)] = u_1(\mu)$. Joint distributions are MPS families in σ with fixed means. Continuation is characterized by a threshold $\bar{u}_1^*(x_{IC,s})$ (which depends on σ only through the equilibrium response of $x_{IC,s}(\sigma)$) derived explicitly in Appendix A.6.

Innovative capacity. At $t = 0$ the firm chooses innovative capacity $x_{IC,s} \geq 0$. If an exploratory project is continued, its $t = 2$ payoff is scaled by

$$g_s(x_{IC,s}) = (1 + x_{IC,s})^{\gamma_s}.$$

The unit baseline ensures that $g_s(0) = 1$: exploratory projects retain their intrinsic value even without dedicated innovative capacity, but capacity investment amplifies the payoff. The exponent γ_s is the key life-cycle parameter. I assume $\gamma_E > 1$ (strong complementarity at early stage) and $\gamma_L = 0$ (no complementarity at late stage). $\gamma_L = 0$ is imposed as a corner case to sharpen the predictions; by continuity the same sign pattern obtains for $\gamma_L \in [0, \bar{\gamma})$ for some $\bar{\gamma} > 0$.[13] Total capital expenditure is

$$I_s^K(\sigma) \equiv \underbrace{x_{IC,s}(\sigma)}_{\text{innovative capacity}} + \underbrace{x_{M,s}(\sigma)}_{\text{mature capacity}}.$$

[12] The estimates $\hat{\alpha}_{\text{inc},E} = 2.053 < \hat{\alpha}_{\text{inc},L} = 8.33$, implying that early-stage firms face a richer incremental opportunity set. This is consistent with early-stage product lines having more low-hanging fruit for incremental improvement, while late-stage product lines have already exhausted many marginal innovations.

[13] In Appendix B, I show that the results hold for different values of γ_L.

Costs. Total costs are

$$C_s \;=\; c_g x_{IC,s} + \tfrac{\alpha_{IC}}{2} x_{IC,s}^2 + \tfrac{\alpha_{\exp,s}}{2} (x_{G,s}^{\exp})^2 + \tfrac{\alpha_{\text{inc},s}}{2} (x_{G,s}^{\text{inc}})^2 + \tfrac{\alpha_{M,s}}{2} x_{M,s}^2, \tag{9}$$

with per-project initiation costs $k_R^{\exp}$, k_R^{inc}, and c_m embedded inside the project values V_j. I treat α_{IC} as stage-invariant; allowing α_{IC} to vary across stages does not affect any of the comparative-statics signs below.

6.2 Firm Objective and Mechanism

For stage s, the firm solves

$$V_0^s(\sigma) = \max_{\substack{x_{G,s}^{\exp}, x_{G,s}^{\text{inc}}, \\ x_{M,s}, x_{IC,s} \geq 0}} \Big\{ x_{G,s}^{\exp} V_G^{\exp}(\sigma; x_{IC,s}) + x_{G,s}^{\text{inc}} V_G^{\text{inc}}(\sigma) + x_{M,s} V_M(\sigma) - C_s \Big\}, \tag{10}$$

where $V_j(\sigma)$ is the value of the *marginal implemented project* of type j, evaluated at the endogenous productivity cutoff $\mu_{j,s}^*(\sigma)$ (and, for exploratory projects, at the endogenous capacity $x_{IC,s}$). For mature and incremental projects, V_j should be interpreted as the net value of initiating at $t = 0$ rather than delaying to $t = 1$: it is the "initiation premium" $\Pi_j \equiv V_j^{\text{now}} - V_j^{\text{wait}}$ that determines which projects clear the extensive margin (see Appendix A.4). Throughout the comparative statics, $\mu_{j,s}^*$ is held at its equilibrium value, so each V_j is a pure function of σ (and, for $V_G^{\exp}$, of $x_{IC,s}$).

The three option channels operate as follows.

Option to delay (mature projects). A firm can postpone mature investment until $t = 1$, when it observes $v_2(\mu)$. The immediate-investment value $V_M^{\text{now}} = \mu(\bar{v}_1 + \bar{v}_2) - c_m$ does not depend on σ. The wait value $V_M^{\text{wait}} = \mathbb{E}\max\{v_2(\mu) - c_m, 0\}$ is convex in $v_2(\mu)$ and therefore, by Jensen's inequality under MPS, strictly increasing in σ. Hence the net advantage of acting now, $\Pi_M = V_M^{\text{now}} - V_M^{\text{wait}}$, is strictly decreasing in σ, which raises the cutoff $\mu_{M,s}^*$ and lowers $x_{M,s}$.

Option to delay (incremental R&D). Incremental R&D has the same timing as mature investment. By identical logic, $\partial x_{G,s}^{\text{inc}} / \partial \sigma < 0$.

Abandonment option (exploratory R&D). Conditional on innovative capacity $x_{IC,s}$ and continuation cost d, the continuation threshold is

$$\bar{u}_1^*(x_{IC,s}) \;=\; \frac{d}{(1 + x_{IC,s})^{\gamma_s}}, \tag{11}$$

so the project is continued iff $u_1(\mu) \geq \bar{u}_1^*$. Evaluating at the marginal project (productivity $\mu^*_{\text{exp},s}$), the $t = 0$ exploratory value is

$$V_G^{\text{exp}}(\sigma; x_{IC,s}) \;=\; -k_R^{\text{exp}} \;+\; \mathbb{E}_{u_1}\Big[\max\{\, u_1\,(1+x_{IC,s})^{\gamma_s} - d,\; 0\,\}\Big].$$

The integrand is convex in u_1 (it is the maximum of a linear function and zero). By Jensen's inequality under MPS, V_G^{exp} is strictly increasing in σ, which lowers the cutoff $\mu^*_{\text{exp},s}$ and raises $x^{\text{exp}}_{G,s}$.[14]

Scalability of the growth option (innovative capacity). The key life-cycle mechanism: because continuation payoffs scale as $(1+x_{IC,s})^{\gamma_s}$, the marginal value of innovative capacity is $\partial V_G^{\text{exp}}/\partial x_{IC,s} = \gamma_s(1+x_{IC,s})^{\gamma_s-1}\,\mathbb{E}[u_1\,\mathbf{1}\{u_1 \geq \bar{u}_1^*\}]$. Under Assumption A.1 (the continuation hurdle $\bar{u}_1^*$ lies at or above the mean of u_1) and the scale-family parameterization of Assumption A.1, this marginal value is strictly increasing in σ for every $\gamma_s > 0$ (Lemma 8): a mean-preserving spread raises $\mathbb{E}[u_1\,\mathbf{1}\{u_1 \geq \bar{u}_1^*\}]$ both through the convex truncated-payoff component $\mathbb{E}[\max\{u_1 - \bar{u}_1^*, 0\}]$ (Rothschild–Stiglitz) and through the threshold-crossing probability $\bar{u}_1^* \cdot \mathbb{P}\{u_1 \geq \bar{u}_1^*\}$ (scale family plus Assumption A.1). The complementarity between innovative capacity and exploratory R&D operates whenever $\gamma_E > 0$: for any positive γ_E, an increase in x_{IC} raises the payoff of exploratory projects through the amplification function $g(x_{IC}) = (1+x_{IC})^{\gamma_E}$, and the first-order condition for x_{IC} involves the product $x_{\text{exp}} \cdot \partial V_G^{\text{exp}}/\partial x_{IC}$, which is positive whenever exploratory R&D is active.[15] The first-order condition

$$c_g + \alpha_{IC} x_{IC,s} \;=\; x^{\text{exp}}_{G,s}(\sigma)\,\frac{\partial V_G^{\text{exp}}(\sigma; x_{IC,s})}{\partial x_{IC,s}} \tag{12}$$

implies $\partial x_{IC,E}/\partial\sigma > 0$ whenever $\gamma_E > 0$; the restriction $\gamma_E > 1$ is invoked only to sign the second-order curvature term entering the SOC. The reduced-form aggregation on the right-hand side (mass times marginal-project derivative) is first-order equivalent to the integral $\int_{\mu \geq \mu^*_{\text{exp},s}} \partial V_G^{\text{exp}}(\sigma; x_{IC,s})/\partial x_{IC,s}\, dF_{\text{exp},s}(\mu)$ around the interior optimum; see

[14] This result holds locally around the baseline distribution. For arbitrarily large mean-preserving spreads, the convexity of the option payoff may interact with boundary constraints (e.g., non-negativity of investment) in ways that could attenuate the response. In the estimated model, the result holds over the empirically relevant range $\sigma \in [\bar{\sigma} - \Delta_\sigma, \bar{\sigma} + \Delta_\sigma]$, where Δ_σ is one standard deviation of the uncertainty measure. Figure 9 confirms that the comparative statics are well-behaved over this range.

[15] The condition $\gamma_E > 1$ is not required for the complementarity channel to operate. What $\gamma_E > 1$ ensures is that the amplification function $g(\cdot)$ is *convex*, so the feedback loop between x_{exp} and x_{IC} strengthens as innovative capacity grows. With $0 < \gamma_E < 1$, complementarity still exists but exhibits diminishing returns. The estimated $\hat{\gamma}_E \approx 1.7$ implies strong convexity.

Appendix A.2. When $\gamma_s = 0$, the right-hand side is independent of $x_{IC,s}$ and $x_{IC,s} = 0$ is a corner solution (see Proposition 4 in Appendix A.6).

6.3 Predictions

The model yields two sharp comparative-statics predictions.[16]

Prediction 1 (Early-stage: investment expands in uncertainty). Under Assumption A.1, for early-stage firms ($s = E$) with θ_E high and $\gamma_E > 1$,

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

Prediction 2 (Late-stage: investment contracts in uncertainty). Under Assumption A.1, for late-stage firms ($s = L$) with θ_L low and $\gamma_L = 0$,

$$\frac{\partial x_{M,L}}{\partial \sigma} < 0, \quad \frac{\partial I_L^K}{\partial \sigma} < 0, \quad \frac{\partial x_{G,L}}{\partial \sigma} \leq 0,$$

with the last inequality strict whenever the incremental channel dominates the exploratory channel.

In sum: uncertainty reallocates investment across project types in a life-cycle–dependent way. For early-stage firms the abandonment-option and scalability channels dominate, so both R&D and Capex rise. For late-stage firms the option-to-delay channel dominates: Capex falls unambiguously, and R&D falls when the incremental-investment contraction outweighs the (small) exploratory expansion that survives at $\gamma_L = 0$.

6.4 Estimation

While the majority of the structural parameters are estimated using the simulated method of moments (SMM), several parameters are set externally using data or normalizations. Throughout the paper, the baseline uncertainty $\bar{\sigma} = 0.457$ and one cross-sectional standard deviation $\Delta\sigma = 0.215$ are set to their empirical counterparts from the distribution of firm-level 365-day option-implied volatility. The late-stage complementarity exponent is $\gamma_L = 0$, as assumed above. The exploratory cost for late-stage firms is set to $\alpha_{\text{exp},L} = 10.0$ (with $\mu_{\text{exp},L} = 0.05$); because $\gamma_L = 0$ renders the exploratory channel inoperative, the exact value is irrelevant, and the large value satisfies the FOSD

[16] Proofs are in Appendix A.

ordering requirement $\alpha_{\text{exp},E} < \alpha_{\text{exp},L}$. The early-stage mature-capital cost is fixed at $\alpha_{M,E} = 250$, reflecting the fact that early-stage firms have negligible mature-capital investment; this parameter is not separately identified from the composition weights. The exploratory productivity $\mu_{\text{exp},E}$ is derived from γ_E via a linear schedule calibrated to keep the exploratory option moderately in-the-money at baseline σ. The remaining fixed parameters are normalizations that pin the scale of project values without affecting comparative statics; Table 7 summarizes all externally-set parameters.

Distributional assumptions. The three payoff shocks in the model are drawn independently from the standard normal distribution: $\tilde{\varepsilon} \sim N(0,1)$ governs the $t = 2$ mature-project payoff ($v_2 = \bar{\mu}_M \bar{v}_2 + \sigma\tilde{\varepsilon}$), $\tilde{\zeta} \sim N(0,1)$ governs the $t = 2$ incremental R&D payoff ($r_2 = \bar{\mu}_{\text{inc}} \bar{r}_2 + \sigma\tilde{\zeta}$), and $\tilde{\eta} \sim N(0,1)$ governs the $t = 1$ exploratory-project signal ($u_1 = \mu_{\text{exp}} + \sigma\tilde{\eta}$). The signal u_1 is truncated below at zero: $u_1 = \max\{\mu_{\text{exp}} + \sigma\tilde{\eta}, 0\}$. The standard normal assumption is a normalization; the key object is the ratio σ/μ, which determines how far into or out of the money each option is. The assumption that shocks are independent across project types implies that uncertainty affects all three channels through the same parameter σ, consistent with the empirical specification in which a single measure of firm-level implied volatility enters the regressions.

Composition weights. The empirical regressions interact uncertainty with a life-cycle indicator. Firms classified as early-stage have average life-cycle weights $(\ell_1, \ell_2, \ell_3, \ell_4) = (0.427, 0.279, 0.244, 0.050)$, while late-stage firms have $(0.215, 0.428, 0.294, 0.064)$, computed from the Hoberg and Maksimovic (2022) classification. I map these weights to the model as follows. R&D investment is split between exploratory and incremental projects: for early-stage firms, the exploratory share is $\ell_1/(\ell_1 + \ell_2) = 60.4\%$; for late-stage firms, it is 33.4%. Capital expenditure for early-stage firms is split between mature capital (share 51.3%) and innovative capacity (48.7%). For late-stage firms, $\gamma_L = 0$ shuts down the innovative-capacity channel, so all Capex maps to mature capital. These data-driven weights replace ad hoc assumptions about opportunity-set composition.

Moment construction. I evaluate the model at $\sigma_{\text{lo}} = \bar{\sigma} - \frac{1}{2}\Delta\sigma$ and $\sigma_{\text{hi}} = \bar{\sigma} + \frac{1}{2}\Delta\sigma$. The simulated response for observable y is the raw level change

$$\hat{m}_y = y(\sigma_{\text{hi}}) - y(\sigma_{\text{lo}}),$$

which maps directly to the regression coefficient on uncertainty in Table 2: $\hat{\beta}_{\text{unc}}$ captures the change in investment per one-standard-deviation increase in σ. To construct the four observables (R&D/Assets, Capex/Assets for each stage), I aggregate the project-level investments $(x_{\text{exp}}, x_{\text{inc}}, x_M, x_{IC})$ using the composition weights described above.

SMM procedure. I estimate the five parameters $(\gamma_E, \alpha_{\text{exp},E}, \alpha_{\text{inc},E}, \alpha_{\text{inc},L}, \alpha_{M,L})$ by minimizing the weighted distance

$$\hat{\theta} = \arg\min_{\theta} \left[\hat{m}(\theta) - m^{\text{data}}\right]' W \left[\hat{m}(\theta) - m^{\text{data}}\right],$$

where $W = \text{diag}(1/\text{SE}_i^2)$ is a diagonal weight matrix. For level moments, I set $\text{SE}_i = 0.10 \times m_i^{\text{data}}$, reflecting that model misspecification dominates sampling error for unconditional means. For regression coefficients, I use the actual regression standard errors from Table 2; for early-stage coefficients (which combine a base and interaction term), the standard error is $\text{SE}_i = \sqrt{\text{SE}^2_{\hat{\beta}_{\text{unc}}} + \text{SE}^2_{\hat{\beta}_{\text{unc}\times E}}}$. I draw $N = 120{,}000$ standard normal shocks and hold them fixed across all evaluations (common random numbers), which reduces simulation variance. Optimization uses coordinate descent with iteratively refined grids (ten rounds, fifteen grid points per coordinate per round). Standard errors are computed via the sandwich formula $\hat{V}(\hat{\theta}) = (G'WG)^{-1}G'W\hat{\Omega}WG\,(G'WG)^{-1}$, where G is the numerical Jacobian and $\hat{\Omega}$ is the bootstrap covariance of the simulated moments (60 bootstrap replications).

6.5 Identification

I select ten moments related to firms' investment rates and their response to uncertainty. The first four moments are the unconditional mean investment rates (R&D/Assets and Capex/Assets for each stage), computed from the Compustat panel. These level moments jointly discipline the adjustment costs: $\alpha_{\text{inc},E}$ is strongly linked to mean early-stage R&D, $\alpha_{\text{inc},L}$ to mean late-stage R&D, and $\alpha_{M,L}$ to mean late-stage Capex. The early-stage Capex level disciplines the innovative-capacity response, and hence γ_E and $\alpha_{\text{exp},E}$, through the composition weights, since mature capital is negligible for early-stage firms ($\alpha_{M,E}$ is fixed at a large value and α_{IC} is normalized).

The next four moments are the investment–uncertainty regression coefficients from Table 2. For early-stage firms, the net coefficient is $\hat{\beta}_{\text{unc}} + \hat{\beta}_{\text{unc}\times\text{Early}}$: $+0.046$ for R&D and $+0.010$ for Capex. For late-stage firms, the coefficient is $\hat{\beta}_{\text{unc}}$ alone: -0.010 for R&D and -0.055 for Capex. These response moments are most informative about γ_E: the

complementarity exponent governs the strength of the growth-option channel, which pushes early-stage investment up with uncertainty. When γ_E is large, exploratory R&D and innovative capacity respond more strongly to uncertainty, producing larger positive coefficients for early-stage firms. The ninth moment is the aggregate offset share: the fraction of the late-stage total-investment contraction that is offset by early-stage expansion. The tenth moment is the average early-stage CapEx/Assets in high-uncertainty periods, which disciplines the right tail of the Capex response function. The system has five free parameters and ten moments, providing five degrees of overidentification.

6.6 Estimation Results

I summarize the results of the structural estimation in Table 8. Panel A contains simulated and actual moments and the normalized difference between the two. Panel B reports the parameter estimates and their standard errors.

Panel A shows that the estimated model fits the data very well across all ten moments, which is reflected by the low values of t-statistics. Importantly, the model correctly reproduces all four sign predictions: R&D and Capex increase with uncertainty for early-stage firms and decrease for late-stage firms, consistent with Predictions 1 and 2. The aggregate offset share—the fraction of the late-stage total-investment contraction offset by early-stage expansion—is 18.3% in the model.

The share of the aggregate total-investment contraction that is offset by early-stage expansion is particularly informative. It is an overidentifying moment that is not mechanically tied to any single parameter: it depends on the *joint* behavior of early- and late-stage firms, weighted by their shares of the economy, and involves a ratio of investment responses that could easily be orders of magnitude off if the model's relative scaling were wrong. The model predicts an offset share of 18.3%, against 18.5% in the data (0.02 SE below the target), correctly identifying the order of magnitude and confirming that the growth-option channel is quantitatively significant. Although the offset is included in the moment vector, no single parameter is calibrated to match it: the offset is a derived consequence of the model's joint predictions for both firm types, and matching it within one standard error provides a test of the model's overidentifying restrictions at the aggregate level.

Panel B documents that all estimated parameters are economically meaningful and precisely estimated. The complementarity exponent $\hat{\gamma}_E = 1.72$ confirms the theoretical requirement $\gamma_E > 1$: early-stage firms enjoy increasing returns to innovative capacity in scaling growth options. This estimate implies that the marginal product of

innovative capacity rises substantially with the scale of the exploratory pipeline, consistent with the empirical observation that R&D-intensive firms simultaneously increase both R&D and physical investment under uncertainty.

The adjustment-cost estimates reveal a pattern of opportunity-set specialization across firm types. For R&D, early-stage firms face similar costs for exploratory and incremental projects ($\hat{\alpha}_{\text{exp},E} = 1.97$, $\hat{\alpha}_{\text{inc},E} = 2.05$), while late-stage firms face much higher incremental costs ($\hat{\alpha}_{\text{inc},L} = 8.33$). This is consistent with incremental R&D in mature product lines operating at lower scale and with higher diminishing returns. For capital expenditure, late-stage firms face low mature-capital costs ($\hat{\alpha}_{M,L} = 0.78$), reflecting established production infrastructure that efficiently absorbs marginal investment. The early-stage mature-capital cost is fixed at $\alpha_{M,E} = 250$ because early-stage firms have negligible mature capital ($x_M \approx 0$); this parameter is not separately identified from the composition weights and its exact value does not affect the results as long as it is sufficiently large.

6.7 Comparative Statics

To understand the quantitative implications of the model, I analyze the comparative statics with respect to uncertainty. Figure 9 plots the response of aggregate investment to uncertainty shocks for both firm types, starting from the baseline $\bar{\sigma} = 0.457$.

Panel (a) shows that R&D responds in opposite directions across stages, consistent with Predictions 1 and 2. For early-stage firms, exploratory R&D x_{exp} rises because the call-option payoff $\max\{u_1 \cdot (1 + x_{IC})^{\gamma_E} - d, 0\}$ is convex in u_1, so a mean-preserving spread raises the exploratory project value via Jensen's inequality. This expansion dominates the decline in incremental R&D, producing the positive net R&D response. For late-stage firms, the exploratory channel is absent ($\gamma_L = 0$), and incremental R&D declines via the option-to-delay logic.

Panel (b) displays the opposing Capex responses. For early-stage firms, innovative capacity x_{IC} rises because the marginal product of x_{IC} inherits the convexity of the exploratory option: with $\gamma_E > 1$, the continuation payoff $u_1 \cdot (1 + x_{IC})^{\gamma_E}$ scales superlinearly in x_{IC}. This expansion more than offsets the decline in mature capital x_M, producing a positive net Capex response. For late-stage firms, the innovative-capacity channel is shut down ($x_{IC,L} = 0$), and the entire Capex response is driven by the decline in mature capital via the option-to-delay mechanism: the wait value $V_M^{\text{wait}}(\sigma) = \mathbb{E}[\max\{\bar{\mu}_M \bar{v}_2 + \sigma\tilde{\varepsilon} - c_m, 0\}]$ is convex in σ, so higher uncertainty increases the value of waiting and reduces $\Pi_M = V_M^{\text{now}} - V_M^{\text{wait}}$.

Mechanism decomposition. Figure 10 decomposes the aggregate responses into project-level investments for each stage. For early-stage firms (panel a), the growth-option channel ($x_{\text{exp}} \uparrow$, $x_{IC} \uparrow$) dominates the option-to-delay channel ($x_M \downarrow$, $x_{\text{inc}} \downarrow$). The two panels illustrate why the sign of the aggregate investment–uncertainty relationship differs across stages: early-stage firms have an active growth-option channel that is absent for late-stage firms. At the calibrated parameters, the exploratory and innovative-capacity components expand by more than the incremental and mature components contract, producing the positive net response documented in Section 4.

Data-model comparison. Figure 11 provides a visual comparison of the four investment–uncertainty regression coefficients implied by the data and by the model. The model reproduces the correct sign for all four coefficients and closely matches the magnitudes.

6.8 Counterfactual Analysis

The first counterfactual eliminates the growth-option channel by setting $\gamma_E = 0$, so that early-stage firms—like late-stage firms—have no complementarity between innovative capacity and exploratory R&D. All other parameters remain at their calibrated values. Figure 12 reports the results. Without the growth-option channel, early-stage total investment (R&D plus Capex) flips from $+0.055$ to -0.015—an unambiguously negative response. Late-stage total investment is unchanged at -0.065, and the aggregate offset share collapses from 18% to zero. With the growth-option channel shut down, *all* firms contract in response to uncertainty, recovering the standard result in the real-options literature.

The second counterfactual studies how the economy's life cycle composition matters. The aggregate offset share depends on the relative prevalence of early- and late-stage firms. In the data, early-stage firms constitute approximately 18% of firm-year observations. But what if the economy were tilted differently?

Figure 13 traces the aggregate investment response and the offset share as the early-stage share varies from 0% (all firms are late-stage) to 100% (all firms are early-stage). Two thresholds stand out. First, when early-stage firms constitute more than 54% of the economy, aggregate *total* investment (R&D plus Capex) turns positive in response to an uncertainty shock—meaning the economy as a whole would invest *more* during periods of heightened uncertainty. Second, when early-stage firms exceed 70%, even aggregate Capex alone turns positive.

These thresholds are far from the current composition, but they are informative about secular trends. As the economy shifts toward more innovation-intensive, early-stage industries, the aggregate investment response to uncertainty becomes less contractionary, suggesting that the aggregate importance of the growth-option channel grows with the economy's innovation intensity.

Finally, I study how the offset share has evolved over time. The aggregate offset share depends on the economy's life-cycle composition, which varies over time. Figure 14 uses the annual share of early-stage firms from the Hoberg and Maksimovic (2022) classification (1997–2019) to trace the model-implied offset over the sample period.

The offset follows a U-shaped pattern. During the dot-com boom (1997–2000), early-stage firms constituted approximately 20% of the sample, and the model-implied offset reached 21%. After the bust, the early-stage share fell to a trough of 15.3% in 2006, and the offset declined to 15%. From 2013 onward, the early-stage share has risen steadily—reaching 21.1% by 2019—and the offset has climbed back to 23%, a 48% increase from its trough.

This pattern has two implications. First, the aggregate investment response to uncertainty has become meaningfully less contractionary over the past decade as the economy has shifted toward more innovation-intensive firms. Second, the growth-option channel's aggregate importance varies substantially over time with the economy's innovation intensity, and it has been gaining importance in recent years.

7. 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 evidence that early-stage firms increase investment and innovation in response to higher uncertainty, while late-stage firms become more conservative, cutting back on both investment and innovation. In the product market, early-stage firms actively reoptimize their portfolios through increased net entry and shift product innovation toward exploratory entry into new product lines, whereas late-stage firms scale back product introduction without altering its composition.

A real-options model with product life-cycle heterogeneity rationalizes these patterns through the interaction of three channels: an abandonment option and a scalability channel that make growth options more valuable under uncertainty, and an option to delay that discourages irreversible investment. A structural estimation of the model shows that early-stage expansion offsets roughly one fifth of the total

investment contraction among late-stage firms. Counterfactual exercises show that the aggregate offset grows with the economy's share of early-stage firms, a share that has been rising over the past two decades.

These findings reconcile mixed results in the literature by showing that the conflicting signs of the investment–uncertainty relationship reflect differences in product life-cycle composition. They also suggest that as the economy shifts toward more innovation-intensive firms, the aggregate investment response to uncertainty will become less contractionary—an insight with implications for macroeconomic modeling and policy design in times of uncertainty.

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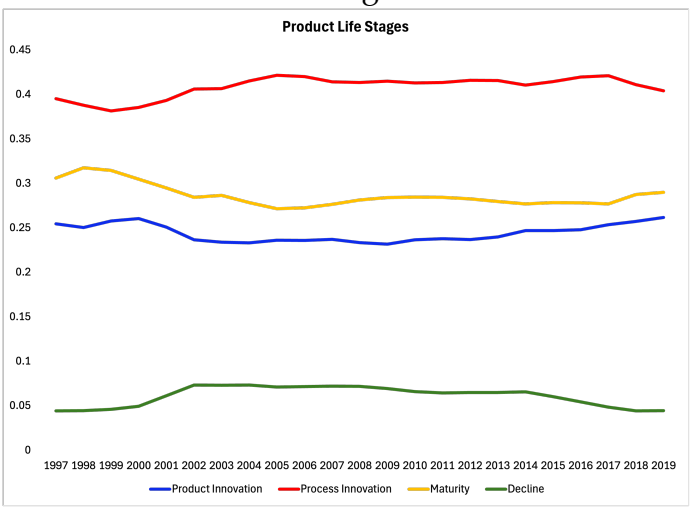
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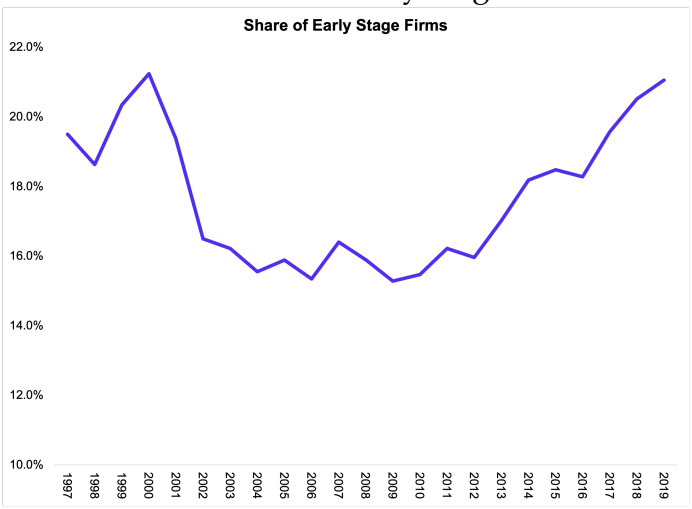
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Figure 1. Product Life Cycle Measures

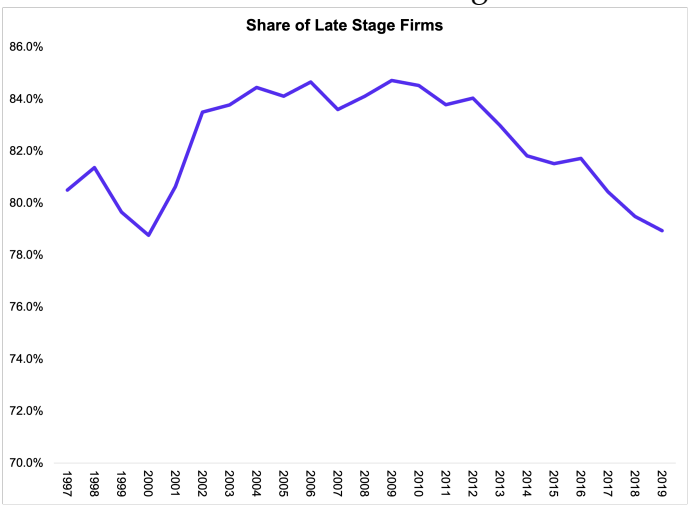
Panel A: Life Stages Over Time



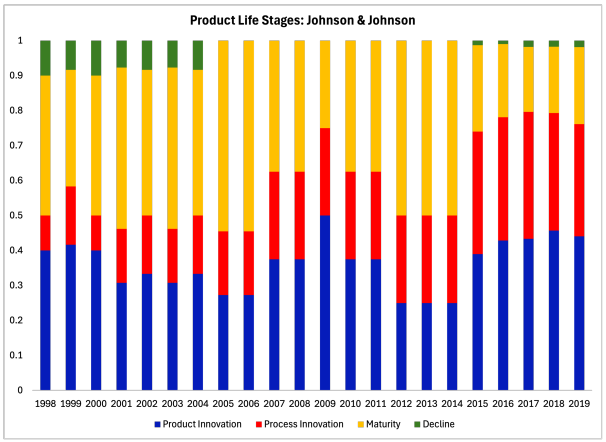
Panel B: Share of Early Stage Firms



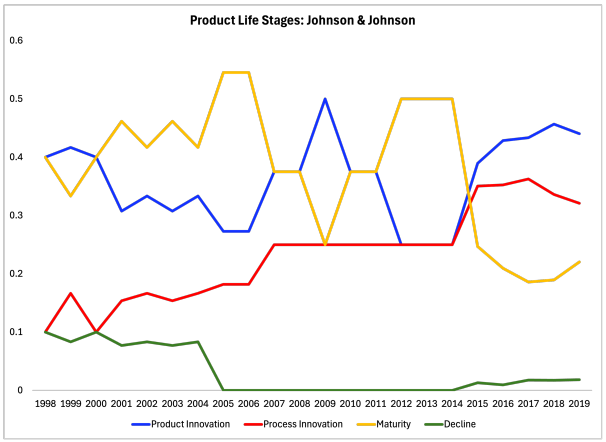
Panel C: Share of Late Stage Firms



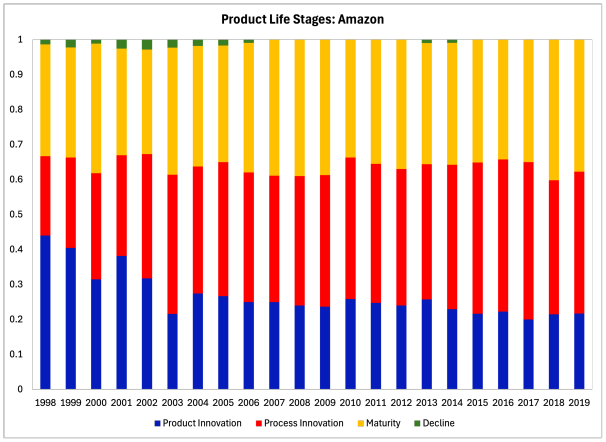
Panel A of this figure shows the average life stage variables over time. Product Stage (Life1) measures the intensity of product innovation; Process Stage (Life2) measures the intensity of process innovation; Mature Stage (Life3) measures the intensity of stable and mature products; and Declining Stage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



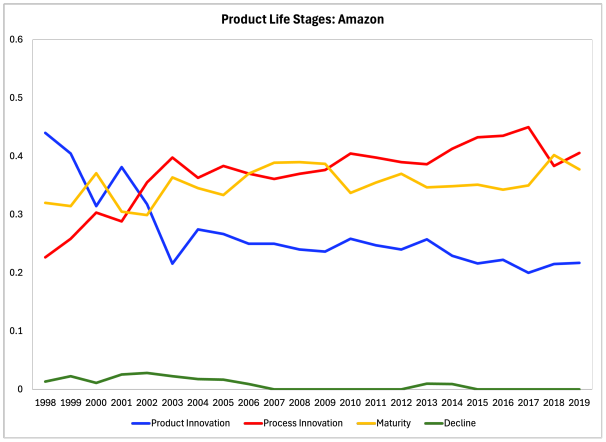
Panel A: Johnson & Johnson



Panel B: Johnson & Johnson



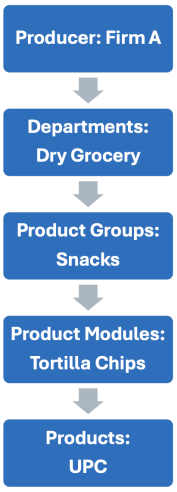
Panel C: Amazon



Panel D: Amazon

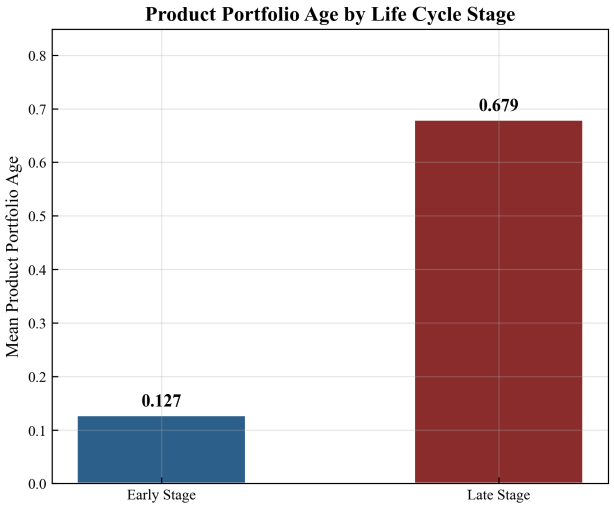
Figure 2. This figure shows the average life stage variables over time. Product Stage (Life1) measures the intensity of product innovation; Process Stage (Life2) measures the intensity of process innovation; Mature Stage (Life3) measures the intensity of stable and mature products; and Declining Stage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

Figure 3. Product Portfolio Hierarchy



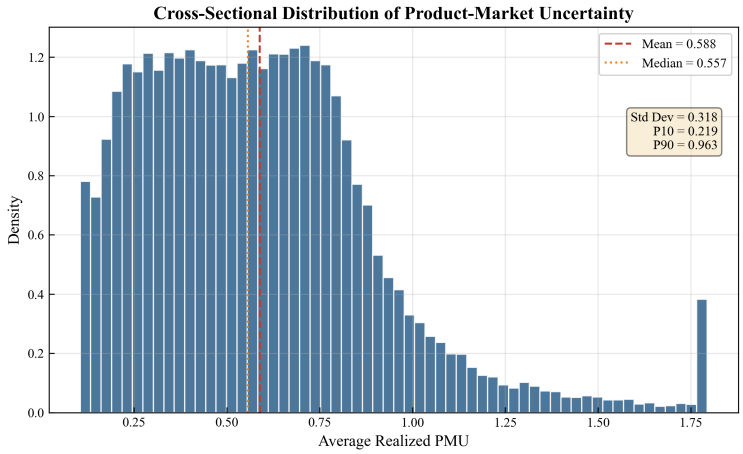
This figure plots the product portfolio hierarchy from the NielsenIQ Retail Scanner Data. Firms' products are categorized into departments, groups, modules, and products (UPC).

Figure 4. Product Portfolio Age



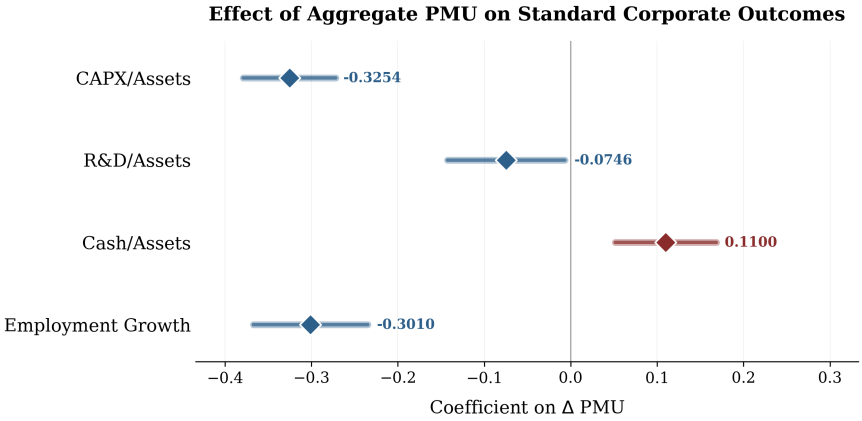
This figure plots the average product portfolio age for early- and late-stage firms. Product portfolio age is defined as the weighted share of old products, whose age exceeds half of their lifespan, in the product portfolio, where the weights correspond to product-specific revenue.

Figure 5. Cross-Sectional Distribution of Product-Market Uncertainty



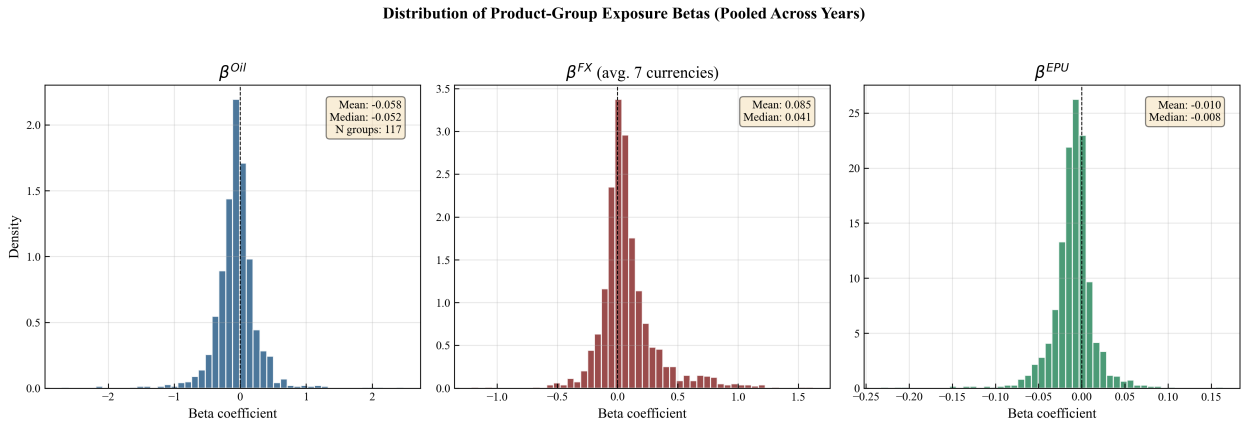
This figure plots the cross-sectional distribution of firm-level product-market uncertainty (PMU). For each firm, PMU is averaged across all quarters in the sample, so the unit of observation is the firm (firm-quarter statistics are in Table 4). The dashed red line indicates the mean (0.588) and the dotted orange line indicates the median (0.557). The distribution is right-skewed, with substantial heterogeneity across firms (standard deviation = 0.318, P10 = 0.219, P90 = 0.963).

Figure 6. PMU Validation: Effect of Aggregate PMU on Standard Corporate Outcomes



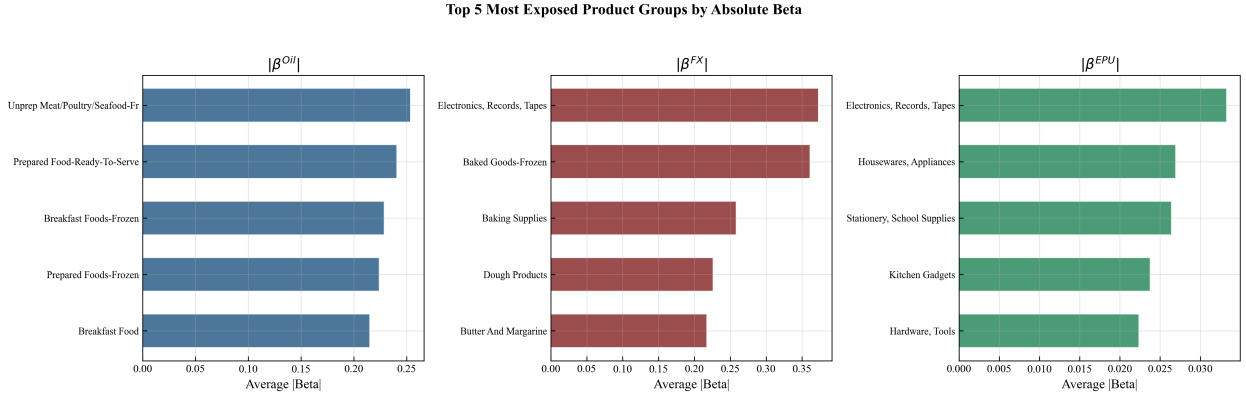
This figure plots the coefficient on ΔPMU from firm-level panel regressions of four standard corporate finance outcomes on changes in aggregate product-market uncertainty. All regressions include firm fixed effects, and control for lagged Tobin's q, log assets, book leverage, cash-to-assets, cash flow-to-assets, and log age. Horizontal bars represent 90% confidence intervals based on standard errors clustered at the firm level. The sample covers Compustat firms over 1997–2019, excluding financial firms, utilities, and government entities.

Figure 7. Distribution of Product-Revenue Betas



This figure plots the cross-group distribution of product-revenue betas for three representative aggregate variables: oil prices (β^{Oil}), the average across seven currencies (β^{FX}), and economic policy uncertainty (β^{EPU}). Betas are estimated from rolling regressions of weekly product-group revenue growth on aggregate returns, with a rolling window of 156 weeks. Distributions are pooled across product groups and years.

Figure 8. Most Exposed Product Groups by Absolute Beta



This figure shows the five product groups with the largest time-averaged absolute betas ($|\beta^k|$) for each aggregate variable: oil prices ($|\beta^{Oil}|$), the average across seven currencies ($|\beta^{FX}|$), and economic policy uncertainty ($|\beta^{EPU}|$). Betas are estimated from rolling regressions of weekly product-group revenue growth on aggregate returns and averaged across years.

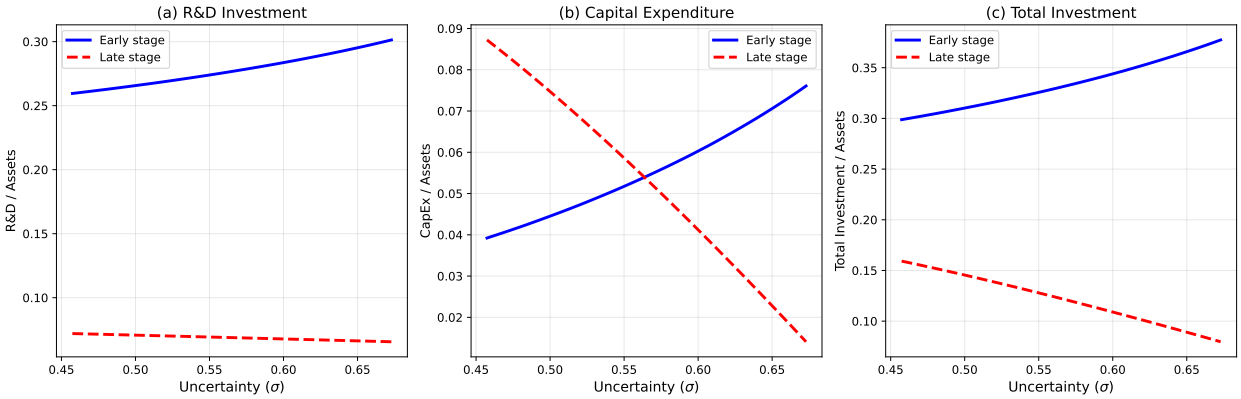


Figure 9. Investment rates (scaled by assets) as a function of uncertainty by life-cycle stage. Solid blue: early-stage firms. Dashed red: late-stage firms. The x-axis covers the range from the mean implied volatility ($\bar{\sigma} = 0.457$) to $\bar{\sigma} + \Delta\sigma$. Panel (a): R&D intensity rises for early-stage firms and falls for late-stage firms. Panel (b): Capex intensity rises for early-stage firms (innovative-capacity channel) and falls for late-stage firms (option to delay). Panel (c): total investment intensity diverges across stages. The early-stage R&D response is visibly convex, reflecting the $x_{\text{exp}} \leftrightarrow x_{IC}$ feedback loop.

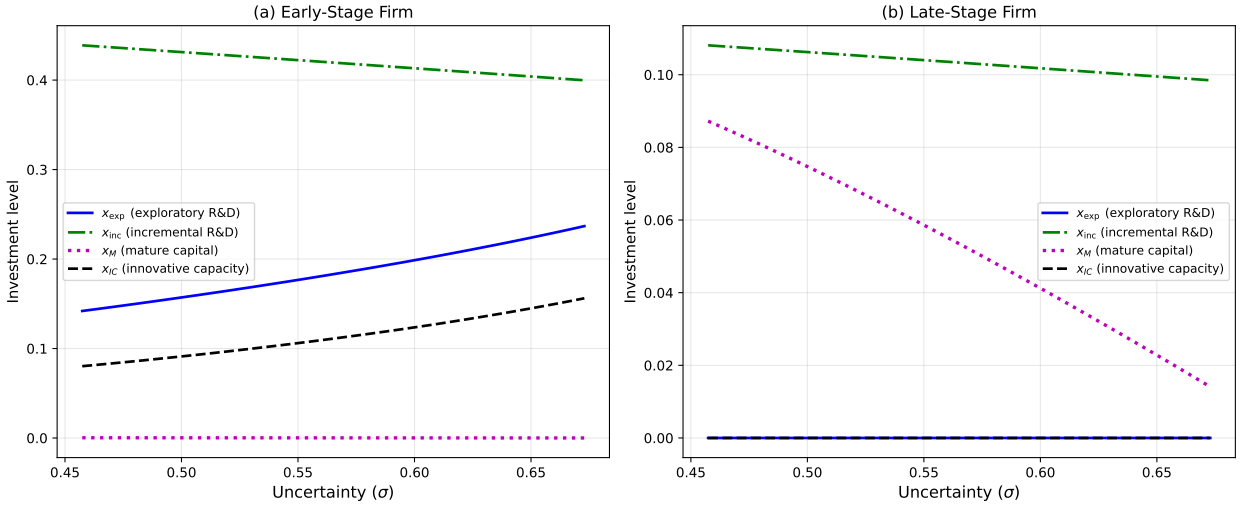


Figure 10. Project-level investment decomposition. Panel (a): early-stage firm. Exploratory R&D (x_{exp}, solid blue) rises with σ; innovative capacity (x_{IC}, black dashed) tracks the exploratory expansion; incremental R&D (x_{inc}, green dash-dot) declines moderately; mature capital (x_M, magenta dotted) declines. Panel (b): late-stage firm. Incremental R&D and mature capital decline monotonically; exploratory R&D (x_{exp}) and innovative capacity (x_{IC}) are flat at approximately zero, confirming that the growth-option channel is inoperative when $\gamma_L = 0$.

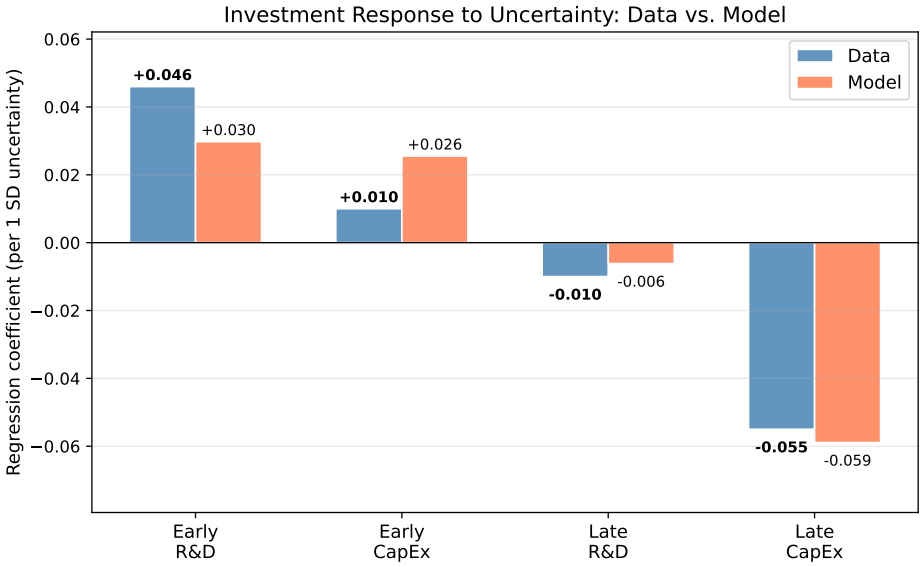


Figure 11. Investment–uncertainty regression coefficients: data (blue) vs. model (coral). Both early-stage coefficients are positive and both late-stage coefficients are negative, consistent with Predictions 1 and 2.

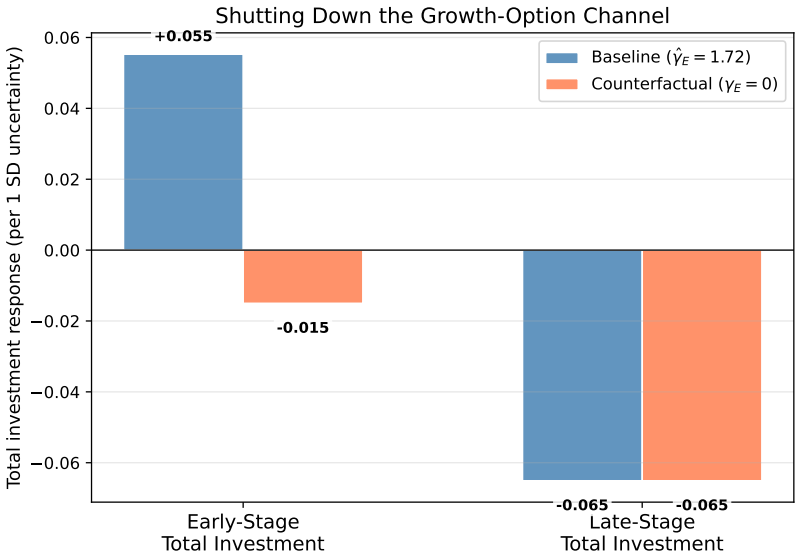


Figure 12. Total investment responses (R&D + Capex) with and without the growth-option channel. The baseline uses the calibrated $\hat{\gamma}_E = 1.72$; the counterfactual sets $\gamma_E = 0$, eliminating complementarity between innovative capacity and exploratory R&D. Without growth options, both early- and late-stage firms reduce total investment, and the aggregate offset share collapses to zero.

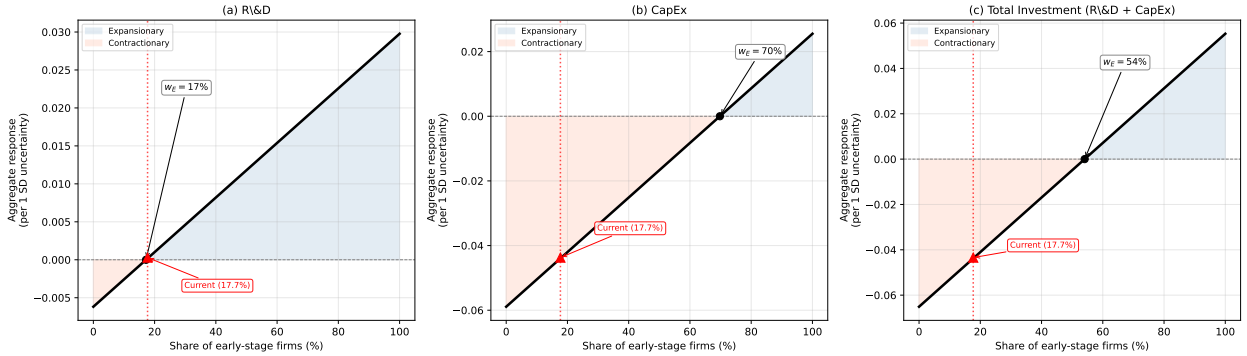


Figure 13. Aggregate investment response as a function of the early-stage share. Panel (a): aggregate R&D response, which turns positive at $w_E = 17\%$. Panel (b): aggregate Capex response, which turns positive at $w_E = 70\%$. Panel (c): aggregate total investment (R&D + Capex), which turns positive at $w_E = 54\%$: above this threshold, the economy as a whole would invest *more* during periods of heightened uncertainty. In all panels, the red triangle marks the current composition ($w_E = 18\%$); shaded regions indicate contractionary (coral) and expansionary (blue) responses.

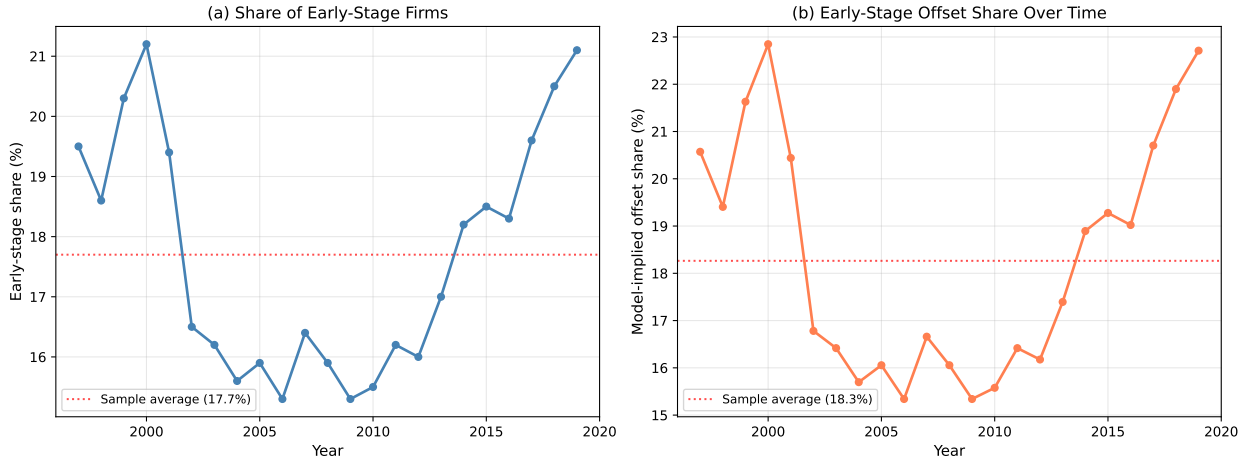


Figure 14. Time-series evolution of the early-stage offset share, 1997–2019. Panel (a): the share of early-stage firms by year. Panel (b): the model-implied offset share, computed by applying each year's early-stage share to the calibrated model. The offset follows a U-shaped pattern, declining from 21% in the late 1990s to 15% in the mid-2000s and rising back to 23% by 2019. The dotted line marks the sample-average offset (18%).

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
	Panel C: Pearson Correlations with Life Cycle Stages			
	R&D/Assets	CAPX/Assets	Tobin's Q	Size
Product Stage (Life1)	0.459	-0.101	0.095	-0.221
Process Stage (Life2)	-0.262	0.186	-0.070	0.145
Mature Stage (Life3)	-0.100	-0.077	0.002	0.040
Declining Stage (Life4)	-0.093	-0.097	-0.020	0.017
	Cash/Assets	Age		
Product Stage (Life1)	0.495	-0.234		
Process Stage (Life2)	-0.286	0.122		
Mature Stage (Life3)	-0.126	0.006		
Declining Stage (Life4)	-0.068	0.138		
	Panel D: Life Cycle Persistence (AR(1) Coefficients)			
Product Stage	Process Stage	Mature Stage	Declining Stage	
0.861	0.870	0.829	0.786	

The sample covers 1997–2019. Panel A reports summary statistics for the overall sample. Panel B reports summary statistics for early-stage firms (Life1 greater than all other life stages). Panel C reports Pearson correlation coefficients between life cycle stages and firm characteristics. Panel D reports AR(1) coefficients from OLS regressions of each life cycle variable on its lagged value. 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 2. 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 3. 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 4. Firm and Product Summary Statistics

Panel A: Firms	**Mean**	**Median**	**25th Pctl**	**75th Pctl**
Number of Products	26	4	2	13
Product Portfolio Age	0.378	0.258	0.039	0.701
Sales (quarterly, US$1,000s)	2,301.5	11	0.7	115
Total Firms: 45,575				

Panel B: Products	**Mean**	**Median**	**25th Pctl**	**75th Pctl**
Sales (quarterly, US$1,000s)	89.9	1.2	0.07	16
Total Products: 1,914,067				

Panel C: Product-Market Uncertainty	**Mean**	**Median**	**25th Pctl**	**75th Pctl**
PMU	0.483	0.367	0.204	0.675

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 45,575 firms and 1,914,067 unique products.

Table 5. Effect of Uncertainty on Product Market Outcomes

	Product Entry		Net Product Entry	
	(1)	(2)	(3)	(4)
PMU	-0.108***	-0.0898***	-0.127***	-0.129***
	(0.0343)	(0.0332)	(0.0296)	(0.0303)
PMU × Early Stage	0.200***	0.189***	0.200***	0.192***
	(0.0287)	(0.0281)	(0.0259)	(0.0263)
Observations	322,431	312,846	321,041	310,981
Firm Controls	Yes	Yes	Yes	Yes
1st Moment Controls	Yes	Yes	Yes	Yes
Lagged Outcome	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

This table reports the 2SLS coefficients of product-market uncertainty (PMU) and its interaction with Early Stage on product market outcomes. In columns (1)–(2), the dependent variable is the product entry rate, defined as the number of new products introduced in period $t + 12$ as a share of the total number of products in period $t + 12$. In columns (3)–(4), the dependent variable is net product entry. PMU is instrumented using nine instruments constructed as the absolute value of firm-level sensitivities to aggregate price shocks (oil, seven currencies, and economic policy uncertainty), lagged by four quarters, interacted with changes in the realized volatility of each aggregate variable. Firm controls include lagged log revenue and lagged revenue growth. First-moment controls are the directional counterparts of the instruments. Heteroskedasticity-robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Effect of Uncertainty on Product Innovation Composition

	Extensive Margin		Composition
	(1)	(2)	(3)
	Old Lines	New Lines	New > Old
PMU	-0.261**	-0.208*	-0.063
	(0.117)	(0.123)	(0.118)
PMU × Early Stage	0.264**	0.316**	0.446***
	(0.121)	(0.142)	(0.134)
Observations	415,773	415,773	415,773
Firm Controls	Yes	Yes	Yes
1st Moment Controls	Yes	Yes	Yes
Lagged Outcome	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

This table reports the 2SLS coefficients of product-market uncertainty (PMU) and its interaction with Early Stage on the composition of product innovation. I classify new product introductions using the NielsenIQ product hierarchy. In column (1), the dependent variable is an indicator equal to one if the firm introduces a new product in an existing product module (old-line entry) in any of the next 12 quarters. In column (2), the dependent variable is an indicator equal to one if the firm introduces a new product in a new-to-firm product module (new-line entry) in any of the next 12 quarters. In column (3), the dependent variable is an indicator equal to one if the firm's new-line entry count exceeds its old-line entry count in any of the next 12 quarters. PMU is instrumented using nine instruments constructed as the absolute value of firm-level sensitivities to aggregate price shocks (oil, seven currencies, and economic policy uncertainty), lagged by four quarters, interacted with changes in the realized volatility of each aggregate variable. Firm controls include lagged log revenue and lagged revenue growth. First-moment controls are the directional counterparts of the instruments. Heteroskedasticity-robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Predefined parameters

Parameter	Value	Source
From data		
$\bar{\sigma}$	0.457	Mean implied volatility
$\Delta\sigma$	0.215	SD of implied volatility
$w_E^{\text{R\&D}}$	$(0.604,\ 0.396)$	Life-cycle weights, early R&D
w_E^{Capex}	$(0.513,\ 0.487)$	Life-cycle weights, early Capex
$w_L^{\text{R\&D}}$	$(0.334,\ 0.666)$	Life-cycle weights, late R&D
w_L^{Capex}	$(1.000,\ 0.000)$	Late Capex: all mature ($\gamma_L = 0$)
From theory / identification		
γ_L	0	Late-stage complementarity
$\alpha_{\text{exp},L}$	10.0	Exploratory cost, late (inoperative; FOSD ordering)
$\mu_{\text{exp},L}$	0.05	Exploratory productivity, late (inoperative)
$\alpha_{M,E}$	250	Mature-capital cost, early (negligible x_M)
$\mu_{\text{exp},E}$	$f(\gamma_E)$	Derived: $\min\{\max\{0.85 - 0.095\gamma_E,\ 0.50\},\ 0.85\}$
Normalizations		
α_{IC}	2.00	Innovative-capacity quadratic cost
c_g	0.005	Linear innovative-capacity cost
d	0.50	Exploratory continuation cost
k_R^{exp}	0.10	Exploratory initiation cost
c_m	1.00	Mature-project initiation cost
k_R^{inc}	1.00	Incremental R&D initiation cost
$\bar{\mu}_M$	1.00	Mature productivity baseline
$\bar{\mu}_{\text{inc}}$	2.00	Incremental productivity baseline
$(\bar{v}_1, \bar{v}_2, \bar{r}_1, \bar{r}_2)$	$(0.6, 0.5, 0.5, 0.6)$	Payoff means

Table 8. Structural estimates and model-implied moments

	Simulated	Actual	Diff/SE
Panel A: Moments			
Mean R&D/Assets, early	0.260	0.265	−0.20
Mean Capex/Assets, early	0.039	0.042	−0.57
Mean R&D/Assets, late	0.072	0.072	+0.05
Mean Capex/Assets, late	0.087	0.087	+0.00
β: Early R&D	+0.030	+0.046	−1.13
β: Early Capex	+0.026	+0.010	+0.41
β: Late R&D	−0.006	−0.010	+0.64
β: Late Capex	−0.059	−0.055	−0.15
Aggregate offset share	0.183	0.185	−0.02
Early Capex (high uncertainty)	0.066	0.050	+1.27
Panel B: Parameters			
	Estimate	Std. Error	
γ_E	1.718	(0.005)	
$\alpha_{\text{exp},E}$	1.968	(0.019)	
$\alpha_{\text{inc},E}$	2.053	(0.005)	
$\alpha_{\text{inc},L}$	8.333	(0.015)	
$\alpha_{M,L}$	0.784	(0.005)	
Derived / Fixed			
$\mu_{\text{exp},E}$	0.687	—	derived from γ_E
$\alpha_{M,E}$	250	—	fixed

The model is estimated using SMM with common random numbers (N = 120,000 draws). Panel A reports the simulated and actual moments and the normalized difference (model − data)/SE. The tenth moment—average early-stage CapEx/Assets when VIX exceeds its sample median—disciplines the right tail of the investment response function and receives a wider tolerance (SE = 25% of target) to reflect the conditional subsample and absence of first-moment controls. Panel B reports the parameter estimates and their standard errors, computed via the sandwich formula with bootstrap covariance (60 replications). The system has 5 free parameters and 10 moments (overidentified by 5). $\mu_{\text{exp},E}$ is derived from γ_E via a linear schedule to ensure the exploratory option is moderately in-the-money at baseline σ; $\alpha_{M,E}$ is fixed because early-stage mature capital is negligible. Weighted SMM loss = 3.84.

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

A. Proofs and Derivations

This appendix derives project values, characterizes the extensive margin via productivity cutoffs, solves the Kuhn–Tucker (KT) system, and proves Predictions 1–2 from Section 6. Throughout, $\sigma \geq 0$ indexes a mean-preserving-spread (MPS) family (Assumption A.1) of all payoff-relevant random variables. Unless otherwise indicated, interior solutions are assumed in the sense of Assumption A.1.

A.1 Standing Assumptions

[MPS family of shocks] Let $(\tilde{\varepsilon}_1, \tilde{\varepsilon}_2, \tilde{\zeta}_1, \tilde{\zeta}_2, \tilde{\eta}_1, \tilde{\eta}_2)$ be a vector of mutually independent, zero-mean random variables with log-concave densities and unit variance. For $\sigma \geq 0$ let

$$\varepsilon_t \equiv \sigma\,\tilde{\varepsilon}_t, \qquad \zeta_t \equiv \sigma\,\tilde{\zeta}_t, \qquad \eta_t \equiv \sigma\,\tilde{\eta}_t, \qquad t = 1, 2.$$

Then $\{(\varepsilon_t, \zeta_t, \eta_t)\}_\sigma$ is a one-parameter family of distributions with fixed mean zero, and for any $\sigma' > \sigma$ the distribution at σ' is a mean-preserving spread of the distribution at σ in the Rothschild–Stiglitz sense, coordinate-wise.

[Interior solutions and SOC] The implementation-cost parameters $(\alpha_j, \alpha_{IC}, c_g)$ are sufficiently large relative to $(R_s, N_s, \bar{v}_2, \bar{r}_2)$ that (i) the upper-bound constraints in (18) are slack at the optimum, and (ii) the second-order condition for innovative capacity, derived from the Hessian of the concentrated objective in $x_{IC,s}$, holds at the candidate FOC:

$$\alpha_{IC} \cdot \alpha_{\exp,s} \;>\; \left(\partial V_G^{\exp} / \partial x_{IC,s}\right)^2 \;+\; V_G^{\exp}(\sigma; x_{IC,s}) \cdot \partial^2 V_G^{\exp} / \partial x_{IC,s}^2, \qquad s \in \{E, L\}, \quad (13)$$

where, using (25),

$$\partial V_G^{\exp} / \partial x_{IC,s} = \gamma_s (1 + x_{IC,s})^{\gamma_s - 1}\, \mathbb{E}\big[u_1\, \mathbf{1}\{u_1 \geq \bar{u}_1^*(x_{IC,s})\}\big],$$

and $\partial^2 V_G^{\exp} / \partial x_{IC,s}^2 = \gamma_s(\gamma_s - 1)(1 + x_{IC,s})^{\gamma_s - 2}\, \mathbb{E}[u_1\, \mathbf{1}\{u_1 \geq \bar{u}_1^*\}] + \gamma_s^2 (1 + x_{IC,s})^{\gamma_s - 2} (\bar{u}_1^*)^2 f_{u_1}(\bar{u}_1^*)$. For $\gamma_s \geq 1$ both summands are non-negative, so

$\partial^2 V_G^{\exp}/\partial x_{IC,s}^2 \geq 0$ and the right-hand side of (13) is bounded below by $(\partial V_G^{\exp}/\partial x_{IC,s})^2$; it is this regime ($\gamma_E > 1$) that is relevant for the paper's main setup.

[Hazard rate] Each $F_{j,s}$ has the increasing hazard-rate property: $f_{j,s}/(1 - F_{j,s})$ is weakly increasing in μ.

[Across-stage opportunity-set orderings] The opportunity-set distributions $\{F_{j,s}\}$ are ordered across stages by first-order stochastic dominance so that

$$F_{\exp,L} \preceq_{FOSD} F_{\exp,E}, \qquad F_{M,E} \preceq_{FOSD} F_{M,L},$$

i.e., early-stage firms draw stochastically higher productivity for exploratory R&D, while late-stage firms draw stochastically higher productivity for mature projects. The distributions are taken to be members of a common location family so that this FOSD ordering translates, via the density-at-cutoff map in Lemma 3, into the reduced-form adjustment-cost ordering

$$\alpha_{\exp,E} < \alpha_{\exp,L}, \qquad \alpha_{M,E} > \alpha_{M,L}. \tag{14}$$

The ordering of incremental R&D costs, $\alpha_{\text{inc},E}$ versus $\alpha_{\text{inc},L}$, is left unrestricted; the model's comparative-statics predictions hold for either sign. In what follows the reduced-form orderings (14) are taken as the operative primitive; the FOSD statement serves as the economic interpretation.

[Abandonment interior] For each stage $s \in \{E, L\}$ with $\gamma_s > 0$, the optimal productivity cutoff $\mu^*_{\exp,s}(\sigma)$ for exploratory projects and the abandonment threshold $\bar{u}_1^*(x_{IC,s}(\sigma))$ satisfy

$$\bar{u}_1^*\big(x_{IC,s}(\sigma)\big) \;\geq\; \mathbb{E}\big[u_1(\mu^*_{\exp,s}(\sigma))\big],$$

so that the marginally initiated exploratory project is abandoned with non-trivial probability under its own signal distribution. Equivalently, $\bar{u}_1^*(x_{IC,s}) \geq \mu^*_{\exp,s}$, where the equality $\mathbb{E}[u_1(\mu^*_{\exp,s})] = \mu^*_{\exp,s}$ uses $\mathbb{E}[\eta_1] = 0$ under Assumption A.1. For the late-stage corner $\gamma_L = 0$, the threshold reduces to $\bar{u}_1^* = d$ and the same bound is assumed.

A.2 Project Heterogeneity, Cutoff Representation, and Reduced-Form Costs

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

Lemma 1 (Monotonicity in productivity)**.** *For every j, s, the $t = 0$ value $V_j(\sigma, \mu)$ is strictly increasing in μ.*

Proof. In each payoff process μ enters additively and linearly in the mean of future cash flows and does not affect dispersion. Continuation and waiting payoffs are strict monotone transformations of expected cash flows; the claim follows. □

Lemma 2 (Cutoff representation)**.** *Under Assumption A.1, for every j, s there is a unique productivity cutoff $\mu^*_{j,s}(\sigma)$ such that all projects with $\mu \geq \mu^*_{j,s}(\sigma)$ are implemented at $t = 0$. The cutoff solves*

$$V_j\big(\sigma, \mu^*_{j,s}(\sigma)\big) \;=\; \alpha_j \, x_{j,s}(\sigma), \tag{15}$$

and the mass of implemented projects satisfies

$$x_{j,s}(\sigma) \;=\; \int_{\mu^*_{j,s}(\sigma)}^{\overline{\mu}_{j,s}} f_{j,s}(\mu)\, d\mu \;=\; 1 - F_{j,s}\big(\mu^*_{j,s}(\sigma)\big). \tag{16}$$

Lemma 3 (Equivalence of cutoff and quadratic-cost representations)**.** *Differentiating (16) with respect to $x_{j,s}$ and combining with (15) yields, at an interior optimum,*

$$\alpha_{j,s} \;=\; \left.\frac{\partial V_j / \partial \mu}{f_{j,s}\big(\mu^*_{j,s}\big)}\right|_{\mu = \mu^*_{j,s}}. \tag{17}$$

Hence the firm problem in (18) with stage-specific quadratic costs $\frac{\alpha_{j,s}}{2} x^2_{j,s}$ is the same as the extensive-margin problem with stage-specific opportunity sets $\{F_{j,s}, N_s, R_s\}$. FOSD of $F_{j,E}$ over $F_{j,L}$ (or vice versa) translates into the ordering of $\alpha_{j,E}$ and $\alpha_{j,L}$ in (17).

Proof. Consider the extensive-margin value function $W_{j,s}(x) \equiv \int_{F^{-1}_{j,s}(1-x)}^{\overline{\mu}_{j,s}} V_j(\sigma, \mu)\, dF_{j,s}(\mu)$, which gives the integrated value of implementing the top x projects. By Leibniz's rule and $\mu^*_{j,s} = F^{-1}_{j,s}(1 - x)$,

$$W'_{j,s}(x) \;=\; V_j\big(\sigma, F^{-1}_{j,s}(1-x)\big), \qquad W''_{j,s}(x) \;=\; -\frac{\partial V_j / \partial \mu}{f_{j,s}\big(F^{-1}_{j,s}(1-x)\big)} \;<\; 0.$$

So the extensive-margin objective is strictly concave in x with curvature $|W''_{j,s}| = (\partial V_j / \partial \mu) / f_{j,s}(\mu^*_{j,s})$. The reduced-form quadratic cost $\frac{\alpha_{j,s}}{2} x^2$ produces a concentrated objective $x \cdot V_j(\sigma, \mu^*_{j,s}) - \frac{\alpha_{j,s}}{2} x^2$ with constant curvature $-\alpha_{j,s}$. Matching curvatures at the interior optimum, $-\alpha_{j,s} = W''_{j,s}(x^*_{j,s})$, yields (17). Matching first-order conditions ($W'_{j,s}(x^*) = \alpha_{j,s} x^*$, equivalent to $V_j(\sigma, \mu^*_{j,s}) = \alpha_{j,s} x^*_{j,s}$) recovers (15). The two representations therefore coincide to second order around the interior optimum. □

In the reduced form the firm's problem is

$$V_0^s(\sigma) = \max_{x_{G,s}^{\exp}, x_{G,s}^{\mathrm{inc}}, x_{M,s}, x_{IC,s} \geq 0} \Big\{ x_{G,s}^{\exp} V_G^{\exp}(\sigma; x_{IC,s}) + x_{G,s}^{\mathrm{inc}} V_G^{\mathrm{inc}}(\sigma) + x_{M,s} V_M(\sigma) \\ - c_g x_{IC,s} - \tfrac{\alpha_{IC}}{2} x_{IC,s}^2 - \tfrac{\alpha_{\exp,s}}{2} (x_{G,s}^{\exp})^2 \\ - \tfrac{\alpha_{\mathrm{inc},s}}{2} (x_{G,s}^{\mathrm{inc}})^2 - \tfrac{\alpha_{M,s}}{2} x_{M,s}^2 \Big\}. \tag{18}$$

The stage subscript on α is now explicit.

A.3 Kuhn–Tucker Conditions

The KT conditions of (18) are

$$V_G^{\exp}(\sigma; x_{IC,s}) \leq \alpha_{\exp,s} x_{G,s}^{\exp}, \quad x_{G,s}^{\exp} \geq 0, \quad \text{c.s.} \tag{19}$$

$$V_G^{\mathrm{inc}}(\sigma) \leq \alpha_{\mathrm{inc},s} x_{G,s}^{\mathrm{inc}}, \quad x_{G,s}^{\mathrm{inc}} \geq 0, \quad \text{c.s.} \tag{20}$$

$$V_M(\sigma) \leq \alpha_{M,s} x_{M,s}, \quad x_{M,s} \geq 0, \quad \text{c.s.} \tag{21}$$

$$x_{G,s}^{\exp} \frac{\partial V_G^{\exp}(\sigma; x_{IC,s})}{\partial x_{IC,s}} \leq c_g + \alpha_{IC} x_{IC,s}, \quad x_{IC,s} \geq 0, \quad \text{c.s.} \tag{22}$$

("c.s." denotes complementary slackness). Under Assumption A.1 these hold with equality at interior optima for the first three projects.

A.4 Mature Projects

For a mature project of productivity μ,

$$V_M^{\mathrm{now}}(\sigma, \mu) = \mu(\bar{v}_1 + \bar{v}_2) - c_m, \qquad V_M^{\mathrm{wait}}(\sigma, \mu) = \mathbb{E} \max\{v_2(\mu) - c_m, 0\}, \tag{23}$$

so $V_M(\sigma, \mu) = \max\{V_M^{\mathrm{now}}, V_M^{\mathrm{wait}}\}$. Note V_M^{now} does not depend on σ; V_M^{wait} does.

Lemma 4. *For any fixed μ, $V_M^{wait}(\sigma, \mu)$ is strictly increasing in σ.*

Proof. The payoff $\max\{v_2 - c_m, 0\}$ is increasing and convex in v_2. By Assumption A.1, $v_2(\mu; \sigma)$ is an MPS family in σ. By Rothschild–Stiglitz (Jensen's inequality for convex transformations of an MPS family), the expectation of a convex function under an MPS family is strictly increasing in σ. □

Proposition 1 ($x_{M,s}$ declines in σ)**.** *$\partial x_{M,s} / \partial \sigma < 0$ for $s \in \{E, L\}$.*

Proof. Define the *initiation premium* $\Pi_M(\sigma,\mu) \equiv V_M^{\text{now}}(\mu) - V_M^{\text{wait}}(\sigma,\mu)$; it is this premium that plays the role of V_M in the reduced-form objective (18). By Lemma 4, $\partial\Pi_M/\partial\sigma < 0$. Direct differentiation in μ gives $\partial V_M^{\text{now}}/\partial\mu = \bar{v}_1 + \bar{v}_2$ and $\partial V_M^{\text{wait}}/\partial\mu = \bar{v}_2 \cdot \mathbb{P}\{v_2(\mu) > c_m\}$, so

$$\partial\Pi_M/\partial\mu \;=\; \bar{v}_1 + \bar{v}_2 \cdot \mathbb{P}\{v_2(\mu) \le c_m\} \;>\; 0.$$

The cutoff $\mu^*_{M,s}(\sigma)$ is pinned down by the cutoff condition (15) applied with $V_M = \Pi_M$: $\Pi_M(\sigma, \mu^*_{M,s}) = \alpha_{M,s} \cdot x_{M,s}$. Totally differentiating both sides in σ (using $x_{M,s} = 1 - F_{M,s}(\mu^*_{M,s})$, so $\partial x_{M,s}/\partial\mu^*_{M,s} = -f_{M,s}(\mu^*_{M,s})$),

$$\frac{\partial\Pi_M}{\partial\sigma} + \frac{\partial\Pi_M}{\partial\mu}\cdot\frac{d\mu^*_{M,s}}{d\sigma} \;=\; -\alpha_{M,s}\, f_{M,s}(\mu^*_{M,s}) \cdot \frac{d\mu^*_{M,s}}{d\sigma},$$

so $d\mu^*_{M,s}/d\sigma = -(\partial\Pi_M/\partial\sigma)/(\partial\Pi_M/\partial\mu + \alpha_{M,s}f_{M,s}) > 0$, both numerator and denominator being positive. By (16), $x_{M,s} = 1 - F_{M,s}(\mu^*_{M,s})$, so $\partial x_{M,s}/\partial\sigma < 0$. □

A.5 Incremental R&D

By identical logic to Appendix A.4, with v_2 replaced by r_2 and c_m by k_R^{inc}:

Lemma 5. *$V_G^{inc,wait}(\sigma,\mu)$ is strictly increasing in σ.*

Proposition 2 ($x_{G,s}^{\text{inc}}$ declines in σ)**.** *$\partial x_{G,s}^{inc}/\partial\sigma < 0$ for $s \in \{E, L\}$.*

A.6 Exploratory R&D and Innovative Capacity

For an exploratory project initiated at $t = 0$, the interim signal is $u_1(\mu) = \mu + \eta_1$ and, conditional on continuation, the $t = 2$ payoff is $(\mu + \eta_1 + \eta_2)$ scaled by $(1 + x_{IC,s})^{\gamma_s}$. By the martingale property $\mathbb{E}[u_2(\mu) \mid u_1(\mu)] = u_1(\mu)$ (which uses $\mathbb{E}[\eta_2] = 0$ from Assumption A.1), the continuation value at $t = 1$ is $u_1(\mu)(1 + x_{IC,s})^{\gamma_s}$ minus the continuation cost d.

Lemma 6 (Continuation threshold)**.** *The project is continued iff*

$$u_1(\mu) \;\ge\; \bar{u}_1^*(x_{IC,s}) \;\equiv\; \frac{d}{(1 + x_{IC,s})^{\gamma_s}}. \tag{24}$$

Proof. Continuation is optimal iff the $t = 1$ continuation value, $u_1(\mu)(1 + x_{IC,s})^{\gamma_s} - d$, is non-negative. Rearranging gives (24). □

The $t = 0$ exploratory value is therefore

$$V_G^{\exp}(\sigma; x_{IC,s}) \;=\; -k_R^{\exp} \;+\; \mathbb{E}_{u_1}\Big[\max\{\, u_1(1+x_{IC,s})^{\gamma_s} - d,\, 0\,\}\Big]. \tag{25}$$

Lemma 7 ($V_G^{\exp}$ increases in σ)**.** *For any $x_{IC,s} \geq 0$ and $\gamma_s \geq 0$, $V_G^{\exp}(\sigma; x_{IC,s})$ is strictly increasing in σ.*

Proof. The function $u_1 \mapsto \max\{u_1(1+x_{IC,s})^{\gamma_s} - d, 0\}$ is convex in u_1 (positive-part of a linear function). By Assumption A.1, $u_1(\mu)$ is an MPS family in σ. Rothschild–Stiglitz gives the result. □

Lemma 8 (Scalability of the growth option)**.** *For $\gamma_s > 0$ and $x_{IC,s} \geq 0$, the marginal value of innovative capacity is*

$$\frac{\partial V_G^{\exp}(\sigma; x_{IC,s})}{\partial x_{IC,s}} = \gamma_s(1+x_{IC,s})^{\gamma_s - 1}\, \mathbb{E}\big[u_1\, \mathbf{1}\{u_1 \geq \bar{u}_1^*(x_{IC,s})\}\big]. \tag{26}$$

Under Assumption A.1 and the scale-family parameterization of Assumption A.1, (26) is strictly increasing in σ for every $\gamma_s > 0$.

Proof. Differentiating (25) under the expectation (the integrand $\max\{u_1(1+x_{IC,s})^{\gamma_s} - d, 0\}$ is Lipschitz in $x_{IC,s}$ with a.e. derivative $\gamma_s(1+x_{IC,s})^{\gamma_s-1}u_1\,\mathbf{1}\{u_1(1+x_{IC,s})^{\gamma_s} > d\}$; the kink at $u_1(1+x_{IC,s})^{\gamma_s} = d$ has measure zero under the log-concave density of u_1) yields (26).

For the comparative static in σ: the factor $\gamma_s(1+x_{IC,s})^{\gamma_s-1}$ is σ-independent, so it suffices to show that $H(\sigma) \equiv \mathbb{E}[u_1\,\mathbf{1}\{u_1 \geq \bar{u}_1^*\}]$ is strictly increasing in σ. Decompose

$$H(\sigma) \;=\; \underbrace{\mathbb{E}\big[\max\{u_1 - \bar{u}_1^*, 0\}\big]}_{=:H_1(\sigma)} \;+\; \underbrace{\bar{u}_1^* \cdot \mathbb{P}\{u_1 \geq \bar{u}_1^*\}}_{=:H_2(\sigma)}.$$

Term H_1. The map $u_1 \mapsto \max\{u_1 - \bar{u}_1^*, 0\}$ is convex, so by Rothschild–Stiglitz applied to the MPS family of u_1 under Assumption A.1, H_1 is strictly increasing in σ.

Term H_2. Under the scale-family parameterization $u_1 = \mu + \sigma\tilde{\eta}_1$ with $\tilde{\eta}_1 \sim G_\eta$ zero-mean and log-concave, at the marginal project $\mu = \mu_{\exp,s}^*$,

$$\mathbb{P}\{u_1 \geq \bar{u}_1^*\} \;=\; 1 - G_\eta\big((\bar{u}_1^* - \mu_{\exp,s}^*)/\sigma\big).$$

Assumption A.1 gives $\bar{u}_1^* \geq \mu_{\exp,s}^*$, so the argument of G_η is non-negative and strictly decreases in σ. Hence $\mathbb{P}\{u_1 \geq \bar{u}_1^*\}$ is weakly increasing in σ, and strictly so whenever

$\bar{u}_1^* > \mu_{\exp,s}^*$. Since $\bar{u}_1^* > 0$, H_2 is weakly increasing in σ. Combining, $H(\sigma) = H_1(\sigma) + H_2(\sigma)$ is strictly increasing in σ. □

Proposition 3 ($x_{G,s}^{\exp}$ increases in σ)**.** *$\partial x_{G,s}^{\exp}/\partial\sigma > 0$ for $s \in \{E, L\}$ (with $\gamma_s > 0$; for the late-stage corner $\gamma_L = 0$, see Proposition 4).*

Proof. By Lemma 7, $V_G^{\exp}$ rises with σ for every μ. The extensive margin $x_{G,s}^{\exp} = 1 - F_{\exp,s}(\mu_{\exp,s}^*)$, and the cutoff $\mu_{\exp,s}^*$ declines in σ (by the same cutoff-condition argument as in Proposition 1 but with the opposite sign), so $x_{G,s}^{\exp}$ rises. □

Lemma 9 (Early-stage innovative capacity)**.** *Under Assumptions A.1 (SOC) and A.1, for early-stage firms with $\gamma_E > 0$ and $x_{G,E}^{\exp} > 0$,*

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

(The parameter restriction $\gamma_E > 1$ in the body text plays no role for this sign; it is invoked elsewhere only to sign the second-order effect $\partial^2 V_G^{\exp}/\partial x_{IC,E}^2 > 0$ entering the SOC.)

Proof. Fix $x_{IC,E}$ and increase σ. Lemma 8 gives $\partial^2 V_G^{\exp}/(\partial x_{IC,E}\partial\sigma) > 0$ and Proposition 3 gives $\partial x_{G,E}^{\exp}/\partial\sigma > 0$. The left-hand side of the FOC (22) is therefore strictly increasing in σ, while the right-hand side depends on σ only through $x_{IC,E}$ itself. Let $\Phi(x_{IC,E}, \sigma)$ denote the excess of RHS over LHS of (22). By the SOC (13), $\partial\Phi/\partial x_{IC,E} > 0$ at any candidate root. The implicit function theorem gives

$$\frac{\partial x_{IC,E}}{\partial\sigma} = -\frac{\partial\Phi/\partial\sigma}{\partial\Phi/\partial x_{IC,E}} > 0.$$ □

Proposition 4 (Late-stage corner at $\gamma_L = 0$)**.** *For late-stage firms with $\gamma_L = 0$, $V_G^{\exp}(\sigma; x_{IC,L})$ is independent of $x_{IC,L}$, so the marginal-value LHS of (22) is zero while the marginal-cost RHS is $c_g > 0$. Hence the KT condition holds with strict inequality and $x_{IC,L} = 0$. By continuity, the same corner obtains for $\gamma_L \in [0, \bar{\gamma})$ with some $\bar{\gamma} > 0$.*

Proof. With $\gamma_L = 0$, the scaling factor $(1 + x_{IC,L})^{\gamma_L} = 1$ for every $x_{IC,L} \geq 0$, so $V_G^{\exp}$ does not depend on $x_{IC,L}$ and $\partial V_G^{\exp}/\partial x_{IC,L} = 0$. Thus LHS of (22) is zero and RHS is $c_g + \alpha_{IC} x_{IC,L} \geq c_g > 0$ whenever $x_{IC,L} \geq 0$. By complementary slackness, $x_{IC,L} = 0$. The continuity statement follows because the inequality is strict at $\gamma_L = 0$ and both sides are continuous in γ_L. □

A.7 Proofs of Predictions 1–2

The proofs below invoke conditions under which the directionally unambiguous channels quantitatively outweigh the opposite-signed channels. In Equation (18), the *early-stage* dominance conditions are:

$$\frac{\partial x_{G,E}^{\text{exp}}}{\partial \sigma} > \left| \frac{\partial x_{G,E}^{\text{inc}}}{\partial \sigma} \right|, \tag{27}$$

$$\frac{\partial x_{IC,E}}{\partial \sigma} > \left| \frac{\partial x_{M,E}}{\partial \sigma} \right|, \tag{28}$$

and the *late-stage* dominance condition (for strict inequality in total R&D) is:

$$\left| \frac{\partial x_{G,L}^{\text{inc}}}{\partial \sigma} \right| > \frac{\partial x_{G,L}^{\text{exp}}}{\partial \sigma}. \tag{29}$$

Conditions (28)–(29) reference the derived comparative statics, which are signed in Lemmas 9 and 7 and Propositions 1–3; they impose quantitative restrictions on the relative magnitudes. Under the reduced-form orderings in Assumption A.1 (14), each condition is the natural regime for its stage: (28) holds because $\alpha_{\text{exp},E}$ is small (the innovative-capacity response, mediated by $\partial x_{G,E}^{\text{exp}}/\partial\sigma$ in the FOC (22), is amplified) while $\alpha_{M,E}$ is large (the mature contraction is damped); (27) similarly reflects $\alpha_{\text{exp},E} < \alpha_{\text{inc},E}$ when it holds;[17] (29) reflects the late-stage pattern, with $\alpha_{\text{exp},L}$ large (so the exploratory expansion is damped), ensuring that the incremental contraction swamps the (small) exploratory expansion. These conditions are verified quantitatively in the calibration.

Proof of Prediction 1 (early-stage). Total R&D response is

$$\frac{\partial x_{G,E}}{\partial \sigma} = \underbrace{\frac{\partial x_{G,E}^{\text{exp}}}{\partial \sigma}}_{>0 \text{ (Prop. 3)}} + \underbrace{\frac{\partial x_{G,E}^{\text{inc}}}{\partial \sigma}}_{<0 \text{ (Prop. 2)}}.$$

Under condition (27) and Assumption A.1, the exploratory term dominates and $\partial x_{G,E}/\partial\sigma > 0$.

[17] Whether $\alpha_{\text{exp},E} < \alpha_{\text{inc},E}$ depends on the specific opportunity-set distributions. The calibration yields comparable magnitudes ($\hat{\alpha}_{\text{exp},E} = 1.97$, $\hat{\alpha}_{\text{inc},E} = 2.05$), so the early-stage R&D dominance condition is driven primarily by the growth-option convexity of exploratory R&D rather than by a large cost differential.

Capex is $I_E^K = x_{IC,E} + x_{M,E}$. By Lemma 9, $\partial x_{IC,E}/\partial\sigma > 0$; by Proposition 1, $\partial x_{M,E}/\partial\sigma < 0$. Under condition (28), the expansion in $x_{IC,E}$ dominates and $\partial I_E^K/\partial\sigma > 0$. □

Proof of Prediction 2 (late-stage). By Proposition 4, $x_{IC,L} = 0$ for all $\sigma \geq 0$, so $\partial x_{IC,L}/\partial\sigma = 0$. By Proposition 1, $\partial x_{M,L}/\partial\sigma < 0$. Hence

$$\frac{\partial I_L^K}{\partial\sigma} = 0 + \frac{\partial x_{M,L}}{\partial\sigma} < 0.$$

For R&D: at $\gamma_L = 0$, Lemma 7 gives $V_G^{\exp}(\sigma; x_{IC,L}) = -k_R^{\exp} + \mathbb{E}[\max\{u_1 - d, 0\}]$ (independent of $x_{IC,L}$ since $(1 + x_{IC,L})^0 = 1$) and strictly increasing in σ. By the cutoff-condition argument of Proposition 1 (with opposite sign), $\partial x_{G,L}^{\exp}/\partial\sigma \geq 0$, with the magnitude scaled by $1/\alpha_{\exp,L}$; since $\alpha_{\exp,L}$ is large by (14), this response is small. Proposition 2 gives $\partial x_{G,L}^{\text{inc}}/\partial\sigma < 0$, with magnitude scaled by $1/\alpha_{\text{inc},L}$; since $\alpha_{\text{inc},L}$ is empirically large, the incremental contraction is moderate in absolute terms but dominates the small exploratory expansion. Hence $\partial x_{G,L}/\partial\sigma \leq 0$ in sign, with strict inequality under the late-stage dominance condition (29). □

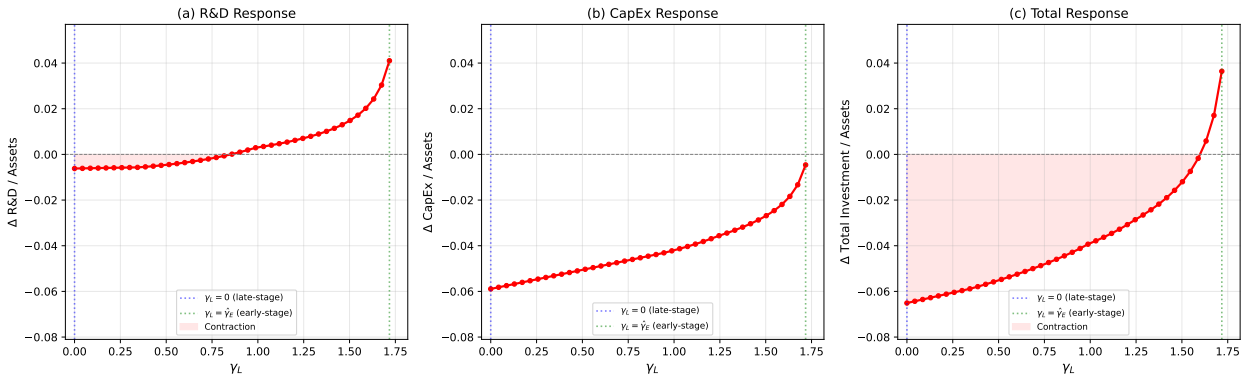
B. Robustness of Structural Estimates

This appendix examines the sensitivity of the structural estimates to key modeling choices: the assumption $\gamma_L = 0$, the value of the fixed parameter α_{IC}, and the weighting matrix.

Sensitivity to γ_L. The assumption $\gamma_L = 0$ is not a knife-edge restriction. Figure B.1 reports the model-implied investment responses as γ_L varies continuously from 0 (calibrated late-stage) to $\hat{\gamma}_E \approx 1.72$ (calibrated early-stage). Three results stand out. First, all investment responses are smooth, continuous functions of γ_L—there is no discontinuity at zero. Second, the R&D response remains *negative* for any γ_L below approximately $0.5\,\hat{\gamma}_E$ while the Capex response is contractionary over the entire range. Third, the total investment response remains negative for $\gamma_L < 0.93\,\hat{\gamma}_E$—reversing the sign requires near-complete convergence to early-stage characteristics. The contractionary prediction for late-stage firms therefore holds over a wide range of positive complementarity values, not only at the boundary $\gamma_L = 0$. Setting $\gamma_L = 0$ sharpens the exposition and is consistent with the data (late-stage firms show no evidence of an expansionary channel), but the qualitative predictions survive for any γ_L well below $\hat{\gamma}_E$.

Sensitivity to α_{IC}. The innovative-capacity adjustment cost α_{IC} is fixed at 2.0 in the baseline calibration. Table B.1 reports the re-estimated $\hat{\gamma}_E$ for $\alpha_{IC} \in \{1.0, 1.5, 2.0, 2.5, 3.0, 4.0\}$. The estimated complementarity parameter increases monotonically with α_{IC}, from $\hat{\gamma}_E = 1.17$ at $\alpha_{IC} = 1.5$ to $\hat{\gamma}_E = 2.79$ at $\alpha_{IC} = 4.0$, which is intuitive: a higher innovative-capacity cost requires stronger complementarity to generate the same investment response. Crucially, $\hat{\gamma}_E > 1$ for all values of α_{IC} in the range, so the qualitative result—strong convexity in the amplification function—is robust. The model fit is best at $\alpha_{IC} = 2.0$ (loss $= 3.84$), with fit deteriorating for $\alpha_{IC} \geq 3.0$ (loss > 26), suggesting that $\alpha_{IC} \approx 2$ is appropriate.

Weighting matrix robustness. The baseline weighting matrix uses $SE_i = 0.10 \times m_i^{\text{data}}$ for level moments, reflecting that model misspecification dominates sampling error for these moments—a common practice when a parsimonious structural model is matched to cross-sectional averages that are measured with high precision but may not lie exactly on the model's manifold. Table B.2 reports the estimates under four weighting schemes: the baseline (10%), a tighter scheme (5%, which upweights levels), a looser scheme (20%, which downweights levels), and the identity matrix. The estimate of $\hat{\gamma}_E$ ranges from 1.54 to 1.72 across schemes—a narrow band that preserves the qualitative result $\hat{\gamma}_E > 1$ in all cases. The remaining parameters are similarly stable.



Appendix Figure B.1. Investment responses as a function of γ_L. Exploratory parameters (α_{exp}, μ_{exp}) and composition weights are interpolated linearly between calibrated late-stage and early-stage values; option-to-delay parameters (α_{inc}, α_M) are held fixed at their late-stage values. The blue dashed line marks $\gamma_L = 0$; the green dashed line marks $\gamma_L = \hat{\gamma}_E$. The shaded region indicates where the response is contractionary. Capex remains negative over the entire range; R&D turns positive at $\gamma_L \approx 0.50\,\hat{\gamma}_E$.

Appendix Table B.1. Sensitivity of $\hat{\gamma}_E$ to the fixed parameter α_{IC}.

α_{IC}	$\hat{\gamma}_E$	$\hat{\alpha}_{\text{exp},E}$	SMM Loss
1.0	1.20	2.74	9.24
1.5	1.17	1.82	4.23
2.0	1.72	1.97	3.84
2.5	1.92	1.82	4.68
3.0	2.74	2.33	26.65
4.0	2.79	1.82	28.06

Appendix Table B.2. Parameter estimates under alternative weighting matrices.

Scheme	$\hat{\gamma}_E$	$\hat{\alpha}_{\text{exp},E}$	$\hat{\alpha}_{\text{inc},E}$	$\hat{\alpha}_{\text{inc},L}$	$\hat{\alpha}_{M,L}$
Baseline (10% SE)	1.72	1.97	2.05	8.33	0.78
Tight (5% SE)	1.61	1.82	2.15	8.41	0.81
Loose (20% SE)	1.54	1.82	2.38	8.17	0.81
Identity	1.54	1.82	2.15	8.64	0.81

C. 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 equal to zero. *SG&A* is annual 0.3 $\times$ 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$\times$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.1 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 (3), including the interaction term between uncertainty and IRR. Table L.1 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 $\times$ Early Stage with IRR. The results are presented in Table L.1 (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.

C.2 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 (3) by adding an interaction term between Uncertainty $\times$ Early Stage and the financial constraint dummy (FC).

Table L.2 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.

D. The Role of Age

One concern is that early-stage status is 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 L.15 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 L.3 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.

E. 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 L.4 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 more in response to higher uncertainty. This is exactly what I find. Column (3) of Table L.4 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.

F. 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:

$$\begin{aligned} Uncertainty_{i,t-1} = \alpha_i + \theta_t + \beta' \, Instruments_{i,t-1} + \mu \, Early_Stage_{i,t-2} \\ + \eta' \, Instruments_{i,t-1} \times Early_Stage_{i,t-2} + \gamma' \, X_{i,t-1} + \epsilon_{it} \end{aligned} \tag{30}$$

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 (3). Table L.5 shows the 2SLS first-stage results for R&D. The F-statistic of 33.42 establishes that the instruments are jointly relevant, which is the condition required for identification, and the Hansen-Sargan over-identification test does not reject the validity of the instruments (the p-value of the J statistic is 0.177). Overall, Table L.5 confirms relevance and provides no evidence against the overidentifying restrictions for the set of nine instruments.

To provide a clear interpretation of each instrument's relation to firm-level uncertainty, Table L.6 reports univariate first stages in which each instrument (and its interaction with *Early_Stage*) enters alone, holding fixed the first-moment controls, firm controls, and fixed effects. All nine coefficients are positive, eight are statistically significant at the 5% level, and six at the 1% level. Each source of aggregate volatility therefore trans-

mits to firm-level uncertainty in the expected direction, and the multivariate first stage combines these individually positive relations into a jointly strong set of instruments.

G. First-Stage Results for Product-Market Outcomes

This section reports the first-stage regressions underlying the 2SLS estimates in Table 5. The two endogenous variables are $PMU_{i,t-1}$ and $PMU_{i,t-1} \times Early_Stage_{i,t-2}$, and each is instrumented using the full set of 18 excluded instruments: nine base instruments $z^k_{i,t-1} = |\beta^k_{i,t-4Q}| \times \Delta\sigma^k_{t-1Q}$ and nine interacted instruments $z^k_{i,t-1} \times Early_Stage_{i,t-2}$.

Table L.7 reports the first stage for PMU and Table L.8 reports the first stage for $PMU \times Early_Stage$. The Kleibergen-Paap F-statistics for the joint significance of the excluded instruments range between 10.5 and 11.2 across the four specifications, exceeding the conventional threshold of 10 for weak instrument concerns.

H. 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 L.9 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 L.9 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%.

I. 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 in testing this channel empirically is the lack of a 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 L.10 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:

$$y_{i,t} = \beta_1 \, Uncertainty_{t-1} + \gamma \, X_{t-1} + \alpha_i + \epsilon_{i,t}, \tag{31}$$

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 L.11 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.

J. 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 are available only from 2010-2019.[18] I then estimate the effect of uncertainty on the number of job postings using Equation (33).

Table L.12 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 L.12 collects the results. I find that early-stage firms significantly increase their number of tech job postings 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.

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

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

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 of good (bad) uncertainty.[19]

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

$$\begin{aligned} y_{i,t} = \alpha_i &+ \beta_1 \times Vg_{t-1} + \beta_2 \times Vb_{t-1} + \beta_3 \times Early_Stage_{i,t-2} \\ &+ \beta_4 \times Vg_{t-1} \times Early_Stage_{i,t-2} + \beta_5 \times Vb_{t-1} \times Early_Stage_{i,t-2} \\ &+ Controls + \epsilon_{it} \end{aligned} \tag{32}$$

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 L.13 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-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.

L. 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. An-

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

nual 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 L.14 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 L.15 shows that the coefficient on the interaction between Uncertainty $\times$ Early Stage remains positive and very similar to the baseline results.

Table L.15 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 $\times$ Q is also positive and statistically significant, but its magnitude is much smaller than that of the interaction between Uncertainty $\times$ 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 is the first-moment effect 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 (3) controlling for both $1st_Moment$ and $1st_Moment^2$ (interacted with the life stage variable as well). Table L.16 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 L.17 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 (3) controlling for all the stages (life2, life3, and life4). Table L.18 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:

$$\begin{aligned} y_{i,t} = \alpha_i + \beta_1 \times Uncertainty_{t-1} + \beta_2 \times Early_Stage_{i,t-2} \\ + \beta_3 \times Uncertainty_{t-1} \times Early_Stage_{i,t-2} + \gamma' X_{i,t-1} + \theta' Z_{t-1} + \epsilon_{it} \end{aligned} \tag{33}$$

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 L.19 and L.21 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 L.20 and L.22 demonstrate that these results are robust to the inclusion of industry $\times$ 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 by estimating a modified version of Equation (3) 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 L.23 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 L.24 shows that the main results are virtually unchanged. In response to higher uncertainty, early-stage firms significantly increase their R&D expenses.

Industry $\times$ Time FEs. To address the concern that the results may be driven by time-varying industry-level shocks, I augment the baseline specification with SIC 1-digit $\times$ year fixed effects, which absorb all time-varying unobservable factors common to firms within broad industry groups. Because the instrumental variable is constructed at the SIC 2-digit level, including SIC 2-digit $\times$ year fixed effects would absorb the identifying variation. SIC 1-digit $\times$ year fixed effects provide a middle ground: they control for broad industry-time shocks while preserving within-industry cross-firm variation in the instrument. Table L.25 reports the results, confirming that the heterogeneous responses across life-cycle stages are not driven by differential exposure to industry-level shocks or by any single industry.

Appendix Table L.1. 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 (3). The dependent variable is R&D/Assets. IRR is a dummy variable equal to one if a firm's asset redeployability is below the median, and zero otherwise (see Section C.1 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.

Appendix Table L.2. 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 (3). The dependent variable is R&D/Assets. FC is a dummy equal 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.

Appendix Table L.3. 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 Young 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 L.4. 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 (3). 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 L.5. 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 table reports the first stage regression results of the excluded instruments used in the 2SLS firm-level R&D regressions estimated using Equation (30). 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 L.6. Univariate First Stages

	CAD	EUR	JPY	AUD	SEK	CHF	GBP	Oil	EPU
$\lvert\text{sensitivity}^k_{j,t-3}\rvert \times \Delta\sigma^k_{t-1}$	0.475	1.146***	1.136**	0.818***	2.207***	0.741***	2.434***	1.212**	0.340***
	(0.319)	(0.168)	(0.567)	(0.228)	(0.445)	(0.151)	(0.379)	(0.527)	(0.116)
Observations	29,505	29,505	29,505	29,505	29,505	29,505	29,505	29,505	29,505
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IV 1st moment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports univariate first-stage regressions. Each column is a separate regression of $Uncertainty_{i,t-1}$ on a single instrument, $\lvert\text{sensitivity}^k_{j,t-3}\rvert \times \Delta\sigma^k_{t-1}$, and its interaction with $Early_Stage_{i,t-2}$ (interaction coefficient not reported), with the same firm controls, IV first-moment controls, and fixed effects as in Table L.5. The EPU instrument is scaled by 1,000. 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 L.7. First Stage: PMU

	Product Entry		Net Product Entry	
	(1)	(2)	(3)	(4)
Base instruments (z^k)				
z^{Oil}	−0.00919	−0.00437	−0.00997	−0.00495
	(0.0185)	(0.0179)	(0.0177)	(0.0172)
z^{EUR}	−0.00606	−0.00658*	−0.00678*	−0.00722*
	(0.00375)	(0.00370)	(0.00374)	(0.00369)
z^{CAD}	0.00194	0.00144	0.000738	0.00106
	(0.00459)	(0.00442)	(0.00457)	(0.00440)
z^{JPY}	−0.0695***	−0.0699***	−0.0706***	−0.0707***
	(0.00764)	(0.00746)	(0.00763)	(0.00745)
z^{GBP}	−0.00732	−0.00564	−0.00620	−0.00345
	(0.00767)	(0.00761)	(0.00763)	(0.00764)
z^{CHF}	0.00260*	0.00200	0.00273*	0.00217
	(0.00152)	(0.00134)	(0.00150)	(0.00133)
z^{AUD}	0.0375***	0.0347***	0.0392***	0.0365***
	(0.00692)	(0.00688)	(0.00691)	(0.00688)
z^{SEK}	0.0232**	0.0200**	0.0196**	0.0161*
	(0.00946)	(0.00930)	(0.00937)	(0.00929)
z^{EPU}	−0.312	−0.250	−0.291	−0.252
	(0.355)	(0.353)	(0.355)	(0.353)
Interacted instruments ($z^k \times Early_Stage$)				
$z^{Oil} \times ES$	0.0625**	0.0746***	0.0602**	0.0740***
	(0.0249)	(0.0242)	(0.0246)	(0.0237)
$z^{EUR} \times ES$	0.00507	0.00485	0.00575	0.00469
	(0.00476)	(0.00465)	(0.00473)	(0.00458)
$z^{CAD} \times ES$	0.0107	0.00992	0.0109*	0.0117*
	(0.00652)	(0.00634)	(0.00651)	(0.00634)
$z^{JPY} \times ES$	0.0121	0.0130	0.0122	0.0131
	(0.00980)	(0.00964)	(0.00980)	(0.00960)
$z^{GBP} \times ES$	−0.0259***	−0.0277***	−0.0274***	−0.0305***
	(0.00929)	(0.00925)	(0.00928)	(0.00928)
$z^{CHF} \times ES$	−0.00248	−0.00170	−0.00277	−0.00168
	(0.00211)	(0.00204)	(0.00210)	(0.00202)
$z^{AUD} \times ES$	−0.0130	−0.0105	−0.0135	−0.0138
	(0.00997)	(0.00987)	(0.00995)	(0.00992)
$z^{SEK} \times ES$	−0.0125	−0.0142	−0.0103	−0.00843
	(0.0132)	(0.0132)	(0.0132)	(0.0130)
$z^{EPU} \times ES$	−0.830*	−0.680	−0.859*	−0.609
	(0.458)	(0.447)	(0.458)	(0.447)
Observations	322,431	312,846	321,041	310,981
Firm Controls	Yes	Yes	Yes	Yes
1st Moment Controls	Yes	Yes	Yes	Yes
Lagged Outcome	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

This table reports the first-stage regression of PMU on the 18 excluded instruments. The dependent variable is $PMU_{i,t-1}$. Base instruments are $z^k = |\beta^k_{i,t-4Q}| \times \Delta\sigma^k_{t-1Q}$. Interacted instruments are $z^k \times Early_Stage_{i,t-2}$. Columns correspond to the second-stage specifications in Table 5. Firm controls include lagged log revenue and lagged revenue growth. First-moment controls are the directional counterparts of the instruments. Heteroskedasticity-robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table L.8. First Stage: PMU × Early Stage

	Product Entry		Net Product Entry	
	(1)	(2)	(3)	(4)
Base instruments (z^k)				
z^{Oil}	0.000837	0.00527	0.00119	0.00925
	(0.0126)	(0.0118)	(0.0124)	(0.0118)
z^{EUR}	−0.0107***	−0.0118***	−0.0106***	−0.0128***
	(0.00272)	(0.00264)	(0.00272)	(0.00264)
z^{CAD}	0.0254***	0.0232***	0.0254***	0.0222***
	(0.00282)	(0.00272)	(0.00280)	(0.00268)
z^{JPY}	−0.00577	−0.00759	−0.00562	−0.00829*
	(0.00477)	(0.00476)	(0.00476)	(0.00475)
z^{GBP}	0.00442	0.00359	0.00447	0.00314
	(0.00470)	(0.00441)	(0.00465)	(0.00442)
z^{CHF}	−0.00226**	−0.00179**	−0.00232**	−0.00155*
	(0.000920)	(0.000879)	(0.000912)	(0.000873)
z^{AUD}	−0.00986**	−0.0109***	−0.0104**	−0.0104***
	(0.00405)	(0.00404)	(0.00405)	(0.00397)
z^{SEK}	0.0130*	0.0142**	0.0129*	0.0132**
	(0.00681)	(0.00662)	(0.00680)	(0.00657)
z^{EPU}	0.581**	0.579**	0.574**	0.602**
	(0.254)	(0.251)	(0.255)	(0.249)
Interacted instruments ($z^k \times Early_Stage$)				
$z^{Oil} \times ES$	0.000848	0.0112	−0.000742	0.00687
	(0.0263)	(0.0259)	(0.0263)	(0.0256)
$z^{EUR} \times ES$	0.0119**	0.0125***	0.0122**	0.0128***
	(0.00487)	(0.00471)	(0.00482)	(0.00464)
$z^{CAD} \times ES$	−0.0522***	−0.0538***	−0.0527***	−0.0520***
	(0.00618)	(0.00609)	(0.00618)	(0.00605)
$z^{JPY} \times ES$	−0.0429***	−0.0412***	−0.0438***	−0.0410***
	(0.00914)	(0.00916)	(0.00915)	(0.00914)
$z^{GBP} \times ES$	−0.0403***	−0.0380***	−0.0394***	−0.0384***
	(0.00836)	(0.00838)	(0.00836)	(0.00838)
$z^{CHF} \times ES$	0.00878***	0.00815***	0.00847***	0.00786***
	(0.00194)	(0.00194)	(0.00194)	(0.00194)
$z^{AUD} \times ES$	0.0495***	0.0529***	0.0520***	0.0525***
	(0.00926)	(0.00925)	(0.00927)	(0.00929)
$z^{SEK} \times ES$	−0.00621	−0.0138	−0.00766	−0.0115
	(0.0141)	(0.0139)	(0.0139)	(0.0137)
$z^{EPU} \times ES$	−3.794***	−3.804***	−3.766***	−3.767***
	(0.468)	(0.457)	(0.468)	(0.455)
Observations	322,431	312,846	321,041	310,981
Firm Controls	Yes	Yes	Yes	Yes
1st Moment Controls	Yes	Yes	Yes	Yes
Lagged Outcome	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

This table reports the first-stage regression of $PMU_{i,t-1} \times Early_Stage_{i,t-2}$ on the 18 excluded instruments. Base instruments are $z^k = |\beta^k_{i,t-4Q}| \times \Delta\sigma^k_{t-1Q}$. Interacted instruments are $z^k \times Early_Stage_{i,t-2}$. Columns correspond to the second-stage specifications in Table 5. Firm controls include lagged log revenue and lagged revenue growth. First-moment controls are the directional counterparts of the instruments. Heteroskedasticity-robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table L.9. 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 L.10. 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 L.11. 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 investments (deals). I estimate Equation (31) 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 I. 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 L.12. 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 (33). The dependent variable is the log of the number of job posts and the log of the number of tech job posts (see Subsection J). 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 L.13. "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 K). 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 L.14. 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(Patent) is a dummy equal to 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 L.15. 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 (3). 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 the firm's 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 L.16. 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(Patent) is a dummy equal to 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 L.17. 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 L.18. 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 (3). 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 L.19. 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 L.20. 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 L.21. 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 L.22. 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 L.23. Uncertainty and Investment Dynamics

	Panel A: R&D/Assets		
	One-Year Ahead	Two-Year Ahead	Three-Year Ahead
Uncertainty × Early Stage	0.056***	0.046***	0.027***
	(0.013)	(0.015)	(0.006)
	Panel B: CAPX/Assets		
	One-Year Ahead	Two-Year Ahead	Three-Year Ahead
Uncertainty × Early Stage	0.065**	-0.001	-0.007
	(0.028)	(0.020)	(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 (3) 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 (3). 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 L.24. Effect of Uncertainty on R&D: Missing Values Not Set Equal 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 variable is R&D/Assets. Missing values of R&D are not set equal 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.

Appendix Table L.25. Effect of Uncertainty on Investment Policies

	R&D/Assets	Intangible Investment	CAPX/Assets	Acquisitions
Uncertainty	-0.0146	-0.0096*	-0.0241**	-0.1469***
	(0.0094)	(0.0057)	(0.0098)	(0.0453)
Uncertainty × Early Stage	0.0550***	0.0226*	0.0329***	0.0569
	(0.0175)	(0.0130)	(0.0098)	(0.0918)
Observations	29,491	27,092	29,379	27,995
Firm Controls	Yes	Yes	Yes	Yes
IV 1st moment 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 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.