Commercialization Margins and Uncertainty[*†]

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Abstract

We develop a new framework to measure the composition of firm-level commercialization using USPTO trademarks linked to verified market-entry dates. Categorizing millions of product launches into business-stealing, quality-improving, and new-variety types, we show that policy uncertainty not only reduces overall commercialization but also fundamentally reshapes its composition. Firms scale back business stealing and market-creating new-variety products (which require large sunk costs and have long-horizon payoffs) while maintaining incremental quality improvements (which require less capital and deliver front-loaded returns). We trace this reallocation to three mechanisms: uncertainty disproportionately penalizes products with (i) back-loaded, long payoff horizons, (ii) irreversible capital requirements, and (iii) high external financing needs. Thus, policy uncertainty impacts commercialization primarily through selection across product types with heterogeneous risk profiles rather than uniform postponement. This compositional shift has first-order implications for firm growth, creative destruction, and aggregate productivity.

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"Constantly shifting deadlines, mixed signals, and threats of new tariffs make it nearly impossible for American businesses to plan, invest, or make long-term decisions—forcing many into reactive mode and even delaying or canceling product development plans."

Gary Shapiro, CEO & Vice Chair, Consumer Technology Association and PYMNTS Intelligence Survey of Product Executives (2025)

1 Introduction

A central insight in the growth and industrial organization literatures is that innovation operates along three distinct margins: creative destruction that displaces rivals, quality improvements to existing products, and the introduction of new varieties that expand consumer choice (Grossman and Helpman, 1991; Aghion and Howitt, 1992; Klette and Kortum, 2004; Garcia-Macia, Hsieh, and Klenow, 2019). Yet, most empirical work relies on input-based proxies (such as, R&D expenditures, patent filings, or researcher counts) that capture inventive effort and not the commercialized innovations that reach the market.

We develop an output-side framework for measuring firm-level product commercialization using the universe of USPTO trademarks linked to examiner-verified market introduction (first-use-in-commerce) dates. Unlike patents, which often reflect inventive intent or strategic disclosure prior to market entry, trademarks are legally contingent on use in commerce, yielding a consistent, historically anchored record of realized product launches. The framework enables a systematic analysis of both the scale of commercialization and its composition, and the allocation of launches across business-stealing (rival-displacing), quality-improving (incremental), and new-variety (market-creating) products. This granularity provides a micro-founded view of which innovations reach consumers. Designed as a general empirical tool, the framework can be applied to study how external (policy, technological, or competitive) shocks reshape firms' commercialization strategies. We demonstrate its usefulness by examining one canonical source of exogenous variation: policy uncertainty.

We construct a classification framework that uses large language models, structured linguistic rules, and expert validation to map trademark descriptions into a taxonomy grounded in growth theory. We distinguish three types of product launches: business-stealing (rival-displacing), quality-improving (incremental upgrades), and new-variety (market-creating). New-variety launches often represent first-generation entries that define novel categories but face limited early adoption, laying the foundation for subsequent refinements. For illustration, the Motorola DynaTAC pioneered the mobile phone category as a new-variety launch; the Motorola StarTAC introduced incremental quality improvements; and the Nokia Cityman exemplified business-stealing entry by a competing firm. This taxonomy allows us to examine how firms allocate commercializations across distinct innovation margins.

To quantify the economic significance of commercialization, we construct two complementary

measures: a count of product launches and a value-weighted measure based on abnormal stock returns around trademark first-use announcements (Kogan et al., 2017). The market-based metric captures investor expectations about the profitability of individual launches. Validation exercises show that these measures align with firms' reported product portfolios, externally verified product awards, and subsequent realized sales. We analyze both the scale of commercialization (total number or value of launches) and its composition (share of launches across business-stealing, quality-improving, and new-variety products).

This framework enables us to examine how policy uncertainty influences firms' commercialization decisions. Policy uncertainty is a natural focus because it is prominent in corporate decision-making and foreshadows declines in real activity. A large literature finds that uncertainty depresses investment, R&D, and hiring (Bloom, Bond, and Van Reenen, 2007; Gulen and Ion, 2016; Baker, Bloom, and Davis, 2016; Campello and Kankanhalli, 2024), yet its effects on the scale and composition of the types of commercialized products remain poorly understood. We provide early empirical evidence on how policy uncertainty reallocates commercialization across a new set of innovation margins.

Theory suggests that responses to uncertainty vary systematically across innovation types. Business-stealing (BS) products, which displace incumbents and reallocate market share, are central to models of creative destruction and quality-ladder growth (Aghion and Howitt, 1992; Klette and Kortum, 2004). These launches typically require large sunk costs, aggressive strategic positioning, and external financing, making their expected payoffs highly sensitive to policy risk. New-variety (NV) products, which expand consumer choice by introducing novel categories, are emphasized in expanding-variety models of growth (Romer, 1990; Grossman and Helpman, 1991). As first-generation entries, they are exploratory and modest in scale, often financed internally, but face substantial uncertainty about eventual adoption. Quality-improving (QI) products, which incrementally upgrade existing offerings, are more reversible and deliver quicker, more predictable returns. Their stability and lower risk could insulate them from uncertainty, consistent with models of operational expansion under financial frictions (Myers and Majluf, 1984; Almeida and Campello, 2007). These distinctions imply that policy risk can shape not only the scale but also the composition of innovation. When policy uncertainty rises, product launches with high sunk costs or uncertain adoption (BS, NV) are more likely to be postponed or scaled back, while incremental upgrades (QI) with near-term, predictable payoffs continue.

Empirically, we examine how firm-level commercialization responds to policy uncertainty using a three-step approach. First, we establish a macro benchmark by relating future commercialization outcomes, both total product growth and its composition to the aggregate Economic Policy Uncertainty index (Baker, Bloom, and Davis, 2016). Second, following the shift–share framework of Alfaro, Bloom, and Lin (2024), we allow firms to differ in their exposure to policy shocks by

interacting each industry's pre-estimated sensitivity of risk-adjusted returns to changes in policy uncertainty with the aggregate shocks in policy uncertainty. This produces an alternative measure that varies across firms through predetermined exposure but moves over time only with changes in aggregate policy risk.

Third, we implement an instrumental variables strategy that uses the shift–share measure to isolate the causal effect of policy-driven idiosyncratic volatility on commercialization activity. To ensure the instrument captures pure second-moment shocks (changes in uncertainty rather than shifts in expected policy outcomes), we control for directional policy news that may affect firms' first-moment expectations. Across these complementary designs, we find consistent results: higher policy uncertainty decreases the overall scale of commercialization and reallocates it away from long-horizon, capital-intensive, rival-displacing products toward short-cycle, incremental, and quality-improving launches, with the strongest effects emerging when using the policy-driven component of firm-level uncertainty.

To understand the mechanisms behind this reallocation, we consider real-option models, which predict that firms invest when the expected value of a product launch exceeds a hurdle that rises with uncertainty, especially for launches involving large sunk costs, distant or uncertain payoffs, and volatile returns (Bernanke, 1983; Dixit and Pindyck, 1994; Barlevy, 2007). Financing models highlight a parallel effect: uncertainty increases risk premia and tightens access to external capital, disproportionately constraining product introductions that require substantial upfront outlays (Bernanke, Gertler, and Gilchrist, 1996; Barrot and Nanda, 2020). We decompose the real-options investment condition into three empirically testable components: the timing and persistence of payoffs, the irreversibility of capital and labor commitments, and the dependence on external financing that amplifies sunk costs under uncertainty. We bring these mechanisms to the data by mapping each component of the real-options condition to observable firm outcomes.

First, we estimate local projection regressions tracking how firm sales and profits evolve in the decade following different product launches. We find pronounced heterogeneity: QI products deliver front-loaded gains that level off in the medium run, with most benefits realized within five years; BS products generate large, persistent gains lasting nearly a decade; and NV products show modest, positive gains that accumulate gradually, reflecting the exploratory nature and gradual adoption of first-generation offerings. These trajectories, the first direct product-level evidence on how innovation types map to firm growth dynamics, align with theoretical expectations: QI's near-term payoffs explain their resilience and even modest relative gains under uncertainty, whereas the long horizon of BS and NV payoffs amplifies their sensitivity. Products with uncertainty-sensitive payoffs (BS and NV) face steeper investment thresholds, while those with quicker, more predictable returns (QI) remain viable. We refer to this mechanism as the payoff-profile channel: uncertainty changes the composition of realized innovation not by uniformly delaying investment, but by

selectively reducing the expected returns to product types whose payoff profiles are long-lived or sensitive to policy risk.

Second, we analyze how different product types map into firms' capital investment by decomposing changes in property, plant, and equipment (PPE) into several categories: buildings & construction and land (less reversible assets); and machinery & equipment and leases (more reversible assets). We find distinct patterns in both magnitude and persistence. BS launches are followed by sustained increases in less reversible asset investments such as buildings & construction and land, consistent with scale-intensive, durable expansion. QI launches generate increases in machinery & equipment investment with little evidence of new building or land acquisition, reflecting their reversible nature. NV launches show minimal changes in tangible capital, with coefficients that are small and statistically insignificant, consistent with exploratory, low-commitment entry.

These patterns reflect a cost-side mechanism that complements our main revenue-side channel. While the payoff-profile channel emphasizes how uncertainty reshapes returns across product types, the capital investment results show that commercialization strategies differ in their reliance on irreversible assets. Business-stealing and new-variety launches involve investments, such as buildings and land, that are harder to unwind, making them more exposed to uncertainty. In contrast, quality-improving launches rely on more flexible, reversible capital investments, helping them remain viable when uncertainty rises.

Third, we examine how commercialization types map into firms' financing behavior, focusing on debt and equity issuance. BS launches are associated with increases in external financing (equity and debt), reflecting the need to fund scale-intensive expansion. NV products show minimal external financing activity and rely primarily on internal capital allocations, consistent with their exploratory nature and uncertain early returns. QI launches, by contrast, are more frequently accompanied by debt issuance, in line with their lower capital intensity and predictable cash flows.

This financing heterogeneity provides a natural bridge to the real-options framework: differences in external funding costs and capital intensity translate directly into variation in the effective exercise cost of commercialization under uncertainty. Because BS products require more external financing, their higher effective sunk costs amplify the option-value effect when uncertainty increases the investment threshold. Projects with long payoff horizons or high sunk-capital requirements (such as BS and NV launches) are less likely to meet the hurdle and are therefore postponed or abandoned. By contrast, QI launches, which yield quicker and more predictable returns and require less outside financing, continue to be implemented.

Our paper contributes to several literatures in growth, industrial organization, corporate finance, and innovation. First, we develop an empirical framework for measuring firm-level commercialization that extends existing innovation metrics. Prior work has developed input-side proxies (R&D expenditures, patent filings, and researcher counts) that capture inventive effort (Cohen, Nelson,

and Walsh, 2000), disclosure-based product measures using SEC filings (Hoberg and Phillips, 2010, 2016), and trademark-based measures that capture product commercialization (Mendonça, Pereira, and Godinho, 2004; Flikkema, Man, and Castaldi, 2014; Faurel et al., 2024). Building on recent advances in trademark-based innovation measurement (Faurel et al., 2024), we refine this approach by exploiting the USPTO's examiner-verified first-use-in-commerce dates to measure realized product commercialization with precise timing. Critically, we introduce a novel classification that maps each launch to business-stealing (rival-displacing), quality-improving (incremental), or new-variety (market-creating) categories, which are grounded in growth theory (Romer, 1990; Aghion and Howitt, 1992; Klette and Kortum, 2004). This taxonomy enables systematic analysis of both the scale and composition of commercialization, showing how firms allocate innovation effort across product types that differ in payoff timing, irreversibility, and financing needs.

Second, we apply this framework to examine how firm commercialization strategy is reshaped by policy uncertainty, a setting where theory predicts heterogeneous responses across investment types. A large literature shows that uncertainty depresses aggregate investment, R&D, and hiring (Bloom, Bond, and Van Reenen, 2007; Gulen and Ion, 2016; Baker, Bloom, and Davis, 2016; Campello and Kankanhalli, 2024). Yet little is known about whether uncertainty changes the composition of commercialization across innovation types. Our evidence demonstrates that uncertainty not only reduces the overall scale of commercialization but also systematically reallocates it away from long-horizon, capital-intensive projects (BS and NV) and toward short-horizon, more flexible upgrades (QI).

Our findings extend traditional real-options theory, which emphasizes the option value of waiting when uncertainty increases (Bernanke, 1983; Dixit and Pindyck, 1994). While prior work documents that uncertainty reduces investment scale (Bloom, 2009; Gulen and Ion, 2016; Campello and Kankanhalli, 2024), we show that when firms face heterogeneous commercialization opportunities, uncertainty also systematically reshapes the product composition of investment. Specifically, firms shift away from products with large sunk costs and long-horizon, fragile payoffs toward those with quicker, more predictable returns, even as overall commercialization declines. This compositional reallocation represents an understudied margin of adjustment to uncertainty. Our analysis contributes to the intersection of corporate finance, uncertainty, and innovation literatures by demonstrating that uncertainty's effects operate not only through investment scale but also through product-level allocation decisions across types with heterogeneous payoff profiles and capital requirements. Because different innovation types have distinct growth implications, our findings suggest that uncertainty's compositional effects may have important consequences for firm growth, technological diffusion, and aggregate productivity.

Third, we provide novel evidence on how product commercialization types relate to long-run firm growth dynamics. While prior research has examined innovation types and firm growth

using patents (Akcigit and Kerr, 2018; Acemoglu et al., 2018), Census microdata (Garcia-Macia, Hsieh, and Klenow, 2019), or product bar codes (Argente et al., 2020), we contribute by analyzing realized commercial launches with precise timing and a theoretically grounded classification. We document that 1) quality-improving products deliver rapid but short-lived gains in profits and capital, 2) business-stealing products yield large and persistent growth in profits and assets over nearly a decade, and 3) new-variety products contribute mainly with a lag, reflecting exploratory adoption patterns. These distinct trajectories highlight that different product types have different cost structures, payoff durations, and sensitivities to uncertainty, implying that policy risk reshapes firm growth not only by uniformly decreasing investment but also by altering the types of products that reach the market. Building on Campello, Kankanhalli, and Kim (2024), who document that uncertainty delays creative destruction in capital allocation, we show that uncertainty also distorts product composition in ways that may have persistent implications for firm growth and aggregate productivity.

2 Construction of Product Measure and Data

In this section, we describe how we measure firm-level product portfolios using USPTO trademark data, classify products into three economic types: new variety (NV), quality improving (QI), and business stealing (BS); and estimate their economic value. We proceed in three steps: (1) construct a dynamic product-level dataset based on trademark filings; (2) classify products using a semantic framework based on the USPTO ID Manual; and (3) estimate the market value of each product at launch using firm-level stock price reactions.

2.1 Trademark Data and Product Measure

We use USPTO trademark data to measure the dynamics of firms' key product (goods and services, G&S) portfolios. A trademark is a word, phrase, symbol, design, color, smell, sound, or combination thereof that identifies and distinguishes the goods and services of one party from those of others (Chapter 22 15 USC. § 1127). It protects trademark owners' investments from misappropriation by preventing one seller from free-riding on another seller's reputation by offering similar goods or services under a confusingly similar mark.[1]

A trademark right is established by use, i.e., it is contingent on market entry. Thus, for a trademark to be registered, the applicant must submit evidence that, as of the filing date, the mark

[1]Trademark law prevents consumer confusion and preserves consumer expectations on the source and quality of the goods and services they purchase. For further information, see the USPTO documentation on "Basic facts about trademarks" (`https://www.uspto.gov/trademarks-getting-started/trademark-basics`) and the detailed description in Graham et al. (2013).

is used in commerce or is intended to be used in commerce within six months (extendable up to 36 months). The trademark cannot be registered without showing evidence of the *actual* G&S use in commerce. The applicant must include the "first-use-in-commerce" date, which is the first date that the product is available in the market, and proof thereof, which is reviewed by the USPTO examiner. We refer to this date as the commercialization date hereafter. This date can precede the filing and publication dates and provides the most reliable and accurate timing of the product introduction to the market, validated by trademark attorneys and USPTO examiners. This legal scrutiny ensures that trademarked products have entered the market, distinguishing it from patents or internal R&D disclosures that may reflect pre-commercial experimentation. As such, trademarks offer a legally grounded and time-consistent signal of commercialization, particularly useful for identifying first-generation innovations that expand the product frontier.

Figure 1 provides an example from a Microsoft Office trademark registration. The trademark data provides the following information, detailed in Table C.1: (1) the trademark's mark characters (the words/texts in the trademark), e.g., Office; (2) important dates in the trademark's life cycle, such as filing, first-use-in-commerce, publication, registration, and cancellation date; (3) the trademark owner's name, address, and postcode; (4) Goods & Services (G&S) class(es); and (5) Goods & Services (G&S) statement which is the owner's description of the G&S covered by the trademark.

The trademark application follows three stages to registration (Graham et al., 2013), summarized in Figure 2. First, a randomly assigned examining attorney assesses the validity and uniqueness of the filing, including the G&S classification. Registration may be refused if the descriptive terms cannot identify the source of the goods and services. This examination step underpins our finer classification of trademarks into distinct product categories. Second, if deemed registrable, the USPTO publishes the trademark for opposition (77% of our sample). Third, if no objections arise within 30 days, or if the applicant successfully overcomes them, the trademark is registered (93% of published trademarks).

The USPTO trademark case files from 1870–2020 include 6.6 million registered trademarks with G&S statements across public and private firms, foreign entities, and individuals. All firms wanting to protect the use of their name (product or brand) in the U.S. need a U.S. trademark. To construct our sample, we match trademark owner names to U.S.-listed firms (including subsidiaries) in CRSP using a name-matching algorithm. This yields 0.97 million trademarks linked to 18,467 publicly listed firms, which have 21.5 live trademarks per year, on average.[2] For other trademarks, we apply the same name matching algorithm to map trademarks to "Large" and "Very Large" firms

[2]Unlike patents, trademarks have not been systematically matched to firms. Appendix A1 details our matching algorithm and disambiguation approach. We consolidate all subsidiaries and acquisitions under the parent firm, as of the acquisition year. We also conduct an expert human audit of 500 randomly selected firms to refine the matching process.

in ORBIS, which includes U.S. private firms as well as non-U.S. public and private firms.[3] We match 1.02 million trademarks to 141,610 ORBIS firms, which have 4.6 live trademarks a year, on average.

We use *all* live USPTO trademarks owned by firm i in year t (including product marks and branding/house marks). We rely exclusively on the G&S statements to infer a firm's product portfolio. We never use the mark characters (brand names, slogans) to define products. This choice reflects standard practice that branding marks are refiled or amended when important products are commercialized. Thus, the associated G&S descriptions are a legally verified, up-to-date inventory of the firm's offered goods and services. Specifically, for firm i in year t, we form the firm–year product vector V_{it} as the union of product terms extracted from the G&S text of all live trademarks:

$$V_{it} = \bigcup_{m \in \mathcal{M}_{it}} \mathcal{P}(m),$$

where $\mathcal{M}_{it}$ is the set of live trademarks for firm i in year t, and $\mathcal{P}(m)$ is the set of product terms mapped from mark m's G&S statement.

As marks are registered, amended, or canceled, V_{it} updates dynamically: terms enter when they first appear in any live mark's G&S and exit when no live mark for the firm contains that term (e.g., cancellation or non-renewal). Because we take a union over marks, multiple filings (e.g., brand hygiene) do not inflate product counts; we de-duplicate at the product-term level rather than the mark level. All statistics are computed from V_{it} (product terms). This design ensures that both product and branding marks contribute information, while measurement remains at the product level. This construction is analogous to text-based product vectors used to measure firm scope and market positioning from 10-Ks (e.g., TNIC, Hoberg and Phillips, 2016, 2025), but here it is grounded in examiner-validated trademark G&S statements. The trademark-based data provides a legally grounded and time-consistent measure of firm-level commercialization. It enables us to track the evolution of product portfolios over time and across industries, capturing both the timing and nature of product launches.

2.2 Defining Product Categories for Trademarked Products

The USPTO classifies each trademark into broad categories of goods or services (Goods and Services Classification Category), as determined by: (1) the Nice International Agreement, and

[3]Companies in ORBIS are classified as "Large" when they meet at least one of the following criteria: operating revenue of >10 million EUR (approx. $13 million), total assets of >20 million EUR (approx. $26 million), a workforce of >150 employees, or they are publicly listed. The "Large" firms threshold in ORBIS corresponds to fairly small firms in the Compustat sample, e.g., a firm with $13 million total assets is at the bottom 3% of the asset distribution of firms in Compustat in 2020. Excluding very small firms allows us to focus on more economically important products.

(2) the U.S. classification system. The Nice Classification (NCL), established in 1957 and adopted by the USPTO in 1973, defines 45 classes—34 for goods and 11 for services.[4] These classes are broadly defined and not suitable for identifying individual products.[5]

To obtain a more granular classification, we utilize the text data from trademark G&S statements written by applicants. During registration, the USPTO asks applicants to consult the Acceptable Identification of Goods and Services Manual (ID Manual), which contains 67,104 product terms (Term IDs) in 2024.[6] The ID Manual is updated annually and serves as a guide for applicants and examiners.[7] Figure 3 illustrates a sample of entries related to mobile phones. The G&S statements are validated by USPTO examiners, and registration may be refused if the descriptive terms cannot identify the source of the goods or services. This validation process supports our finer classification of trademarks into distinct product categories by mapping product phrases from G&S statements to Term IDs in the ID Manual.

The granularity of the Term ID manual is important for the categorization of both BS and NV products. If the Term ID is too broad (e.g., "Computer Software"), two firms filing under this ID could produce very different, non-competing goods. One firm might release an accounting platform while another that releases a graphic design suite might be classified as BS. However, excess granularity may represent changes in nomenclature used by the USPTO to describe goods, leading to over-counting NV products. We address semantic redundancy using vector-based entity resolution, which identifies conceptual equivalence. Our final Term ID set $\mathcal{T}$ includes 34,067 unique terms k.

We parse each G&S statement into product phrases (e.g., "mobile phones," "lithium battery chargers") and map them to unique Term IDs in the USPTO ID Manual. Specifically, we embed both extracted phrases and Term IDs and match them via cosine similarity (Appendix A2).[8] The output for each mark is a set of Term IDs; the firm–year product vector V_{it} is the union of Term IDs

[4]Nice Classification details are available at `https://www.wipo.int/classifications/nice/en/preface.html`. The USPTO retroactively populated NCL equivalents for pre-1973 trademarks. The U.S. classification remains relevant for older filings, see `https://www.uspto.gov/trademarks/trademark-updates-and-announcements/nice-agreement-current-edition-version-general-remarks` and Graham et al. (2013).

[5]This level of aggregation is analogous to 2-digit SIC codes. For example, Class 9 includes scientific instruments, IT equipment, audiovisual devices, and safety gear.

[6]The ID Manual is derived from the NCL and maintained by the USPTO's Office of the Administrator for Trademark Classification Policy and Practice. It is more granular than the 8-digit SIC system, which includes roughly 18,000 categories. In electronic filings (TEAS Plus), applicants are encouraged to use exact entries from the ID Manual, see `https://idm-tmng.uspto.gov/id-master-list-public.html`.

[7]An example of a recent product category is "Self-driving cars," introduced in the ID Manual in 2019 under Term ID 012-1525.

[8]We embed both extracted product terms and Term ID descriptions using the Gemini 2.5 LLM. Pairwise cosine similarity identifies the best semantic match between the two, see Appendix A2 for full details. For example, a G&S statement containing "Mobile phone" is matched to "Mobile phone," rather than "Mobile phone batteries," based on semantic proximity.

over all live marks owned by firm i in year t (see Section 2.1). Because branding (house) marks are amended when important product offerings are added, their G&S statements provide systematic coverage of the firm's portfolio; our union and de-duplication rules ensure that branding activity does not mechanically increase product counts.

This semantic matching framework enables scalable classification of trademarked products into economically meaningful categories. The semantic classification system, grounded in legal documentation and enriched by machine learning and human validation, provides a robust foundation for tracking innovation dynamics across firms and industries.

2.2.1 Classifying Product Types

Using the product vectors generated through our semantic and human classification framework, we categorize trademarked products into three commercialization types: new variety (NV), quality improving (QI), and business stealing (BS), in the spirit of Garcia-Macia, Hsieh, and Klenow (2019). This taxonomy allows us to distinguish between products that expand the firm's commercial portfolio, enhance existing offerings, or enter markets already served by competitors. We can identify new product varieties that represent first-generation products, which expand the frontier of what is commercially available. These NV products typically emerge in the early stages of an innovation cycle, when technological opportunities are abundant and there are few existing offerings. Quality-improving products reflect incremental upgrades within a firm's existing portfolio. Business-stealing products capture competitive displacement, where a firm introduces a product already commercialized by a rival, mostly an enhanced product.

We define a new-variety product as a first-generation market entry, a product that is new to both the focal firm and the broader trademarked product space. Specifically, a Term ID is classified as an NV if it appears for the first time in the USPTO trademark data and has not been previously registered by any firm. These products represent genuine additions to the commercial landscape, expanding both the firm's portfolio and the diversity of offerings available in the market. An NV example in the sample is the Motorola DynaTAC 8000X, the first commercially available handheld mobile phone, which marked the beginning of mobile telephony as a consumer product in 1983. The product category "Mobile telephone" (Term ID 009-1000, which we disambiguate to "Mobile phone") is classified as a new variety based on its first appearance in our trademark data, associated with Motorola's trademark filing.[9]

A quality-improving product enhances a firm's existing offerings without introducing a new category to the firm or the market. These products represent refinements, upgrades, or extensions of previously trademarked goods or services. A product is classified as QI if it already exists in the firm's product vector and does not represent a new entry for any other firm. For example, the

[9] See `https://en.wikipedia.org/wiki/Motorola_DynaTAC`.

Motorola MicroTAC, launched in 1989, introduced the flip-phone design and built on the mobile phone category already established by Motorola's DynaTAC model. Since the product was already in Motorola's portfolio, MicroTAC is classified as QI.

A business-stealing product is new to the focal firm but not to the market. These products reflect competitive entry into an existing product space and are associated with market reallocation rather than expansion. BS product entry is common among large, well-capitalized firms entering mature markets with established demand, not just small imitators or fringe entrants. These firms often leverage scale, brand recognition, and distribution networks to compete aggressively with incumbents. For example, the Nokia Cityman, released in 1987, was Nokia's first handheld mobile phone, entering a market already served by Motorola's DynaTAC. Its trademark represents Nokia's business-stealing entry into a category (mobile telephone) already commercialized by another firm.

Specifically, a *commercialization event* for firm i and Term ID k occurs in year t when $k \in V_{it}$ but $k \notin V_{i,t-1}$. Our classification follows the taxonomy: NV if k has never appeared in any other firm's product vector before t. All firms that launch the same NV Term ID in year t are considered NV, to avoid an artificial dichotomy between the pioneer and immediate competitors who may have undertaken identical R&D risks. BS if k previously appeared in at least one other firm's vector but not in $V_{i,t-1}$; QI if product k exists in the firm's portfolio $V_{i,t-1}$. A QI entry expands an existing firm category (same Term ID). Because we de-duplicate within V_{it}, multiple marks listing the same Term ID do not create multiple events.

To avoid misclassifying widely adopted goods as new varieties (e.g., gold, tomatoes), we first remove historically established products from the NV list. These are identified using historical searches via ChatGPT and Gemini, focusing on the earliest recorded commercial use. Products with documented existence prior to 1850 are excluded from the NV category, as they pre-date our sample and cannot plausibly represent first-generation market entries. All exclusions are human expert reviewed to ensure accuracy.

This procedure allows us to construct a dynamic and firm-specific taxonomy of commercialization grounded in trademark filings and validated through USPTO examination. While our analysis covers U.S.-listed firms only, our data covers all firms with U.S. operations. As such, our classification captures both domestic innovation and international competitive dynamics within the U.S. commercial landscape.

2.3 Validation of Trademarked Products as Key Products

Trademarks generate value for a firm by indicating the origin of goods and services and by facilitating product differentiation. Because trademarks are relatively inexpensive to acquire and have low granting requirements, firms have strong incentives to trademark their economically significant

offerings. As a result, most firms operating in the U.S. (domestic and foreign) systematically apply for trademarks, for individual products or brands, which cover their main product offerings. However, trademarked products are still a proxy for the full product space of a firm.

We assess the trademark coverage of individual firm key goods and services by comparing trademarked products to three external sources: (i) trademarked products firms report in SEC 10-K annual filings, (ii) the Compustat Segment product database (Cohen, Diether, and Malloy, 2013), and (iii) award-winning products featured at the Consumer Electronics Show (CES), a leading venue for commercial product launches in the technology sector.

2.3.1 10-K Filings

When firms introduce important products or refer to trademarked products in their annual reports, they annotate these products with ® or ^{TM} symbols. We search the 10-K filings of all CRSP firms in EDGAR for trademark annotations over the sample period 1996 to 2020. Specifically, we download the 10-Ks for all sample firms and search for ® or ^{TM} symbols to identify trademarked products. We find 53,996 unique trademark names from 7,766 firms' 10-Ks. We match these annotated trademarks to our trademark data and find that 74% are captured in USPTO records. A manual check of the remaining trademarks shows that they mostly belong to non-U.S.-based firms and refer to trademarks filed with foreign IP offices.

2.3.2 Compustat Product Segments

We use product information from firms' annual 10-K filings, as captured by the segment-level product data from the Compustat Segment data file (Segment product henceforth), for further validation. The Segment product data provides business and geographic details for over 70% of the companies in the North American database. Our analysis focuses on the Business segment data, which presents industry segments or product lines reported by a company to capture firm-level product information. In this section, we refer to product lines and individual products collectively as products.

The Segment product data includes major products that a firm discloses as a product segment. Most firms report product lines rather than individual product names. For example, pharmaceutical companies often report "Drugs" as a category without naming individual compounds; car companies report general models such as "SUVs" rather than specific models. Therefore, the Segment data undercounts product numbers. There are 9,705 firms in the Segment product data for the sample period 1998–2018, and each firm reports nine products on average.[10] This is much lower

[10]The Segment product data provides the following information: GVKEY, product identifier number, NAICS code, product name, sales, and sales date. Each product has a unique product number and carries that product number through time (e.g., XBOX is product number 7 and Microsoft Office is product number 4 for Microsoft). The Segments

than the 51 products in the average firm-year trademark product vector.

We use the Segment product data to carry out two types of analysis. First, we assess the relation between the number of product lines and trademarked products for each firm through a regression analysis. Second, we extract all individual products identified by name and examine their coverage in the USPTO trademark data. Table 1 presents a firm-year panel regression of the log number of segment products reported by firm i in year t on the (log) number of trademarked products held by firm i in year t, where a product remains in a firm's portfolio as long as the trademark is in use, i.e., between the trademark's first-use-commerce date and the cancellation date. The regression coefficients indicate a positive contemporaneous relation between trademarked and Segment products. This relation is statistically and economically significant after accounting for firm, time, and industry×time fixed effects. Economically, a 1% increase in trademarked products is related to a 0.152% increase in Segment products (column 1). This elasticity estimate is reasonable given the 1 to 6 ratio between the number of segments and products in a firm's trademark vector. Firms do not generally report all of their products in 10-K filings and often aggregate individual products into broader segments. The positive and significant relation suggests that trademarked products provide a good indication of firms' new commercial offerings.

To further gauge the coverage of trademarks for firms' product space, we name-match the list of individual products reported in the Segment data to trademarks for 250 firms in the period 1998 to 2018. The smaller number of firms in this trademark–CRSP–Compustat–Segment product sample is driven by most firms' practice of reporting just broad product categories or terms (such as cloth, glassware, software, hardware, etc.) rather than the exact product names in their 10-K filings.[11] We find that 87.6% of the individual products reported in the Segment data are trademarked. The high match rate reinforces the credibility of trademarks as a proxy for firms' key product offerings.

2.3.3 Award Winning Products

A firm's most significant and innovative products are often recognized not only by consumers and markets but also through formal prizes. One prominent source of such recognition is the CES (Consumer Electronics Show) Innovation Awards.[12] These Awards honor outstanding design and

data sample starts in 1996; however, it is sparsely populated prior to 1998.

[11] Specifically, we list all unique product names in the Segment product sample and strip off all generic terms, which do not represent firms' individual products and services. To remove generic terms, we recursively look up and remove product names that appear in the English dictionary. This allows us to capture unique product names such as XBOX in the 10-K filing of Microsoft Inc. There may be shortcomings to this method, e.g., Microsoft reports sales for the Windows operating system as "Windows." Since "window" (after stemming) is in the English dictionary, the product is excluded from the list. However, these cases are relatively rare because firms often use unique names to distinguish their products. We also remove all chemical compound names, as these compounds are generally sold under associated drug names.

[12] CES is held annually in Las Vegas and is one of the world's largest technology exhibitions. It showcases advancements across industries, including cars, health and wellness, home appliances, entertainment, and digital

engineering in consumer technology products. Entries are evaluated by a panel of independent experts based on criteria including technical specifications, aesthetic design, functionality, and originality. Winning a CES Innovation Award is widely regarded as a mark of excellence and commercial promise, with recipients featured in dedicated showcases and amplified through media coverage and industry publications.

Given the commercial and reputational importance of award-winning products, firms have strong incentives to protect them with trademark registrations. Trademarks offer a legally grounded signal of commercialization, as registration requires evidence of use in commerce. To assess the coverage of such products in our data, we examine the USPTO trademark status of CES Innovation Award winners from 2021 to 2023. We find that 80.7% (1,257 out of 1,556) of these award-winning products are registered in trademarks.[13] The unmatched products are primarily associated with non-U.S. firms or represent pre-commercial prototypes (minimum viable products) that have not entered the market as of 2023.

These findings reinforce the broader conclusion that trademarked products offer extensive coverage of firms' commercial portfolios, including those disclosed in regulatory filings and recognized through external awards. They also highlight the role of trademarks in capturing first-generation innovations that anchor the early stages of commercialization and signal market readiness.

2.4 Economic Value of Products

Not all products are equally consequential: while some generate modest incremental revenues, others represent transformative growth opportunities. To distinguish between frequent but low-value and high-value product launches that disproportionately shape firm dynamics, we estimate the market value of each product at the first commercialization date. This measure corresponds to the present value of expected future cash flows, following the approach of Kogan et al. (2017) as detailed in Appendix B.

A key challenge in estimating product value is identifying the precise date when new product information becomes available to the market. Prior work has used press releases or Factiva searches to approximate launch dates (Mukherjee, Singh, and Žaldokas, 2017), but such methods are incomplete, especially for services or intermediary goods. We address this by leveraging the USPTO's requirement that trademark registration must be based on actual or intended use in commerce. Applicants must declare a "first-use-in-commerce" date, which is reviewed by USPTO examiners and provides a legally grounded signal of market entry. For each trademarked product, we use the earlier of the "first-use-in-commerce" date and the publication-for-opposition date to

infrastructure, see `https://www.ces.tech`.

[13] USPTO trademark data was available through 2023, and CES award data was sourced from the CES website for the most recent three years.

anchor the timing of commercialization.[14] This approach ensures consistency across firms and time and avoids reliance on discretionary public disclosures.

To estimate product-level economic value, we merge trademark data with CRSP stock price data. We exclude trademarks issued to firms prior to their exchange listing, due to lack of stock price information. Our valuation sample includes 312,579 trademarked products. While smaller than the patent sample in Kogan et al. (2017), our dataset reflects actual commercialization events and includes nearly the full universe of listed firms.[15]

At the firm-year level, we aggregate product values by economic type. Let $\hat{\xi}_c$ denote the market value in 1982 dollars of trademarked product c, and $C_{i,T}$ the total number of products commercialized by firm i in year T. We define the firm-year commercialization value as:

$$\Theta^{C}_{i,T} = \sum_{c=1}^{C_{i,T}} \hat{\xi}_c, \tag{1}$$

where products $C \in \{BS, QI, NV\}$ are categorized as described in Section 2.2.1.

2.4.1 Product Values and Future Sales

To validate our estimates of product-level economic value, we examine their relation with realized future sales. The underlying premise is that the market value of a trademarked product, captured at the point of commercialization, should reflect the present value of its expected future cash flows. Accordingly, products with higher estimated market value should generate higher cumulative sales over time.

We focus on the subset of trademarked products that are also covered in the Segment product data, as described in Section 2.3.2. This allows us to link product-level value estimates to sales reported in firms' financial disclosures. For each product, we aggregate total sales over the full reporting period available in the sample. Since the product value (ξ) represents the net present value of all future cash flows, we treat each product as a single observation, summing its realized sales from 1998 to 2018 and converting all quantities to 1982 dollars for consistency.

Figure 5 plots the relation between product value and total sales. The Y-axis displays the cumulative product sales (ln) in 1982 dollars, while the X-axis shows ξ the estimated product value (ln). The figure reveals a strong positive correlation between the two measures. The relation is approximately log-linear: a 1% increase in estimated product value is associated with a 0.64% increase in realized sales. This result supports the validity of our valuation approach and suggests

[14] Only 16% of trademarks in our sample have a publication date preceding the first-use-in-commerce date. Both dates occur well before the registration date.

[15] Patents often include inventions that are never commercialized; only 63% of patents are renewed beyond eight years. Moreover, many products rely on multiple patents (e.g., the iPhone involves over 200 patents).

that trademark-based product value captures meaningful variation in commercial performance.

2.5 Financial and Accounting Data

For the empirical analyses that require asset prices, industry classification, and firm financial and accounting information, we merge trademark data to financial data using a name-matching algorithm described in Appendix A1 for U.S.-listed firms. For financial data, we use stock price information from the Center for Research in Security Prices (CRSP) and firm accounting information from Compustat.[16] Table C.2 provides a list and definitions for all the variables used in the paper. The CRSP sample period covers 1926-2020, while the Compustat sample period starts in 1950, but it provides the most comprehensive coverage from 1976. Our firm-level analysis focuses on U.S.-listed firms from 1976-2020, with additional results for the 1950-2020 sample presented in Online Appendix IA.B.

In the publicly-listed firm sample, 78% of firm-years of AMEX-, NYSE- and NASDAQ-listed firms with common equity have at least one live trademark for the 1976 to 2020 sample. There are on average 51 unique products in the firm-year product vector. Tables 2 and IA.B.1 present the sample characteristics of all Compustat firms and the sample with trademarks starting from 1976 and 1950 respectively. Firms with registered trademarks during the sample period are larger, older, and less levered than the average firm in the sample.

2.6 Descriptive Statistics

Figures 6 and C.1 depict the time series of product type introductions and portfolios by U.S.-listed firms across industries from 1950 to 2020, respectively. A product enters a firm's portfolio in the year of its first-use-in-commerce date and exits when canceled or not renewed. Over the sample period, the rate and share of quality-improving (QI) and business-stealing (BS) introductions have increased over time, while new-variety (NV) entries have become rarer. This pattern is consistent with a first-generation NV innovation cycle: as the baseline of available products expands, the cost and complexity of generating entirely new products increase, making incremental improvements and competitive displacement more prevalent. Much like the declining productivity of idea generation documented in Bloom et al. (2020), the frontier of product space becomes harder to expand, even as firms continue innovating within it.

The average firm now introduces and holds more QI products. This reflects the cumulative nature of innovation in mature sectors, where performance upgrades and refinements become the primary

[16] We exclude firm-years with missing total assets and SIC classification codes. For firm and industry analysis, we also exclude the heavily regulated industries of utilities (SIC code 4900-4949) and financial firms (SIC code 6000-6799). We winsorize all unbounded variables at the 1% level using annual breakpoints.

mode of progress. It aligns with evidence that most aggregate growth arises from incumbents enhancing their own products rather than expanding the product space or displacing rivals (Garcia-Macia, Hsieh, and Klenow, 2019). The rising share of QI products is more pronounced in industries like ICT and consumer goods, where post-1980s innovation has increasingly focused on usability, design, and incremental technical improvements.

Until the mid-1990s, firms in the Chemicals and Allied Products sector introduced the most products and held the largest portfolios across all product types. This reflects the long dominance of chemicals as sources of innovation and productivity growth, with substantial product entry documented in Broda and Weinstein (2010) and Bernard, Redding, and Schott (2010). Chemicals' lead was overtaken within a single decade by consumer nondurables in QI and telecom in BS. This transition lines up with two well-documented macro trends. First, Broda and Weinstein (2010) shows that consumer nondurables exhibit intense product churn. Frequent but incremental upgrades (formulations, packaging, design tweaks) mean that nondurable portfolios naturally tilt toward QI introductions. Second, the ICT boom of the late 1990s attracted capital and talent into communications, fueling rapid product turnover and rivalry (Hombert and Matray, 2018; Berlingieri et al., 2025). Firms in the Healthcare and Oil and Gas industries introduce the least number of products, which is in line with the low product differentiation in the oil and gas industry, and the high cost of developing new or improved products in the healthcare and pharmaceutical industry.

These facts illustrate the lifecycle of commercial innovation across sectors. Chemicals led the early NV wave, expanding the product frontier. As that frontier matured, nondurables and telecom rose through QI and BS strategies, respectively. This divergence highlights that product-portfolio composition reflects not only technological opportunity, but also the stage of the innovation cycle, financing, and competitive environment in which firms operate.

Table 3 presents univariate characteristics of firms in the commercialization year of different product types. The same firm can appear in all three categories in any given year if it introduces three different product types in that year. NV products are introduced by smaller, high-growth (Tobin's Q) firms, with more patents and operating in less concentrated markets, consistent with theory and evidence that entrants expand product scope and that small firms' patents are tightly linked to commercialization (Argente et al., 2020). BS launches are concentrated among younger but less profitable firms, echoing product-switching behavior documented in Bernard, Redding, and Schott (2010). QI products are disproportionately introduced by older, larger firms with slower growth opportunities (Tobin's Q), consistent with incumbents' role in incremental upgrades when expansion opportunities are limited.

Table 4 presents summary statistics for the private market value $\hat{\xi}_p$ of each product type, which reflects market expectations of future cash flows at the time of commercialization. QI products have the highest average expected value at \$9.97 million, followed by NV products at \$9.28 million,

and BS products at $6.43 million. This ranking aligns with investor preferences for scalable, reliable improvements (QI) over riskier displacement strategies (BS). NV products, while less frequent, remain economically significant: their relatively high expected value and concentration among high-Q entrants suggest that markets perceive them as exploratory innovations with long-run potential. The distribution of $\hat{\xi}_p$ is heavily right-skewed, with some products generating exceptional expectations—such as the 2011 version of MS Office 365, valued at $155 million in 1982 dollars.

These patterns reinforce the lifecycle view: NV products represent foundational experimentation by smaller, high-Q firms, often serving as platforms for future improvement. BS products reflect competitive gambles by younger, less profitable firms, while QI products deliver consistent returns for mature incumbents. Our empirical design captures commercialization and market expectations at launch, but not the cumulative trajectory of performance upgrades that may follow. As such, NV products should be interpreted as frontier-expanding introductions, economically meaningful despite their declining share, whose payoff may unfold gradually through subsequent innovation. Firms continue to innovate, but the mode of innovation evolves with the frontier.

3 Commercialization Under Uncertainty

Our analysis of the relation between product commercialization and uncertainty follows three steps, each increasing the granularity of the uncertainty regressor and sharpening causal identification. First, we establish a macro-level benchmark using aggregate policy uncertainty. Second, we exploit heterogeneous firm-level exposure to aggregate shocks via a shift–share proxy. Third, we implement an instrumental variable strategy to isolate the causal effect of policy-driven idiosyncratic volatility, separating uncertainty (second-moment) from directional policy news (first moment).

3.1 Macro benchmark: uncertainty and commercialization

We begin with a parsimonious macro-level specification that relates future commercialization outcomes to the standardized aggregate US policy uncertainty index, EPU_t (Baker, Bloom, and Davis, 2016). The objective is to establish a clean benchmark: if policy uncertainty matters, higher EPU_t should be followed by changes in the scale and composition (BS/QI/NV) of product launches in year t+1.

Following Alfaro, Bloom, and Lin (2024), we measure commercialization scale using the symmetric (arc) growth rate, defined as:

$$\frac{\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} - \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}}{0.5 \times [\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} + \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}]},$$

where $C \in \{BS, QI, NV\}$ denote the number of new-variety (NV), quality-improving (QI), and business-stealing (BS) products introduced by firm i in year t. This measure is bound in $[-2, 2]$, treats increases and decreases symmetrically, and avoids distortions from small denominators. To study whether high uncertainty causes firms to shift their portfolio towards QI over time, we measure commercialization composition by the relative allocation between QI on one hand and NV and BS on the other, as NV introductions are very sparse.

Formally, our baseline specification is:

$$Y_{i,t+1} = \alpha_i + \beta\, EPU_t + \Gamma' X_{i,t} + \varepsilon_{i,t+1}, \tag{2}$$

where $Y_{i,t+1}$ denotes commercialization scale and composition outcomes, as defined above. $X_{i,t}$ is a vector of control variables including firm size, leverage, HHI, cash flow, Tobin's Q, R&D stock, and patent stock, and α_i are firm fixed effects.[17]

In this baseline specification, we treat all firms as equally exposed to aggregate policy uncertainty. The coefficient β in equation (2) can be interpreted as an average semi-elasticity: it reflects the change in commercialization outcomes associated with a one unit change in EPU_t. This step establishes a macro-level benchmark before introducing industry-level heterogeneity in exposure and isolating effects via firm-level idiosyncratic uncertainty projected onto EPU-specific instrumental variables.

We find a strong negative relation between EPU_t and new product introductions in columns (1)-(2) of Table 5. Focusing on column (2), which includes control variables, a one–unit rise in EPU_t is negatively associated with a -0.013 ($t = -8.85$) change in next–year total product growth. A 10–point increase in EPU_t implies about 12.2% decline in the total number of product launches. This scale effect echoes the well–documented slowdown of CAPEX, R&D, and hiring under uncertainty (Bloom, Bond, and Van Reenen, 2007; Gulen and Ion, 2016; Baker, Bloom, and Davis, 2016; Campello and Kankanhalli, 2024).

Turning to composition, we find a statistically and economically significant tilt toward quality-improving products with increasing EPU. The QI/(BS+NV) ratio increases by 0.048 per one–unit increase in EPU_t in column (4). For a 10–point increase in EPU_t, this corresponds to an increase of about 0.5 in the ratio. For a firm that launches 10 new products a year with a 50-50 composition, the total number of launches falls (e.g., from 10 to 9) during the shock, and within the surviving portfolio the mix shifts strongly toward QI ($\approx$ 5.5 QI) and away from BS ($\approx$ 3.5 BS).[18]

This result indicates a new margin of adjustment to uncertainty: beyond reducing the level of commercialization, firms reallocate toward quality-improving rather than rivalry-intensive,

[17] Year fixed effects are omitted because EPU_t is common across firms in a given year.

[18] These magnitudes are illustrative. The actual counts depend on the pre-shock mix, but they capture the economic size of the composition tilt implied by our estimates.

business-stealing introductions. The pattern is consistent with recent industry practices, where automakers facing regulatory and supply-chain uncertainty postpone new product entries while emphasizing face lifts, software updates, and range enhancements, the QI tilt captured in our results.

3.2 Heterogeneous exposure based on Shift–Share approach

We refine the baseline analysis by allowing a common aggregate policy uncertainty shock to generate heterogeneous firm-level exposures. Using a shift–share design, we construct a firm-level proxy that interacts a common shift (the policy uncertainty shock) with a predetermined share that reflects each industry's sensitivity to policy news. This design enhances the granularity of the uncertainty measure and isolates cross-sectional variation in exposure. By leveraging industry-level sensitivity as a source of exogenous variation, the shift–share approach enables us to identify firm-level heterogeneity in response to aggregate uncertainty shocks.

The share is defined as the absolute, predetermined sensitivity of industry returns to policy news:

$$\omega_{i,t-2} \equiv \left|\beta^{\text{EPU}}_{j(i),t-2}\right|,$$

where $j(i)$ maps firm i to its corresponding (2-digit SIC) industry j, and $\beta^{\text{EPU}}_{j(i),t-2}$ is the estimated sensitivity of industry j to policy uncertainty shocks, lagged by two years to ensure predetermined weights.[19] The industry-level sensitivity is estimated as:

$$r^{\text{risk-adj}}_{i,t} = \alpha_j + \beta^{\text{EPU}}_{j,\tau}\Delta\text{EPU}_t + u_{k,t},$$

where $r^{\text{risk-adj}}_{i,t}$ are Carhart-residual returns for firms i in industry j, estimated in rolling 5-year windows τ. This specification ensures that the exposure weights $\omega_{i,t-2}$ are based on ex-ante industry-level sensitivity to policy uncertainty.[20] We find that industries such as social services and transport exhibit high $\omega_{i,t-2}$, reflecting their strong dependence on government spending, regulation, and policy stability. These sectors are especially vulnerable to shifts in fiscal and regulatory uncertainty. In addition, manufacturing firms show elevated $\omega_{i,t-2}$ due to their exposure to trade-related policy risks, including tariffs, subsidies, and cross-border regulatory changes that directly affect supply chains and market access.

We test firm responses to a common aggregate shock using the innovation in policy uncertainty

[19] Outcomes are measured at t+1, so we end the exposure window at $t-2$ to ensure weights are predetermined and do not overlap with the t shock window. This mirrors Alfaro, Bloom, and Lin (2024)'s $t-3$ choice when outcomes are measured at t. Results are unchanged if we use $t-3$ instead and are available from the authors on request.

[20] Risk adjustment and windowing follow Alfaro, Bloom, and Lin (2024). Results are robust to significance-weighted exposures and alternative windows.

(ΔEPU_t) that captures unexpected changes or surprises in the policy environment.[21] As illustrated in Figure IA.A.1, major spikes in ΔEPU_t coincide with events such as tight U.S. presidential elections (e.g., 2000 Bush–Gore, 2016 Trump–Clinton), the Gulf Wars (1990–1991, 2003), the 9/11 terrorist attacks (2001), the Lehman Brothers collapse (2008), the U.S. debt ceiling crisis (2011), and the Eurozone sovereign debt crisis (2010–2012), all of which are associated with heightened policy uncertainty.

The firm-specific exposure is:

$$U_{i,t} = \omega_{i,t-2} \times \Delta\text{EPU}_t,$$

which varies within year t via $\omega_{i,t-2}$ and across years via the common shock. We estimate:

$$Y_{i,t+1} = \alpha_i + \beta\, U_{i,t} + \Gamma' X_{i,t} + \varepsilon_{i,t+1},$$

a canonical shift–share specification where the aggregate shock is orthogonal to firm-specific noise and the shares are predetermined. We hypothesize that higher exposure to policy uncertainty shock leads to a contraction in commercialization scale, as firms respond to sudden increases in perceived uncertainty. Accordingly, we expect $\beta < 0$.[22]

Our shift–share design generalizes the logic of event-based difference-in-differences (DiD) studies that exploit discrete uncertainty-inducing events, such as close elections or geopolitical shocks. In those designs, firms are typically classified into treated and control groups based on their exposure to the event, and treatment effects are estimated by comparing outcomes before and after the shock. In our framework, the aggregate policy uncertainty shock ΔEPU_t plays the role of the event, while the firm-level exposure weight $\omega_{i,t-2}$ captures the intensity of treatment. For example, firms in highly regulated industries (e.g., telecom) may be more sensitive to policy shocks, similar to how firms in politically exposed sectors respond more strongly to close elections. The interaction term $\omega_{i,t-2} \times \Delta\text{EPU}_t$ thus represents a continuous treatment effect, allowing us to trace heterogeneous firm responses to a common shock. This approach avoids reliance on discrete event timing and enables scalable identification of cross-sectional variation in uncertainty exposure, complementing traditional DiD designs with an exposure-weighted alternative.

[21] The innovation shock ΔEPU_t captures unexpected changes in policy uncertainty, such as surprise announcements or abrupt shifts in government stance. For example, a sudden announcement of a corporate tax overhaul that is not anticipated by markets would generate a spike in ΔEPU_t, prompting firms to reassess commercialization plans due to heightened perceived risk.

[22] As a robustness check, we also examine firm responses to policy uncertainty volatility (σ_t^{EPU}), which reflects the level of uncertainty, independent of directional changes. Results using $\omega_{i,t-2} \times \sigma_t^{EPU}$ reported in Table IA.A.2 are qualitatively similar. For example, prolonged political gridlock over tariff legislation (e.g., repeated delays, reversals, and inconsistent signals) can create a volatile policy environment that discourages long-term commercialization investments even in the absence of discrete shocks.

Our findings based on the exposure-weighted EPU shocks confirm our benchmark results. To facilitate comparison between the macro benchmark and shift-share specifications, we evaluate both with the same scenario: a 10-point increase in EPU_t. Evaluated at the exposure weight $\bar{\omega} = 2$, this yields an effect of $-0.005 \times 2 \times 10 = -0.10$, implying roughly a 10% decline in commercialization scale. Turning to composition, the macro specification shows the QI/(BS+NV) ratio increasing by $0.048 \times 10 = 0.48$, while the shift-share estimate implies an increase of $0.011 \times 2 \times 10 = 0.22$. The shift-share estimate is somewhat smaller, likely reflecting attenuation from measurement error in the exposure weights and the fact that the cross-sectional variation isolates only the policy-sensitive component of firm responses.

Both specifications thus confirm that large uncertainty shocks substantially reduce commercialization activity while tilting the remaining portfolio toward quality-improving products, with the macro estimates providing an upper bound and the shift-share results isolating the cross-sectional, policy-driven component of these effects. The consistency of both scale and composition effects across these alternative specifications underscores the robustness of the empirical relation between policy uncertainty and firms' commercialization choices.

3.3 IV with policy–driven idiosyncratic uncertainty

While the shift–share analysis highlights systematic differences in exposure to policy uncertainty, it does not fully disentangle policy-related movements from other firm-specific dynamics. We therefore complement it with an instrumental-variable specification that leverages policy-induced variation in firm-level uncertainty. Our instrumental variable strategy isolates exogenous, policy-induced variation in firms' idiosyncratic uncertainty. The instrument interacts aggregate exogenous shocks in policy uncertainty with firms' predetermined exposure, following the logic of Alfaro, Bloom, and Lin (2024), who show that financial frictions amplify uncertainty shocks and that cross-industry variation in exposure can be used to construct valid instruments for firm-level volatility.

To ensure the instrument captures second-moment (volatility) effects rather than first-moment directional policy news, we control for directional policy exposure ($\text{DirExp}_{i,t}$), which proxies for firms' expected policy stance. The resulting instrument reflects how the same policy shock differentially affects firms based on their historical sensitivity.[23]

Our setup is as follows. First, let $\sigma_{i,t}$ be the 252–day realized volatility of Carhart–residual daily returns for firm i (annualized). Our uncertainty regressor is:

$$\Delta\sigma_{i,t} = \sigma_{i,t} - \sigma_{i,t-1}.$$

[23]For example, telecom firms, highly exposed to regulatory shifts, experience stronger volatility responses than consumer staples firms, which operate in more stable policy environments.

Then EPU_t denotes the 252-day average of the daily Economic Policy Uncertainty index (Baker, Bloom, and Davis, 2016). We define the policy uncertainty shock as

$$\Delta EPU_t = EPU_t - EPU_{t-1},$$

which corresponds to a change in the perceived level of policy uncertainty and thus serves as a second-moment shock.

We interact this aggregate second–moment shock with firms' predetermined exposure,

$$z_{i,t}^{EPU} = \omega_{i,t-2} \times \Delta EPU_t, \qquad \omega_{i,t-2} \equiv \left|\beta_{j(i),t-2}^{EPU}\right|,$$

where $\beta_{j(i),t-2}^{EPU}$ is the industry $j(i)$ sensitivity to policy news estimated in rolling pre–sample windows. This is a standard shift–share construction described in Section 3.2: a common second–moment shock scaled by a predetermined share. To isolate second-moment (uncertainty) from directional policy news, we also include a first-moment control, $DirExp_{i,t}$ provided by Alfaro, Bloom, and Lin (2024).

The identification of our specification comes from within–year exogenous cross–sectional exposure to the aggregate policy uncertainty shock:

$$\begin{aligned} \text{First stage:} \quad & \Delta\sigma_{i,t} = \pi_1 \, z_{i,t}^{\text{EPU}} + \pi_2 \, \text{DirExp}_{i,t} + \Psi' X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t}, \\ \text{Second stage:} \quad & Y_{i,t+1} = \beta \, \widehat{\Delta\sigma}_{i,t} + \theta \, \text{DirExp}_{i,t} + \Gamma' X_{i,t} + \alpha_i + \delta_t + \eta_{i,t+1}. \end{aligned} \tag{3}$$

We include firm and year fixed effects and cluster standard errors by firm. Controls $X_{i,t}$ mirror the prior specifications with the additional inclusion of stock volatility.

The first-stage estimates confirm strong instrument relevance across all outcomes, with F-statistics > 20. In the second stage, a policy-induced rise in firm-specific residual volatility significantly reduces next-year product introductions, consistent with a decrease in commercialization scale. The composition results mirror earlier patterns where the QI/(BS+NV) ratio increases by about 0.41. The coefficients on the directional policy-news control, $DirExp_{i,t}$, are small and statistically insignificant, confirming that the effects are not driven by first-moment policy changes.

To assess the economic significance across specifications, we evaluate all three approaches at a common 10-point shock. The IV estimates capture the policy-driven component of firm-level volatility: for a firm exposure of 2, the 10-point EPU shock generates $z_{i,t}^{\text{EPU}} = 20$, which induces a first-stage volatility increase of $\Delta\sigma_{i,t} = 0.027 \times 20 = 0.54$. This translates to a second-stage scale effect of $-0.142 \times 0.54 = -0.08$ and a composition effect of $0.409 \times 0.54 = 0.22$. The IV scale effect is somewhat smaller than both the macro and shift-share estimates, while the composition effects converge across all three specifications. These results show that policy-driven idiosyncratic

uncertainty decreases commercialization scale and disproportionately discourages rival-displacing products, leaving incremental, quality-improving innovations comparatively resilient.

4 From Real-Option Condition to Testable Channels

The real-options view of investment offers a natural framework for understanding how policy uncertainty shapes firms' commercialization choices. At the moment of commercialization ($t = 0$), the firm weighs the expected stream of payoffs from launching a product against both the sunk costs of committing capital and labor and the alternative of preserving the option to wait. Investment occurs when the expected net benefit of commercialization today exceeds the value of waiting for uncertainty to resolve. Formally, the firm invests when:

$$[v_1 + \mathbb{E}(v_2) - (\kappa + \lambda)\tilde{n}] \geq \mathbb{E}\left[\max\left(v_2 - (\kappa + \lambda)\tilde{n}, 0\right)\right]. \tag{4}$$

Here, v_1 denotes the first-period payoff from commercialization (e.g., immediate profit, cost savings, or sales gains), $\mathbb{E}(v_2)$ is the expected payoff in later periods, $(\kappa + \lambda)\tilde{n}$ is the sunk cost of capital (κ) and labor (λ) scaled by project size $\tilde{n}$. The right-hand-side of the inequality denotes the option value of waiting, which is the expected benefit of postponing the investment decision. The inequality can therefore be interpreted simply: invest now if the expected payoff net of sunk costs is at least as large as the value of waiting.

Suppose the firm can commercialize one of two product types (business stealing BS or quality improving QI, as NV introductions are rare), each characterized by distinct payoff profiles and cost structures. For product type $C \in$ QI, BS, define its net option value as:

$$\Delta_T = \underbrace{v_1^C + \mathbb{E}[v_2^C]}_{\text{Expected payoff}} - \underbrace{(\kappa + \lambda)\tilde{n}_C}_{\text{Sunk cost}} - \underbrace{\mathbb{E}\left[\max v_2^C - (\kappa + \lambda)\tilde{n}_C, 0\right]}_{\text{Value of waiting}}. \tag{5}$$

$$v_1^{QI} + E[v_2^{QI}] > v_1^{BS} + E[v_2^{BS}], \tag{6}$$

$$(\kappa + \lambda)\tilde{n}_{QI} + E[\max(v_2^{QI} - (\kappa + \lambda)\tilde{n}_{QI}, 0)] < (\kappa + \lambda)\tilde{n}_{BS} + E[\max(v_2^{BS} - (\kappa + \lambda)\tilde{n}_{BS}, 0)]. \tag{7}$$

Equation 6 compares products' expected payoffs, while equation 7 compares their total exercise costs, the combination of sunk costs and the foregone option value of waiting. The preference for QI over BS can be understood through two comparisons: (i) a payoff advantage (higher $v_1 + E[v_2]$) and (ii) a lower total exercise cost (sunk cost plus lost option value). A QI project will be chosen over BS if it offers both a payoff advantage (inequality 6) and a lower total exercise cost (inequality 7). Alternatively, if only one inequality holds, QI is preferred when its payoff advantage is large

enough to offset any cost disadvantage (or vice versa).

The conceptual benchmark in Eq. 5 decomposes the commercialization decision into three objects: (i) the expected payoff stream $v_1^C + \mathbb{E}[v_2^C]$, (ii) irreversible costs $(\kappa + \lambda)\,\tilde{n}_C$, and (iii) the value of waiting. Our empirical strategy mirrors this decomposition. First, we use local projections to recover the timing and persistence of realized payoffs across product types. Second, we measure irreversible capital and labor commitments to establish differences in $(\kappa + \lambda)\,\tilde{n}_C$. Third, we show that BS products require significantly more and more expensive external finance than QI products, consistent with a financing wedge $\phi_{\text{BS}} > \phi_{\text{QI}}$ that raises the effective sunk cost and amplifies the option-value channel under uncertainty.

4.1 Payoffs Profile Channel

For the payoff mechanism test, we estimate local-projection regressions tracing firm profitability and sales over a ten-year horizon after the introduction of each product type. Specifically, we estimate dynamic impulse responses using Local Projection Regressions (LPR; Jordà, 2005), interacting each product-type commercialization measure with contemporaneous policy uncertainty, EPU_t. The impulse-response profiles capture the timing and persistence of payoffs and trace how the timing and persistence of firm-performance responses vary across uncertainty regimes. Under high policy uncertainty, we expect BS products to show weaker and more delayed profitability responses, while QI products display steadier or slightly front-loaded gains. This dynamic contrast identifies the differential payoff timing embedded in the real-options mechanism. We estimate:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \sum_{C\in\{\text{BS,QI,NV}\}} \left(\beta_\tau^C\, N_{i,t}^C + \psi_\tau^C\, N_{i,t}^C \times EPU_t\right) + \sum_{l=1,2} \gamma_\tau \ln(Y_{i,t-l}) + \Gamma' X_{i,t} + \alpha_{\text{sic3}} + \delta_t + \varepsilon_{i,t}, \tag{8}$$

where $Y_{i,t+\tau}$ is profits or sales at horizon τ, $N_{i,t}^C$ is the number of commercialized products of type C by firm i in year t, $X_{i,t}$ is a vector of control variables which includes firm size, age, employment, and idiosyncratic volatility, and α_{sic3} and δ_t are industry and time fixed effects.[24] All regressors are standardized for comparability.

The baseline coefficients β_τ^C tell us the timing and magnitude of payoffs for product type C at the mean EPU. In the real-option framework, they reflect how much immediate payoff (v_1^C) and continuing payoff (v_2^C over time) the firm realizes from that product type. The interaction coefficients ψ_τ^C show how the payoffs change under uncertainty. If ψ_τ^C is negative at certain horizons, it indicates that when uncertainty increases, the payoff at that horizon decreases. In other

[24] We cannot include EPU_t as a regressor because its effect is absorbed by the time fixed effects δ_t.

words, the firm is not reaping as much benefit in that period, consistent with either delaying some investment or the project underperforming due to uncertainty. We expect an attenuation pattern, if the option value of waiting is high, particularly for projects with long-dated payoffs (BS). A positive ψ_τ^C indicates that product type C performance improves with higher uncertainty, either because its payoffs are more front-loaded or because it benefits from reallocation effects as consumers and firms shift toward lower-risk alternatives.

Table 8 reports LPR estimates for profits and sales. Under normal conditions, all product types contribute positively to firm growth but with distinct timing profiles. QI products yield rapid gains, coefficients increase to about 0.035 by year six before leveling off, consistent with incremental innovations that boost efficiency almost immediately. BS products follow a similar start but continue to accumulate, increasing from roughly 0.02 in year one to about 0.06 by year ten, reflecting compounding returns from rival displacement and market-share capture. NV products show smaller yet positive medium-term effects, consistent with early-stage experimentation.

Policy uncertainty reshapes these trajectories. High EPU_t significantly reduces medium-term returns to BS products (-0.008 to -0.013), while QI products show positive interaction coefficients (0.007 to 0.014), indicating relative resilience: they maintain or exceed baseline performance even as uncertainty penalizes longer-horizon commercialization strategies. The pattern is consistent with demand-side flight to quality: when economic uncertainty increases, risk-averse consumers favor familiar products and established brands over new market entrants or unfamiliar categories (Villas-Boas, 2004). QI innovations, which enhance existing product lines, benefit from this shift, while BS products (entering competitive markets) and NV products (exploring new categories) face heightened consumer skepticism and adoption risk. NV interactions remain small and statistically insignificant.[25]

To illustrate magnitudes, we construct payoff profiles for each product type under normal and high-uncertainty regimes in Figure 7. Baseline coefficients β_τ^C capture normal-state effects, while $\beta_\tau^C + \psi_\tau^C$ reflect outcomes when EPU_t increases by one standard deviation. The graph shows how uncertainty compresses the duration of returns: BS payoffs flatten beyond year three, whereas QI payoffs remain front-loaded and resilient. Cumulative ten-year payoffs for BS products decline by approximately 15% under high uncertainty, while QI products decline by 10%. The divergence between these product types' payoff profiles is most pronounced in the early years: under high uncertainty, QI payoffs exceed BS from year one and remain higher through year five, reflecting

[25]In robustness analyses, we show that our findings are not driven by cross-sectional scale heterogeneity or by the growth denominator's accounting arithmetic. To not mix uncertainty's effect with firm size or secular scope growth, we scale product commercialization by total assets in estimating Equation 8. These coefficients speak to commercialization propensity conditional on capacity, which is important in real-options and financing models where option values and funding costs scale with firm size. Results in Table IA.A.3 show that the horizon profiles remain qualitatively similar. Analysis in Table IA.A.4 conditions on the time 0 response which economically distinguishes "level shifts at launch" from true persistence (or mean reversion) in payoffs. The results remain qualitatively similar.

the QI front-loaded efficiency gains. In contrast, BS payoffs flatten under high uncertainty, failing to catch up within the five-year window. This supports the interpretation that uncertainty not only delays innovation but also reallocates it. This pattern suggests that under high uncertainty, firms either scale back the expansion trajectory of BS products, consistent with firms keeping their options more open with higher discount-rate risk on long-dated cash flows, or these projects struggle to gain traction in later years.

These dynamics provide direct evidence of a payoff-profile channel. Whereas Campello and Kankanhalli (2024) emphasizes option value through staging flexibility of R&D, our mechanism operates through differences in the intrinsic duration of commercialization payoffs. BS products depend on sustained post-launch expansion and long-dated cash flows, making them vulnerable when discount-rate uncertainty increases. QI products deliver quicker, more predictable returns and thus retain value. It is not only about when payoffs occur, but also how long and sustained they need to be for a project to succeed. Uncertainty penalizes projects that require a long period of continued success (BS) far more than those that yield most of their gains upfront (QI).

These results show that policy uncertainty not only slows commercialization but also changes the payoff profile. By shortening the effective payoff horizon, uncertainty significantly reduces returns to rival-displacing products across most time horizons, while quality-improving products demonstrate resilience through positive interaction effects in early years. Firms respond by pivoting towards products that yield faster, less volatile short to medium-term payoffs. The differential sensitivity, payoff-profile channel, explains the compositional QI tilt observed earlier and shows how uncertainty rewires the corporate growth engine, from long-horizon creative destruction toward short-cycle, defensive innovation.

4.2 Capital Investment (Irreversibility) Channel

We now map the cost term in Eq. 7, $(\kappa + \lambda)\,\tilde{n}_C$, into observables. We estimate dynamic cost responses using the same local-projection setting as in Eq. 8 with dependent variables that proxy irreversible commitments: the components of property, plant and equipment (PPE) and labor. A project that requires significant new capital buildout or hiring indicates a high sunk cost. Conversely, a project that can be executed with existing capacity or minimal new investment would show little change in those measures. Larger and more persistent responses indicate higher irreversibilities for type C. By interacting product launches with EPU_t, we analyze if firms commit differently under high uncertainty.

Table 9 reports the local-projection estimates for firm-level capital (PPE), decomposed into buildings & construction, land, leases, and machinery & equipment. We find considerable heterogeneity in cost dynamics across product types. BS commercialization is the most capital-intensive:

coefficients rise steadily from roughly 0.01 in the first year to 0.04–0.06 by year ten across most asset categories, with particularly strong and persistent increases in building & construction and land. These patterns indicate large and irreversible fixed-cost commitments that accumulate over time. QI products display smaller, front-loaded responses: coefficients peak around 0.02 in years three to five (mainly in machinery and equipment) and then stabilize, consistent with incremental upgrades that draw on existing production capacity. NV products exhibit muted or slightly negative cost responses, with small and statistically insignificant coefficients across horizons, suggesting exploratory activity that does not immediately translate into fixed investment.[26]

Employment responses in Table 10 mirror the capital patterns. BS products generate persistent employment growth, rising from 0.01 in year one to 0.04 by year ten. QI products reach similar long-run levels (0.038) but accumulate more gradually. NV products show modest effects.

Interaction terms with EPU in both tables are small and statistically insignificant across all product types, confirming that neither capital nor labor commitments vary with policy uncertainty. The composition shift reflects selection among product types with distinct fixed-cost requirements, not time-varying marginal costs. Uncertainty does not change the sunk costs $(\kappa+\lambda)\tilde{n}_{BS}$ themselves, but makes BS projects less attractive because their large, irreversible cost base amplifies the option value of waiting. These cost results indicate that $(\kappa+\lambda)\tilde{n}_{BS} > (\kappa+\lambda)\tilde{n}_{QI}$. Hence, when uncertainty increases the option value of waiting, this option value increases more for BS projects due to their larger sunk costs (the option value depends on $v_2^{BS} - (\kappa+\lambda)\tilde{n}_{BS}$). Consequently, the total exercise cost (sunk costs plus foregone option value) increases more sharply for BS than for QI, making BS relatively less attractive under high uncertainty.

These results reinforce the broader mechanism established earlier. Firms facing heightened uncertainty tilt toward QI products not because their costs fall, but because BS innovations carry heavier upfront commitments and longer recovery periods. Thus, policy uncertainty induces a selection effect on the cost dimension: firms reallocate toward commercialization strategies that are cheaper, quicker, and more reversible. Together with the payoff analysis, this evidence shows that uncertainty compresses both the expected duration of returns and the feasible scale of investment, rewiring the firm's growth engine toward short-cycle, cost-efficient innovation.

Overall, the payoff and cost analyses provide a unified picture of how uncertainty reshapes firm innovation strategy. Policy uncertainty does not change the investment costs; rather, it shifts firms' selection toward commercialization projects with inherently shorter payoffs and lighter capital intensity. This reallocation has direct implications for firm financing. If BS innovations are both long-horizon and capital-intensive, while QI innovations are quick and asset-light, then uncertainty should also reshape firms' financing choices, particularly their reliance on debt versus equity.

[26]The standard PPE measure is net PPE, which we also use here. Alternatively, one can use gross PPE components. Results in Table IA.A.5 remain qualitatively unchanged using gross PPE.

4.3 Financing Channel

Finally, we connect financing outcomes to the effective exercise cost in Eq. 7. Even absent changes in a firm's borrowing costs, BS and QI projects may differ in their reliance on external finance. We capture this heterogeneity by augmenting the sunk-cost term with a type-specific financing wedge:

$$(\kappa + \lambda)\tilde{n}_C^{\text{eff}} = (\kappa + \lambda)\tilde{n}_C[1 + \phi_C], \tag{9}$$

where $\phi_C \geq 0$ measures the financing friction for product type C, with $\phi_{\text{BS}} > \phi_{\text{QI}}$, and ϕ_{NV} near zero reflecting NV's reliance on internal funds. We test this mechanism by examining how financing structures differ across product types. If BS products systematically require more external finance, then the higher base cost $(\kappa+\lambda)\tilde{n}_C^{\text{eff}}$ amplifies the option-value channel documented earlier. Specifically, we estimate two-way fixed-effects regressions with dependent variables that proxy firms' financing structure: debt and equity issuance, leverage, and cash holdings.

Table 11 reports firm-level regressions linking financing outcomes: debt and equity issuance, leverage, capital expenditures (CapEx), and operating cash flow (OCF), to commercialized products. BS products are associated with more external financing (equity and debt) and investment intensity. CapEx rises significantly, while operating cash flow declines with BS introductions. These patterns indicate that BS commercialization is heavily externally financed, consistent with its capital-intensive and expansionary nature. QI products correlate positively with debt but negatively with equity issuance, suggesting a preference for moderate debt financing. Their CapEx response is smaller and OCF effects are muted, consistent with incremental, lower-risk investments that rely partly on internal liquidity. NV products exhibit weak or negative correlations with external financing and a slight positive association with cash flow, implying that exploratory commercialization depends primarily on internal resources and flexible capacity rather than external funding.

The economic magnitudes of these effects are also meaningful. For a one standard deviation increase in BS products commercialized in one year, the likelihood of issuing equity increases by 1.2%, an 11% increase from the mean, and of issuing debt by 1.5%, a 17% increase from the mean. The equity amount raised increases by 9.1%, and debt amount issued increases by 12%. For a one standard deviation increase in QI products commercialized in one year, the likelihood of issuing debt increases by 1.5%, 17% increase from the mean, while equity issuance likelihood does not change. By contrast, the equity amounts raised decreases 7%, and debt issuance increases by 31%.

Firm fixed effects difference out all time-invariant traits (business model, capital structure, persistent product mix), and coefficients in Table 11 are identified from a firm's year-on-year shifts in BS, QI, and NV launches. This specification could "over-control," if part of the effect reflects cross-sectional reallocations among firms facing the same industry conditions. We re-estimate the financing relation using industry and year fixed effects, where identification comes from cross-firm

differences within industries, soaking up common industry shocks, and asking whether firms that commercialize different product types in the same market finance differently. Tables IA.A.6 and IA.A.7 present results using SIC4 and TNIC as industry fixed effects, respectively. TNIC is the sharper test because it defines industries from product-market text similarity (rather than coarse SIC), hence it better aligns the peer set with product-market competitors. Moving from firm to industry fixed effects can attenuate magnitudes and alter standard errors because the identifying variation changes. However, results remain qualitatively similar across different specifications, indicating that our findings are not driven by persistent firm traits or industry-wide cycles.

Because BS products require more expensive external financing (equity), their higher effective sunk cost $(\kappa + \lambda)\tilde{n}_C^{\text{eff}}$ amplifies the option-value effect. When uncertainty increases the value of waiting, this mechanism penalizes externally (equity) financed projects more heavily, inducing firms to shift toward QI products that can be executed with debt or internal capital. This financing-structure channel complements the timing and cost mechanisms, providing a coherent account of how policy uncertainty reshapes firm innovation from long-horizon, equity-financed expansion toward short-cycle, debt or internally funded commercialization.

The three mechanisms together reveal how uncertainty reconfigures the commercialization process rather than simply slowing it. The payoff-profile channel shows that uncertainty shortens the effective duration of returns, reducing the value of long-horizon, rival-displacing projects. The cost-structure channel shows that firms selectively avoid projects with large, irreversible capital requirements. The financing-structure channel shows that BS projects' heavier reliance on equity finance raises their effective sunk cost, amplifying the option-value mechanism that makes them less attractive under uncertainty. Together, these forces compress both the temporal and financial horizons of innovation: firms reallocate from business-stealing products (long-dated, capital-intensive, and equity financed) toward quality-improving products that are shorter-cycle, lower-cost, and debt funded. This integrated framework explains why aggregate commercialization decreases under uncertainty and why its composition shifts toward incremental innovation, providing a coherent micro-foundation for the macro link between uncertainty, financing structure, and the pace of creative destruction.

5 Robustness

A potential concern is that the growth effects attributed to commercialization may simply reflect upstream innovation activity. Patents and R&D are widely used proxies for inventive effort, and it is important to establish whether product-level commercialization carries distinct information about firm performance beyond these traditional inputs. To address this, we include patent counts and firm R&D stock as control variables in Equation 8. Table C.3 presents the results. Three findings

emerge: first, commercialization remains a stronger and more consistent predictor of growth than invention. BS, QI, and NV products are significantly associated with subsequent firm performance, while patent coefficients are smaller and often statistically insignificant until the very long run. For example, a one-standard-deviation increase in BS products corresponds to cumulative gains of 4–4.5% in profits and sales over a decade, while patents alone contribute only 2–3%.

Second, the differentiated roles of product types persist even after controlling for invention. BS products generate persistent gains, consistent with models of creative destruction and demand reallocation (Aghion and Howitt, 1992). QI products yield robust short- and medium-run increases, while NV products, though less frequent, are associated with positive long-run effects on sales and profit, consistent with exploratory expansion into new demand segments (Cohen, Nelson, and Walsh, 2000). Third, traditional innovation inputs contribute modestly once commercialization is accounted for. R&D stock shows short-run positive associations, about 1% higher profits and sales within three years, but these fade quickly at longer horizons. This pattern suggests that R&D captures resource commitment rather than realized payoff, and that commercialization is the channel through which invention translates into firm growth.

These results establish commercialization as a distinct strategic margin beyond inventive activity. Even after controlling for patents and R&D, product launches carry independent explanatory power for firm growth, with BS and QI products generating persistent gains that dwarf the modest contributions of invention alone. The robustness of this pattern across both count- and value-weighted specifications underscores the importance of distinguishing product types when analyzing innovation-led expansion.

To further test whether the intensity of commercialization matters beyond counts alone, we estimate a value-weighted specification, scaling product types by their estimated market value (θ). The results in Table C.4 indicate that high-value launches disproportionately drive long-run expansion. BS and QI products yield larger and more persistent coefficients, while NV products remain significant but economically smaller. This mirrors findings in the invention literature that patent value sharpens predictive power (Kogan et al., 2017), and suggests that value-weighted commercialization indices capture the economic weight of realized innovation.

We exploit our longer sample availability to investigate the robustness of our results. Starting in 1950 brings in additional policy regimes, high-uncertainty post-war episodes (e.g., Bretton Woods, oil shocks, Volcker disinflation), and adds more business-cycle variation. The analysis is presented in Appendix D. In the extended sample, the macro benchmark is unchanged in Table IA.B.2, where uncertainty continues to lower total commercialization and to raise the QI share, with magnitudes similar and often slightly larger in absolute value. The mechanism effects also remain qualitatively similar. Payoff profiles in Table IA.B.3 keep the same ordering (QI front-loaded, BS persistent, NV gradual), and uncertainty loads most negatively on BS. PPE investment and employment responses

in Tables IA.B.4 and IA.B.5 show BS as the most scale-intensive margin. The financing patterns in Table IA.B.6 show that BS is even more tied to equity finance, while QI is more debt-financed. Overall, results remain qualitatively unchanged; if anything, the longer sample slightly strengthens the case that uncertainty compresses scale and tilts firms toward quality-improvement products.

6 Conclusion

This paper introduces a new approach to measuring firm-level commercialization using the universe of U.S. trademarks linked to legally verified first-use-in-commerce dates. The resulting classification (business-stealing, quality-improving, and new-variety products) captures what firms actually bring to market, moving beyond input-based proxies like patents and R&D. Linked to nearly a century of firm-level data, this measure reveals systematic heterogeneity in how different product types drive growth, investment, and financing.

We document three forces that govern firms' commercialization choices under uncertainty. Business-stealing products generate slow, compounding returns through market-share capture, require large irreversible capital commitments, and depend heavily on external finance. Quality-improving products deliver front-loaded payoffs, use existing capacity, and rely on internal funds. Policy uncertainty, therefore, operates through selection: by raising the option value of waiting, it disproportionately penalizes products with long horizons, high fixed costs, and external financing needs. Firms respond by reallocating toward shorter-cycle, lower-cost, internally funded product commercialization.

This selection mechanism reconciles several strands of theory. Real-options models predict that uncertainty delays investment, but cannot explain why some projects proceed while others stall. Financing-frictions models emphasize credit constraints, but typically treat innovation as homogeneous. Growth models distinguish product types by their effect on market structure, but abstract from firms' dynamic commercialization decisions. Our evidence shows these channels operate jointly: uncertainty compresses the temporal and financial horizons of innovation by shifting composition toward products that are naturally quicker, leaner, and less dependent on external capital.

The framework generalizes beyond uncertainty. Technological shocks, regulatory reforms, and competitive pressures all affect the relative attractiveness of business-stealing versus quality-improving strategies. By opening the product portfolio to systematic measurement, this paper provides empirical tools for testing when firms pursue creative destruction, how competition shapes innovation intensity and direction, and whether financial frictions bind differently across innovation types. The answer to when and why firms innovate depends not just on how much they invest, but on what they choose to commercialize.

Tables and Figures

Figure 1
Example trademark page

The figure provides an example page (screenshot) of a trademark publication in the Trademark Electronic Search System (TESS, `https://tmsearch.uspto.gov/`). We underline in red the most relevant fields in the trademark publication, including the first-use and the first-use-in-commerce dates.



Word Mark	OFFICE
Goods and Services	IC 009. US 021 023 026 036 038. G & S: Computer software and computer programs for use in database management, electronic spreadsheets, designing, creating, editing and publishing documents, note taking, email, calendaring, scheduling, contact information storage and management, accounting, customer relationship management, project management, presentation graphics, desktop publishing, web publishing, document management, database management, data collection, data analysis, graphics, presentation graphics, word processing, instant messaging, Voice over Internet Protocol (VoIP), video conferencing, audio conferencing, web conferencing and document sharing, application sharing, computer desktop sharing, file transfer, sensing and providing user presence information, telephony, real-time communications featuring instant messaging, audio, video and data exchange, mapping geographical locations, manipulating video, audio and graphics; communications software for managing the exchange of communications and data and information over computer networks, wireless networks, and global communications networks; computer communications software for use in accessing web sites and exchanging information and data and obtaining services from web sites; computer software for use in developing web sites, operating electronic mail and providing computer security; computer software for recording, organizing, editing and transmitting information in typed written and voice format; computer communications software for accessing web messaging and shared documents from web sites on the Internet; computer utility programs; computer software development programs; computer security and authentication software for controlling access to and communications with computers; computer software for computer network security, anti-virus protection, and intrusion detection and prevention; computer game software; house mark for a full line of business software applications. FIRST USE: 20121212. FIRST USE IN COMMERCE: 20121212
Mark Drawing Code	(3) DESIGN PLUS WORDS, LETTERS, AND/OR NUMBERS
Design Search Code	26.05.21 - Triangles that are completely or partially shaded 26.11.02 - Plain single line rectangles ; Rectangles (single line)
Serial Number	85799081
Filing Date	December 10, 2012
Current Basis	1A
Original Filing Basis	1B
Published for Opposition	May 21, 2013
Registration Number	4456462
Registration Date	December 24, 2013
Owner	(REGISTRANT) **Microsoft** Corporation CORPORATION WASHINGTON One **Microsoft** Way Redmond WASHINGTON 980526399
Attorney of Record	Matthew E. Moersfelder
Disclaimer	NO CLAIM IS MADE TO THE EXCLUSIVE RIGHT TO USE "OFFICE" APART FROM THE MARK AS SHOWN
Description of Mark	Color is not claimed as a feature of the mark. The mark consists of a three-dimensional geometric design with two vertical sides and two horizontal sides. The vertical sides and top side are three-dimensional images of rectangular solids and the bottom side is a three-dimensional image of a triangle. To the right of the geometrical design is the word "Office".
Type of Mark	TRADEMARK
Register	PRINCIPAL
Affidavit Text	SECT 15. SECT 8 (6-YR).
Live/Dead Indicator	LIVE

Figure 2
Process of trademark registration

The figure shows the typical timeline in the trademark application process. The process entails three steps: (1) An application is filed on the filing date to be examined by a randomly assigned attorney. (2) If it passes the examination, it is approved for publication and published for opposition in the Official Gazette on the publication date. (3) If there is no opposition the trademark is registered on the registration date.

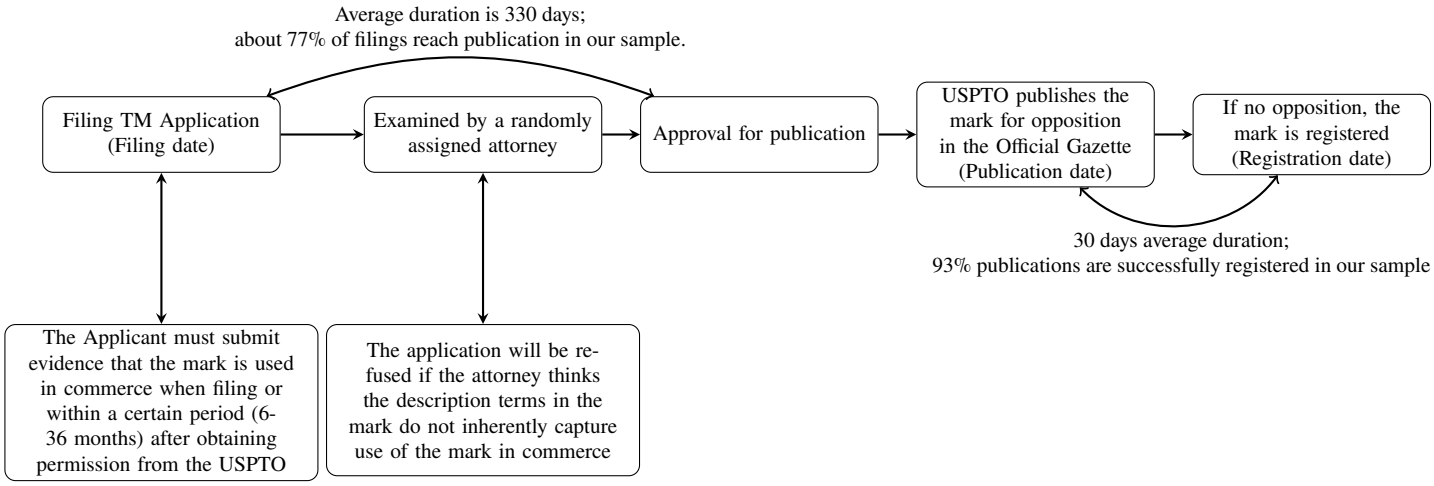


Figure 3
Example page for Trademark ID manual

The figure presents the output page for the search for "mobile phone" in the Trademark ID Manual, which contains 67,104 unique Term IDs as of July 1, 2024.

Term ID	Class	Description	Status	Type
009-2657	009	*Mobile phones*	A	GOODS
009-5849	009	Braille *mobile phones*	A	GOODS
009-1618	009	Keyboards for *mobile phones*	A	GOODS
009-1360	009	Cases for *mobile phones*	A	GOODS
009-3665	009	Straps for *mobile phones*	A	GOODS
038-177	038	Communications by *mobile phones*	A	SERVICES
042-2350	042	Unlocking of *mobile phones*	A	SERVICES
009-6662	009	Batteries for *mobile phones*	A	GOODS
009-6538	009	Lanyards for *mobile phones*	A	GOODS
009-7101	009	Mounts for *mobile phones*	A	GOODS
009-3054	009	Downloadable graphics for *mobile phones*	A	GOODS
009-4545	009	Cases adapted for *mobile phones*	A	GOODS
009-5290	009	Battery chargers for *mobile phones*	A	GOODS
009-6034	009	Leather cases for *mobile phones*	A	GOODS
009-4770	009	Stands adapted for *mobile phones*	X	GOODS
026-4079	026	Decorative charms for *mobile phones*	A	GOODS
009-5502	009	Downloadable emoticons for *mobile phones*	A	GOODS
009-6937	009	Protective cases for *mobile phones*	A	GOODS

Figure 4
Process of matching trademark statement text to ID Manual

The figure presents an example of the matching procedure we follow to match the trademark goods & services (G&S) statement text to the Term IDs in the Trademark ID Manual. We use the iPhone trademark (Serial No. 77078484) as example to illustrate the matching procedure.

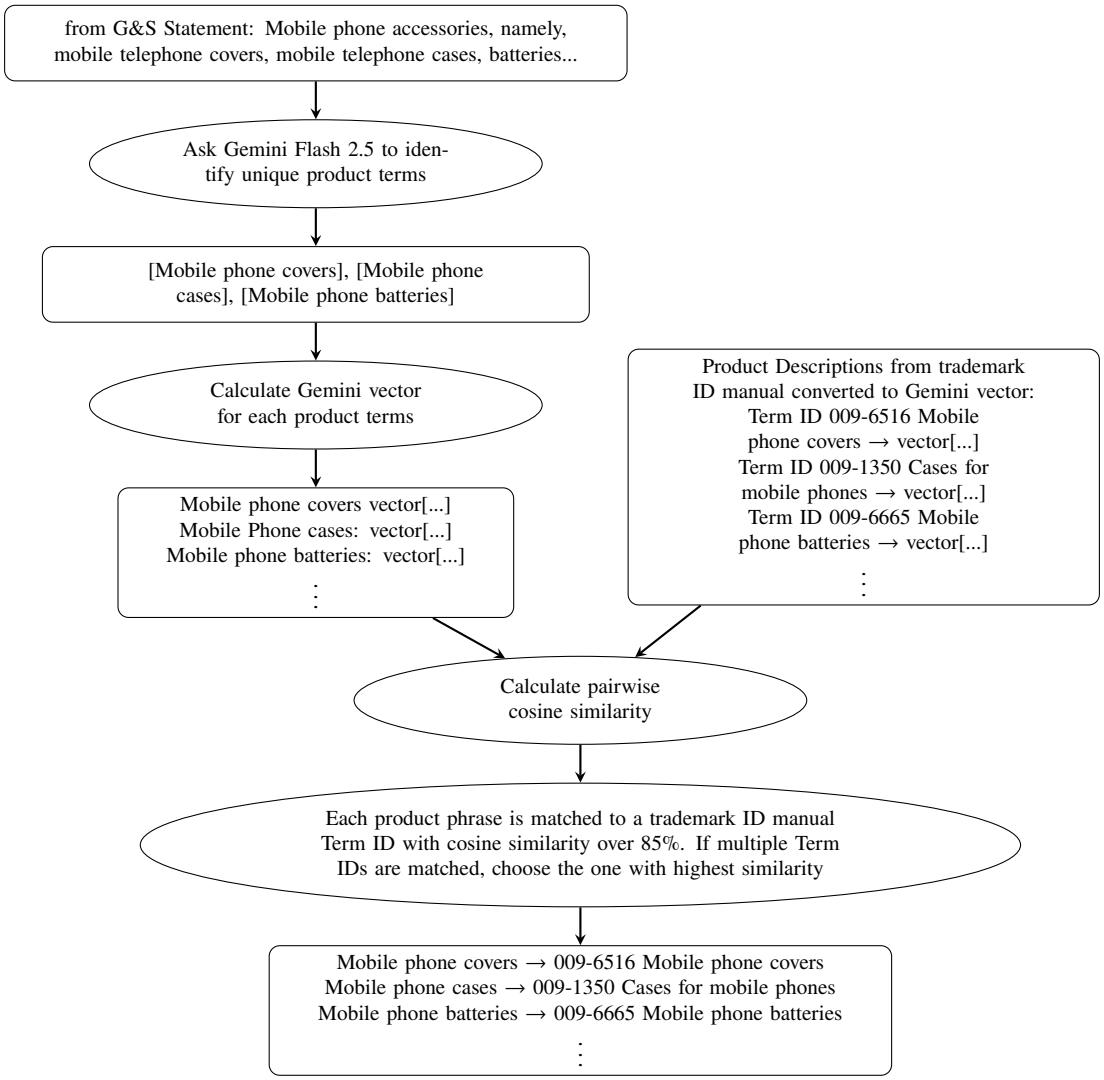


Figure 5
Trademark product value and product sales

The figure presents a scatter plot of the relation between product sales and trademark product value. The aggregate value of the product sales (1982 dollars in millions) is from the Compustat Segments product database. The trademark product value is the market value (ξ in 1982 dollars in millions, calculated as described in Appendix A2) of individual trademarks as per the trademark commercialization date. The y-axis presents the log of total product sales from 1998 to 2018, the x-axis presents the log trademarked product value ξ.

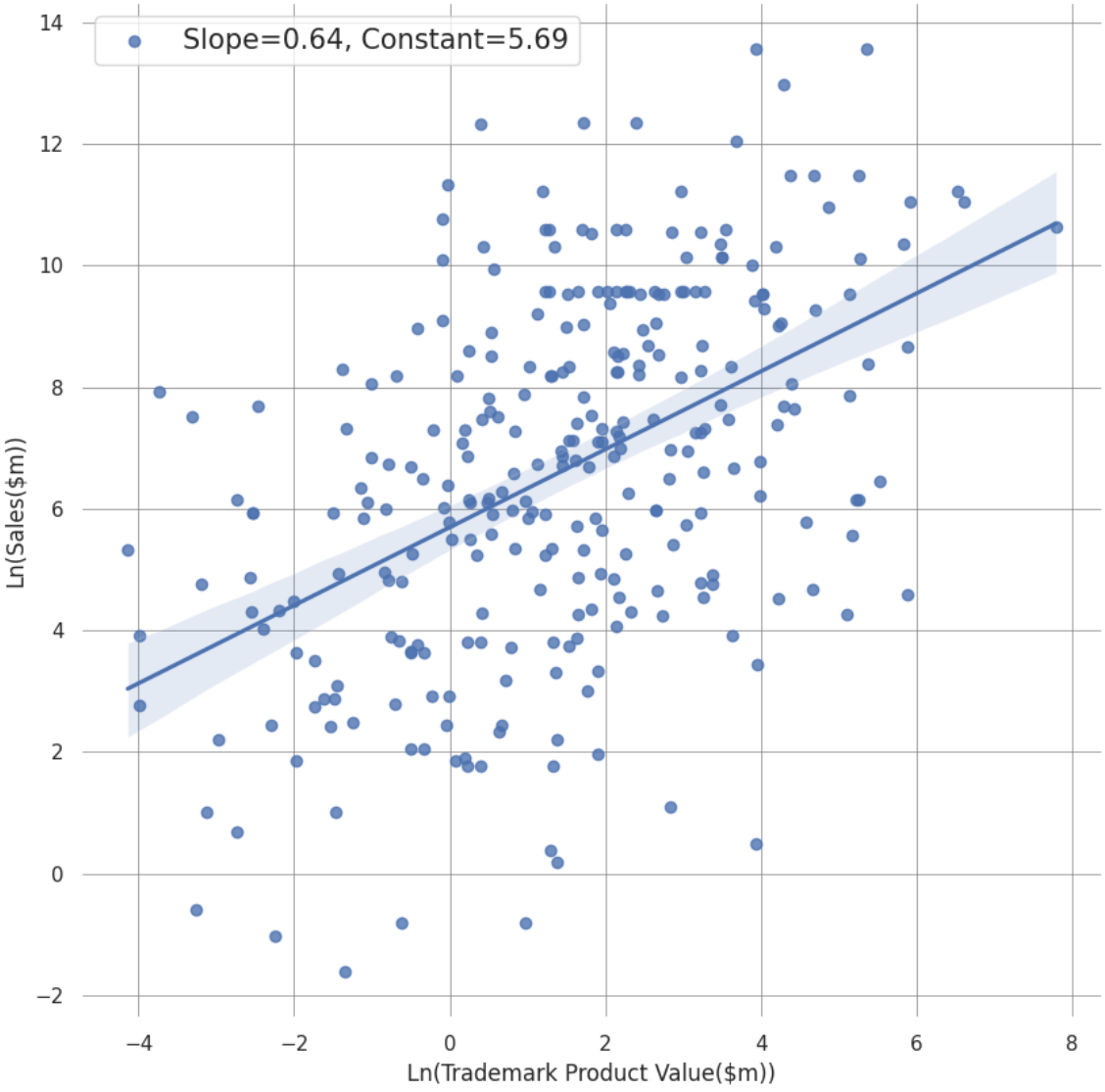


Figure 7
Product type payoffs and uncertainty estimated coefficients

The figure plots local-projection impulse responses of cumulative firm profit growth, $\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right)$, over horizons $\tau = 1, ..., 10$ following commercialization at time t, as presented in Panel A of Table 8. For each product type $C \in \{BS, QI, NV\}$, the solid lines show the baseline effect (β_τ^C) at mean policy uncertainty, and the dashed lines show the effect at high uncertainty (ψ_τ^C). High uncertainty is estimated as one standard deviation increase in EPU. The sample period is 1976 to 2020.

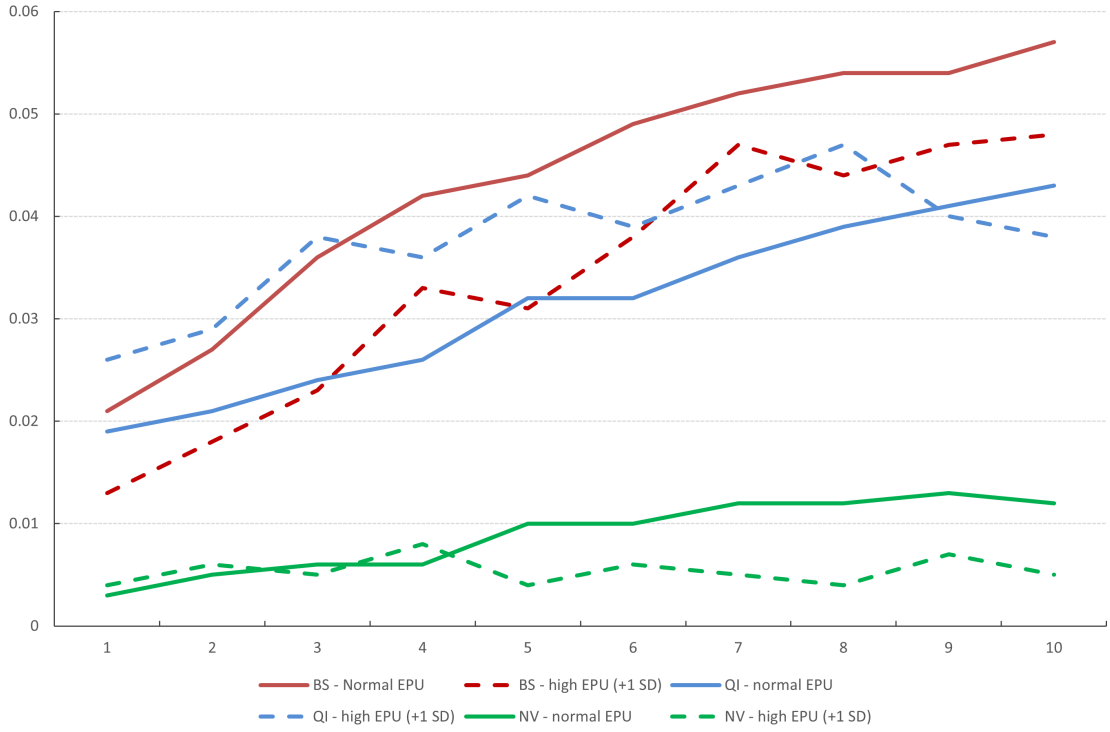


Figure 6
Time series variation of product types

The figure presents the average number of products commercialized per firm by product type for each Fama-French industry and year. Business stealing (BS) and quality improvement (QI) are presented on the right Y-axis, new variety (NV) is on the left Y-axis. Product types are defined in Section 2.2.

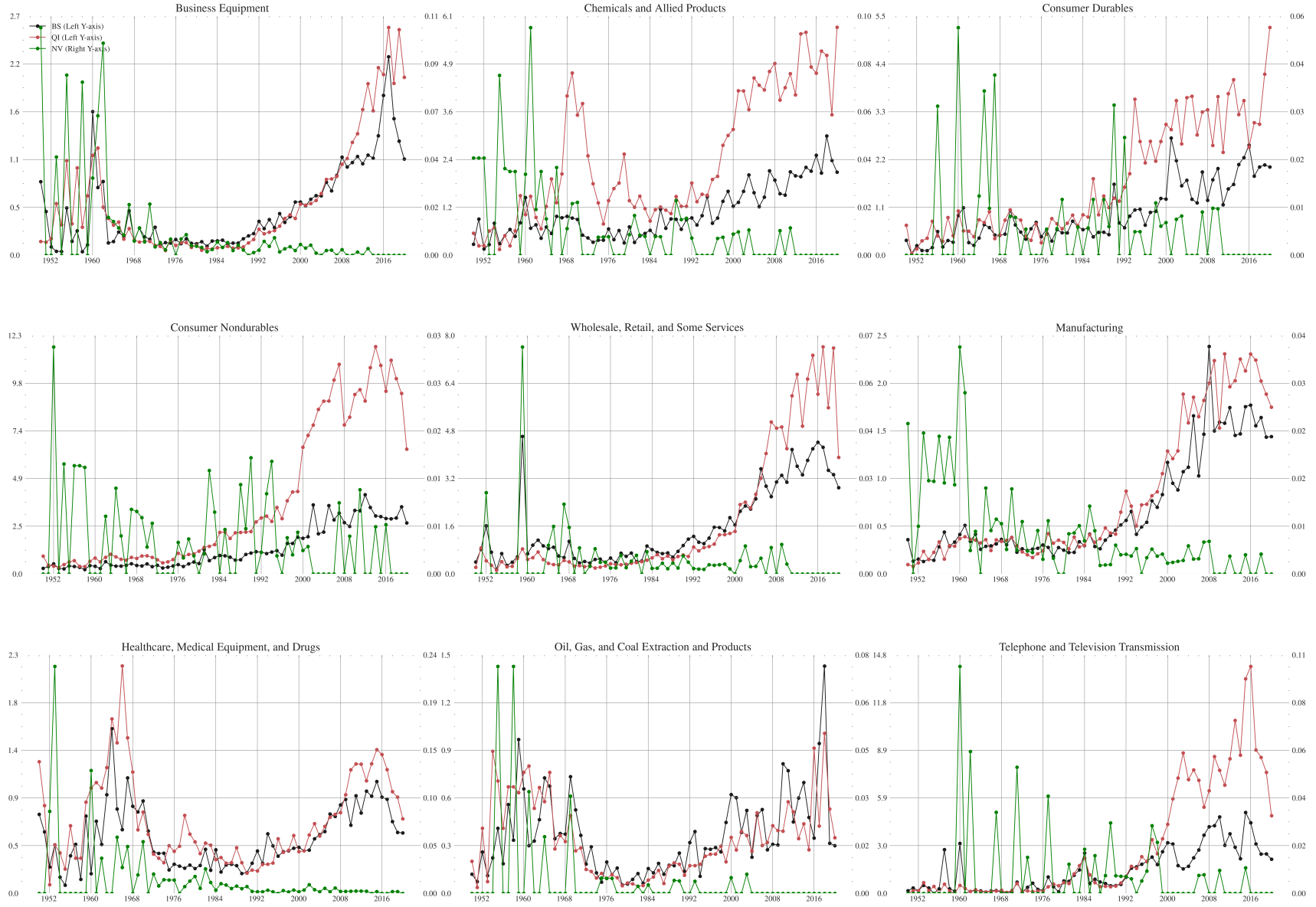


Table 1
Product segments and product lines

The table presents the regression results for the relation between Compustat Segments products and product lines measured by trademarks. Columns (1)-(3) present OLS regression coefficients where the dependent variable is ln(1+number of product segments). Columns 4-6 present Poisson regression coefficients where the dependent variable is the number of product segments. T-statistics adjusted for clustered standard errors at firm level are reported in the parentheses. ***, **, * indicate significance at 1%, 5% and 10% level. The sample period is 1999 to 2018.

	OLS			Poisson		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(Product Lines (NICE))	0.152***	0.036***	0.038**	0.222***	0.032**	0.044***
	(13.64)	(2.71)	(2.47)	(11.23)	(1.96)	(3.41)
SIC4 FE	✓			✓		
Year FE	✓	✓		✓	✓	
Firm FE		✓	✓		✓	✓
SIC4 × Year FE			✓			✓
Obs.	32,739	31,911	30,042	32,739	31,911	30,042
Adj. R^2	0.31	0.87	0.88			

Table 2
Trademark firm characteristics

The table reports univariate characteristics of firms with and without trademarks, and their difference. TM presents the characteristics of firm-years, where each firm has at least one live trademark. Non-TM presents the characteristics of firm-years where the firm does not have any live trademarks. Diff. is the difference between TM and non-TM, and t-stat is the associated t-statistic. A trademark is considered live until not renewed or canceled. All variable definitions are presented in Table C.1. ***, **, * indicate significance at 1%, 5% and 10% level. All potentially unbounded variables are winsorized at 1% level. The sample period is 1976 to 2020.

	All				TM				All − TM	
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	Diff.	t-stat
ln(Assets)	168,597	4.91	4.77	2.20	131,411	5.35	5.23	2.13	-0.43***	-54.27
ROA	168,594	-0.05	0.03	0.27	131,409	-0.03	0.04	0.24	-0.02***	-22.42
CAPX	168,597	0.07	0.04	0.07	131,411	0.06	0.04	0.06	0.01***	20.43
PPE	168,397	0.28	0.22	0.22	131,250	0.27	0.21	0.21	0.01***	15.17
R&D	168,597	0.05	0.00	0.10	131,411	0.05	0.00	0.10	0.00***	4.77
Leverage	168,588	0.71	0.34	2.15	131,406	0.69	0.35	2.08	0.02**	2.40
Tobin's Q	166,654	2.01	1.42	1.74	130,583	1.98	1.43	1.66	0.03***	4.91
Sales Growth	154,387	0.19	0.09	0.59	122,904	0.17	0.09	0.53	0.02***	8.26
Asset Growth	154,387	0.14	0.06	0.42	122,904	0.14	0.07	0.40	-0.00	-0.16
Equity Issue	168,597	0.11	0.00	0.32	131,411	0.11	0.00	0.31	0.00***	2.73
Debt Issue	168,597	0.09	0.00	0.28	131,411	0.10	0.00	0.30	-0.02***	-14.35
Equ. Repur.	168,597	0.39	0.00	0.49	131,411	0.42	0.00	0.49	-0.03***	-16.50
Firm age	168,597	14.17	9.00	15.37	131,411	16.02	11.00	16.31	-1.85***	-31.90
HHI	168,597	0.27	0.22	0.20	131,411	0.28	0.22	0.20	-0.00***	-5.92
No. Patents	168,597	5.77	0.00	25.59	131,411	7.25	0.00	28.69	-1.49***	-14.95

Table 3
Firm characteristics by product type

The table reports firm univariate characteristics by product type introductions: business stealing (BS), quality improvement (QI), and product variety (NV). Product types are defined in Section 2.2. A firm is included in a product category, if it commercializes that product type in year t. A firm can be in multiple categories in the same year, if it introduces multiple product types a year. All variable definitions are presented in Table C.1. The sample period is 1976 to 2020.

	BS			QI			NV		
	Mean	Median	Std. Dev	Mean	Median	Std. Dev	Mean	Median	Std. Dev
ln(Assets)	6.66	6.74	2.12	6.90	6.99	2.00	6.53	6.74	2.23
ROA	0.01	0.05	0.20	0.02	0.05	0.16	0.02	0.06	0.19
CAPX	0.06	0.04	0.05	0.05	0.04	0.05	0.07	0.06	0.06
PPE	0.26	0.21	0.19	0.26	0.22	0.19	0.28	0.25	0.18
R&D	0.03	0.00	0.08	0.03	0.00	0.06	0.04	0.01	0.06
Leverage	0.75	0.45	2.15	0.78	0.47	2.18	0.77	0.40	2.20
Tobin's Q	2.03	1.53	1.57	1.96	1.51	1.45	2.07	1.60	1.71
Sales Growth	0.17	0.08	0.50	0.13	0.08	0.38	0.22	0.10	0.53
Asset Growth	0.14	0.07	0.38	0.12	0.06	0.33	0.18	0.10	0.36
Equity Issue	0.10	0.00	0.31	0.09	0.00	0.29	0.12	0.00	0.32
Debt Issue	0.19	0.00	0.39	0.20	0.00	0.40	0.21	0.00	0.41
Equ. Repur.	0.51	1.00	0.50	0.54	1.00	0.50	0.43	0.00	0.50
Firm age	21.49	15.00	20.30	23.52	18.00	20.71	21.56	16.00	19.86
HHI	0.29	0.23	0.21	0.30	0.23	0.21	0.27	0.21	0.20
No. Patents	34.98	0.00	221.20	37.57	0.00	224.76	80.77	2.00	321.46

Table 4
Commercialization value of product types

The table presents the distribution of commercialization value of the trademarked products, measured as described in Section 2.4. The sample period is 1976 to 2020.

	BS	QI	NV
Mean	6.43	9.97	9.28
Std	35.49	46.16	38.70
10%	0.02	0.04	0.02
25%	0.09	0.18	0.09
40%	0.26	0.52	0.29
50%	0.47	0.97	0.60
60%	0.86	1.81	1.10
75%	2.46	4.83	3.33
90%	10.50	18.05	15.97
Obs.	107,952	181,987	349

Table 5
Product commercialization and uncertainty

The table presents the relation between economic uncertainty and product commercialization scale and tilt. We estimate regressions of the following form:

$$Y_{i,t+1} = \alpha_i + \beta EPU_t + \Gamma' X_{i,t} + \varepsilon_{i,t+1},$$

where $Y_{i,t+1}$ is the product commercialization scale $\Delta Prod.$ (columns 1-2) defined as $\frac{\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} - \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}}{0.5\times[\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} + \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}]}$, and the tilt (columns 3-4) defined as the QI/(BS+NV) product ratio, EPU_t is the standardized economic uncertainty index (Baker, Bloom, and Davis, 2016) by demeaning and divided by its standard deviation, $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, cash flow, industry HHI, leverage, patent stock and R&D stock, and α_i are firm fixed effects. Standard errors are clustered at the firm and year level. ***, **, * indicate significance at 1%, 5% and 10% level. The sample period is 1976 to 2020.

	$\Delta Prod._{t,t+1}$		QI/(BS+NV)$_{t+1}$	
	(1)	(2)	(3)	(4)
EPU	-0.023***	-0.013***	0.105***	0.048***
	(-4.35)	(-3.21)	(4.26)	(3.93)
ln(Assets)		-0.019***		0.140***
		(-7.76)		(14.80)
Tobin's Q		0.007***		-0.001
		(6.41)		(-0.29)
Cash Flow		0.052***		-0.082***
		(3.16)		(-4.20)
HHI		-0.004		0.064
		(-0.37)		(1.04)
Leverage		-0.000		-0.000
		(-0.41)		(-0.05)
Patent Stock		-0.016***		0.053***
		(-7.11)		(3.54)
R&D Stock		-0.000		0.001
		(-0.48)		(0.25)
Firm FE	✓	✓	✓	✓
Obs.	105,893	105,338	105,392	104,839
R^2	0.16	0.17	0.80	0.81

Table 6
Product commercialization and uncertainty: Shift-share

The table presents the shift-share regression of the relation between uncertainty and product commercialization scale and tilt. We estimate regression of the following form:

$$Y_{i,t+1} = \alpha_i + \beta\, U_{i,t} + \Gamma' X_{i,t} + \varepsilon_{i,t+1},$$

where $Y_{i,t+1}$ is the product commercialization scale $\Delta Prod.$ (columns 1-2) defined as $\frac{\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} - \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}}{0.5\times[\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} + \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}]}$, and the tilt (columns 3-4) defined as the QI/(BS+NV) product ratio. $z^{EPU}_{i,t} = \omega_{i,t-2} \times \Delta\text{EPU}_t$, where $\omega_{i,t-2} \equiv \left|\beta^{\text{EPU}}_{j(i),t-2}\right|$ is estimated from $r^{\text{risk-adj}}_{i,t} = \alpha_j + \beta^{\text{EPU}}_{j,\tau}\Delta\text{EPU}_t + u_{i,t}$, where $r^{\text{risk-adj}}_{i,t}$ are Carhart-residual returns for firms i in industry j, estimated in rolling 5-year windows τ. EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, cash flow, industry HHI, leverage, patent stock and R&D stock, and α_i are firm fixed effects. Standard errors are clustered at the industry level. ***, **, * indicate significance at 1%, 5% and 10% level. The sample period is 1991 to 2020.

	$\Delta Prod._{t,t+1}$		QI/(BS+NV)$_{t+1}$	
	(1)	(2)	(3)	(4)
$z^{EPU}_{i,t}$	-0.005***	-0.004**	0.017***	0.009**
	(-2.72)	(-2.15)	(3.78)	(2.50)
ln(Assets)		-0.019***		0.141***
		(-6.92)		(10.96)
Tobin's Q		0.005***		-0.005
		(4.28)		(-0.92)
Cash Flow		-0.002		-0.090***
		(-0.15)		(-5.60)
HHI		-0.028		0.232***
		(-1.42)		(2.83)
Leverage		-0.000		-0.002
		(-0.01)		(-0.99)
Patent Stock		-0.022***		0.084***
		(-5.82)		(4.68)
R&D Stock		-0.001		0.011***
		(-0.57)		(3.06)
Firm FE	✓	✓	✓	✓
Obs.	64,739	64,728	64,348	64,337
R^2	0.18	0.18	0.84	0.85

Table 7
Product commercialization and uncertainty: IV

The table presents 2SLS regressions coefficients of the relation between uncertainty shocks and product scale and tilt. We estimate regressions of the following form:

$$\text{First stage:} \quad \Delta\sigma_{i,t} = \pi_1 z_{i,t}^{\text{EPU}} + \pi_2 \,\text{DirExp}_{i,t} + \Psi' X_{i,t} + \alpha_i + \delta_t + \varepsilon_{i,t},$$
$$\text{Second stage:} \quad Y_{i,t+1} = \beta\, \widehat{\Delta\sigma}_{i,t} + \theta\, \text{DirExp}_{i,t} + \Gamma' X_{i,t} + \alpha_i + \delta_t + \eta_{i,t+1}.$$

$Y_{i,t+1}$ is the product commercialization scale $\Delta Prod.$ (columns 1-2) defined as $\frac{\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} - \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}}{0.5\times[\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} + \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}]}$, and the tilt (columns 3-4) defined as the QI/(BS+NV) product ratio. $z_{i,t}^{EPU} = \omega_{i,t-2} \times \Delta\text{EPU}_t$, where $\omega_{i,t-2} \equiv \left|\beta^{\text{EPU}}_{j(i),t-2}\right|$, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $DirExp_{i,t}$ is the direct policy exposure, $X_{i,t}$ is a vector of control variables including realized returns, log total assets, Tobin's Q, cash flow, industry HHI, leverage, patent stock and R&D stock. α_i and δ_t are firm and time fixed effects. Standard errors are clustered at the firm level. ***, **, * indicate significance at 1%, 5% and 10% level. The sample period is 1991 to 2020.

Panel A. First Stage

	Realized Vol Shock			
	(1)	(2)	(3)	(4)
$z_{i,t}^{EPU}$	0.027***	0.027***	0.027***	0.027***
	(15.50)	(15.70)	(15.36)	(15.52)
$DirExp_{i,t}$		0.008***		0.008***
		(5.81)		(5.69)
Realized Return		-0.036***		-0.036***
		(-14.78)		(-14.73)
Controls	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Obs.	64,728	64,728	64,337	64,337

Panel B. Second Stage

	$\Delta Prod._{t,t+1}$		QI/(BS+NV)$_{t+1}$	
	(1)	(2)	(3)	(4)
Realized Vol Shock	-0.139**	-0.142**	0.415**	0.411**
	(-2.08)	(-2.16)	(2.41)	(2.33)
$DirExp_{i,t}$		-0.000		-0.003
		(-0.04)		(-0.79)
Realized Return		-0.002		0.019**
		(-0.58)		(2.48)
ln(Assets)	0.010***	0.009***	0.036***	0.040***
	(3.13)	(3.10)	(3.09)	(3.38)
Tobin's Q	0.006***	0.006***	-0.010*	-0.009
	(3.93)	(3.86)	(-1.82)	(-1.59)
Cash Flow	-0.033*	-0.033**	0.015	0.014
	(-1.94)	(-1.98)	(0.51)	(0.47)
HHI	0.033**	0.034**	0.043	0.043
	(2.33)	(2.33)	(0.61)	(0.60)
Leverage	-0.000	-0.000	-0.001	-0.001
	(-0.50)	(-0.48)	(-0.32)	(-0.37)
Patent Stock	-0.015***	-0.015***	0.061***	0.061***
	(-6.38)	(-6.38)	(3.61)	(3.61)
R&D Stock	0.001	0.001	0.004	0.004
	(0.69)	(0.69)	(1.23)	(1.24)
Firm FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Obs.	64,728	64,728	64,337	64,337
Kleibergen-Paap rk Wald F	240	246	236	240

Table 8
Product type payoffs and economic uncertainty

The table presents the regression results for the relation between product type payoffs and economic uncertainty. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}$$

where Y are the firm payoff variables, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for firm gross profits (sales minus cost of goods sold) and Panel B for firm sales. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
					Panel A. Profits					
N^{BS}	0.021***	0.027***	0.036***	0.042***	0.044***	0.049***	0.052***	0.054***	0.054***	0.057***
	(8.92)	(8.66)	(10.35)	(10.81)	(10.01)	(10.31)	(10.12)	(9.63)	(8.99)	(8.86)
$N^{BS} \times$ EPU	-0.008***	-0.009**	-0.013***	-0.009*	-0.013**	-0.011**	-0.005	-0.010*	-0.007	-0.009
	(-2.76)	(-2.34)	(-3.01)	(-1.77)	(-2.44)	(-2.16)	(-1.02)	(-1.76)	(-1.09)	(-1.25)
N^{QI}	0.019***	0.021***	0.024***	0.026***	0.032***	0.032***	0.036***	0.039***	0.041***	0.043***
	(6.74)	(5.79)	(5.44)	(5.23)	(6.07)	(5.58)	(5.67)	(5.60)	(5.46)	(5.42)
$N^{QI} \times$ EPU	0.007***	0.008*	0.014***	0.010*	0.010**	0.007	0.007	0.008	-0.001	-0.005
	(2.68)	(1.96)	(2.85)	(1.82)	(2.02)	(1.46)	(1.52)	(1.60)	(-0.19)	(-0.75)
N^{NV}	0.003**	0.005***	0.006***	0.006**	0.010***	0.010***	0.012***	0.012***	0.013***	0.012***
	(1.98)	(2.88)	(2.74)	(1.99)	(4.12)	(3.90)	(4.35)	(4.05)	(4.06)	(3.60)
$N^{NV} \times$ EPU	0.001	0.001	-0.001	0.002	-0.006	-0.004	-0.007	-0.008	-0.006	-0.007
	(0.31)	(0.18)	(-0.29)	(0.33)	(-1.24)	(-0.82)	(-1.43)	(-1.57)	(-1.00)	(-1.02)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.17	0.16	0.16	0.15	0.16	0.16	0.17	0.18	0.18	0.18
					Panel B. Sales					
N^{BS}	0.018***	0.025***	0.029***	0.034***	0.039***	0.043***	0.047***	0.048***	0.048***	0.050***
	(9.95)	(11.36)	(10.99)	(10.90)	(11.06)	(10.96)	(10.65)	(10.15)	(9.22)	(9.04)
$N^{BS} \times$ EPU	-0.004**	-0.007***	-0.006**	-0.005	-0.008**	-0.012***	-0.013***	-0.014***	-0.010*	-0.010
	(-2.49)	(-2.76)	(-2.15)	(-1.57)	(-2.21)	(-2.90)	(-2.96)	(-3.05)	(-1.90)	(-1.61)
N^{QI}	0.005***	0.010***	0.015***	0.019***	0.023***	0.025***	0.026***	0.029***	0.031***	0.034***
	(2.62)	(3.83)	(4.75)	(4.99)	(5.32)	(4.97)	(4.53)	(4.58)	(4.46)	(4.49)
$N^{QI} \times$ EPU	0.006***	0.007***	0.007**	0.006*	0.005	0.006	0.008*	0.009**	0.005	0.001
	(3.81)	(3.07)	(2.51)	(1.79)	(1.57)	(1.64)	(1.84)	(2.14)	(1.11)	(0.24)
N^{NV}	0.003***	0.005***	0.006***	0.008***	0.009***	0.011***	0.011***	0.011***	0.014***	0.013***
	(2.66)	(3.39)	(3.60)	(4.34)	(4.67)	(4.79)	(4.68)	(4.29)	(4.86)	(4.60)
$N^{NV} \times$ EPU	0.001	0.000	-0.001	0.000	-0.003	-0.002	-0.004	-0.004	-0.005	-0.008
	(0.50)	(0.20)	(-0.27)	(0.01)	(-0.78)	(-0.54)	(-0.99)	(-0.97)	(-1.01)	(-1.39)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.19	0.18	0.17	0.17	0.17	0.17	0.18	0.19	0.19	0.20

Table 9
Product types, economic uncertainty and investments

The table presents the regression results for the relation among firm investments, product types and economic uncertainty. We estimate regressions of the form:

$$ln(\frac{Y_{i,t+\tau}}{Y_{i,t}}) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are categories within net PPE investments, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for building & construction, Panel B for land, Panel C for machine & equipment, and Panel D for leases. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Building & Construction										
N^{BS}	0.010***	0.019***	0.031***	0.043***	0.047***	0.057***	0.062***	0.068***	0.070***	0.065***
	(3.60)	(4.13)	(5.07)	(5.43)	(4.86)	(5.02)	(4.42)	(4.12)	(3.95)	(3.51)
$N^{BS}\times$ EPU	0.001	-0.020	-0.019	0.003	0.007	0.035	-0.011	-0.041	-0.056	-0.027
	(0.12)	(-1.45)	(-1.07)	(0.13)	(0.18)	(0.76)	(-0.21)	(-0.73)	(-1.02)	(-0.49)
N^{QI}	0.007**	0.014***	0.018***	0.024**	0.027**	0.017	0.010	0.010	0.005	0.020
	(2.27)	(2.92)	(2.70)	(2.54)	(2.46)	(1.28)	(0.59)	(0.52)	(0.19)	(0.87)
$N^{QI}\times$ EPU	-0.004	0.005	0.004	0.026	0.038	0.018	0.038	0.073	0.039	0.035
	(-0.45)	(0.42)	(0.28)	(1.11)	(1.23)	(0.44)	(0.84)	(1.38)	(0.73)	(0.67)
N^{NV}	-0.000	-0.002	-0.004	-0.008**	-0.004	-0.003	-0.004	-0.002	0.003	0.000
	(-0.12)	(-0.95)	(-1.37)	(-2.05)	(-0.92)	(-0.57)	(-0.69)	(-0.31)	(0.55)	(0.01)
$N^{NV}\times$ EPU	-0.003	-0.007	0.005	-0.005	-0.004	-0.012	-0.005	-0.030	-0.013	-0.032
	(-0.52)	(-0.69)	(0.36)	(-0.30)	(-0.24)	(-0.62)	(-0.19)	(-1.25)	(-0.55)	(-1.64)
Obs.	21,557	18,172	15,222	12,951	10,993	9,271	7,797	6,468	5,349	4,401
Adj. R^2	0.04	0.07	0.10	0.12	0.14	0.16	0.18	0.22	0.25	0.28
Panel B. Land										
N^{BS}	0.006**	0.015***	0.023***	0.036***	0.041***	0.043***	0.048***	0.043***	0.051***	0.044**
	(2.05)	(3.08)	(3.61)	(4.81)	(4.55)	(4.04)	(3.79)	(2.80)	(3.07)	(2.35)
$N^{BS}\times$ EPU	-0.014	-0.020	-0.011	0.018	0.039	0.067	0.074	0.015	0.017	0.028
	(-1.37)	(-1.40)	(-0.53)	(0.67)	(1.10)	(1.49)	(1.41)	(0.30)	(0.32)	(0.56)
N^{QI}	0.005*	0.012**	0.020***	0.024**	0.033***	0.030**	0.032*	0.034*	0.025	0.035
	(1.80)	(2.49)	(2.79)	(2.54)	(2.70)	(2.18)	(1.87)	(1.67)	(1.05)	(1.42)
$N^{QI}\times$ EPU	-0.003	-0.008	-0.004	-0.018	-0.012	-0.011	-0.021	0.030	-0.024	-0.020
	(-0.36)	(-0.67)	(-0.24)	(-0.78)	(-0.39)	(-0.29)	(-0.51)	(0.58)	(-0.43)	(-0.37)
N^{NV}	-0.002	-0.001	-0.004	-0.004	-0.005	-0.004	-0.007	-0.002	-0.001	-0.012*
	(-1.30)	(-0.52)	(-1.24)	(-1.12)	(-1.31)	(-0.93)	(-1.42)	(-0.38)	(-0.07)	(-1.88)
$N^{NV}\times$ EPU	-0.006	-0.013	-0.015	-0.011	-0.003	-0.009	-0.013	-0.026	-0.022	-0.058**
	(-1.10)	(-1.25)	(-1.28)	(-0.77)	(-0.15)	(-0.49)	(-0.59)	(-1.10)	(-0.81)	(-2.56)
Obs.	20,570	17,351	14,544	12,371	10,509	8,874	7,476	6,205	5,141	4,232
Adj. R^2	0.03	0.05	0.08	0.11	0.13	0.15	0.16	0.19	0.21	0.24
Panel C. Machine & Equipment										
N^{BS}	0.004**	0.016***	0.026***	0.034***	0.043***	0.049***	0.055***	0.049***	0.043***	0.044**
	(2.13)	(4.13)	(4.87)	(5.05)	(5.44)	(5.27)	(4.96)	(3.80)	(2.89)	(2.54)
$N^{BS}\times$ EPU	0.002	-0.002	0.005	0.037	0.016	0.024	0.005	-0.027	-0.064	-0.032
	(0.33)	(-0.14)	(0.33)	(1.54)	(0.52)	(0.65)	(0.12)	(-0.57)	(-1.44)	(-0.58)
N^{QI}	0.005**	0.010**	0.017***	0.022***	0.022**	0.013	0.006	0.022	0.022	0.023
	(2.34)	(2.42)	(2.80)	(2.75)	(2.26)	(1.12)	(0.41)	(1.32)	(1.10)	(1.03)
$N^{QI}\times$ EPU	0.004	-0.006	0.008	0.012	0.042	0.037	0.033	0.120***	0.092**	0.062
	(0.58)	(-0.63)	(0.60)	(0.59)	(1.49)	(1.09)	(0.94)	(2.93)	(2.28)	(1.41)
N^{NV}	0.000	0.002	-0.001	-0.002	-0.001	-0.001	-0.006	-0.005	0.004	0.003
	(0.09)	(0.62)	(-0.19)	(-0.45)	(-0.12)	(-0.15)	(-0.83)	(-0.58)	(0.82)	(0.61)
$N^{NV}\times$ EPU	-0.011	-0.003	-0.009	-0.009	-0.005	-0.018	-0.016	-0.030	0.007	-0.001
	(-1.44)	(-0.36)	(-0.83)	(-0.63)	(-0.28)	(-0.78)	(-0.53)	(-0.72)	(0.36)	(-0.03)
Obs.	25,297	21,060	17,427	14,679	12,367	10,355	8,657	7,143	5,875	4,810
Adj. R^2	0.07	0.09	0.12	0.14	0.17	0.19	0.20	0.22	0.23	0.26
Panel D. Lease										
N^{BS}	0.009	0.007	0.015	0.018	0.032*	0.032	0.017	0.013	-0.023	0.036
	(1.29)	(0.72)	(0.97)	(0.84)	(1.70)	(1.61)	(0.73)	(0.50)	(-0.68)	(0.98)
$N^{BS}\times$ EPU	-0.014	-0.019	-0.038	-0.024	0.100	0.088	0.051	0.031	-0.148	0.005
	(-0.67)	(-0.57)	(-0.75)	(-0.28)	(1.59)	(1.24)	(0.65)	(0.30)	(-1.23)	(0.04)
N^{QI}	-0.002	0.012	0.024	0.026	0.015	0.026	0.040	0.055	0.099*	0.046
	(-0.16)	(0.69)	(0.96)	(0.86)	(0.46)	(0.75)	(1.02)	(1.22)	(1.82)	(0.74)
$N^{QI}\times$ EPU	0.008	-0.020	-0.023	-0.011	-0.122*	-0.110	-0.147*	-0.029	-0.002	-0.202
	(0.39)	(-0.55)	(-0.52)	(-0.16)	(-1.95)	(-1.54)	(-1.84)	(-0.28)	(-0.01)	(-1.38)
N^{NV}	0.005	0.010	-0.003	-0.005	-0.011	-0.029	-0.057	0.010	-0.005	0.054*
	(0.39)	(0.96)	(-0.44)	(-0.40)	(-1.00)	(-1.10)	(-1.47)	(0.55)	(-0.17)	(1.73)
$N^{NV}\times$ EPU	0.035	0.058	0.039	0.047	0.033	0.007	-0.080	0.108	0.067	0.249***
	(0.71)	(1.37)	(1.57)	(1.00)	(0.75)	(0.09)	(-0.58)	(1.36)	(0.60)	(2.76)
Obs.	10,556	8,459	6,750	5,527	4,521	3,692	3,005	2,409	1,918	1,532
Adj. R^2	0.05	0.10	0.14	0.18	0.22	0.28	0.32	0.37	0.40	0.43

Table 10
Product types, economic uncertainty and employment

The table presents the regression results for the relation between product types and employment during economic uncertainty. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}$$

where Y is firm employment, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
N^{BS}	0.011***	0.018***	0.025***	0.029***	0.034***	0.038***	0.040***	0.042***	0.043***	0.044***
	(8.29)	(9.46)	(10.85)	(10.61)	(10.95)	(10.46)	(9.71)	(9.43)	(8.59)	(8.05)
$N^{BS} \times$ EPU	-0.003*	-0.004*	-0.003	-0.002	-0.004	-0.007*	-0.006	-0.009*	-0.006	-0.007
	(-1.84)	(-1.76)	(-1.13)	(-0.69)	(-1.11)	(-1.70)	(-1.45)	(-1.94)	(-1.13)	(-1.13)
N^{QI}	0.005***	0.011***	0.017***	0.022***	0.026***	0.028***	0.029***	0.033***	0.034***	0.038***
	(3.71)	(5.65)	(6.29)	(6.75)	(6.51)	(5.77)	(5.18)	(5.12)	(4.81)	(4.88)
$N^{QI} \times$ EPU	0.002*	0.003	0.000	-0.003	-0.003	-0.001	0.001	0.003	0.001	-0.001
	(1.90)	(1.31)	(0.03)	(-1.00)	(-0.79)	(-0.41)	(0.19)	(0.77)	(0.21)	(-0.28)
N^{NV}	-0.000	0.003*	0.004**	0.004**	0.005***	0.008***	0.008***	0.010***	0.012***	0.010***
	(-0.21)	(1.87)	(2.44)	(2.40)	(2.79)	(3.50)	(3.08)	(3.67)	(4.04)	(3.07)
$N^{NV} \times$ EPU	-0.003	-0.002	-0.008*	-0.007	-0.009**	-0.004	-0.007	-0.007	-0.005	-0.009
	(-1.23)	(-0.82)	(-1.80)	(-1.60)	(-2.07)	(-0.84)	(-1.53)	(-1.51)	(-1.02)	(-1.48)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.46	0.34	0.29	0.26	0.24	0.23	0.23	0.23	0.23	0.23

Table 11
Product types and financing

The table presents the two-way fixed effect regression coefficients for the relation between product types and firms' financing choices. We estimate regressions of the following form:

$$Y_{i,t+1} = \sum_{C \in \{BS,QI,NV\}} \beta_\tau^C N_{i,t}^C + \Gamma' X_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

where $Y_{i,t+1}$ are firm financing variables, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, ROA, PPE, cash holding, patent and R&D stock. α_i and δ_t are firm and year fixed effects. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	Debt Issue	ln(Debt Amt.)	Equity Issue	ln(Equity Amt.)	Leverage	CAPX	OCF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N^{BS}	0.005***	0.039***	0.004***	0.029***	0.001	0.053***	-0.001***
	(3.94)	(3.92)	(4.22)	(4.17)	(0.32)	(3.72)	(-3.13)
N^{QI}	0.005***	0.089***	-0.001	-0.024***	0.003	0.013	-0.001*
	(2.80)	(5.38)	(-1.28)	(-3.03)	(0.61)	(0.61)	(-1.93)
N^{NV}	-0.001	-0.014**	-0.000	0.003	0.002	0.007	0.000**
	(-0.79)	(-2.30)	(-0.48)	(0.57)	(0.94)	(0.66)	(2.22)
ln(Assets)	0.121***	0.905***	0.022***	0.334***	0.213***	-0.503***	0.031***
	(32.23)	(28.10)	(5.43)	(14.13)	(14.10)	(-5.54)	(17.60)
Tobin's Q	0.003***	0.041***	0.038***	0.254***	-0.035***	0.922***	0.004***
	(3.56)	(5.92)	(22.35)	(25.09)	(-9.62)	(28.68)	(5.79)
ROA	-0.036***	-0.259***	0.089***	0.379***	-0.048***	3.750***	0.591***
	(-12.24)	(-12.59)	(18.24)	(15.23)	(-2.61)	(34.12)	(120.87)
PPE	-0.055***	-0.519***	-0.107***	-0.581***	0.076	2.166***	0.050***
	(-5.38)	(-6.02)	(-9.16)	(-9.20)	(1.52)	(6.09)	(10.23)
Cash Holding	0.012*	0.083*	0.313***	1.424***	-0.313***	3.301***	
	(1.90)	(1.78)	(33.17)	(28.40)	(-12.97)	(18.14)	
Patent Stock	0.001	0.015	-0.073***	-0.426***	-0.040***	-0.350***	-0.007***
	(0.24)	(0.39)	(-19.19)	(-18.54)	(-3.23)	(-4.75)	(-5.13)
R&D Stock	0.004***	0.045***	0.005***	0.024**	0.005	-0.087***	0.000
	(2.59)	(3.56)	(2.69)	(2.02)	(1.03)	(-4.03)	(0.30)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Obs.	164,944	164,944	164,944	164,944	164,938	164,944	164,709
Adj. R^2	0.22	0.27	0.18	0.20	0.19	0.46	0.87

REFERENCES

Acemoglu, D., U. Akcigit, H. Alp, N. Bloom, and W. Kerr. 2018. Innovation, reallocation, and growth. American Economic Review 108:3450–91–.

Aghion, P., and P. Howitt. 1992. A model of growth through creative destruction. Econometrica 60:323–51.

Akcigit, U., and W. R. Kerr. 2018. Growth through heterogeneous innovations. Journal of Political Economy 126:1374–443.

Alfaro, I., N. Bloom, and X. Lin. 2024. The finance uncertainty multiplier. Journal of Political Economy 132:437–93.

Almeida, H., and M. Campello. 2007. Financial constraints, asset tangibility, and corporate investment. Review of Financial Studies 20:1429–60.

Argente, D., S. Baslandze, D. Hanley, and S. Moreira. 2020. Patents to products: Product innovation and firm dynamics. Working Paper 2020-4, FRB Atlanta.

Baker, S. R., N. Bloom, and S. J. Davis. 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131:1593–636.

Barlevy, G. 2007. On the cyclicality of research and development. American Economic Review 97:1131–64.

Barrot, J.-N., and R. Nanda. 2020. Aggregate and firm-level identifications of financial frictions in business-cycle fluctuations. Journal of Monetary Economics 113:1–19.

Berlingieri, G., M. D. Ridder, D. Lashkari, and D. Rigo. 2025. Creative destruction through innovation bursts. Discussion Papers DP2095, Centre for Economic Performance, LSE.

Bernanke, B. S. 1983. Irreversibility, uncertainty, and cyclical investment. Quarterly Journal of Economics 98:85–106.

Bernanke, B. S., M. Gertler, and S. Gilchrist. 1996. The financial accelerator and the flight to quality. Review of Economics and Statistics 78:1–15.

Bernard, A. B., S. J. Redding, and P. K. Schott. 2010. Multiple-Product Firms and Product Switching. American Economic Review 100:70–97.

Bloom, N. 2009. The impact of uncertainty shocks. Econometrica 77:623–85.

Bloom, N., S. Bond, and J. Van Reenen. 2007. Uncertainty and investment dynamics. Review of Economic Studies 74:391–415.

Bloom, N., C. I. Jones, J. Van Reenen, and M. Webb. 2020. Are ideas getting harder to find? American Economic Review 110:1104–44.

Broda, C., and D. E. Weinstein. 2010. Product creation and destruction: Evidence and price implications. American Economic Review 100:691–723.

Campello, M., and G. Kankanhalli. 2024. Corporate decision-making under uncertainty: Review and future research directions. In D. J. Denis, ed., The Handbook of Corporate Finance, chap. 15, 548–90. Edward Elgar Publishing.

Campello, M., G. Kankanhalli, and J. Kim. 2024. Delayed creative destruction: How uncertainty shapes corporate assets. Journal of Financial Economics 153.

Cohen, L., K. Diether, and C. Malloy. 2013. Misvaluing innovation. The Review of Financial Studies 26:635–66.

Cohen, W. M., R. R. Nelson, and J. P. Walsh. 2000. Protecting their intellectual assets: Appropriability conditions and why U.S. manufacturing firms patent (or not). Working Paper, NBER.

Dixit, A. K., and R. S. Pindyck. 1994. Investment under uncertainty. Princeton University Press.

Faurel, L., Q. Li, D. Shanthikumar, and S. H. Teoh. 2024. Bringing innovation to fruition: Insights from new trademarks. Journal of Financial and Quantitative Analysis 59:474–520–.

Flikkema, M., A.-P. D. Man, and C. Castaldi. 2014. Are trademark counts a valid indicator of innovation? Results of an in-depth study of new Benelux trademarks filed by SMEs. Industry and Innovation 21:310–31.

Garcia-Macia, D., C.-T. Hsieh, and P. J. Klenow. 2019. How destructive is innovation? Econometrica 87:1507–41.

Graham, S. J., G. Hancock, A. C. Marco, and A. F. Myers. 2013. The USPTO trademark case files dataset: Descriptions, lessons, and insights. Journal of Economics & Management Strategy 22:669–705.

Grossman, G. M., and E. Helpman. 1991. Quality ladders in the theory of growth. The Review of Economic Studies 58:43–61.

Gulen, H., and M. Ion. 2016. Policy uncertainty and corporate investment. Review of Financial Studies 29:523–64.

Hoberg, G., and G. Phillips. 2010. Product market synergies and competition in M&A. Journal of Finance 65:1168–201.

———. 2016. Text-based network industries and endogenous product differentiation. Journal of Political Economy 124:1423–65.

Hoberg, G., and G. M. Phillips. 2025. Scope, scale, and concentration: The 21st-century firm. The Journal of Finance 80:415–66.

Hombert, J., and A. Matray. 2018. Can innovation help U.S. manufacturing firms escape import competition from China? The Journal of Finance 73:2003–39.

Jordà, O. 2005. Estimation and inference of impulse responses by local projections. American Economic Review 95:161–182–.

Klette, T. J., and S. Kortum. 2004. Innovating firms and aggregate innovation. Journal of Political Economy 112:986–1018.

Kogan, L., D. Papanikolaou, A. Seru, and N. Stoffman. 2017. Technological innovation, resource allocation, and growth. Quarterly Journal of Economics 132:665–712.

Mendonça, S., T. S. Pereira, and M. M. Godinho. 2004. Trademarks as an indicator of innovation and industrial change. Research Policy 33:1385–404.

Mukherjee, A., M. Singh, and A. Žaldokas. 2017. Do corporate taxes hinder innovation? Journal of Financial Economics 124:195–221.

Myers, S. C., and N. S. Majluf. 1984. Corporate financing and investment decisions when firms have information that investors do not have. Journal of Financial Economics 13:187–221.

Romer, P. M. 1990. Endogenous technological change. Journal of Political Economy 98:S71–S102.

Villas-Boas, J. M. 2004. Consumer learning, brand loyalty, and competition. Marketing Science 23:134–45.

Appendix A. Additional Information

A1 Name Matching Algorithm

To match trademark owners to CRSP firms, we carry out a name matching procedure using a name-matching algorithm. We employ a two step process: (1) name standardization, and (2) text similarity calculation. Trademark owner names in the trademark database are not standardized, and therefore one cannot treat each unique name as a separate entity. Entity names can be expressed differently and have spelling errors and thus the same entity can appear with different names. To standardize firm names, we use an extensive list of name variations to standardize individual words in names, e.g., changing "Corp" to "Corporation," "Ltd" to "Limited," etc. This name variation list is populated from several sources. First, we use CRSP firm name abbreviations as provided by CRSP; second we use recursive searches in Wikidata to find common firm name abbreviations (e.g., IBM for International Business Machines); and third we manually collect name abbreviations from several databases including CRSP, Compustat, Google Patents, and the USPTO Trademark case file.

In our second step, we compute the pairwise text similarity between trademark owner's name and the firm name using a Levenshtein-based string distance. To account for possible spelling errors, we conduct the text similarity both at the phrase and word level and similarity thresholds are set to allow for spelling errors. In addition, based on the uniqueness of the words/phrases present in the name, we decide on whether to keep or drop the match. Non-unique words or phrases that are commonly observed in the English dictionary are matched when overall similarity is high. Unique words need a lower similarity score to be matched (similar to TF-IDF approach used in the other matching algorithms).

We benchmark our matching output to existing name matching databases created by other researchers like Kogan et al. (2017). Kogan et al. (2017) also use a name-matching algorithm to match patent assignees to CRSP firms and match 1.8 million patents for the period 1926 to 2010 out of 7.8 million patents. We use the same dataset from Google Patents and conduct a similar name-matching exercise using our name matching algorithm. We match over two million patents. We manually check the additional matches and confirm that they are correctly mapped due to our extensive firm name standardization. There is also a subset of firms that are matched in the Kogan et al. (2017) data, which are unmatched using our algorithm (less than 20%). We also manually check this sample and find that the unmatched patents often belong to subsidiaries with significantly different names from parent companies, and they are outside the scope of a text matching algorithm. Generally, these additional observations are hand-matched. Based on this analysis, we conclude that our matching algorithm is of good quality to conduct fuzzy name matching in firm names.

Finally, we take into account firm ownership structures and M&A activity. We collect firm subsidiary information from public-firms SEC 10-K filings Exhibit 21. All reported firm sub-

sidiaries' trademarks are grouped under the same entity. We collect M&A information from SDC Platinum. All live trademarks owned by the acquired firm at the acquisition year are grouped under the acquiring entity. Finally, reported owner-name changes, i.e., cases where same entity appears under different names in CRSP, Compustat or Wikidata, are grouped as the same entity.

A2 Mapping G&S Trademark Text to USPTO ID manuals

This appendix details how we transform examiner-validated Goods & Services (G&S) statements in *all live* trademarks (product and branding marks) into a dynamic, firm–year product vector V_{it} that we carry over time. We rely exclusively on the G&S text; we never use the mark characters (brand names, slogans) to define products. Because branding/house marks are refiled or amended as product lines evolve, their G&S sections provide a legally verified, up-to-date inventory of offered goods/services. Our construction mirrors text-based product-space methods familiar from the TNIC literature, but is grounded in trademark G&S descriptions and the USPTO ID Manual.[27] Figure 4 provides a sketch of the process of cleaning the statement text and mapping the statement to the Trademark ID Manual.

For firm i in year t, let $\mathcal{M}_{it}$ denote all live USPTO trademarks (goods & services) owned by i. Each mark $m \in \mathcal{M}_{it}$ has a G&S statement $S(m)$ that may list multiple goods/services across Nice classes. Our goal is to map the G&S statement $S(m)$ to a finite set Term IDs $\mathcal{P}(m) \subset \mathcal{T}$, where $\mathcal{T}$ is the (de-duplicated) universe of Term IDs. The *firm–year product vector* is the union

$$V_{it} = \bigcup_{m \in \mathcal{M}_{it}} \mathcal{P}(m),$$

de-duplicated at the Term-ID level. Dynamics are induced by mark additions, amendments, and cancellations. A Term ID enters V_{it} when it first appears in any live mark's G&S and exits when no live mark lists it. This ensures branding activity cannot inflate product counts: we count products, not marks.[28]

Our construction is a trademark-based analogue of text-derived product vectors in 10-Ks used to measure scope (Hoberg and Phillips, 2025) and competition (Hoberg and Phillips, 2016). We adapt the same logic to examiner-validated G&S statements and the ID Manual to ensure product labels correspond to legally recognized goods/services. This allows us to define a dynamic, granular V_{it} that is appropriate for commercialization analysis.

We follow these three steps for each goods and services (G&S) description $S(m)$ in mark m from the set of trademarks $m \in \mathcal{M}_{it}$ and Term ID $\mathcal{P}(m)$ from the ID Manual set $\mathcal{T}$.

[27] For text-based product-space methods in 10-Ks, see Hoberg and Phillips (2016); for scope measures built from product text, see Hoberg and Phillips (2025).

[28] Event definition for NV/QI/BS uses V_{it} as described in Section 2.2.1: a commercialization event (i, k, t) occurs when $k \in V_{it}$ but $k \notin V_{i,t-1}$, with classification rules described in Section 2.2.1.

1. Preprocessing and phrase extraction: We segment the G&S description $S(m)$ on USPTO-recommended delimiters (semicolons; "namely," "consisting of," "particularly") to isolate atomic items.[29] We retain Nice classes but do not treat them as products, e.g., IC009 and IC042 in Figure 4. After we split the paragraph by semi-colons, we are left with "Mobile phone accessories, namely, batteries, cases ..." and "Accessories for motor vehicles" and "Mobile phone repair services." Each segment is then fed into Gemini Flash 2.5 through the Gemini API using the following prompt:

```
For the below product(s) or service(s),
clearly identify the specific "kind" of product(s) or service(s) being provided.
Clearly identify any descriptive information. Do not add your own information.
For each of them, return them in the format "kind (description)" nothing else, on separate lines.
--- {part of the statement text here}
```

The model will return the product phrases. In our example, the output is:

- batteries (Mobile phone accessories)
- cases (Mobile phone accessories)
- accessories (for motor vehicles)
- repair services (mobile phone).

We post-process to enforce head nouns (kind) and keep descriptive qualifiers (parenthetical). The output is a set of product phrases per segment. We lowercase, strip punctuation, lemmatize head nouns, and drop boilerplate expressions ("online retail services," "brand management services") unless accompanied by specific goods/services. We preserve multiword technical terms (e.g., "lithium-ion battery chargers").

2. Canonicalization to ID-Manual Term IDs: We snapshot the USPTO ID Manual and build $\mathcal{T}$, a de-duplicated set of Term IDs. We collapse near-duplicates differing only by orthography ("flavoured" vs. "flavored"), trivial pluralization, or synonymous head nouns ("ear phones" vs. "earphones") via string rules plus embedding similarity. This avoids spurious "new varieties" that are an artifact of wording changes in the Manual.

We address semantic redundancy using vector-based entity resolution, which offers better accuracy than string-matching algorithms (e.g., Levenshtein distance) by identifying conceptual rather than character-level equivalence. We use Google's Gemini embedding model to project Term ID descriptions into a high-dimensional vector space, ensuring that synonyms and morphological variations yield spatially proximal vectors. We compute pairwise cosine similarity to quantify semantic proximity. Our sensitivity analyses on the optimal cut-off show that the 0.80–0.85 thresholds introduce semantic drift, inadvertently merging related but taxonomically distinct concepts (e.g., "Mobile phone" and "Smartphone"). Thus, we use a threshold of $T = 0.90$ to maximize cluster purity. This high-precision cutoff ensures the aggregation of strict duplicates-such as 'Mobile telephone" and "mobile phones," while maintaining the granularity required to distinguish closely

[29] Semicolons are officially used to separate distinct goods/services; see TMEP 1902.02(f).

related entities. Finally, terms exceeding the 0.90 similarity threshold form edges in an undirected graph. We extract the connected components to define unified term groups. This transitive logic ensures that if Term A links to B, and B links to C, all three consolidate under a single ID regardless of their direct pairwise similarity. Our final Term ID set $\mathcal{T}$ includes 34,067 unique terms.

3. Embeddings and matching: We embed both (i) extracted product phrases and (ii) de-duplicated and streamlined ID-Manual term descriptions using a sentence-embedding model and compute cosine similarity.[30] We use Google's Gemini 2.5 embedding model (`https://ai.google.dev/gemini-api/docs/embeddings`), which is state-of-the-art and ranks first on the MTEB leaderboard (`https://huggingface.co/spaces/mteb/leaderboard`, Aug. 2025). For each phrase, we select the nearest Term ID; we keep matches with cosine similarity ≥ 0.85 to prioritize precision and route $[0.80, 0.85)$ to a light-touch review queue. Matches below 0.80 are dropped. When multiple Term IDs tie within < 0.01, we choose the more specific ID (longer description or narrower NCL scope).

4. Building the dynamic product vector V_{it}: For firm i and year t, we take the union of Term IDs matched from the G&S text of all live marks $m \in \mathcal{M}_{it}$:

$$V_{it} := \bigcup_{m \in \mathcal{M}_{it}} \mathcal{P}(m).$$

A Term ID enters V_{it} when it first appears in any live mark's G&S; it exits when none of the firm's live marks contain it (e.g., cancellation, non-renewal, or amendment removing the item). This is the object used for counts, event definitions, and NV/QI/BS classification.

5. Quality assurance and sensitivity: We run a stratified human audit (by decade $\times$ sector $\times$ goods/services) on a random sample of firm–mark–phrase triples. Annotators assign the closest Term ID in the ID Manual. Results are robust to (i) excluding marks whose G&S consists only of generic brand/retail descriptors without specific goods/services, and (ii) excluding marks identical to owner names.

The commercialization event for firm i and Term ID k occurs in the first year t with $k \in V_{it}$ and $k \notin V_{i,t-1}$. We classify events as NV/QI/BS using V_{it}: NV if k has not appeared in any firm's $V_{\cdot,\cdot}$ previously; BS if $k \notin V_{i,t-1}$ but previously appears for some $j \neq i$; QI if k expands an existing firm category already present in $V_{i,t-1}$. Because we de-duplicate within V_{it}, multiple marks listing the same Term ID do not create multiple events.

Appendix B. Economic Value of Products

It is necessary to separate the product-related market reaction from other factors. The net firm return around the commercialization date, after accounting for aggregate market fluctuations, should

[30] We use the same embedding family throughout the paper for reproducibility; details available upon request.

represent the market's perceived value of the product. We conduct the analysis within a three-day window starting on the commercialization date.

On the product commercialization date, the market learns that the firm has a new product and reacts conditioning on the product information. The market reaction ΔV on the commercialization day of product c is given by:

$$\Delta V_c = (1 - \pi_p)\xi_c, \tag{B1}$$

where π is the probability the market expects the firm to successfully commercialize product c, and ξ_c is the dollar value of the commercialized product c. For example, if the market anticipates a firm will produce and successfully commercialize a product with probability π, this should be accounted for in the estimation of ξ_c. However, the unconditional probability of the commercialization of a new product for a particular firm on a particular day is likely to be very small. Therefore, we approximate equation (B1) by $\Delta V_c \approx \xi_c$.[31] This implies that we underestimate the product value if no adjustment is made. However, we think we still capture most of the products' value in the economy without the adjustment factor for two reasons. First, only a small fraction of the products in the economy are announced before launch, and they are concentrated in a few industries. Second, the product release date is when consumers can get the products for the first time, and assess and evaluate accurately. Thus, the product value calculated without adjustment still captures a substantial share of the actual product value.

To isolate returns related to only product commercialization, we first remove observations with commercialization dates that coincide with scheduled announcements like earning announcements. Second, we focus on stock's abnormal return R_i, firm return minus market return (proxied by CRSP value-weighted returns). We further decompose the abnormal return R_i into return related to the product value v_p plus unrelated factors ϵ_i:

$$R_i = v_c + \epsilon_i.$$

From equation (B1), the estimated economic value $\hat{\xi}_c$ of the product c for $\pi = 0$ is,

$$\hat{\xi}_c \approx \frac{1}{N_i} E[v_c|R_i] M_i, \tag{B2}$$

where N_i is the total number of products commercialized by firm i on the event date. $\hat{\xi}_c$ is the expected product value v_c times the firm market capitalization M_i. If multiple products are commercialized on the event date, these products are assigned an equal value of a fraction $\frac{1}{N_i}$ of the total value. Majority of the sample firms commercialize one product per day.

To implement equation (B2), we make the following assumptions about the distribution of v

[31] It is possible for firms to make product announcements before a product release and the market will increase it anticipation of a new product launch therefore affecting the estimate of the product value.

and ϵ. First, we allow v and t to vary across firm i and across time t. Second, we assume a strictly positive value of v, which is normally distributed truncated at 0, $v_c \sim N^+(0, \sigma^2_{v,it})$; we also assume a normal distribution for $\epsilon_i \sim N(0, \epsilon^2_{\epsilon,it})$. Under these assumptions, the expected value of product c produced by firm i for abnormal return R (denoted as $v_c|R_i$) is

$$E[v_c|R_i] = \delta_{it} R_i + \sqrt{\delta_{it}}\sigma_{\epsilon,it} \frac{\phi\Big(-\sqrt{\delta_{it}}\frac{R_i}{\sigma_{\epsilon,it}}\Big)}{1 - \Phi\Big(-\sqrt{\delta_{it}}\frac{R_i}{\sigma_{\epsilon,it}}\Big)}, \tag{B3}$$

where ϕ and Φ are the standard normal pdf and cdf functions, respectively; and δ is the signal-to-noise ratio:

$$\delta_{it} = \frac{\sigma^2_{v,it}}{\sigma^2_{v,it} + \sigma^2_{\epsilon,it}}. \tag{B4}$$

Next, we estimate parameters $\sigma_{v,it}$ and $\sigma_{\epsilon,it}$. To make the estimation feasible, the signal-to-noise ratio is constant across firms and time. This assumption implies that $\sigma^2_{\epsilon,it}$ and $\sigma^2_{v,it}$ vary across firms and time, but in constant proportions to each other. To estimate δ, we regress the log squared returns on the product commercialization date dummy C:

$$log(R_{id})^2 = \gamma C_{id} + cZ_{id} + u_{id}, \tag{B5}$$

where R_{id} is the 3-day abnormal return of firm i, starting on commercialization day d. Z is a vector of control variables indicating the day of week and firm×year fixed effects to control for seasonal return fluctuations and volatility. Then, the signal-to-noise estimate can be recovered from the estimated value of γ using $\hat{\delta} = 1 - e^{-\hat{\gamma}}$. We estimate $\hat{\gamma} = 0.0162$ and $\hat{\delta} = 0.016$. We use these values to compute the benchmark results.

Finally, we estimate $\sigma^2_{\epsilon,it}$ using the sum of squared abnormal returns, which allows the estimate to vary at an annual frequency. Specifically, we first estimate the realized mean abnormal squared returns, $\hat{\sigma}^2_{it}$ and the fraction of trading days that are commercialization dates, d_{it}. The variance of the measurement error can be recovered through:

$$\sigma^2_{\epsilon,it} = 3\hat{\sigma}^2_{it}(1 + 3d_{it}(e^{\hat{\gamma}} - 1))^{-1}. \tag{B6}$$

Appendix C. Additional Tables and Figures

Figure C.1
Time series variation of product portfolios

The figure presents the average number of commercialized products in a firm's product portfolio by product type for each Fama-French industry and year. Business stealing (BS) and quality improvement (QI) are presented on the right Y-axis, new variety (NV) is on the left Y-axis. Product types are defined in Section 2.2.

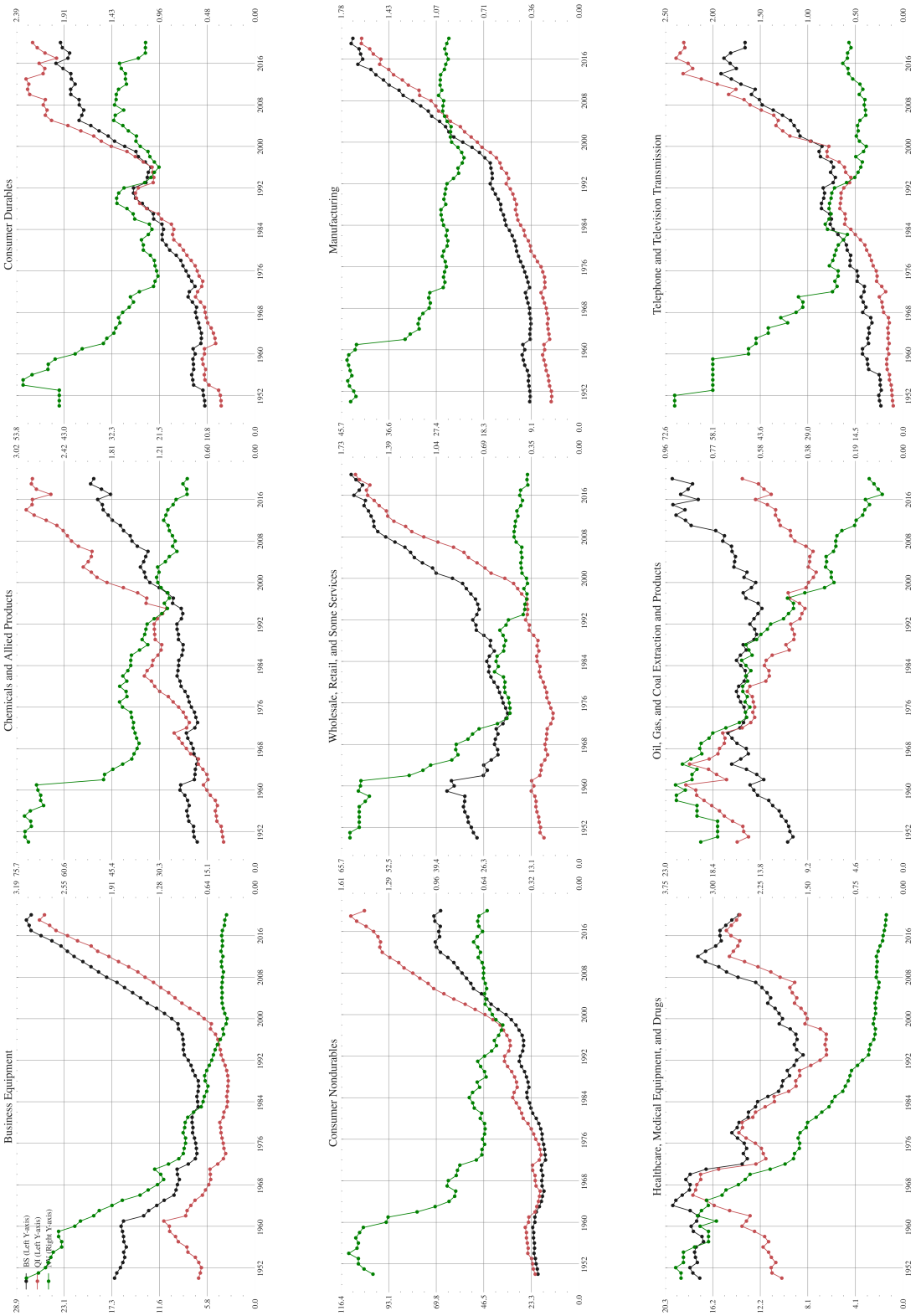


Table C.1
Trademark data variable description

The table presents the definitions for the key variables in the trademark data. The trademark referred in the example is in Figure 1.

Variable	Notes	Example
Word Mark	Actual characters of mark text	OFFICE
Goods and Services Statement	Owner's description of the use of the mark	Computer software and computer programs . . .
Primary G&S Class	G&S Classification primary code for the use of the mark under 45 G&S classes	Class IC 009 Electronics
Mark Drawing Code	Identifies mark physical characteristics	Design plus words, letters and/or numbers
Design Search Code	Identifies Mark Graphic Design characteristics	26.05.21 Triangles that are completely or partially shaded
Serial Number	Unique Identifier for trademark application	85799081
Registration Number	Registration number	0010164
First Use in Anywhere Date	First time for the G&S classification used in anywhere	2012-12-12
First Use in Commerce Date	First time for the G&S classification used in commercial activities (first commercialization date)	2012-12-12
Filing Date	Date application is filed	December 10, 2012
Filing Basis (current)	Whether trademark is used in commerce	1A: Used in Commerce
Filing Basis (original)	Whether trademark is used in commerce when filed	1B: Intent to use
Publication Date	Date mark published for opposition	May 21, 2013
Registration Cancel Date	Cancellation date of registration	
Renewal Date	Date Trademark registration renewed	
Owner Name	Name of owning party	Microsoft Corporation
Owner Address	Owner address	Microsoft Way, Redmond Washington 98052-6399
Attorney		Matthew E. Moersfeider

Table C.2
Variable description

Variable Name	Abbrev.	Description
Product Measures		
Commercialization Value	$\hat{\xi}_c$	3-day market reaction to product commercialization date following KPSS methodology
Business Stealing	BS	Term ID $k \notin V_{i,t-1}$ but previously appears for some $j \neq i$
Quality Improving	QI	Term ID k expands an existing firm category already present in $V_{i,t-1}$
New Variety	NV	Term ID k has not appeared in any firm's $V_{\cdot,\cdot}$ previously
Uncertainty Variables		
Economic Policy Uncertainty index	EPU	EPU measure from Baker, Bloom, and Davis (2016)
Shift-share EPU instrument	$z_{i,t}^{EPU}$	Shift-share EPU instrument from Alfaro, Bloom, and Lin (2024)
Direct EPU Exposure	Dir. Exp	first-moment EPU instrument from Alfaro, Bloom, and Lin (2024)
Firm characteristics		
Profits		Sales minus cost of goods sold [COMPUSTAT: SALE - COGS deflated by CPI]
Sales		Sales (COMPUSTAT: sale) plus change in inventory [COMPUSTAT: INVT deflated by CPI]
Capital		[COMPUSTAT: PPEGT deflated by the NIPA price of equipment]
Employment		[COMPUSTAT: EMP]
Ln(Assets)		Natural log of (1 + Firm's total asset [COMPUSTAT AT])
Tobin's Q		Sum of total assets plus market value of equity minus book value of equity divided by total assets [COMPUSTAT (AT+CSHO× PRCC_F - CEQ) / AT)].
Log Market Cap		Natural log of total market capitalization [COMPUSTAT CSHO×PRCC_F]
Leverage		Firm's total debt divided by total assets [COMPUSTAT (DLTT + DLC)/AT]
HHI		Herfindahl-Hirschman Index of firm's SIC4 industry sales concentration in a given year [COMPUSTAT: SALES, SIC]
Return on Assets	ROA	Earnings before interest and taxes divided by total assets [COMPUSTAT EBIT/AT]
Sales Growth		Sales growth from last fiscal year end [COMPUSTAT ($SALE_t$/$SALE_{(t-1)}$ -1)].
Asset Growth		Sales growth from last fiscal year end [COMPUSTAT (AT_t/$AT_{(t-1)}$ -1)].
Capital expenditure	CAPX	Capital expenditures divided by total assets [COMPUSTAT CAPX/AT]
Property, plant, and equipment	PPE	Property, plant, and equipment scaled by asset [COMPUSTAT PPENT/AT]
Building & Construction		Building and Construction PPE [COMPUSTAT PPENB + PPENC]
Land		Land PPE [COMPUSTAT PPENLI]
Machine & Equipment		Machine & Equipment [COMPUSTAT PPENME]
Lease		Lease [COMPUSTAT PPENLS]
Cash Holding		Cash assets scaled by asset [COMPUSTAT CHE/AT]
Cash Flow	OCF	Cash Flow scaled by asset [COMPUSTAT CHECH/AT]
R&D	R&D	Research and development expenses divided by total assets [COMPUSTAT XRD/AT]
R&D stock		R&D expenditure accumulated from previous years with amortization of 15% [COMPUSTAT XRD/AT]
Missing R&D		Indicator variable equal to 1 if R&D expense is missing, zero otherwise
Patent Stock		Number of live patents granted from previous years with a patent life of 20 years.
Firm Age		Number of years since founding year (Jay R. Ritter website)
Equity Issue		Indicator variable equal to one if firm issues equity in year t, zero otherwise [SDC]
Equity Amount		Dollar amount of Equity issued in a given year [SDC]
Debt Issue		Indicator variable equal to one if firm issues debt in year t, zero otherwise [SDC]
Debt Amount		Dollar amount of debt issued in a given year [SDC]
Idiosyncratic volatility	$\sigma_{i,t}$	Sum of squared abnormal returns [CRSP DSF: $\sum_{d\in t}(r_i - r_m)^2$]
Realized Vol Shock		Change in Idiosyncratic volatility $t-1$ to t
Realized Returns		Annual stock return [COMPUSTAT (PRCC_F(t) / AJEX(t) + DVPSX_F(t)/AJEX(t)) / (PRCC_F(t-1) / AJEX_F(t-1))].

Table C.3
Product types payoffs, innovation and economic uncertainty

The table presents the regression results for the relation between product types and firm-level payoffs controlling for innovation inputs. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \beta_0 + \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C \theta_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \beta_\tau^P N_{i,t}^{\text{Pats}} + \psi_\tau^P N_{i,t}^{\text{Pats}} \times EPU_t + \beta_\tau^R \text{R\&D} + \psi_\tau^R \text{R\&D}_{i,t} \times EPU_t + \gamma_1 \ln(Y_{i,t-1}) + \gamma_2 \ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{\text{sic3}} + \delta_t + \epsilon_{i,t},$$

where Y are the firm payoffs, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for gross profits and Panel B for sales. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
					Panel A. Profits					
N^{BS}	0.009***	0.016***	0.025***	0.030***	0.032***	0.037***	0.039***	0.041***	0.041***	0.044***
	(6.34)	(6.28)	(8.73)	(8.91)	(8.22)	(8.64)	(8.68)	(8.38)	(7.57)	(7.62)
$N^{BS} \times$ EPU	-0.006***	-0.008**	-0.013***	-0.010**	-0.015***	-0.014***	-0.007	-0.012**	-0.010*	-0.011
	(-2.93)	(-2.34)	(-3.43)	(-2.17)	(-2.83)	(-2.74)	(-1.51)	(-2.46)	(-1.73)	(-1.50)
N^{QI}	0.005***	0.006**	0.007**	0.010**	0.015***	0.017***	0.021***	0.024***	0.026***	0.028***
	(3.27)	(2.23)	(2.15)	(2.43)	(3.56)	(3.44)	(3.92)	(3.92)	(3.88)	(3.90)
$N^{QI} \times$ EPU	0.004**	0.006*	0.012***	0.009*	0.009*	0.006	0.005	0.007	-0.002	-0.007
	(2.25)	(1.70)	(2.77)	(1.71)	(1.87)	(1.35)	(1.22)	(1.51)	(-0.30)	(-1.02)
N^{NV}	0.002*	0.004***	0.005***	0.005*	0.009***	0.009***	0.010***	0.010***	0.011***	0.011***
	(1.84)	(2.58)	(2.62)	(1.85)	(4.00)	(3.67)	(4.18)	(3.63)	(3.80)	(3.42)
$N^{NV} \times$ EPU	-0.002	-0.002	-0.004	-0.000	-0.008*	-0.005	-0.008*	-0.009*	-0.007	-0.007
	(-0.84)	(-0.77)	(-1.14)	(-0.02)	(-1.67)	(-1.12)	(-1.75)	(-1.81)	(-1.25)	(-0.99)
N^{Pat}	0.004	0.006	0.008	0.012	0.014	0.018	0.022*	0.025*	0.027*	0.028*
	(1.25)	(1.29)	(1.33)	(1.47)	(1.47)	(1.61)	(1.77)	(1.82)	(1.82)	(1.82)
$N^{Pat} \times$ EPU	-0.004*	-0.004**	-0.005**	-0.006**	-0.004*	-0.005*	-0.009***	-0.009***	-0.004	-0.003
	(-1.70)	(-2.00)	(-2.12)	(-2.48)	(-1.91)	(-1.73)	(-2.62)	(-2.74)	(-1.40)	(-1.07)
R&D Stock	0.004**	0.007**	0.009**	0.010**	0.010*	0.008	0.005	0.003	0.001	-0.001
	(2.25)	(2.35)	(2.40)	(2.11)	(1.82)	(1.38)	(0.71)	(0.37)	(0.13)	(-0.12)
R&D Stock × EPU	0.002*	0.002	0.002	0.003	0.001	0.003	0.008*	0.009	0.006	0.004
	(1.77)	(1.03)	(0.65)	(0.82)	(0.38)	(0.78)	(1.87)	(1.62)	(1.02)	(0.70)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.03	0.04	0.05	0.06	0.07	0.07	0.09	0.10	0.11	0.11
					Panel B. Sales					
N^{BS}	0.009***	0.016***	0.021***	0.026***	0.030***	0.034***	0.037***	0.039***	0.038***	0.040***
	(9.10)	(10.55)	(10.42)	(10.10)	(10.20)	(10.15)	(9.69)	(9.25)	(8.16)	(7.94)
$N^{BS} \times$ EPU	-0.003***	-0.005***	-0.006**	-0.006*	-0.008**	-0.012***	-0.012***	-0.014***	-0.010*	-0.010*
	(-2.70)	(-2.89)	(-2.24)	(-1.83)	(-2.43)	(-3.11)	(-3.02)	(-3.25)	(-1.96)	(-1.71)
N^{QI}	0.001	0.005***	0.009***	0.012***	0.016***	0.018***	0.019***	0.021***	0.023***	0.025***
	(1.19)	(2.99)	(3.73)	(4.06)	(4.43)	(4.09)	(3.75)	(3.71)	(3.60)	(3.61)
$N^{QI} \times$ EPU	0.004***	0.004**	0.004*	0.003	0.003	0.004	0.004	0.006	0.002	-0.002
	(3.68)	(2.26)	(1.65)	(1.04)	(1.05)	(1.04)	(1.17)	(1.60)	(0.46)	(-0.43)
N^{NV}	0.002**	0.004***	0.005***	0.007***	0.008***	0.009***	0.010***	0.010***	0.012***	0.012***
	(2.25)	(3.19)	(3.36)	(4.18)	(4.41)	(4.57)	(4.44)	(3.91)	(4.51)	(4.34)
$N^{NV} \times$ EPU	-0.000	-0.002	-0.004	-0.002	-0.005	-0.004	-0.006	-0.006	-0.007	-0.009
	(-0.29)	(-0.77)	(-1.18)	(-0.71)	(-1.48)	(-1.18)	(-1.59)	(-1.50)	(-1.51)	(-1.57)
N^{Pat}	0.003	0.005	0.008	0.011	0.013	0.017*	0.020*	0.022*	0.024*	0.025*
	(1.36)	(1.44)	(1.49)	(1.55)	(1.56)	(1.69)	(1.78)	(1.82)	(1.81)	(1.78)
$N^{Pat} \times$ EPU	-0.002***	-0.003**	-0.004**	-0.005**	-0.004*	-0.005**	-0.007***	-0.008***	-0.004	-0.003
	(-2.76)	(-2.40)	(-2.35)	(-2.41)	(-1.92)	(-2.29)	(-2.80)	(-3.00)	(-1.44)	(-1.40)
R&D Stock	0.002**	0.005**	0.007**	0.009**	0.010*	0.009	0.007	0.006	0.006	0.005
	(2.32)	(2.42)	(2.30)	(2.16)	(1.95)	(1.57)	(1.14)	(0.90)	(0.76)	(0.63)
R&D Stock × EPU	0.002***	0.002	0.002	0.002	0.001	0.002	0.006	0.008**	0.007*	0.007**
	(2.66)	(1.42)	(0.75)	(0.61)	(0.27)	(0.66)	(1.58)	(1.98)	(1.83)	(2.09)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.06	0.07	0.08	0.09	0.09	0.10	0.11	0.12	0.13	0.14

Table C.4
Product type payoffs and uncertainty product value weighted

The table presents the regression results for the relation between the market value of product types and firm-level payoffs. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C \theta_{i,t}^C + \psi_\tau^C \theta_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}$$

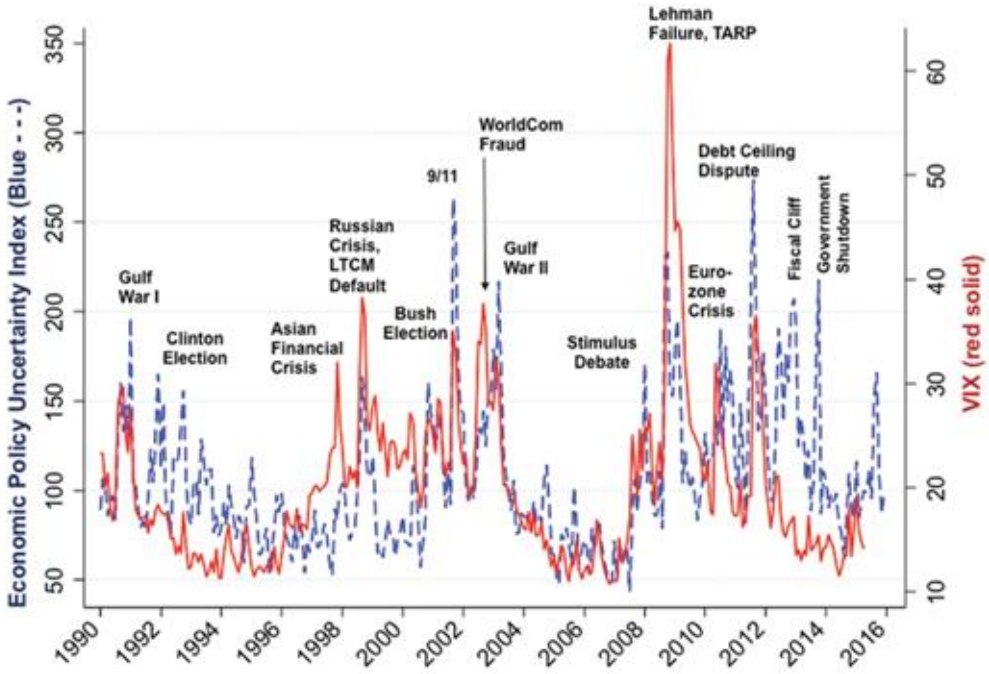
where Y are the firm payoffs, θ^{NV}, θ^{QI} and θ^{BS} are the market values of commercialized products by firm i in year t scaled by total assets, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for firm gross profits (sales minus cost of goods sold) and Panel B for firm sales. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
					Panel A. Profits					
θ^{BS}	0.005***	0.011***	0.018***	0.020***	0.021***	0.023***	0.026***	0.025***	0.027***	0.024***
	(2.80)	(4.23)	(6.68)	(6.73)	(5.83)	(6.15)	(6.96)	(5.34)	(5.25)	(4.41)
$\theta^{BS} \times$ EPU	-0.000	-0.003	-0.012***	-0.010**	-0.019***	-0.011**	-0.003	-0.003	0.002	-0.006
	(-0.13)	(-0.69)	(-2.91)	(-2.26)	(-3.07)	(-2.23)	(-0.89)	(-0.59)	(0.41)	(-0.93)
θ^{QI}	0.009***	0.010***	0.013***	0.018***	0.022***	0.023***	0.025***	0.030***	0.029***	0.032***
	(5.83)	(3.87)	(4.29)	(5.25)	(5.77)	(5.28)	(5.15)	(5.32)	(4.90)	(5.15)
$\theta^{QI} \times$ EPU	0.002	0.003	0.010***	0.006	0.011**	0.006	0.001	0.002	-0.005	-0.001
	(0.76)	(0.67)	(2.62)	(1.57)	(2.30)	(1.28)	(0.30)	(0.39)	(-0.91)	(-0.26)
θ^{NV}	0.001***	0.001***	0.001**	0.001	0.002***	0.002*	0.001	0.001	0.001	0.001
	(3.73)	(3.01)	(2.01)	(1.12)	(2.78)	(1.82)	(1.32)	(0.87)	(0.72)	(0.59)
$\theta^{NV} \times$ EPU	-0.000	-0.000*	-0.000	-0.001**	-0.002**	-0.002**	-0.003***	-0.004***	-0.004***	-0.003***
	(-0.95)	(-1.94)	(-0.66)	(-2.27)	(-2.26)	(-2.21)	(-4.30)	(-4.74)	(-4.26)	(-2.86)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.03	0.04	0.05	0.06	0.07	0.07	0.09	0.10	0.10	0.11
					Panel B. Sales					
θ^{BS}	0.007***	0.012***	0.017***	0.021***	0.024***	0.026***	0.028***	0.028***	0.027***	0.025***
	(7.26)	(8.42)	(9.04)	(8.92)	(8.73)	(8.08)	(7.78)	(6.96)	(6.05)	(5.01)
$\theta^{BS} \times$ EPU	0.000	-0.001	-0.004**	-0.006**	-0.008***	-0.009***	-0.008**	-0.004	0.000	-0.002
	(0.11)	(-0.70)	(-2.14)	(-2.36)	(-2.81)	(-2.77)	(-2.29)	(-1.04)	(0.00)	(-0.37)
θ^{QI}	0.004***	0.009***	0.013***	0.018***	0.021***	0.023***	0.024***	0.025***	0.026***	0.028***
	(4.12)	(5.82)	(6.16)	(6.57)	(6.53)	(5.95)	(5.22)	(4.84)	(4.76)	(4.83)
$\theta^{QI} \times$ EPU	0.002**	0.002	0.002	0.001	0.001	0.000	0.001	-0.000	-0.002	-0.001
	(2.12)	(0.97)	(1.18)	(0.56)	(0.30)	(0.10)	(0.25)	(-0.04)	(-0.42)	(-0.17)
θ^{NV}	0.000***	0.001***	0.001***	0.001***	0.002***	0.002***	0.002**	0.002*	0.002	0.002*
	(3.24)	(3.24)	(3.14)	(2.93)	(3.33)	(2.87)	(2.50)	(1.86)	(1.60)	(1.73)
$\theta^{NV} \times$ EPU	0.000	0.000	0.000	0.000	0.001**	0.001**	0.001*	0.000	-0.000	0.000
	(1.18)	(0.69)	(0.82)	(1.08)	(2.09)	(2.15)	(1.67)	(0.30)	(-0.20)	(0.12)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.05	0.07	0.08	0.08	0.09	0.10	0.11	0.12	0.13	0.14

Internet Appendix
Additional Tables and Figures

Figure IA.A.1
EPU time series

The figure presents the time-series evolution of EPU and VIX from Baker, Bloom, and Davis (2016) Figure 6.



The figure shows the U.S. EPU Index from Figure I and the monthly average of daily values for the 30-day VIX.

Table IA.A.1
Commercialization value of product types — Full sample

The table presents the distribution of commercialization value of the trademarked products, measured as described in Section 2.4. The sample period is 1929 to 2020.

	BS	QI	NV
Mean	6.14	9.63	6.89
Std	34.18	44.75	30.77
10%	0.02	0.04	0.03
25%	0.09	0.18	0.09
40%	0.25	0.52	0.27
50%	0.46	0.98	0.48
60%	0.84	1.81	0.96
75%	2.38	4.77	2.87
90%	10.08	17.40	12.09
Obs.	117,261	194,728	590

Table IA.A.2
Product commercialization and uncertainty: Shift-share with σEPU

The table presents the shift-share regression of the relation between uncertainty and product commercialization scale and tilt. We estimate regression of the following form:

$$Y_{i,t+1} = \alpha_i + \beta\, U_{i,t} + \Gamma' X_{i,t} + \varepsilon_{i,t+1},$$

where $Y_{i,t+1}$ is the product commercialization scale $\Delta Prod.$ (columns 1-2) defined as $\frac{\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} - \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}}{0.5\times[\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} + \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}]}$, and the tilt (columns 3-4) defined as the QI/(BS+NV) product ratio. $U_{i,t} = \omega_{i,t-2} \times \sigma\text{EPU}_t$, where $\omega_{i,t-2} \equiv \left|\beta^{\text{EPU}}_{j(i),t-2}\right|$ is estimated from $r^{\text{risk-adj}}_{i,t} = \alpha_j + \beta^{\text{EPU}}_{j,\tau}\Delta\text{EPU}_t + u_{i,t}$, where $r^{\text{risk-adj}}_{i,t}$ are Carhart-residual returns for firms i in industry j, estimated in rolling 5-year windows τ. EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, cash flow, industry HHI, leverage, patent stock and R&D stock, and α_i are firm fixed effects. Standard errors are clustered at the industry level. ***, **, * indicate significance at 1%, 5% and 10% level. The sample period is 1987 to 2020.

	$\Delta Prod._{t,t+1}$		QI/(BS+NV)$_{t+1}$	
	(1)	(2)	(3)	(4)
$\lvert\omega_{j,t-2}\rvert \times \sigma EPU$	-0.006***	-0.002	0.039***	0.017**
	(-2.95)	(-1.21)	(4.32)	(2.56)
ln(Assets)		-0.021***		0.146***
		(-10.00)		(9.84)
Tobin's Q		0.007***		-0.002
		(6.36)		(-0.41)
Cash Flow		0.052***		-0.090***
		(5.07)		(-4.75)
HHI		-0.013		0.147**
		(-0.63)		(2.08)
Leverage		0.000		-0.001
		(0.01)		(-0.45)
Patent Stock		-0.022***		0.074***
		(-6.27)		(4.86)
R&D Stock		-0.000		-0.000
		(-0.28)		(-0.03)
Firm FE	✓	✓	✓	✓
Obs.	82,489	82,357	82,024	81,896
R^2	0.17	0.18	0.80	0.80

Table IA.A.3
Product type payoffs and uncertainty - scaled by TA

The table presents the regression results for the relation between product types payoffs and economic uncertainty, where number of product types is scaled by total assets. We estimate regressions of the form:

$$ln(\frac{Y_{i,t+\tau}}{Y_{i,t}}) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C/AT + \psi_\tau^C N_{i,t}^C/AT \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are the firm payoffs, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t scaled by total assets, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for firm gross profits (sales minus cost of goods sold) and Panel B for firm sales. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
					Panel A. Profits					
N^{BS}/AT	0.011***	0.017***	0.023***	0.026***	0.032***	0.034***	0.040***	0.044***	0.045***	0.052***
	(5.57)	(6.19)	(6.77)	(6.75)	(7.77)	(7.05)	(7.45)	(7.73)	(7.33)	(7.59)
N^{BS}/AT × EPU	-0.007**	-0.014***	-0.019***	-0.016**	-0.010	-0.016*	-0.005	-0.017*	-0.017	-0.013
	(-2.14)	(-2.97)	(-2.88)	(-2.19)	(-1.36)	(-1.84)	(-0.53)	(-1.77)	(-1.56)	(-1.10)
N^{QI}/AT	0.006***	0.010***	0.013***	0.017***	0.024***	0.025***	0.023***	0.027***	0.029***	0.032***
	(3.56)	(4.09)	(4.13)	(4.38)	(5.48)	(4.95)	(3.75)	(4.08)	(3.93)	(3.97)
N^{QI}/AT × EPU	-0.001	-0.004	0.000	0.003	-0.001	-0.001	-0.006	-0.005	-0.013*	-0.022**
	(-0.30)	(-1.04)	(0.03)	(0.40)	(-0.12)	(-0.12)	(-0.75)	(-0.68)	(-1.66)	(-2.39)
N^{NV}/AT	0.009***	0.007	0.011	0.007	0.014	0.003	0.009	0.012	0.010	0.009
	(3.06)	(0.97)	(0.99)	(0.81)	(1.08)	(0.16)	(0.68)	(0.94)	(0.75)	(0.70)
N^{NV}/AT × EPU	-0.019**	-0.012	0.010	-0.012	0.013	0.004	-0.011	-0.028	-0.037	-0.015
	(-2.34)	(-0.61)	(0.29)	(-0.46)	(0.34)	(0.11)	(-0.36)	(-0.79)	(-1.00)	(-0.43)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.03	0.04	0.05	0.06	0.07	0.07	0.09	0.10	0.11	0.11
					Panel B. Sales					
N^{BS}/AT	0.012***	0.018***	0.020***	0.024***	0.028***	0.033***	0.034***	0.036***	0.041***	0.048***
	(7.10)	(7.43)	(6.07)	(6.38)	(7.04)	(7.12)	(6.29)	(6.02)	(6.67)	(7.02)
N^{BS}/AT × EPU	-0.002	-0.007*	-0.009	-0.009	-0.010	-0.012	-0.010	-0.017	-0.013	-0.011
	(-0.71)	(-1.66)	(-1.57)	(-1.34)	(-1.43)	(-1.57)	(-1.10)	(-1.63)	(-1.14)	(-0.86)
N^{QI}/AT	0.004***	0.009***	0.015***	0.018***	0.021***	0.023***	0.023***	0.027***	0.026***	0.029***
	(3.36)	(4.31)	(5.12)	(4.94)	(5.09)	(4.94)	(4.05)	(4.25)	(3.67)	(3.86)
N^{QI}/AT × EPU	0.001	-0.001	0.001	0.002	0.004	0.002	-0.005	-0.003	-0.006	-0.017*
	(0.27)	(-0.31)	(0.31)	(0.35)	(0.59)	(0.33)	(-0.66)	(-0.37)	(-0.71)	(-1.81)
N^{NV}/AT	0.007*	0.011	0.014	0.011	0.015	0.014	0.017	0.013	0.013	0.014
	(1.69)	(1.41)	(1.41)	(1.13)	(1.29)	(1.22)	(1.32)	(1.12)	(1.02)	(1.16)
N^{NV}/AT × EPU	-0.012	-0.024	-0.008	-0.018	-0.009	-0.032	-0.034	-0.038	-0.044	-0.026
	(-1.18)	(-1.12)	(-0.22)	(-0.70)	(-0.24)	(-1.02)	(-0.98)	(-1.01)	(-1.13)	(-0.79)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.06	0.07	0.08	0.08	0.09	0.10	0.11	0.12	0.13	0.14

Table IA.A.4
Product types payoffs and uncertainty — ylag

The table presents the regression results for the relation between product types payoffs and uncertainty, including contemporaneous effects. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t-1}}\right) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}$$

where Y are the firm payoffs, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for firm gross profits (sales minus cost of goods sold) and Panel B for firm sales. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
					Panel A. Profits					
N^{BS}	0.021***	0.027***	0.036***	0.042***	0.044***	0.049***	0.052***	0.054***	0.054***	0.057***
	(8.92)	(8.66)	(10.35)	(10.81)	(10.01)	(10.31)	(10.12)	(9.63)	(8.99)	(8.86)
$N^{BS} \times$ EPU	-0.008***	-0.009**	-0.013***	-0.009*	-0.013**	-0.011**	-0.005	-0.010*	-0.007	-0.009
	(-2.76)	(-2.34)	(-3.01)	(-1.77)	(-2.44)	(-2.16)	(-1.02)	(-1.76)	(-1.09)	(-1.25)
N^{QI}	0.019***	0.021***	0.024***	0.026***	0.032***	0.032***	0.036***	0.039***	0.041***	0.043***
	(6.74)	(5.79)	(5.44)	(5.23)	(6.07)	(5.58)	(5.67)	(5.60)	(5.46)	(5.42)
$N^{QI} \times$ EPU	0.007***	0.008*	0.014***	0.010*	0.010**	0.007	0.007	0.008	-0.001	-0.005
	(2.68)	(1.96)	(2.85)	(1.82)	(2.02)	(1.46)	(1.52)	(1.60)	(-0.19)	(-0.75)
N^{NV}	0.003**	0.005***	0.006***	0.006**	0.010***	0.010***	0.012***	0.012***	0.013***	0.012***
	(1.98)	(2.88)	(2.74)	(1.99)	(4.12)	(3.90)	(4.35)	(4.05)	(4.06)	(3.60)
$N^{NV} \times$ EPU	0.001	0.001	-0.001	0.002	-0.006	-0.004	-0.007	-0.008	-0.006	-0.007
	(0.31)	(0.18)	(-0.29)	(0.33)	(-1.24)	(-0.82)	(-1.43)	(-1.57)	(-1.00)	(-1.02)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.17	0.16	0.16	0.15	0.16	0.16	0.17	0.18	0.18	0.18
					Panel B. Sales					
N^{BS}	0.018***	0.025***	0.029***	0.034***	0.039***	0.043***	0.047***	0.048***	0.048***	0.050***
	(9.95)	(11.36)	(10.99)	(10.90)	(11.06)	(10.96)	(10.65)	(10.15)	(9.22)	(9.04)
$N^{BS} \times$ EPU	-0.004**	-0.007***	-0.006**	-0.005	-0.008**	-0.012***	-0.013***	-0.014***	-0.010*	-0.010
	(-2.49)	(-2.76)	(-2.15)	(-1.57)	(-2.21)	(-2.90)	(-2.96)	(-3.05)	(-1.90)	(-1.61)
N^{QI}	0.005***	0.010***	0.015***	0.019***	0.023***	0.025***	0.026***	0.029***	0.031***	0.034***
	(2.62)	(3.83)	(4.75)	(4.99)	(5.32)	(4.97)	(4.53)	(4.58)	(4.46)	(4.49)
$N^{QI} \times$ EPU	0.006***	0.007***	0.007**	0.006*	0.005	0.006	0.008*	0.009**	0.005	0.001
	(3.81)	(3.07)	(2.51)	(1.79)	(1.57)	(1.64)	(1.84)	(2.14)	(1.11)	(0.24)
N^{NV}	0.003***	0.005***	0.006***	0.008***	0.009***	0.011***	0.011***	0.011***	0.014***	0.013***
	(2.66)	(3.39)	(3.60)	(4.34)	(4.67)	(4.79)	(4.68)	(4.29)	(4.86)	(4.60)
$N^{NV} \times$ EPU	0.001	0.000	-0.001	0.000	-0.003	-0.002	-0.004	-0.004	-0.005	-0.008
	(0.50)	(0.20)	(-0.27)	(0.01)	(-0.78)	(-0.54)	(-0.99)	(-0.97)	(-1.01)	(-1.39)
Obs.	120,431	108,776	98,565	89,554	81,543	74,369	67,948	62,184	56,963	52,212
Adj. R^2	0.19	0.18	0.17	0.17	0.17	0.17	0.18	0.19	0.19	0.20

Table IA.A.5
Product types, economic uncertainty and investments at cost

The table presents the regression results for the relation among firm investments (at cost), product types and economic uncertainty. We estimate regressions of the form:

$$ln(\frac{Y_{i,t+\tau}}{Y_{i,t}}) = \beta_0 + \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are categories within gross PPE, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for building & construction costs, Panel B for land, Panel C for machine & equipment, and Panel D for leases. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Building & Construction										
N^{BS}	0.005***	0.007**	0.008**	0.011***	0.015***	0.020***	0.020***	0.022***	0.021***	0.020**
	(2.70)	(2.50)	(2.35)	(2.84)	(3.19)	(3.98)	(3.29)	(3.34)	(2.86)	(2.50)
$N^{BS}\times$ EPU	-0.002	-0.001	-0.001	-0.003	-0.000	0.002	0.005	0.004	0.003	0.004
	(-0.94)	(-0.29)	(-0.39)	(-0.69)	(-0.10)	(0.31)	(0.91)	(0.65)	(0.40)	(0.44)
N^{QI}	0.004**	0.009***	0.013***	0.017***	0.019***	0.018***	0.018***	0.020***	0.020**	0.021**
	(2.50)	(2.93)	(3.48)	(3.59)	(3.43)	(2.96)	(2.66)	(2.58)	(2.24)	(2.18)
$N^{QI}\times$ EPU	0.002	-0.001	-0.002	0.001	-0.001	-0.003	-0.007	-0.003	-0.002	-0.004
	(0.89)	(-0.44)	(-0.41)	(0.15)	(-0.15)	(-0.77)	(-1.31)	(-0.61)	(-0.35)	(-0.46)
N^{NV}	-0.001	0.000	0.006**	0.006**	0.004	0.004	0.006*	0.007*	0.009**	0.007
	(-0.50)	(0.03)	(2.20)	(2.27)	(1.46)	(1.11)	(1.65)	(1.66)	(2.26)	(1.47)
$N^{NV}\times$ EPU	0.004	-0.005	-0.009***	-0.004	-0.007	-0.006	-0.003	-0.004	-0.007	-0.007
	(1.17)	(-1.63)	(-2.62)	(-1.09)	(-1.38)	(-1.08)	(-0.53)	(-0.47)	(-0.86)	(-0.79)
Obs.	49,693	44,559	40,209	36,466	33,149	30,210	27,541	25,104	22,819	20,704
Adj. R^2	0.02	0.04	0.07	0.08	0.10	0.11	0.13	0.14	0.16	0.18
Panel B. Land										
N^{BS}	0.006***	0.005*	0.009**	0.010**	0.009*	0.014***	0.017***	0.014**	0.016**	0.015*
	(3.49)	(1.83)	(2.56)	(2.55)	(1.95)	(2.61)	(2.66)	(2.08)	(2.20)	(1.90)
$N^{BS}\times$ EPU	-0.004**	-0.000	-0.001	0.000	-0.000	-0.001	-0.004	0.003	0.007	0.012
	(-2.27)	(-0.16)	(-0.27)	(0.07)	(-0.07)	(-0.20)	(-0.59)	(0.36)	(0.98)	(1.42)
N^{QI}	-0.000	0.003	0.007*	0.010**	0.015***	0.015**	0.014*	0.016*	0.018*	0.018*
	(-0.24)	(1.16)	(1.76)	(2.18)	(2.59)	(2.26)	(1.89)	(1.94)	(1.90)	(1.76)
$N^{QI}\times$ EPU	0.004***	-0.000	-0.001	-0.004	-0.005	-0.002	0.002	-0.000	-0.005	-0.010
	(2.60)	(-0.06)	(-0.27)	(-1.03)	(-0.89)	(-0.39)	(0.26)	(-0.01)	(-0.73)	(-1.46)
N^{NV}	-0.001	0.000	-0.003	-0.001	0.000	0.001	0.003	0.004	0.006	0.005
	(-0.61)	(0.22)	(-0.84)	(-0.46)	(0.03)	(0.48)	(0.72)	(0.83)	(1.24)	(0.89)
$N^{NV}\times$ EPU	-0.002	-0.004	-0.005	-0.000	-0.006	-0.005	-0.001	0.005	0.008	0.002
	(-1.32)	(-1.29)	(-1.15)	(-0.05)	(-1.06)	(-0.72)	(-0.18)	(0.57)	(0.96)	(0.25)
Obs.	43,149	38,883	35,244	32,097	29,313	26,785	24,496	22,392	20,400	18,545
Adj. R^2	0.03	0.05	0.07	0.09	0.11	0.12	0.14	0.15	0.16	0.18
Panel C. Machine & Equipment										
N^{BS}	0.005***	0.006***	0.011***	0.013***	0.016***	0.021***	0.024***	0.025***	0.025***	0.028***
	(3.87)	(3.45)	(4.63)	(4.59)	(4.32)	(5.33)	(5.43)	(4.92)	(4.50)	(4.53)
$N^{BS}\times$ EPU	-0.000	0.001	0.001	0.001	-0.001	-0.005	-0.007	-0.007	-0.006	-0.005
	(-0.23)	(0.42)	(0.30)	(0.49)	(-0.32)	(-1.26)	(-1.58)	(-1.37)	(-0.90)	(-0.69)
N^{QI}	0.002	0.005***	0.009***	0.012***	0.016***	0.016***	0.016***	0.017***	0.017**	0.016**
	(1.52)	(2.72)	(3.41)	(3.39)	(3.62)	(3.38)	(2.97)	(2.66)	(2.36)	(2.05)
$N^{QI}\times$ EPU	0.002*	0.000	-0.003	-0.003	-0.004	-0.003	-0.000	0.002	0.001	-0.002
	(1.74)	(0.05)	(-1.11)	(-1.22)	(-1.24)	(-0.71)	(-0.01)	(0.41)	(0.29)	(-0.28)
N^{NV}	0.001	0.002	0.006**	0.005**	0.006**	0.006**	0.007**	0.006*	0.009**	0.007*
	(0.79)	(0.80)	(2.53)	(2.21)	(2.42)	(2.23)	(2.33)	(1.74)	(2.35)	(1.70)
$N^{NV}\times$ EPU	-0.002	-0.004	-0.005	-0.003	-0.004	-0.001	-0.000	0.003	0.000	-0.006
	(-1.11)	(-1.23)	(-1.36)	(-0.70)	(-0.88)	(-0.17)	(-0.08)	(0.53)	(0.01)	(-0.81)
Obs.	62,865	55,564	49,498	44,359	39,891	36,043	32,645	29,564	26,676	24,019
Adj. R^2	0.05	0.08	0.10	0.11	0.12	0.14	0.15	0.16	0.17	0.19
Panel D. Leases										
N^{BS}	0.009***	0.015***	0.013**	0.016**	0.021***	0.021**	0.030***	0.033***	0.028***	0.032***
	(3.09)	(3.43)	(2.41)	(2.41)	(2.83)	(2.44)	(3.11)	(3.20)	(2.66)	(2.77)
$N^{BS}\times$ EPU	-0.002	0.000	0.000	0.000	0.004	-0.003	-0.011	-0.017	-0.019	-0.025*
	(-0.55)	(0.02)	(0.04)	(0.07)	(0.54)	(-0.31)	(-1.03)	(-1.33)	(-1.32)	(-1.76)
N^{QI}	0.004*	0.011**	0.020***	0.024***	0.027***	0.033***	0.037***	0.039***	0.046***	0.051***
	(1.65)	(2.29)	(3.36)	(3.17)	(3.01)	(3.29)	(3.20)	(3.00)	(3.27)	(3.33)
$N^{QI}\times$ EPU	0.001	-0.002	-0.002	-0.004	-0.010	-0.006	-0.005	0.003	0.002	-0.001
	(0.44)	(-0.41)	(-0.38)	(-0.63)	(-1.25)	(-0.73)	(-0.52)	(0.30)	(0.15)	(-0.09)
N^{NV}	0.004	0.008	0.004	0.014*	0.015**	0.016**	0.010	0.018**	0.024**	0.036***
	(0.64)	(1.02)	(0.43)	(1.89)	(1.98)	(2.05)	(1.29)	(2.10)	(2.47)	(2.79)
$N^{NV}\times$ EPU	0.007	-0.001	-0.004	-0.001	0.000	0.003	-0.001	-0.000	-0.007	0.012
	(1.46)	(-0.18)	(-0.45)	(-0.18)	(0.00)	(0.33)	(-0.08)	(-0.00)	(-0.60)	(0.82)
Obs.	37,173	32,014	27,841	24,363	21,446	18,982	16,839	14,934	13,224	11,692
Adj. R^2	0.13	0.18	0.17	0.18	0.18	0.18	0.19	0.21	0.22	0.23

Table IA.A.6
Product types and financing - industry (SIC) FEs

The table presents the two-way fixed effect regression coefficients for the relation between product types and firms' financing choices with industry (SIC4) fixed effects. We estimate regressions of the following form:

$$Y_{i,t+1} = \sum_{C \in \{BS,QI,NV\}} \beta_\tau^C N_{i,t}^C + \Gamma' X_{i,t} + \alpha_{SIC4} + \delta_t + \epsilon_{i,t}.$$

where $Y_{i,t+1}$ are firm financing variables, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, ROA, PPE, cash holding, patent and R&D stock. α_{SIC4} and δ_t are industry and year fixed effects. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1976 to 2020.

	Debt Issue	ln(Debt Amt.)	Equity Issue	ln(Equity Amt.)	Leverage	CAPX	OCF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N^{BS}	0.007***	0.070***	0.003**	0.017**	-0.005	0.076***	-0.001***
	(5.97)	(6.26)	(2.43)	(2.24)	(-1.40)	(4.86)	(-2.98)
N^{QI}	0.015***	0.179***	-0.009***	-0.074***	0.002	0.008	0.001
	(7.91)	(9.74)	(-7.70)	(-9.40)	(0.36)	(0.41)	(1.44)
N^{NV}	-0.000	-0.010	0.000	0.004	-0.000	0.018	0.000*
	(-0.17)	(-1.63)	(0.59)	(0.95)	(-0.10)	(1.59)	(1.80)
ln(Assets)	0.105***	0.774***	0.046***	0.431***	0.091***	-0.031	0.029***
	(48.43)	(42.39)	(26.55)	(38.96)	(12.51)	(-0.73)	(33.78)
Tobin's Q	0.002***	0.036***	0.028***	0.190***	-0.043***	0.898***	-0.003***
	(2.88)	(5.64)	(19.75)	(22.06)	(-14.37)	(32.58)	(-5.24)
ROA	-0.082***	-0.516***	-0.015***	-0.061***	-0.098***	3.390***	0.713***
	(-27.64)	(-25.66)	(-3.40)	(-2.73)	(-7.17)	(39.16)	(190.02)
PPE/AT	0.002	-0.040	-0.020***	-0.135***	0.027	12.039***	0.099***
	(0.29)	(-0.71)	(-2.96)	(-3.32)	(0.82)	(52.89)	(29.99)
Cash Holding	-0.009*	-0.178***	0.280***	1.491***	-0.440***	2.975***	
	(-1.89)	(-4.82)	(39.48)	(36.17)	(-25.07)	(24.36)	
Patent Stock	0.013***	0.126***	-0.049***	-0.311***	-0.039***	-0.215***	-0.008***
	(6.62)	(6.84)	(-28.88)	(-28.80)	(-6.70)	(-6.90)	(-10.93)
R&D Stock	-0.004**	-0.024*	0.006***	0.029***	-0.014***	0.163***	0.000
	(-2.52)	(-1.65)	(4.03)	(2.99)	(-2.99)	(6.21)	(0.41)
SIC4 FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Obs.	166,364	166,364	166,364	166,364	166,358	166,364	166,128
Adj. R^2	0.17	0.20	0.08	0.09	0.05	0.33	0.82

Table IA.A.7
Product types and financing - industry (TNIC) FEs

The table presents the two-way fixed effect regression coefficients for the relation between product types and firms' financing choices with industry (TNIC) fixed effects. We estimate regressions of the following form:

$$Y_{i,t+1} = \sum_{C \in \{BS,QI,NV\}} \beta_\tau^C N_{i,t}^C + \Gamma' X_{i,t} + \alpha_{TNIC} + \delta_t + \epsilon_{i,t}.$$

where $Y_{i,t+1}$ are firm financing variables, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, ROA, PPE, cash holding, patent and R&D stock. α_{TNIC} and δ_t are industry and year fixed effects. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1987 to 2020.

	Debt Issue	ln(Debt Amt.)	Equity Issue	ln(Equity Amt.)	Leverage	CAPX	OCF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N^{BS}	0.006***	0.062***	0.003**	0.018**	-0.007	0.066***	-0.001***
	(4.65)	(5.01)	(2.46)	(2.16)	(-1.51)	(4.17)	(-3.92)
N^{QI}	0.013***	0.158***	-0.009***	-0.073***	-0.002	0.004	-0.001
	(6.84)	(8.24)	(-7.07)	(-8.38)	(-0.41)	(0.21)	(-1.42)
N^{NV}	-0.001	-0.018**	0.001	0.007	0.001	0.017	0.001*
	(-1.20)	(-2.02)	(0.79)	(1.00)	(0.32)	(1.17)	(1.79)
ln(Assets)	0.117***	0.941***	0.044***	0.446***	0.107***	0.073	0.029***
	(45.30)	(41.52)	(22.48)	(33.75)	(13.49)	(1.59)	(28.92)
Tobin's Q	-0.000	0.017**	0.028***	0.209***	-0.054***	0.747***	-0.001
	(-0.24)	(2.28)	(17.52)	(20.10)	(-16.86)	(28.40)	(-0.91)
ROA	-0.100***	-0.701***	-0.017***	-0.017	-0.084***	2.530***	0.692***
	(-28.07)	(-27.50)	(-3.31)	(-0.63)	(-5.64)	(29.44)	(166.54)
PPE/AT	0.017*	0.112	-0.043***	-0.284***	0.097**	11.690***	0.083***
	(1.87)	(1.46)	(-5.40)	(-5.60)	(2.57)	(47.92)	(22.64)
Cash Holding	-0.005	-0.086**	0.259***	1.487***	-0.382***	2.874***	
	(-0.87)	(-2.00)	(31.63)	(30.19)	(-19.23)	(21.96)	
Patent Stock	0.018***	0.175***	-0.051***	-0.355***	-0.024***	-0.128***	-0.005***
	(7.90)	(7.96)	(-27.12)	(-27.54)	(-3.52)	(-4.11)	(-5.84)
R&D Stock	-0.006***	-0.041**	0.005***	0.030**	-0.016***	0.039	0.001*
	(-3.10)	(-2.29)	(2.66)	(2.53)	(-2.72)	(1.44)	(1.68)
TNIC300 FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Obs.	119,954	119,954	119,954	119,954	119,950	119,954	119,797
Adj. R^2	0.17	0.21	0.09	0.09	0.05	0.34	0.83

Robustness: Sample from 1950

Table IA.B.1
Trademark firm characteristics

The table reports univariate characteristics of firms with and without trademarks, and their difference. TM presents the characteristics of firm-years, where each firm has at least one live trademark. Non-TM presents the characteristics of firm-years where the firm does not have any live trademarks. Diff. is the difference between TM and non-TM, and t-stat is the associated t-statistic. All variable definitions are presented in Table C.1. ***, **, * indicates significance at 1%, 5% and 10% level. The sample period is 1950 to 2020.

	All				**TM**				**All – TM**	
	N	Mean	Median	Std. Dev.	N	Mean	Median	Std. Dev.	Diff.	t-stat
ln(Assets)	200,265	4.79	4.62	2.13	157,082	5.19	5.04	2.08	-0.39***	-55.42
ROA	200,231	-0.03	0.04	0.24	157,049	-0.01	0.04	0.22	-0.02***	-23.67
CAPX	200,265	0.07	0.04	0.07	157,082	0.06	0.04	0.06	0.00***	19.66
PPE	200,052	0.29	0.24	0.22	156,908	0.28	0.23	0.21	0.01***	15.21
R&D	200,265	0.04	0.00	0.09	157,082	0.04	0.00	0.09	0.00***	4.96
Leverage	200,256	0.69	0.33	1.90	157,077	0.66	0.34	1.83	0.03***	4.12
Tobin's Q	188,821	1.94	1.37	1.66	148,435	1.92	1.38	1.59	0.02***	4.41
Sales Growth	185,465	0.18	0.09	0.51	148,250	0.16	0.09	0.46	0.01***	8.42
Asset Growth	185,465	0.14	0.07	0.38	148,250	0.14	0.07	0.37	-0.00	-0.25
Equity Issue	200,265	0.10	0.00	0.30	157,082	0.10	0.00	0.29	0.00***	3.08
Debt Issue	200,265	0.08	0.00	0.27	157,082	0.09	0.00	0.29	-0.01***	-14.03
Equ. Repur.	200,265	0.35	0.00	0.48	157,082	0.37	0.00	0.48	-0.02***	-14.72
Firm age	200,265	14.11	9.00	15.20	157,082	15.90	11.00	16.05	-1.79***	-34.12
HHI	200,265	0.29	0.22	0.21	157,082	0.29	0.23	0.21	-0.01***	-7.76
No. Patents	200,265	6.68	0.00	27.64	157,082	8.38	0.00	30.88	-1.70***	-17.28

Table IA.B.2
Product commercialization and uncertainty — 1950

The table presents the relation between economic uncertainty and product commercialization scale and tilt. We estimate regressions of the following form:

$$Y_{i,t+1} = \alpha_i + \beta EPU_t + \Gamma' X_{i,t} + \varepsilon_{i,t+1},$$

where $Y_{i,t+1}$ is the product commercialization scale $\Delta Prod.$ (columns 1-2) defined as $\frac{\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} - \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}}{0.5\times[\sum_{C\in\{BS,QI,NV\}} N^C_{i,t+1} + \sum_{C\in\{BS,QI,NV\}} N^C_{i,t}]}$, and the tilt (columns 3-4) defined as the QI/(BS+NV) product ratio, EPU_t is the standardized economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, cash flow, industry HHI, leverage, patent stock and R&D stock, and α_i are firm fixed effects. Standard errors are clustered at the firm and year level. ***, **, * indicate significance at 1%, 5% and 10% level. The sample period is 1950 to 2020.

	ΔProd.		QI/(BS+NV)	
	(1)	(2)	(3)	(4)
EPU	-0.026***	-0.013***	0.141***	0.043***
	(-6.03)	(-3.28)	(6.32)	(3.55)
ln(Assets)		-0.016***		0.128***
		(-7.36)		(12.48)
Tobin's Q		0.007***		-0.002
		(6.03)		(-0.45)
Cash Flow		0.056***		-0.087***
		(3.33)		(-4.17)
HHI		-0.000		0.103
		(-0.03)		(1.60)
Leverage		-0.000		0.001
		(-0.34)		(0.43)
Patent Stock		-0.015***		0.047***
		(-7.62)		(2.98)
R&D Stock		0.000		0.001
		(0.88)		(0.71)
Firm FE	✓	✓	✓	✓
Obs.	127,912	120,579	127,410	120,080
R^2	0.15	0.16	0.80	0.81

Table IA.B.3
Product type payoffs and economic uncertainty — 1950

The table presents the regression results for the relation between product type payoffs and economic uncertainty. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}$$

where Y are the firm payoff variables, N^C are the number of commercialized products by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for firm gross profits (sales minus cost of goods sold) and Panel B for firm sales. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1950 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
					Panel A. Profits					
N^{BS}	0.009***	0.015***	0.023***	0.029***	0.031***	0.035***	0.039***	0.041***	0.042***	0.045***
	(6.85)	(7.35)	(9.90)	(10.06)	(8.70)	(9.32)	(10.08)	(9.46)	(8.60)	(8.40)
$N^{BS} \times$ EPU	-0.004**	-0.005**	-0.008***	-0.006*	-0.011**	-0.010**	-0.005	-0.010**	-0.009*	-0.009
	(-2.48)	(-2.03)	(-2.90)	(-1.73)	(-2.48)	(-2.42)	(-1.39)	(-2.41)	(-1.83)	(-1.62)
N^{QI}	0.007***	0.010***	0.013***	0.016***	0.022***	0.024***	0.028***	0.031***	0.031***	0.032***
	(5.44)	(4.46)	(4.78)	(4.86)	(5.79)	(5.56)	(5.88)	(5.64)	(5.09)	(4.86)
$N^{QI} \times$ EPU	0.003**	0.004	0.008**	0.005	0.005	0.002	0.002	0.003	-0.005	-0.009*
	(2.10)	(1.35)	(2.36)	(1.20)	(1.26)	(0.56)	(0.52)	(0.71)	(-1.08)	(-1.80)
N^{NV}	0.002*	0.003**	0.004**	0.005**	0.007***	0.008***	0.009***	0.009***	0.011***	0.011***
	(1.92)	(2.53)	(2.55)	(2.16)	(3.82)	(3.87)	(4.37)	(3.85)	(4.17)	(3.81)
$N^{NV} \times$ EPU	0.001	0.001	0.001	0.001	0.000	0.001	0.002	0.001	0.002	0.003
	(1.07)	(1.13)	(0.46)	(0.52)	(0.20)	(0.83)	(0.88)	(0.45)	(0.92)	(1.28)
Obs.	149,058	136,578	125,504	115,615	106,723	98,708	91,394	84,705	78,533	72,840
Adj. R^2	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.10	0.11	0.12
					Panel B. Sales					
N^{BS}	0.008***	0.015***	0.020***	0.025***	0.029***	0.033***	0.036***	0.038***	0.038***	0.041***
	(9.81)	(11.44)	(11.65)	(11.29)	(11.29)	(11.15)	(10.82)	(10.31)	(9.14)	(8.80)
$N^{BS} \times$ EPU	-0.001*	-0.003**	-0.003*	-0.003	-0.006**	-0.009***	-0.009***	-0.011***	-0.008**	-0.008*
	(-1.65)	(-1.97)	(-1.67)	(-1.40)	(-2.27)	(-2.81)	(-2.85)	(-3.11)	(-1.96)	(-1.83)
N^{QI}	0.003***	0.007***	0.012***	0.015***	0.019***	0.021***	0.023***	0.025***	0.026***	0.027***
	(2.85)	(4.87)	(5.56)	(5.75)	(5.89)	(5.52)	(5.11)	(4.94)	(4.53)	(4.32)
$N^{QI} \times$ EPU	0.003***	0.002*	0.002	0.001	0.001	0.000	0.001	0.002	-0.002	-0.006
	(3.46)	(1.69)	(1.11)	(0.42)	(0.35)	(0.08)	(0.29)	(0.63)	(-0.51)	(-1.45)
N^{NV}	0.002***	0.003***	0.004***	0.006***	0.007***	0.008***	0.009***	0.009***	0.011***	0.011***
	(2.71)	(3.22)	(3.29)	(4.15)	(4.15)	(4.65)	(4.60)	(4.19)	(4.73)	(4.44)
$N^{NV} \times$ EPU	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.002	0.002
	(1.34)	(1.60)	(0.58)	(0.86)	(0.45)	(1.04)	(0.87)	(0.74)	(1.12)	(1.02)
Obs.	149,058	136,578	125,504	115,615	106,723	98,708	91,394	84,705	78,533	72,840
Adj. R^2	0.06	0.07	0.08	0.09	0.10	0.11	0.12	0.13	0.14	0.15

Table IA.B.4
Product types, economic uncertainty and investments — 1950

he table presents the regression results for the relation among firm investments, product types and economic uncertainty. We estimate regressions of the form:

$$ln(\frac{Y_{i,t+\tau}}{Y_{i,t}}) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \psi_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t},$$

where Y are categories within net PPE investments, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, employment, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Panel A presents results for building & construction, Panel B for land, Panel C for machine & equipment, and Panel D for leases. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1950 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
Panel A. Building & Construction										
N^{BS}	0.009***	0.016***	0.026***	0.042***	0.048***	0.064***	0.070***	0.077***	0.079***	0.088***
	(3.18)	(3.70)	(4.60)	(5.57)	(5.37)	(5.92)	(5.26)	(5.04)	(4.71)	(4.88)
$N^{BS} \times$ EPU	0.004	-0.004	-0.001	0.018	0.028	0.043**	0.029	0.036	0.046	0.050
	(0.71)	(-0.48)	(-0.06)	(1.21)	(1.51)	(2.07)	(1.13)	(1.34)	(1.48)	(1.54)
N^{QI}	0.005*	0.014***	0.020***	0.026***	0.032***	0.024**	0.025*	0.032*	0.027	0.037*
	(1.83)	(3.11)	(3.24)	(3.12)	(3.17)	(2.00)	(1.75)	(1.78)	(1.32)	(1.85)
$N^{QI} \times$ EPU	-0.002	0.003	0.006	0.018	0.021	-0.004	0.001	0.015	0.010	0.018
	(-0.35)	(0.40)	(0.56)	(1.32)	(1.37)	(-0.20)	(0.06)	(0.63)	(0.34)	(0.62)
N^{NV}	-0.000	-0.002	-0.002	-0.006*	-0.003	-0.003	-0.005	-0.002	0.002	-0.002
	(-0.15)	(-1.02)	(-0.82)	(-1.72)	(-0.90)	(-0.77)	(-0.96)	(-0.32)	(0.32)	(-0.38)
$N^{NV} \times$ EPU	0.001	-0.003	0.002	-0.009	-0.007	-0.006	-0.013	-0.024*	-0.020	-0.025
	(0.25)	(-0.51)	(0.23)	(-0.92)	(-0.65)	(-0.49)	(-0.99)	(-1.79)	(-1.34)	(-1.42)
Obs.	33,768	29,812	26,240	23,018	20,120	17,520	15,238	13,221	11,415	9,837
Adj. R^2	0.04	0.07	0.10	0.13	0.14	0.15	0.17	0.20	0.22	0.25
Panel B. Land										
N^{BS}	0.003	0.010**	0.018***	0.034***	0.043***	0.048***	0.053***	0.048***	0.054***	0.056***
	(1.40)	(2.35)	(3.06)	(4.59)	(4.85)	(4.65)	(4.25)	(3.35)	(3.43)	(3.06)
$N^{BS} \times$ EPU	0.001	-0.001	-0.002	0.012	0.023	0.027	0.009	-0.000	0.021	0.045
	(0.26)	(-0.11)	(-0.20)	(0.81)	(1.25)	(1.27)	(0.32)	(-0.00)	(0.61)	(1.14)
N^{QI}	0.005*	0.012***	0.018***	0.022**	0.029**	0.030**	0.038**	0.046**	0.038*	0.048**
	(1.91)	(2.67)	(2.78)	(2.38)	(2.57)	(2.26)	(2.37)	(2.41)	(1.73)	(2.09)
$N^{QI} \times$ EPU	-0.002	-0.004	0.006	0.005	0.011	0.003	0.019	0.019	0.001	-0.011
	(-0.39)	(-0.51)	(0.49)	(0.31)	(0.65)	(0.16)	(0.87)	(0.74)	(0.03)	(-0.37)
N^{NV}	-0.002	-0.001	-0.002	-0.004	-0.005	-0.003	-0.005	-0.002	-0.001	-0.011*
	(-1.10)	(-0.36)	(-0.88)	(-1.01)	(-1.32)	(-0.79)	(-1.09)	(-0.34)	(-0.15)	(-1.69)
$N^{NV} \times$ EPU	-0.006*	-0.007	-0.014*	-0.010	-0.010	-0.008	-0.021	-0.024	-0.031*	-0.048**
	(-1.65)	(-1.27)	(-1.74)	(-1.14)	(-1.10)	(-0.79)	(-1.61)	(-1.61)	(-1.68)	(-2.56)
Obs.	32,547	28,774	25,350	22,250	19,462	16,959	14,757	12,796	11,041	9,512
Adj. R^2	0.04	0.06	0.09	0.12	0.14	0.15	0.17	0.19	0.20	0.23
Panel C. Machine & Equipment										
N^{BS}	0.005**	0.014***	0.024***	0.033***	0.045***	0.052***	0.058***	0.055***	0.052***	0.056***
	(2.46)	(4.13)	(5.05)	(5.40)	(6.04)	(6.01)	(5.68)	(4.49)	(3.69)	(3.43)
$N^{BS} \times$ EPU	-0.001	-0.000	0.003	0.020	0.030*	0.044**	0.042**	0.046*	0.047*	0.056*
	(-0.24)	(-0.01)	(0.28)	(1.48)	(1.83)	(2.38)	(1.98)	(1.85)	(1.70)	(1.78)
N^{QI}	0.006***	0.011***	0.020***	0.029***	0.031***	0.027***	0.026**	0.044***	0.046***	0.048***
	(2.88)	(3.04)	(3.94)	(4.18)	(3.61)	(2.78)	(2.11)	(2.98)	(2.67)	(2.62)
$N^{QI} \times$ EPU	0.006	0.004	0.018**	0.034***	0.037**	0.024	0.019	0.046**	0.047*	0.040
	(1.55)	(0.54)	(1.96)	(2.70)	(2.43)	(1.44)	(1.01)	(2.07)	(1.86)	(1.49)
N^{NV}	-0.000	0.000	-0.002	-0.003	-0.002	-0.002	-0.007	-0.006	0.003	0.002
	(-0.04)	(0.13)	(-0.68)	(-0.90)	(-0.45)	(-0.44)	(-1.04)	(-0.73)	(0.80)	(0.49)
$N^{NV} \times$ EPU	-0.006*	-0.002	-0.008	-0.010	-0.010	-0.014	-0.021	-0.025	-0.010	-0.008
	(-1.77)	(-0.51)	(-1.53)	(-1.42)	(-1.08)	(-1.29)	(-1.52)	(-1.44)	(-0.92)	(-0.59)
Obs.	38,545	33,722	29,430	25,601	22,197	19,186	16,567	14,306	12,290	10,551
Adj. R^2	0.07	0.10	0.12	0.15	0.17	0.18	0.19	0.22	0.24	0.26
Panel D. Lease										
N^{BS}	0.007	0.004	0.003	0.003	0.021	0.025	0.013	0.012	-0.011	0.035
	(1.17)	(0.44)	(0.21)	(0.13)	(1.13)	(1.30)	(0.65)	(0.47)	(-0.44)	(1.03)
$N^{BS} \times$ EPU	-0.023	-0.039	-0.051	-0.053	-0.015	-0.044	-0.063	-0.083	-0.128*	-0.044
	(-1.41)	(-1.63)	(-1.61)	(-1.11)	(-0.32)	(-0.81)	(-1.15)	(-1.27)	(-1.92)	(-0.59)
N^{QI}	0.002	0.012	0.027	0.031	0.026	0.042	0.057	0.075	0.101*	0.067
	(0.30)	(0.86)	(1.25)	(1.06)	(0.75)	(1.13)	(1.28)	(1.38)	(1.76)	(1.04)
$N^{QI} \times$ EPU	-0.014	-0.015	0.000	0.013	-0.047	-0.041	-0.033	-0.003	0.032	-0.078
	(-0.76)	(-0.55)	(0.00)	(0.31)	(-0.93)	(-0.70)	(-0.47)	(-0.03)	(0.36)	(-0.77)
N^{NV}	0.005	0.006	-0.007	-0.008	-0.015	-0.031	-0.046	-0.001	-0.014	0.003
	(0.40)	(0.58)	(-0.80)	(-0.67)	(-1.39)	(-1.40)	(-1.49)	(-0.09)	(-0.57)	(0.09)
$N^{NV} \times$ EPU	0.006	0.015	-0.009	-0.021	-0.036	-0.059	-0.088	0.003	-0.013	0.021
	(0.21)	(0.60)	(-0.44)	(-0.88)	(-1.57)	(-1.38)	(-1.52)	(0.10)	(-0.27)	(0.35)
Obs.	16,416	13,918	11,811	9,994	8,420	7,075	5,931	4,956	4,103	3,389
Adj. R^2	0.05	0.10	0.15	0.19	0.24	0.28	0.31	0.36	0.38	0.41

Table IA.B.5
Product types, economic uncertainty and employment — 1950

The table presents the regression results for the relation between product types and employment during economic uncertainty. We estimate regressions of the form:

$$\ln\left(\frac{Y_{i,t+\tau}}{Y_{i,t}}\right) = \sum_{C\in\{BS,QI,NV\}} \left[\beta_\tau^C N_{i,t}^C + \lambda_\tau^C N_{i,t}^C \times EPU_t\right] + \gamma_1 ln(Y_{i,t-1}) + \gamma_2 ln(Y_{i,t-2}) + \Gamma' X_{i,t} + \alpha_{sic3} + \delta_t + \epsilon_{i,t}$$

where Y is firm employment, N^C are the number of commercialized products by firm i in year t, EPU_t is the economic uncertainty index (Baker, Bloom, and Davis, 2016), $X_{i,t}$ is a vector of control variables including log capital, idiosyncratic volatility, and firm age, and $\tau \in 1-10$. α_{sic3} and δ_t are industry and year fixed effects. All right-hand-side variables are scaled to unit standard deviation. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is 1950 to 2020.

	t+1	t+2	t+3	t+4	t+5	t+6	t+7	t+8	t+9	t+10
N^{BS}	0.011***	0.016***	0.022***	0.027***	0.032***	0.035***	0.039***	0.041***	0.042***	0.044***
	(9.18)	(10.15)	(11.36)	(11.22)	(11.47)	(10.99)	(10.71)	(10.17)	(9.31)	(8.81)
$N^{BS} \times$ EPU	-0.001	-0.002	0.000	-0.001	-0.002	-0.004	-0.005	-0.007*	-0.005	-0.006
	(-1.18)	(-0.89)	(0.02)	(-0.22)	(-0.77)	(-1.15)	(-1.30)	(-1.85)	(-1.04)	(-1.17)
N^{QI}	0.005***	0.012***	0.017***	0.021***	0.024***	0.027***	0.028***	0.031***	0.031***	0.034***
	(4.58)	(6.65)	(7.03)	(7.10)	(6.60)	(6.12)	(5.58)	(5.44)	(4.92)	(4.81)
$N^{QI} \times$ EPU	0.001	-0.000	-0.003	-0.006**	-0.006*	-0.007**	-0.005	-0.004	-0.007*	-0.010**
	(0.69)	(-0.16)	(-1.62)	(-2.27)	(-1.96)	(-2.12)	(-1.51)	(-1.05)	(-1.79)	(-2.15)
N^{NV}	-0.000	0.002*	0.003**	0.004**	0.004**	0.007***	0.007***	0.008***	0.010***	0.009***
	(-0.26)	(1.94)	(2.17)	(2.06)	(2.12)	(3.39)	(2.83)	(3.32)	(3.72)	(2.86)
$N^{NV} \times$ EPU	-0.001*	-0.000	-0.002	-0.002	-0.002	0.000	-0.001	-0.001	0.005	0.004
	(-1.73)	(-0.53)	(-1.23)	(-1.03)	(-0.99)	(0.01)	(-0.33)	(-0.28)	(1.12)	(0.84)
Obs.	149,058	136,578	125,504	115,615	106,723	98,708	91,394	84,705	78,533	72,840
Adj. R^2	0.05	0.07	0.08	0.10	0.11	0.11	0.12	0.14	0.15	0.16

Table IA.B.6
Product types and financing - 1950

The table presents the two-way fixed effect regression coefficients for the relation between product types and firms' financing choices. We estimate regressions of the following form:

$$Y_{i,t+1} = \sum_{C \in \{BS,QI,NV\}} \beta_\tau^C N_{i,t}^C + \Gamma' X_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}.$$

where $Y_{i,t+1}$ are firm financing variables, N^C are the number of commercialized products (BS, QI, and NV) by firm i in year t, $X_{i,t}$ is a vector of control variables including log total assets, Tobin's Q, ROA, PPE, cash holding, patent and R&D stock. α_i and δ_t are firm and year fixed effects. Standard errors are clustered at the firm level. ***, **, * indicates significance at 1%, 5% and 10% level, respectively. The sample period is from 1950 to 2020.

	Debt Issue	ln(Debt Amt.)	Equity Issue	ln(Equity Amt.)	Leverage	CAPX	OCF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
N^{BS}	0.005***	0.041***	0.004***	0.026***	0.000	0.052***	-0.001***
	(4.39)	(4.53)	(4.19)	(4.23)	(0.13)	(3.96)	(-3.19)
N^{QI}	0.008***	0.105***	-0.001	-0.019***	0.004	0.021	-0.001*
	(4.76)	(6.93)	(-0.75)	(-2.83)	(0.93)	(1.07)	(-1.72)
N^{NV}	-0.001	-0.013**	-0.000	0.002	0.001	0.016	0.000**
	(-0.67)	(-2.25)	(-0.27)	(0.59)	(0.69)	(1.27)	(2.03)
ln(Assets)	0.115***	0.836***	0.022***	0.307***	0.221***	-0.522***	0.025***
	(32.68)	(27.93)	(6.20)	(15.02)	(14.71)	(-6.37)	(16.55)
Tobin's Q	0.003***	0.039***	0.038***	0.241***	-0.039***	0.913***	0.007***
	(3.93)	(5.63)	(23.95)	(26.08)	(-10.96)	(30.05)	(9.88)
ROA	-0.034***	-0.236***	0.092***	0.388***	-0.081***	4.095***	0.597***
	(-11.40)	(-11.23)	(18.92)	(15.60)	(-4.05)	(36.86)	(127.41)
PPE/AT	-0.056***	-0.533***	-0.088***	-0.476***	0.106**	3.101***	0.052***
	(-5.59)	(-6.21)	(-8.36)	(-8.46)	(2.16)	(9.02)	(11.51)
Cash Holding	0.006	0.037	0.307***	1.378***	-0.361***	3.452***	
	(1.04)	(0.79)	(33.71)	(28.89)	(-14.48)	(19.36)	
Patent Stock	-0.003	-0.005	-0.070***	-0.399***	-0.058***	-0.324***	-0.007***
	(-0.79)	(-0.14)	(-20.00)	(-19.22)	(-4.34)	(-4.54)	(-5.57)
R&D Stock	0.001	0.016	0.002*	0.018**	0.010***	-0.025	-0.001*
	(0.73)	(1.48)	(1.89)	(2.15)	(2.62)	(-1.58)	(-1.71)
Firm FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
Obs.	187,141	187,141	187,141	187,141	187,135	187,141	186,883
Adj. R^2	0.21	0.26	0.19	0.21	0.21	0.46	0.87