The Anatomy of Firm Scope: Intangible Composition, Markups, Productivity and Competitive Threat*

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Abstract

In this paper, I investigate how closely related and distant firm scope creates different consequences for innovation. I measure related scope using Hoberg and Phillips (2025) text-based product-market clusters and distant scope using the Compustat segment count. Using a panel of U.S. public firms over 1990–2019, I estimate local projections in response to innovation shocks and find that these two dimensions govern opposite regimes. Closely related scope generates synergy: firms tilt intangible investment toward more R&D, attract rival entry, and convert innovation into persistent productivity and markup gains. High distant scope generates friction: rents dissipate, productivity gains vanish, and intangible investment in R&D weakens after the innovation shock. The results show that innovation consequences emerge from the structure, not the level, of scope.

Keywords: firm scope, diversification, intangibles, productivity, markups

JEL Classification: L25, O31, E22.

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1. Introduction

Modern firms rarely confine themselves to a single product market, yet the scope of their operations varies substantially. Some firms operate across multiple closely related sub-markets that draw on a common technological base, whereas others span technologically and operationally distant business domains that share little beyond common ownership.

This distinction is consequential for innovation. When a firm expands into closely related sub-markets, it remains within a common technological boundary, and proximity makes knowledge movable: a patent, a production process, or a body of engineering know-how developed for one sub-market can be redeployed in neighbouring ones at little additional cost. The firm thus internalises its own knowledge spillovers, and the returns to R&D compound with related scope (Jaffe, 1986; Bena and Li, 2014). Moreover, because new ideas build on existing ones, an innovation does more than improve the product for which it was developed: it can open follow-on research directions in neighbouring markets, accelerating progress there as well (Scotchmer, 1991; Weitzman, 1998). By contrast, when a firm instead expands into operationally distant domains, technological proximity breaks down, and two distinct forces may come into play. The first is a span-of-control constraint: managerial attention and coordination capacity must stretch across domains that share no common substrate, so each additional domain weakens managerial control (Lucas, 1978). The second concerns which intangibles can still transfer. Organizational capital attaches to the firm rather than to any particular technology, so a reputation for quality or a set of management practices (Prescott and Visscher, 1980; Eisfeldt and Papanikolaou, 2013), and evidence on intra-firm flows confirms that what moves across a firm's establishments is precisely this kind of input rather than physical goods (Atalay *et al.*, 2014; Keskin, 2026). Thus, this paper examines how the structure of firm scope shapes the returns to innovation in terms of productivity, markups, the composition of intangible investment, and exposure to competitive threats.

To answer this question, I measure related scope using the text-based product-market clusters developed by Hoberg and Phillips (2025) (hereafter HP), which map the product descriptions in a firm's 10-K filings into fine-grained markets that lie close to one another in product space. For distant scope, I use the number of business segments a firm reports in the Compustat Historical Segment file. Segments are disclosed under SFAS 131 precisely to partition activity into operationally distinct lines of business, so the segment count records how many largely non-overlapping domains a firm spans. For instance, HP resolves Tesla, Inc. into eleven product-market clusters, covering automotive subsystems (brakes, trim, axles, chassis), automotive safety, car dealerships, batteries, solar and renewable energy, utility-scale electric power, smart metering, power electronics, hardware and software solutions, and ticketing systems, all anchored in a common electrochemical and energy-systems substrate, while Compustat aggregates the same firm into two operationally distant segments, Automotive and Energy Generation & Storage.[1]

To test how the structure of scope shapes the response to innovation, I use Compustat Fundamentals from 1990 to 2019 to construct firm-level total factor productivity, markups, and the composition of intangible investment. Following Peters and Taylor (2017), I split intangible investment into R&D and organizational capital. To identify competitive threat, I use the product-market fluidity index of Hoberg *et al.* (2014), which captures how quickly rivals introduce innovations within a firm's product space. I then estimate local projections (Jordà, 2005) using innovation shocks (Kogan *et al.*, 2017) to characterize how the dynamic responses of these outcomes differ between related and distant scope regimes.

Results show that firms with higher related scope respond to an innovation shock on every margin: they raise the intangible investment ratio, defined as R&D investment over investment in organisational capital, rivals move into their product space, and their productivity and markups rise persistently over the three-year horizon. Firms spread across many operationally distant segments also raise the investment ratio: the point estimate is roughly half as large,. Their markup response is about half the size, and their productivity response is statistically indistinguishable from zero, so their markups rise without any gain in efficiency.

[1] See Table A1 for details.

These findings connect two sets of facts that the literature has treated separately. Firms that combine a high closely related scope with few distant segments display the joint rise of productivity and markups that Autor *et al.* (2020) and De Loecker *et al.* (2020) associate with superstar firms and the rise of market power. Those studies define superstar firms by their outcomes. The estimates here tie that profile to an observable firm characteristic, the structure of scope, and show that it comes with rising competitive threat. Firms that combine many distant segments with narrow related scope display the configuration of the diversified conglomerates studied by Lang and Stulz (1994), Berger and Ofek (1995), and Schoar (2002), and in the estimates their markups rise without productivity while their innovations provoke little rival response. The familiar cross-firm gradients in productivity, markups, intangible composition, and competitive pressure therefore vary systematically with the structure of scope rather than with its extent.

Related literature. First, the empirical innovation literature built on patent-value (Kogan *et al.*, 2017; Bena and Li, 2014) and the work relating competition to innovation (Aghion *et al.*, 2005). Relative to existing applications of the patent-value measure, I show that the response to the same shock varies sharply with the firm's scope structure. The literature mostly focuses on how competition shapes innovation. I trace the reverse arrow, the competitive response that innovation provokes, and show that rivals enter the product space of higher closely-related firms and retreat from that of distant ones. Second, this paper contributes to the literature on intangible capital and its growing economic importance (Corrado *et al.*, 2009; Prescott and Visscher, 1980; Eisfeldt and Papanikolaou, 2013; Eisfeldt and Papanikolaou, 2014; Peters and Taylor, 2017; Haskel and Westlake, 2017; Keskin, 2026). That literature measures the components of intangible investment and documents their rise. I add evidence on what moves their composition at the firm level: an innovation shock shifts the intangible investment ratio, R&D relative to organisational capital, toward research, and the size of the reallocation varies with The firm's scope is high when the related scope is large. The third is the literature on corporate diversification and its discount (Panzar and Willig, 1981; Teece, 1980; Helfat and Raubitschek, 2000; Lang and

Stulz, 1994; Berger and Ofek, 1995; Schoar, 2002; Maksimovic and Phillips, 2002; Villalonga, 2004; Custódio, 2014), together with the span-of-control tradition of Lucas (1978). That work largely measures scope with segment counts and debates the sources of the discount. Separating segment counts from text-based related scope shows that the discount is a distant-scope phenomenon with an innovation mechanism, and that a related-scope premium coexists with it inside the same firm.

Paper organisation. The remainder of the paper proceeds as follows. Section 2 describes the data sources and presents summary statistics on the two scope measures. Section 3 details the firm-level measurement of productivity, markups, and the components of intangible investments. Section 4 estimates the dynamic responses to patent-value innovation shocks across the two scope dimensions. Section 5 concludes.

2. Data and Summary Statistics

The analysis combines five firm-level data sources. Compustat Fundamentals supplies the financial variables from which productivity, markups, and the composition of intangible investment are constructed. The Compustat Historical Segment file supplies the measure of distant scope, and the HP text-based scope dataset supplies the measure of related scope. The fluidity index of Hoberg *et al.* (2014) measures the competitive threat each firm faces, and the patent-value dataset of Kogan *et al.* (2017) provides the innovation shocks that drive the dynamic analysis. All sources are merged at the firm-year level, and the sample covers fiscal years 1990 to 2019. This section describes each source in turn and then documents the cross-sectional behaviour of the two scope measures, which is itself informative about the structure of firm scope.

Firm-level financial data. Compustat Fundamentals provides comprehensive financial information for publicly listed U.S. firms, with longitudinal coverage of balance-sheet items, income-statement components, and cash-flow data, and with firm identifiers that permit clean linkage to the scope, fluidity, and patent datasets. I use Compustat to construct the firm-level measures of markups, productivity, and intangible composition described in Section 3, and as the spine onto which the remaining datasets are merged. The sample excludes the finance and utilities sectors, whose regulated pricing and distinct accounting conventions make production functions and markups incomparable with the rest of the economy, and drops firm-years with missing or non-positive R&D, SG&A, employment, or sales.

Distant scope. Measuring distant scope, the operationally separable lines of business a firm spans, requires data on the broad units that firms themselves treat as substantively distinct. I obtain this from the Compustat Historical Segment file, which compiles firms' mandated segment-level disclosures from 1976 to the present. From 1976 to 1997 these disclosures were governed by SFAS No. 14, under which segments were defined along industry lines. From fiscal year 1998 onward they are governed by SFAS No. 131, codified as ASC 280 in 2009, which replaced the industry approach with a *management approach*: reportable segments must correspond to the components of the enterprise whose operating results the chief operating decision maker regularly reviews to allocate resources and assess performance.[2] The standard imposes quantitative thresholds, so that a component becomes reportable when it accounts for at least ten percent of the firm's revenue, profits, or assets, and it permits aggregation of components only when they share similar economic characteristics. Distinct reported segments are therefore, by regulatory construction, units that the firm's own management runs and evaluates separately. Compustat assigns a unique identifier (`sid`) to each reported segment, and I define distant scope as the number of distinct business segments a firm reports in a given year.[3] In practice

[2] Year fixed effects in every specification absorb aggregate shifts in reporting practice, including the 1998 transition between regimes.

[3] The Historical Segment dataset reports several segment classifications at the firm-year level. I retain business segments and exclude geographic and operating classifications, as well as residual corporate or eliminations segments, since these do not correspond to lines of business. Beginning in 2015, the WRDS Compustat Segment files additionally provide product–service (PD_SRVC) information, which directly identifies the products and services associated with each segment. To construct a consistent measure, I use business segments prior to 2015 and PD_SRVC-based definitions thereafter. Firms without segment

this yields broad partitions that distinguish operationally and informationally separable lines of business rather than fine-grained product variety, so the segment count captures diversification across domains rather than breadth within them.

Related scope. Measuring related scope, the fine-grained product-market clusters a firm spans within its operational domain, requires data of a different kind, constructed from what firms sell rather than from how managers report. I use the HP text-based scope dataset (Hoberg and Phillips, 2025), which applies natural-language processing to the business descriptions firms file in their annual 10-Ks. The construction embeds each firm's product description in a high-dimensional vector-space representation of the U.S. product market and assigns the firm to a set of product-market clusters according to its proximity to other firms in that space. The variable `d2vscope` reports the number of distinct clusters a firm occupies in a given year, and I use it as the measure of related scope throughout. The text-based construction has two advantages for present purposes. First, it is independent of managerial reporting discretion and of static industry classifications, updating annually as firms reposition their products. Second, because clusters are recovered from product-description language, they are typically much narrower than Compustat segments and, for a given firm, lie close to one another in product space. The cluster count therefore captures exactly the within-domain product variety that the segment count is constructed to abstract away from. Table A1 illustrates the contrast for Tesla, Inc., which Compustat aggregates into two distant segments while HP resolves into eleven related product-market clusters.

Competitive threat. To capture the competitive pressure firms face, I use the product-market fluidity metric of Hoberg *et al.* (2014). Fluidity measures the overlap between a firm's own product vocabulary and the year-over-year *change* in the vocabulary used by all rival firms, so it rises when competitors are actively moving into the product space the firm occupies. A high fluidity score therefore indicates that rivals are rapidly reconfig-

records in a given year are excluded from the sample.

uring their offerings around the firm's position, and it serves in the analysis as a direct measure of the competitive threat surrounding a firm's product market.

Table 1. Summary Statistics

Variable	N	Mean	SD	P25	Median	P75
Sale	61,104	2,068,272	11,797,105	19,109	98,265	595,534
Emp	61,104	6,104	26,107	119	482	2,691
AT	61,101	2,728,453	18,443,129	22,153	110,624	677,513
XRD	61,104	100,848	628,530	1,361	6,282	27,861
XSGA	61,104	405,702	1,991,132	10,240	36,839	156,267
Productivity	55,845	19.781	23.080	7.706	10.879	22.907
Markup	55,316	1.537	1.030	0.987	1.212	1.663
Competitive Threat	50,285	6.769	3.203	4.437	6.365	8.603

Notes: This table reports summary statistics for Compustat Fundemental, restricted to firm-years with positive sales, employment, R&D, and SG&A.

Innovation shocks. To trace how firm outcomes evolve around innovation events, I use the patent-value dataset of Kogan *et al.* (2017), which provides patent identifiers, filing and grant dates, firm identifiers, forward citations, and a market-based estimate of each patent's value. The value measure is constructed from the firm's idiosyncratic stock return within a narrow event window around the patent grant date, filtered of market movements and converted into a dollar magnitude. Because the exact grant date is set by the Patent Office, the short-window design isolates the surprise component of the market's valuation of the grant, abstracting from anticipation effects and concurrent firm-level news.

Summary statistics. Table 1 reports pooled summary statistics for the main variables over fiscal years 1990–2019. The underlying Compustat sample exceeds 70,000 firm-year observations on the raw size measures (sales, employment, total assets, R&D, and SG&A) and displays the pronounced right-skew familiar from the Compustat cross-section: median sales and total assets are roughly two orders of magnitude smaller than their means, and all size variables accordingly enter the analysis in logarithms. Because the two scope datasets cover overlapping but non-identical subsets of Compustat, the merged estimation samples are smaller than the fundamentals panel. Appendix Table A4 reports summary statistics separately for the distant-scope and related-scope merged samples and confirms that the merges do not distort the distributions of size, productivity, or markups.

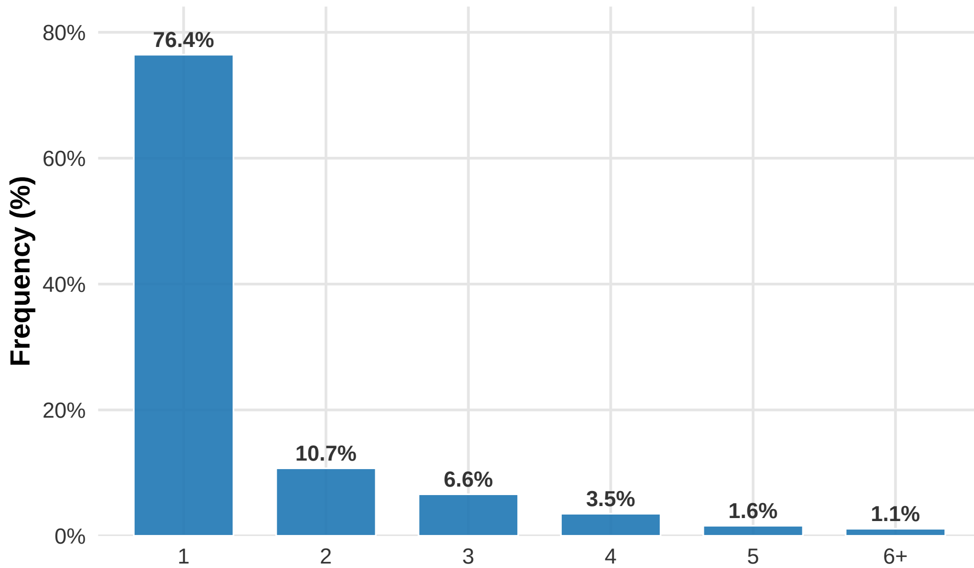

Figure 1. Firm Distribution across Scope (Compustat)

Note: The figure shows the distribution of firm-year observations across the number of reported business segments (*sid_count*). Observations with zero segments are excluded. Values greater than five are grouped into the "6+" category.

The two margins of scope. Figures 1 and 2 plot the pooled firm-year distributions of the two scope measures, and the contrast between them is the first substantive fact of the paper. Distant scope is heavily concentrated at a single segment: 76.4% of firm-year observations report one business segment, 10.7% report two, and the share declines sharply thereafter, with only 6.6% of observations reporting four or more segments. Diversification across operationally separable lines of business is, in the panel, the exception rather than the rule, confined to a narrow upper tail. Related scope, in contrast, is widely dispersed. The modal firm-year occupies a single cluster, but the mode accounts for only 13% of observations. Mass is spread smoothly across the interior of the support, with roughly 59% of observations falling between two and ten clusters and a non-trivial right tail in which 5.8% of observations occupy twenty or more. The same population of firms is therefore narrow along one dimension and broad along the other: firms rarely straddle operationally distant domains, yet within their domain they routinely spread across many neighbouring product markets. This is precisely the pattern the introduction anticipates. The two measures record different margins of expansion rather than the same margin at different resolutions, and collapsing them into a single count would average a dimension along which almost all firms are concentrated with one along which they are widely dispersed.

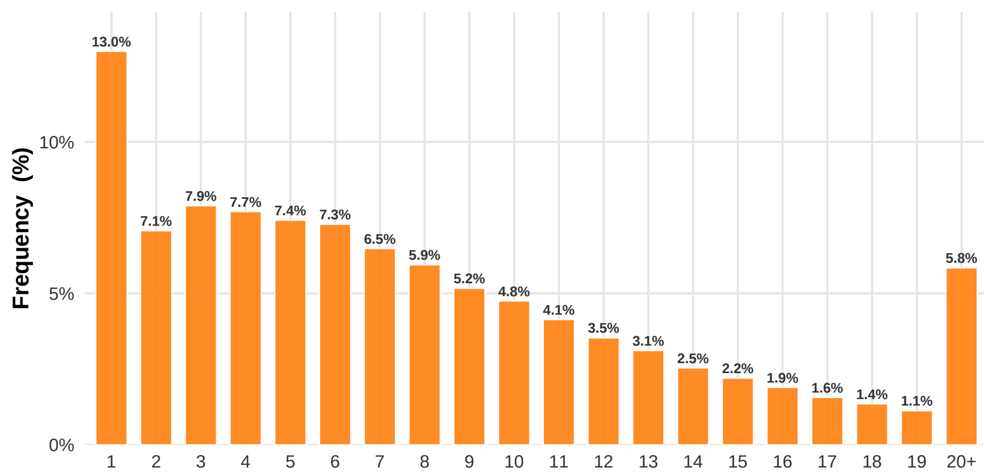

Figure 2. Firm Distribution across Scope (Hoberg-Phillips)

Note: The figure shows the distribution of firm-year observations across the firm scope measure (*d2vscope*), which captures the breadth of a firm's product market activity. Observations with a scope value of zero are excluded. Values greater than nineteen are grouped into the "20+" category.

3. Measurement

The dynamic analysis requires firm-level measures of total factor productivity, markups, and the composition of intangible investment. This section describes how each is constructed from the Compustat data.

Production function and productivity. I estimate firm-level total factor productivity with the two-stage proxy-variable approach of Olley and Pakes (1996), separately for each two-digit NAICS industry. Consider the gross-output production function

$$y_{it} = \beta_l\, l_{it} + \beta_k\, k_{it} + \beta_m\, m_{it} + \omega_{it} + \varepsilon_{it}, \tag{1}$$

where y_{it}, l_{it}, k_{it}, and m_{it} denote log sales, log employment, log capital stock, and log intermediate inputs for firm i in year t,[4] ω_{it} is a productivity state observed by the firm before it chooses inputs, and ε_{it} is an i.i.d. disturbance uncorrelated with input choices. The estimation sample is restricted to observations satisfying `sale` > 0, `ppent` > 0, `cogs` > 0, `emp` > 0, `capx` > 0, and `cogs` $<$ `sale`, where the final restriction ensures positive gross profits. The restriction to strictly positive capital expenditure also serves the estimator, since the investment inversion below is defined only where investment is strictly positive. All nominal variables are deflated to real terms prior to estimation: output by the GDP deflator, intermediate inputs by the Producer Price Index, and the capital stock and capital expenditure by the Gross Private Domestic Investment deflator.[5]

Markups. Firm-level markups follow the production approach of De Loecker *et al.* (2020), which requires no assumptions on demand or on the mode of competition. Cost minimisation implies that, for any input free of adjustment costs, the output elasticity of that input equals the markup multiplied by the input's expenditure share in revenue. Rearranging gives

$$\sigma_{it} \;=\; \frac{\hat{\beta}_m}{s^m_{it}}, \tag{2}$$

where $\hat{\beta}_m$ is the intermediate-input elasticity using the first stage of OP and s^m_{it} is the firm's expenditure on intermediate inputs divided by its sales revenue.

[4] The Compustat counterparts are `SALE` (sales), `EMP` (employment), `PPENT` (net property, plant, and equipment), and `COGS` (intermediate inputs).

[5] GDP deflator: https://fred.stlouisfed.org/series/A191RD3A086NBEA. PPI: https://fred.stlouisfed.org/series/WPUID61. Investment deflator: https://fred.stlouisfed.org/series/A006RD3A086NBEA.

Intangible ratio and its composition. Following Peters and Taylor (2017), I measure R&D investment as total R&D expenditure (`XRD`), and investment in brand value and organisational capital as 30% of Selling, General, and Administrative expenses net of R&D (`XSGA` − `XRD`).[6] SG&A encompasses a broad range of expenditures, including advertising, employee compensation, and general operating costs. Once R&D is netted out, most of what remains is routine operating expense consumed within the period, but a portion accumulates inside the firm as lasting intangible capital: advertising builds brand recognition, and the compensation of managers and skilled employees builds organisational knowledge and routines. The 30% fraction isolates this accumulating component, the firm-specific intangible capital composed of brand value and organisational capital, and treats the remainder as operating cost that generates no lasting value. The composition measure used throughout the paper is the ratio of R&D investment to investment in brand and organisational capital, so that an increase in the ratio indicates a tilt of the firm's intangible portfolio toward research.

4. Dynamic Response to Innovation Shocks

I estimate impulse responses with local projections (Jordà, 2005), which recover horizon-specific responses without imposing a parametric model of the outcome dynamics and accommodate group heterogeneity directly. The innovation shock is the firm-year aggregate of the Kogan *et al.* (2017) patent values, $V_{it} = \sum_{p \in \mathcal{P}_{it}} \text{PatentValue}_{p,t}$, where $\mathcal{P}_{it}$ is the set of patents granted to firm i in year t, entering as $\log(1 + V_{it})$ to retain firm-years with zero grants. Two features support a causal reading. The specification is

$$\Delta_h Y_{ijt} = \alpha_h + \beta^h_{\text{High}} V_{it} D_{it} + \beta^h_{\text{Low}} V_{it} (1 - D_{it}) + \mathbf{\Gamma}_h^\top \mathbf{X}_{i,t-1} + \delta_h Y_{i,t-1} + \theta_j + \lambda_t + u_{ijt}, \quad (3)$$

where $\Delta_h Y_{ijt} \equiv Y_{i,t+h} - Y_{it}$ is the h-period log change in outcome Y for firm i in industry j, estimated at horizons $h = 0, 1, 2, 3$, and $D_{it} \in \{0, 1\}$ indicates the high-scope group along

[6] Peters and Taylor (2017) refer to the R&D-based component as knowledge capital and to the SG&A-based component as organisation capital.

one of the two dimensions. The vector $\mathbf{X}_{i,t-1}$ collects lagged firm-level controls (sales, R&D, and SG&A), $Y_{i,t-1}$ absorbs the pre-shock level of the outcome, and θ_j and λ_t denote two-digit-industry and year fixed effects. Standard errors are clustered at the firm level. I estimate the specification separately for each scope dimension on the corresponding merged sample of Section 2. For the distant-scope split, $D_{it} = 1$ identifies multi-segment firms and $D_{it} = 0$ single-segment firms. A median split is uninformative along this dimension, because the median firm-year reports exactly one segment. For the related-scope split, $D_{it} = 1$ identifies firms whose `d2vscope` lies at or above the sample median and $D_{it} = 0$ firms below it. Scope status is fixed at each firm's pre-shock classification and held constant over the estimation window, so β^h_{High} and β^h_{Low} trace the responses of two predetermined groups of firms to the same shock.

Figure 3 contrasts single distant scope with high distant scope. Responses build with a lag: neither group moves in the shock year, the two groups separate from the first year onward, and the separation widens through the three-year horizon. Single-distant firms raise the intangible investment ratio sharply, with a point estimate roughly twice the high distant scope response by year three, although the confidence bands of the two groups overlap and the difference is not statistically significant (Panel A). They draw rivals into their product space, with competitive threat rising steadily and significantly, whereas the multi-segment response is positive but imprecise, with confidence bands that include zero at most horizons (Panel B). They convert the shock into real gains on both remaining margins: productivity rises significantly and persistently (Panel C), and markups climb steadily over the horizon (Panel D). The high distant scope pattern across these panels is the more revealing one. Multi-segment firms are not inert. They raise the investment ratio, with a point estimate roughly half the single-segment response but statistically indistinguishable from it, and their markups rise by roughly half the single-segment response at year three. What they never do is become more productive: the multi-segment productivity response is flat to mildly negative at every horizon and statistically indistinguishable from zero (Panel C). The diversified firm thus converts innovation into margin without converting it into efficiency, which is the signature of the friction regime.

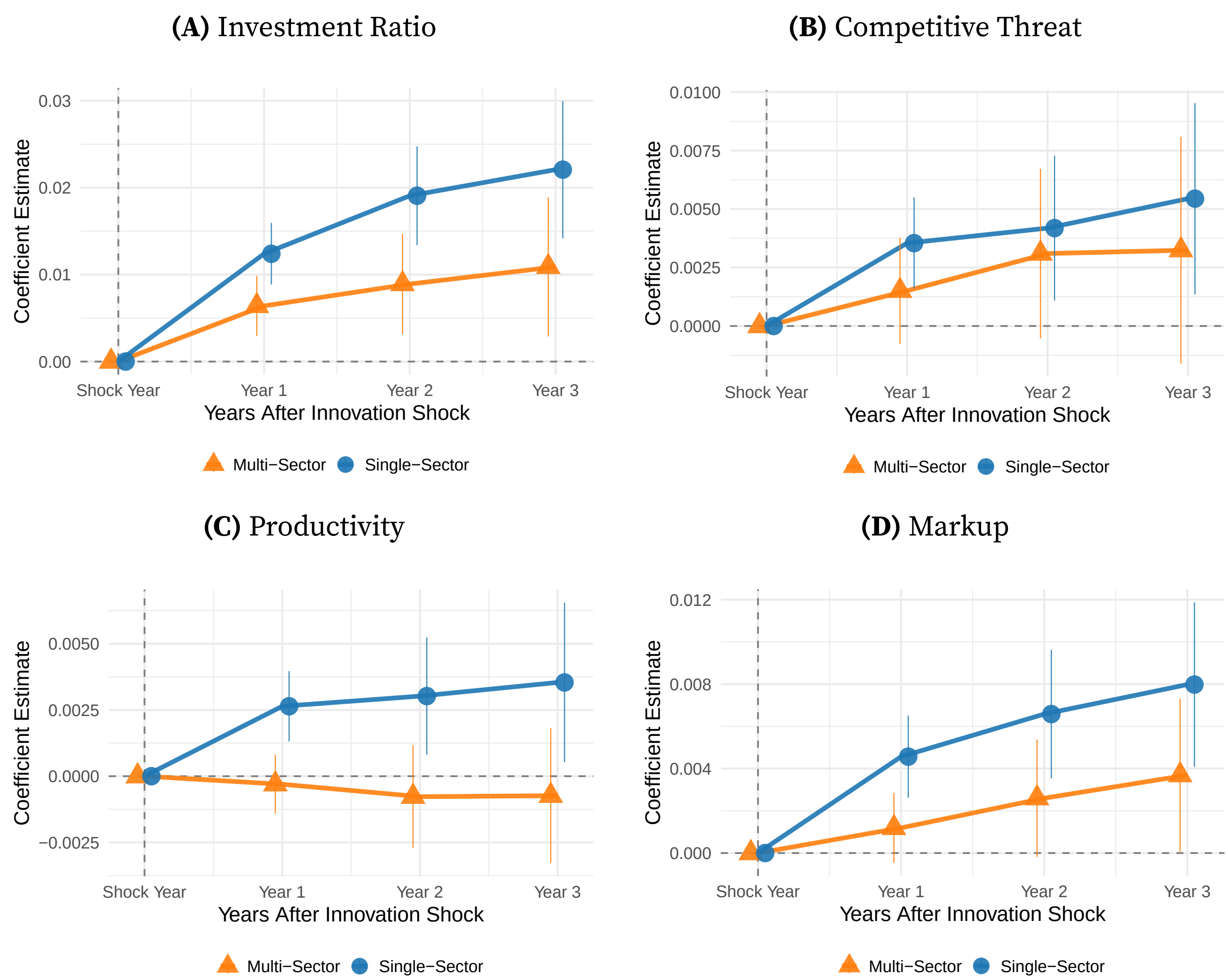

Figure 3. Dynamic Responses to Innovation Shocks by Distant Scope (Compustat Business Segments)

Note: The figure plots local-projection impulse responses to a patent-value innovation shock, estimated by equation (3), separately for two groups defined by distant scope. *Single-Sector* firms (low distant scope, focused) report one Compustat business segment in the year prior to the shock; *Multi-Sector* firms (high distant scope, diversified) report two or more. The shock enters as $\log(1 + V_{it})$, where V_{it} is the firm-year sum of Kogan *et al.* (2017) patent values, to retain firm-years with zero patent grants. Outcomes are defined as the h-year log change, $\Delta_h \log(Y)$, and all controls enter in logs; productivity and markup use the Olley–Pakes baseline. The sample covers fiscal years 1990–2019 and excludes utilities, finance, and firm-years with missing or non-positive R&D, SG&A, employment, or sales. Scope status is fixed at the pre-shock classification and held constant over the projection horizon. Vertical bars denote 95% confidence intervals based on standard errors clustered at the industry–year level.

Figure 4 reports the parallel exercise for related scope, contrasting firms above and below the sample median of `d2vscope`. Here the weak group does not merely respond less. It responds in the opposite direction. Higher-related scope firms tilt their intangible investment toward R&D roughly 2.5 times as strongly as narrow-related scope firms by year 3 (Panel A), attract a significant and growing rise in competitive threat (Panel B), and secure persistent gains in productivity and markups (Panels C and D). Narrowly related scope firms experience the mirror image. Rivals retreat from their product space, with the competitive threat response significantly negative in the first year and recovering to zero only at the end of the horizon (Panel B). Their productivity turns negative and stays negative through year three (Panel C), consistent with these firms bearing the input costs of R&D without the deployment outlets across which its returns compound: innovation inputs rise while output gains fail to materialise beyond a single narrow market. Their markups sit flat at zero throughout (Panel D). For a firm whose related scope is too narrow to form a portfolio, an innovation of a given market value is, on the operating margins, a net burden.

Taken together, the two figures deliver one sharp contrast. When a firm's scope is concentrated in closely related product markets, innovation lands on a shared technological space and synergy takes over. The firm raises its intangible investment ratio, because the innovation opens new research directions across those neighbouring markets and research is the input whose returns multiply there. The redeployed innovation raises productivity, and the productivity advantage sustains higher markups. Competitive threat rises as well, and this is a mark of success rather than weakness: rivals converge on the firm's product space precisely because its innovation has made that space valuable, so the rising threat measures how much the innovation matters to competitors. When a firm's scope instead spans operationally distant segments, the story turns. There is no shared technological space for the innovation to land on. The intangible investment ratio rises by about half as much in point estimate, a difference that is not statistically significant, markups rise only half as much, productivity does not move at all, and rivals barely react. The markup gain without a productivity gain reveals the nature of these rents: they are defended by organisational capital, not created by efficiency. The narrow-related case completes the picture, since a firm with too few related markets loses productivity outright and watches rivals retreat from a space no longer worth contesting. Innovation is thus converted into productivity-backed leadership where scope supplies synergy, and into defensive entrenchment where it does not. That contrast is invisible to any single count of markets, and it is the precise sense in which scope is not a scalar.

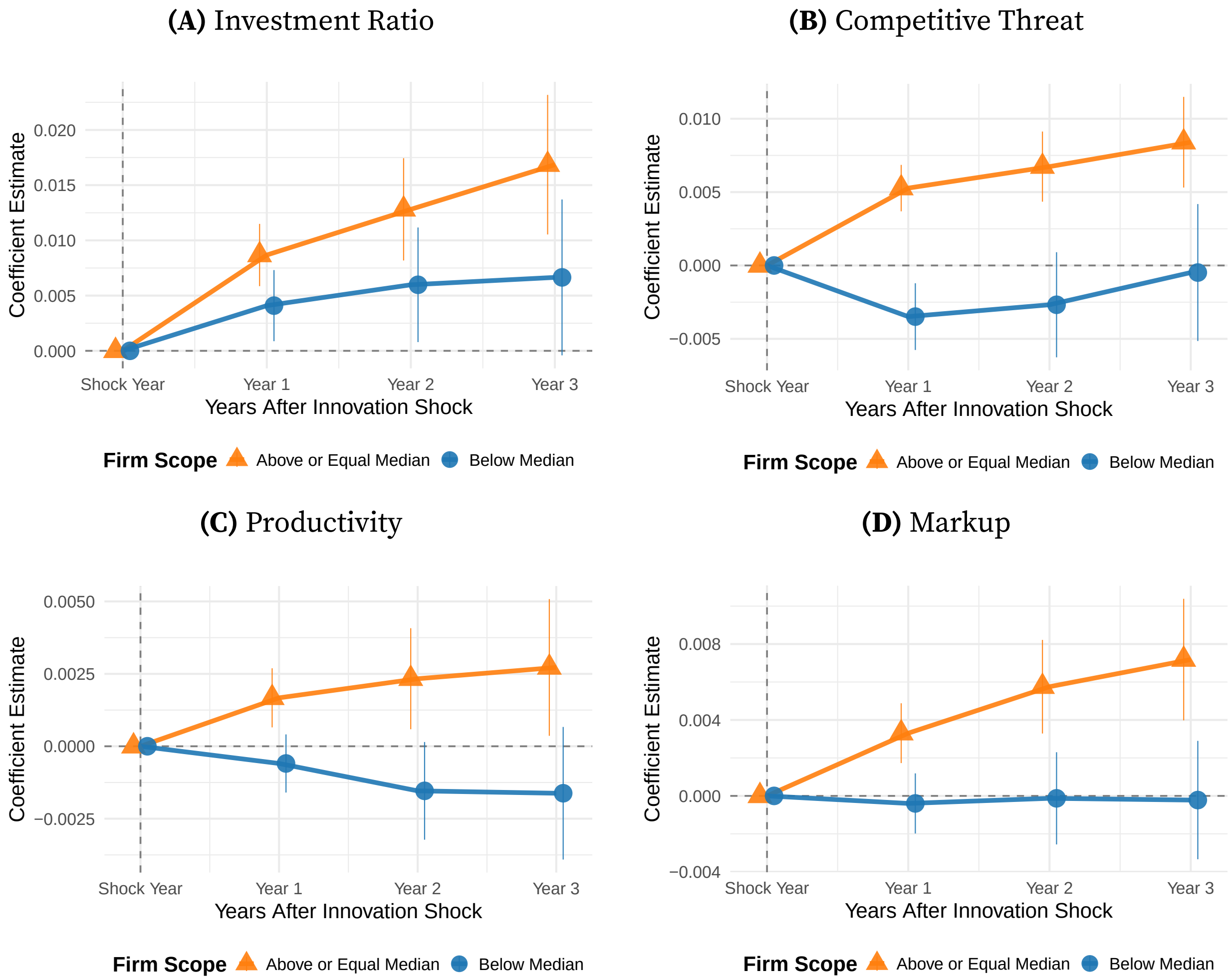

Figure 4. Dynamic Responses to Innovation Shocks by Related Scope (Hoberg–Phillips Product-Market Clusters)

Note: The figure plots local-projection impulse responses to a patent-value innovation shock, estimated by equation (3), separately for two groups defined by related scope. *Above or Equal Median* firms (broad related scope) are firm-years whose Hoberg–Phillips `d2vscope` lies at or above the sample median in the year prior to the shock; *Below Median* firms (narrow related scope) lie below the median. The shock enters as $\log(1 + V_{it})$, where V_{it} is the firm-year sum of Kogan *et al.* (2017) patent values, to retain firm-years with zero patent grants. Outcomes are defined as the h-year log change, $\Delta_h \log(Y)$, and all controls enter in logs; productivity and markup use the Olley–Pakes baseline. The sample covers fiscal years 1990–2019 and excludes utilities, finance, and firm-years with missing or non-positive R&D, SG&A, employment, or sales. Scope status is fixed at the pre-shock classification and held constant over the projection horizon. Vertical bars denote 95% confidence intervals based on standard errors clustered at the industry–year level.

5. Conclusion

Firm scope is not a scalar. It decomposes into related scope, the closely related submarkets a firm serves within a shared technological base, and distant scope, the operationally distinct domains it spans beyond that base. This paper has measured the two dimensions separately, related scope from text-based product-market clusters and distant scope from Compustat business segments, and shown that they carry opposite economics. The two dimensions describe different margins of expansion, since the typical firm reports a single segment while occupying many related clusters, and they govern opposite responses to the same well-identified innovation shock.

The results carry three implications beyond the estimates. First, they give the superstar-firm narrative and the conglomerate discount a common structural reading. The profile of high productivity and persistent markups belongs to firms that combine closely related scope with few distant segments, and the discount belongs to the opposite configuration, so the two literatures describe the two ends of a single configuration space rather than separate phenomena. Second, they discipline the debate on rising market power. A markup gain backed by productivity signals successful innovation in a contested product space, while a markup gain without productivity signals, and the structure of a firm's scope predicts which case obtains. That distinction matters for how competition authorities should read margins. Third, they bear on innovation policy. Uniform R&D subsidies will be absorbed very differently by firms with and without deployment outlets for new knowledge, and the scope-conditional instruments studied by Keskin (2026), which tax distant scope incumbents while subsidising focused innovation and entry, are the natural response to the friction regime documented here. For all three questions, measuring scope along both dimensions is the prerequisite, since any single count of markets conflates a regime of synergy with a regime of friction that the data cleanly separate.

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Appendices

A. Datasets

Table A1. Firm Scope: Compustat vs. Hoberg-Phillips

Company	Scope (Compustat)	Scope (Hoberg-Phillips)
TESLA INC	Energy Generation & Storage Automotive	Batteries Automotive (Brakes, Trim, Axle, Engines, Chassis) Automotive Safety (Airbags) Car Dealerships Energy / Cogeneration Utilities / Electric Power Smart Metering / Grid Tech Power Electronics / Voltage Solar / Renewable Energy Hardware & Software Solutions Ticketing / Scanning (Software/Systems)

B. Additional Figures and Empirical Results

Table A2. Regression Results: Compustat

Panel A: *Markup* and *Productivity*

	Pooled OLS		Two-way FE	
	(1) *Markup*	(2) *Productivity*	(3) *Markup*	(4) *Productivity*
Segment	-0.058^{***}	-0.026^{**}	-0.070^{***}	-0.005
	(0.005)	(0.009)	(0.005)	(0.004)
Controls	Yes	Yes	Yes	Yes
Num. Obs.	33,376	33,376	33,376	33,376
Adj. R^2	0.045	0.027	0.091	0.759
RMSE	0.53	0.79	0.51	0.39
FE: *Year*	No	No	Yes	Yes
FE: *Industry*	No	No	Yes	Yes

Panel B: *Investment Ratio* and *Competitive Threat*

	Pooled OLS		Two-way FE	
	(5) *RD/XSGA*	(6) *Comp. Threat*	(7) *RD/XSGA*	(8) *Comp. Threat*
Segment	-0.117^{***}	-0.461^{***}	-0.115^{***}	-0.313^{***}
	(0.014)	(0.032)	(0.015)	(0.034)
Controls	Yes	Yes	Yes	Yes
Num. Obs.	35,824	30,097	35,824	30,097
Adj. R^2	0.056	0.042	0.146	0.169
RMSE	1.29	3.04	1.22	2.83
FE: *Year*	No	No	Yes	Yes
FE: *Industry*	No	No	Yes	Yes

Notes: Each column reports coefficients from a separate regression. Standard errors clustered by *firm id* (gvkey) are in parentheses. Significance levels: $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Controls include *sale*, *at* (assets), *xrd* (R&D), and *xsga* (SG&A). Columns 1–2 and 5–6: Pooled OLS specifications; Columns 3–4 and 7–8: Two-way fixed effects (year and 2-digit NAICS industry).

Table A3. Regression Results: HP Scope

Panel A: *Markup* and *Productivity*

	Pooled OLS		Two-way FE	
	(2) *Markup*	(3) *Productivity*	(6) *Markup*	(7) *Productivity*
HP-Scope	0.010^{***}	0.023^{***}	0.007^{***}	0.012^{***}
	(0.001)	(0.002)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes
Num. Obs.	52,323	52,323	52,323	52,323
Adj. R^2	0.036	0.050	0.070	0.779
RMSE	0.52	0.77	0.51	0.37
FE: *Year*	No	No	Yes	Yes
FE: *Industry*	No	No	Yes	Yes

Panel B: *Investment Ratio* and *Competitive Threat*

	Pooled OLS		Two-way FE	
	(1) *RD/XSGA*	(4) *Comp. Threat*	(5) *RD/XSGA*	(8) *Comp. Threat*
HP-Scope	0.039^{***}	0.201^{***}	0.037^{***}	0.248^{***}
	(0.002)	(0.006)	(0.002)	(0.006)
Controls	Yes	Yes	Yes	Yes
Num. Obs.	56,484	50,285	56,484	50,285
Adj. R^2	0.074	0.158	0.152	0.339
RMSE	1.26	2.94	1.21	2.60
FE: *Year*	No	No	Yes	Yes
FE: *Industry*	No	No	Yes	Yes

Notes: Each column reports coefficients from a separate regression. Standard errors clustered by *firm id* (gvkey) are in parentheses. Significance levels: $^{+}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. Controls include *sale*, *at* (assets), *xrd* (R&D), and *xsga* (SG&A). Columns (1)–(4): Pooled OLS specifications; Columns (5)–(8): Two-way fixed effects (year and 2-digit NAICS industry).

Table A4. Summary Statistics

Panel A: Compustat–Segment Merged

Variable	N	Mean	SD	P25	Median	P75
Sale	56,734	2,075,346	11,681,302	21,007	104,878	636,445
Emp	56,734	6,064	24,512	126	510	2,800
AT	56,734	2,745,416	18,470,719	24,663	120,218	718,334
XRD	56,734	102,283	631,498	1,461	6,707	29,709
XSGA	56,734	415,856	2,024,726	10,964	39,256	166,198
Productivity	52,323	19.871	23.355	7.736	10.887	22.931
Markup	51,824	1.537	1.026	0.988	1.214	1.665
Competitive Threat	50,285	6.769	3.203	4.437	6.365	8.603

Panel B: Hoberg–Phillips Scope Merged

Variable	N	Mean	SD	P25	Median	P75
Sale	35,964	2,171,465	10,468,548	25,104	135,367	826,899
Emp	35,964	6,440	23,946	133	571	3,212
AT	35,964	3,083,646	19,749,630	30,984	167,030	977,718
XRD	35,964	127,011	736,443	1,813	8,868	39,625
XSGA	35,964	476,449	2,256,258	13,128	50,168	208,927
Productivity	33,376	20.553	24.627	7.888	11.079	23.674
Markup	33,035	1.545	1.048	0.986	1.207	1.673
Competitive Threat	30,097	6.451	3.104	4.189	6.005	8.156

Notes: This table reports summary statistics for the two estimation samples. Panel A shows Compustat Fundamentals merged with the Compustat Segment dataset, while Panel B shows Compustat Fundamentals merged with the HP Firm Scope dataset.