Scope, Scale and Competition: The 21st Century Firm

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Abstract

We provide evidence that over the past 30 years, U.S. firms have expanded their scope of operations. Increases in scope and scale were achieved largely without increasing traditional operating segments. Scope expansion significantly increases valuation and is primarily realized through acquisitions and investment in R&D, but not through capital expenditures. We show that traditional concentration ratios do not capture this expansion of scope and are upward biased. Our findings point to a new type of firm that increases scope through related expansion, which is highly valued by the market.

Keywords: Firm scope, economies of scope, products, concentration, firm size.

JEL Codes: O31, O34, D43, F13

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"Product diversification came from opportunities to use existing production, marketing, and research facilities ... Such expansion was based on organizational capabilities that had been developed by exploiting economies of scope." *p. 38 Chandler and Hikino (1994).*

1 Introduction

The interplay between scope, scale and competition has been the focus of numerous authors including both business historians and economists.[1] A principle focus of authors has been defining firms by the basket of products firms produce and the industries to which these products belong. Recent authors have also documented the rise in firm size, a rise in traditional industry concentration measures, and a drop in the number of U.S. listed firms.[2]

In this paper, we provide a new perspective on the 21st Century version of a multi-product firm and how it produces in different-but-related markets. It differs markedly from the concept of a diversified conglomerate with a multi-division organizational structure producing products across unrelated industries that was the focus of the early corporate finance literature. Instead of multiple distinct segments, firms might have flexible production and redeployable assets that allow them to pursue multi-sector production without the potential negative consequences of a complex multi-division organization.

We develop new firm-year measures of product market scope using the text describing the product markets in which firms operate. We document that the average firm's scope in related industries has increased steadily and dramatically (71%) during our sample period from 1989 to 2017. Moreover, firms have increases scope without increasing the number of operating segments they report during the period of our sample. Our results are consistent with multi-product firms having synergies across related products and with unrelated diversification not being a major consideration for the increases in scope we document.

[1]See Chandler and Hikino (1994), Hart and Moore (1990), Panzar and Willig (1977) and Williamson (1975).

[2]See Autor, Dorn, Katz, Patterson, and Van Reenen (2020), Doidge, Karolyi, and Stulz (2017), Grullon, Larkin, and Michaely (2019) and Philippon and Gutierrez (2017) for aggregate trends. Matvos, Seru, and Silva (2018) examine the link between scope expansion and episodes of financial market frictions.

An important question is how do corporate investment policies react to incentives to increase scope? To shed light on this question, we examine how plausibly exogenous variation in the ex ante incentives to increase scope impact ex post investment decisions and measures of firm performance. We consider two sources of such variation. The first measures each firm's scope-expansion opportunity set using the diversity of related markets served by each firm's distant peers. When these peers have operations that are distributed across multiple well-defined markets, it suggests that the focal firm itself likely sees a larger opportunity set of potential scope-enhancing projects all else equal. Our second measure considers the cost-side and asset redeployability. We examine the asset portfolios of the firm's closer industry peers as compared to the firm's more distant industry peers (where distance is in product market space). If the closer industry peers' assets are easily redeployed to more distant peers' industries, it follows that the focal firm likely faces a low relative cost to expanding scope as its assets can be redeployed to more potential markets with lower adjustment costs.

Both variables measure a focal firm's incentives to increase scope, and neither is measured using any data about the focal firm itself. Instead, both are based on the characteristics of more distant industry peers, whose characteristics are not easily influenced by the focal firm and vice-a-versa. Our approach thus follows prior studies in the network econometrics literature that highlight the fact that endogenous effects are mitigated by focusing on distant peers and not the focal firm itself.[3] Although the literature indicates that this approach reduces the scope for endogeneity, we nevertheless interpret these results conservatively and view them to be strong tests of our predicted mechanisms rather than pure tests of causality.

We find that firm scope is significantly related to more acquisitions, fewer divestitures, and more spending on research and development. In contrast, we find no link to capital expenditures. These results are consistent with an ongoing process of asset redeployment across and within firms, which is reinforced by innovation that facilitates flexible and efficient

[3]See Bramoulle, Djebbari, and Fortin (2009) for theory and Cohen-Cole, Kirilenko, and Patacchini (2014) for a recent application in finance. These studies indicate that distant peers can produce exogenous variation that can be used as instruments.

redeployment of assets for multi-industry production. Importantly, this suggests that acquisitions and innovation facilitate scope increases, but our results are novel and are missed by existing studies because these scope increases are accomplished without increasing the number of formal operating segments in the Compustat database.

We also find that increased scope is associated with higher valuations as a business strategy, and thus it is unlikely that increases in scope are due to bad governance or private benefit extraction. This evidence of higher value is important given the prior literature and possible empire building incentives managers would have to increase scope. We also find evidence of higher ex post sales growth and asset growth. However, we do not find any significant impact for profitability in the form of return on assets. Put together, these results suggest that scope expansion creates positive net present value and sales growth opportunities, and profit maximizing firms likely pick the most profitable industries to operate in first, and then expand into still-profitable but lower return on assets industries second. Our valuation results - which show that firm market-to-book equity ratios increase with our scope measures - are in contrast to the historical conglomerate literature (Berger and Ofek (1995) and Lang and Stulz (1994)) that finds that firm market-to-book valuation measures decrease with an increased number of reported Compustat segments.

We also examine how firm scope expansion is likely financed. Firms with higher ex ante incentives to increase scope issue more shares and pay lower dividends ex post. We find no significant link to debt financing. These results favoring equity are consistent with intangibles and the redeployment of existing assets playing an important role in scope expansion. In particular, this method of expansion through intangibles and better utilizing existing assets does not create much new collateral, which favors financing with equity.

We note that these conclusions are drawn without using the traditional measure of scope: the number of Compustat segments. In particular, the average Compustat segment count of firms has not increased over time. A key issue with reported segment data is that, almost by definition, it does not facilitate measurement of the "new conglomerate" we hypothesize,

which emphasizes expansion in related (not distant) markets. Our results favor the conclusion that this "new conglomerate" can span multiple product spaces while preserving a single segment organizational form. Additionally, SFAS 131, which governs segment reporting, does not require that reporting segments need to be based on the number of industries served. We thus further examine the comparative validity of our textual scope measures and the Compustat segments by relating both to the frequency of explicit statements in firm 10-Ks where firms indicate they serve multiple product markets. Our new measures are highly significant in predicting these statements, whereas the number of Compustat segments are only borderline significant in these regressions, and they become mostly insignificant when included in the same regression as our new text-based scope measures.

We conclude with an analysis of whether increases in scope can provide new insights on why traditional measures of concentration are increasing over time. We first replicate this well-known stylized fact using HHIs based on traditional industry classifications, and then illustrate that these measures do not account for the changes in scope we document. This issue turns out to be economically important. To put this in perspective, scope has increased so much during our 30 year sample that competition essentially plays out at the level of 2-digit SIC codes late in our sample (broad scope), and at the narrower 3-digit SIC code level early in our sample (narrow scope). We proceed to adjust traditional HHIs for this scope-induced shift in granularity, and find that horizontal concentration measured using adjusted HHIs is not increasing during our sample.

Going beyond traditional SIC-based classifications, we also assess the trend in concentration using multi-industry assignments generated by our textual scope measures. The resulting scope-adjusted HHIs again show that horizontal concentration is not increasing during our sample period. We further note that concentration adjustments are not possible using the Compustat segment tapes. As noted above, this is because firms increase scope by producing more related products without increasing their reported number of business segments.

Our results suggest that an enhanced narrative that incorporates increasing scope might more fully explain the evidence of increasing market power documented in the existing literature. For example, increases in purely horizontal concentration are smaller when scope is taken into account, and hence changes in purely horizontal configurations might only partially explain why market power might be higher. Increases in scope, however, might motivate different concerns. Although scope increases reduce horizontal concentration as the same number of firms serve more markets, scope can increase anti-competitive conduct along the supply chain, through product bundling, by increasing barriers to new entry, or it can induce kill zones in the market for innovation (see Kamepalli, Rajan, and Zingales (2020)). Understanding the separate influences of horizontal competition and increased scope at the micro level, or within single industries, would be a fruitful area for future researchers to consider. In particular, regulatory interventions might differ for scope-induced versus horizontal market power.

2 Literature

Theories of economies of scale and scope were first developed by Panzar and Willig (1977) and Panzar and Willig (1981). Teece (1980) further develops relevant theory and suggests that a multi-product enterprise is particularly likely to emerge when economies of scope are based on a recurrent use of proprietary know-how. This theory therefore illustrates why our finding that R&D spending is increased when scope expansion incentives are high is consistent with theories that examine economies of scope. Henderson and Cockburn (1996) provide empirical support for a link between economies of scope and innovation investment in the pharmaceutical industry. Braguinsky, Ohyama, Okazaki, and Syverson (2020) provide further empirical support for these ideas in a novel historical setting: Japan's cotton spinning industry from 1893 to 1914. In particular, the authors show that technological capability was a major ingredient that fostered horizontal scope expansion and firm success in this

early environment.

More recent theory by Maksimovic and Phillips (2002) postulates an efficiency based view of multi-industry operations based on neoclassical profit optimization. In the model, a conglomerate discount can still emerge even when governance is aligned with shareholders and optimal policies are undertaken. However, if low cost scope expansion is possible through economies of scope with sharing a scarce resource such as innovation or managerial talent, this discount may result in a premium . Our results favor this perspective on a few dimensions. In particular, we find that scope expansion with higher R&D brings higher valuations, consistent with rational expansion. Moreover, value increases and sales grow even though return on accounting assets experiences some initial dilution.

Our paper also has further implications for the older literature documenting a diversification discount including highly visible works by Berger and Ofek (1995) and Lang and Stulz (1994). Although many recent studies call the diversification discount into question (see Custodio (2012) and Hund, Monk, and Tice (2020) for example), our paper takes a different approach and portrays an entirely new perspective on multi-industry firms and how they are growing in prevalence. The overall conclusion is that the modern multiple-industry firm may share scarce valuable resources, is able to serve multiple industries while maintaining an efficient single segment organizational form and has a high market valuation.

Our study also contributes to the broader literature on acquisition motives and innovative investment. Our focus is on new synergies due to related operations and redeployable assets. Other studies examining synergies and related-industry acquisitions include Hoberg and Phillips (2010a), Rhodes-Kropf and Robinson (2008), Bena and Li (2014), and Fresard, Hoberg, and Phillips (2020).

3 Data and Methods

3.1 Sample Selection and Panel Structure

Our sample begins with the universe of Compustat firm-years with available 10-K filings either on the EDGAR system (later years) or scanned 10-Ks from the Dartmouth and Harvard libraries (earlier years of our sample). As the standard TNIC database (see Hoberg and Phillips 2016) is based purely on EDGAR filings, its coverage begins in 1996. An important contribution of the current study is thus that we back-extend the TNIC database to 1988 using the 10-Ks obtained from the two aforementioned libraries. To remain in our sample, a firm must have an available 10-K filing both in the current year of observation, and also in the previous year. We exclude financial firms and regulated utilities (SIC 6000 - 6999 and 4900 - 4949, respectively) and limit the sample to firm-years with sales and assets of at least $1 million. We are left with 100,525 firm-year observations from 1989 to 2017.

3.2 Novel Measures of Scope

We develop new measures of firm-specific product market scope, which are updated annually. We do so using the textual network spatial representation of the product market developed by Hoberg and Phillips (2010a) and Hoberg and Phillips (2016) (henceforth HP2016), which uses the text in each firm's business description filed with the U.S. Securities and Exchange Commission in each year. These descriptions are updated every year and are required by Regulation S-K to accurately represent the products sold by the firm in the given fiscal year of the 10-K that is filed. Prior research including Hoberg, Phillips, and Prabhala (2014) illustrates that these filings are updated in a highly dynamic way as firms evolve their product portfolios.

At a high level, measuring scope requires scoring firm i in year t regarding how many industry vocabularies (industries are indexed $j \in J$) are discussed in its specific product description. Following the approach in HP, we specify the product market space as the set

of all product market words that are in the TNIC database.[4] If there are N words in the product space, then each firm is represented in this space by a vector $V_{i,t}$, which is an N dimensional vector containing a one for words that firm i uses in year t and a zero for words that firm i does not use. Following HP2016, we also set to zero the element for any stop words, which are those appearing in more than 25% of all Item 1's in year t.

Analogously, we generate vector representations for industries $j \in J$. Crucially, unlike firm vectors, we lock in each industry's vocabulary vector and do not allow industry vectors to vary with time. As we discuss later, this ensures that we can measure changes in scope in its purest form, and without measuring the separate and potentially confounding matter of product market innovation, which can include the creation of entirely new markets.[5] We note that studying the creation of new markets is separately interesting, although it is not the focus of the current study. We also focus on a fixed set industry vocabularies because it is conservative, as it favors under-measuring the true increase in firm scope that has occurred due to new industries.

We consider two methods for identifying the spatial location of industries. The first draws industry vocabularies from the "Fixed Industry Classification" technology developed in HP2016, which uses a clustering algorithm applied on the sample of single segment firms to identify product market clusters. This approach develops vocabularies for each industry, which are computed as the average of the vectors $V_{i,t}$ after normalization based on the firms assigned to each cluster. We specifically use the FIC-300 classification developed by HP2016, which is based on 300 industries, and we use the FIC-300 classification from 1997, which is the base year used by HP2016. We denote the resulting industry vocabulary vectors by $D_{FIC,j}$, where $j \in 1, ..., 300$. The vocabularies are obtained directly from HP2016 without modification. Each vector is then normalized to sum to unity and resides in the same N-dimensional space as do the firm-vectors $V_{i,t}$.

[4] This is the set of all words that appear in the union of all firm 10-K Item 1's.

[5] Although test clarity indicates that it is philosophically important to lock in industry definitions, we note that our results are very similar if we instead re-define industries every year (we run this alternative specification using dynamically recomputed FIC-300 industries).

Our second method is based on NAICS industry definitions, as provided in the 2017 version of the NAICS Manual, which is a 963 page document providing extensive and detailed descriptions of each NAICS industry. We use the four-digit NAICS granularity, and group all vocabulary for all industries having the same four digits of their NAICS code into each NAICS' code's total vocabulary that we use to determine the spatial location of each 4-digit NAICS code in our N-dimensional space. Our approach has natural stop-wording built in, as we will ignore any words that are not part of the stop-word-adjusted TNIC vocabulary in each year, as explained above. As an additional precaution, we reviewed the list of common words that appear in the NAICS manual and manually identified a list of stop words (see Appendix) that we additionally remove from the NAICS dialects. We thus create one vector $D_{NAICS,j}$ for each four digit NAICS industry from the 2017 manual, where $j \in 1, ..., 311$, as there are 311 four digit NAICS that we capture using this approach. Each element of this vector is populated with the number of times each word is used in the NAICS manual for the given industry, and the vector is normalized to sum to unity. Each vector resides in the same N-dimensional space as do the firm-vectors $V_{i,t}$.

Now that we have spatial locations for each firm-year and for each industry, we score each firm-year based on how much of each industry's vocabulary it uses. Crucially, we avoid pairwise cosine calculations as that would overly penalize firms that have large product descriptions that cover many industries (because the fraction of each industry in the overall vector of such firms would become small). Instead, we compute the fraction of each industry's vocabulary that appears in each firm-year's product description as the following overlap ratio (we develop an analogous ratio and method for the NAICS-based scope measure):

$$Q_{i,j,t,FIC} = \frac{\#\text{words overlapping in } D_{FIC,j} \text{ and } V_{i,t}}{\#\text{words in } D_{FIC,j}} \tag{1}$$

Finally, to compute how many FIC industries a given firm might operate in, we identify a fixed threshold $\bar{Q_{FIC}}$ above which we deem a firm having $Q_{i,j,t,FIC} > \bar{Q}$ to be operating

in industry j in the given year t (we call this an "operating pair"). Crucially, we hold $\bar{Q_{FIC}}$ fixed and do not allow it to vary with time, as otherwise we might create false inferences in our time series analysis. We thus use our base year of 1997 to compute $\bar{Q_{FIC}}$ as the threshold such that 2% of all firm-industry combinations are deemed to be operating-pairs in 1997. We choose the 2% threshold as that is the threshold used in HP2016 to determine the granularity of three-digit SIC industries. Our results are robust to using 1% or 5%. Our main variable FIC-scope is then simply the number of industries the given firm likely operates in, i.e., the number of industries with a similarity above the fixed threshold $\bar{Q_{FIC}}$ (NAICS-scope is computed analogously):

$$FIC - Scope_{i,t} = \sum_{j=1,...300} Indicator\{Q_{i,j,t,FIC} > \bar{Q_{FIC}}\} \tag{2}$$

$$NAICS - Scope_{i,t} = \sum_{j=1,...300} Indicator\{Q_{i,j,t,NAICS} > \bar{Q_{NAICS}}\} \tag{3}$$

These measures are estimates of how many markets a given firm operates in based on its disclosed product market offerings. Hence these measures estimate how wide-ranging a firm's product scope is across well-defined and intuitive market definitions. To mitigate the impact of outliers, we winsorize our scope variables at the 1/99% level.

Finally, we also consider a third measure of scope based on the Latent Dirichlet Allocation (LDA) topic model developed by Blei, Ng, and Jordan (2003). We summarize how we construct this measure in the Online Appendix, and we also report a series of tables illustrating that all of our main results are fully robust to this alternative.

3.3 Local Asset Redeployability and Outward Scope Expansion

We develop two instrumentals for firm scope, which allow us to examine the extent to which plausibly exogenous incentives for firms to increase scope may lead firms to alter their corporate finance policies and to relate scope expansion to ex post outcomes. We use these instruments to control for endogeneity but do not ascribe causality to the final results. We

thus view our results based on these instruments as suggestive, given some limitations remain and given the difficulties associated with further testing the exclusion restriction. Our first instrument is based on the redeployability of each firm's assets specifically to redeploy in product markets that are nearby in the product space. The intuition is that a firm that can easily redeploy assets in spatially proximate product markets likely has strong incentives to increase scope because the cost of doing so is likely to be low. In particular, the firm can use its existing asset base with low adjustment costs to expand in these related markets. We focus on this concept of local redeployability rather than broader measures of redeployability to increase the power of our instrument. This is motivated by empirical work by Hoberg and Phillips (2018) and the theory of Crémer, Garicano, and Prat (2007), which indicate that firms expand scope by operating in groups of highly related industries and not highly diversified (or distant) industries.

Our approach to measuring local redeployability follows Kim and Kung (2017) (KK2017), who use the capital flows tables from the Bureau of Economic Analysis to compute measures of broad asset redeployability. We extend and refine their methodology to focus on localized redeployability. In particular, the BEA tables indicate the extent to which each of 123 BEA industries (which can be mapped to NAICS codes) utilizes a set of 180 types of assets (and in what fraction). Intuitively, if two BEA industries utilize the 180 assets in very similar proportions, we would conclude that a firm operating in one of the two industries faces a high degree of asset redeployability should it choose to operate in the second. We view a lack of asset redeployability as a barrier to scope expansion, or analogously, the presence of redeployability across a pair of industries can be seen as an incentive to expand scope in that direction, as it would indicate that scope expansion can be achieved at a low cost. To the extent that the asset allocation vectors across industries are exogenous from a given firm's perspective, it would follow that a firm facing high levels of asset redeployability between its current industries and its nearby industries faces an exogenously higher incentive to increase scope as part of its forward-looking business strategy.

Of course, as innovation can change the distribution of asset allocations within an industry, it follows that asset-allocation vectors are not fully exogenous. We take additional precautions to further improve the extent to which these variables are more plausibly exogenous. First, following KK2017, we use a single BEA table from 1997 for our entire sample and fix the asset allocation vectors in time. Second, we compute local redeployability for each focal firm using an approach that examines the product market around the firm, and strictly avoids using any data from the focal firm itself. In particular, we compute the redeployability of the firm's close peers (based on the TNIC3 classification) to expand into the industries covered by the focal firm's more distant peers (those in the focal firm's TNIC2 classification but not those in its TNIC3 classification).[6]

We compute local asset redeployability by first mapping each BEA industry to a four digit NAICS code (following KK2017), and representing the underlying assets used by each NAICS industry as a 180 element vector, which we denote as A_j for a given NAICS-4 industry j. Each vector is obtained directly from the 1997 capital flows table, which has reported dollar amounts for 180 assets tracked by BEA for each industry. Next, for each focal firm in each year, we obtain two sets of peers. Close peers are those in the focal firm's TNIC-3 industry (excluding the focal firm itself). Distant peers are those in the focal firm's TNIC-2 industry but not in its TNIC-3 industry. There are no overlapping peers in these two sets. Next we compute the fraction of each set of peers in each NAICS-4 industry.[7] $F_{i,t,j,near}$ is the fraction of focal firm i's close peers that are in 4-digit NAICS industry j in year t. $F_{i,t,j,distant}$ is analogously defined for distant peers. These two industry distributions reflect likely paths that firms would take if they are outwardly expanding scope, as the close peers would indeed consider the types of industries that the distant peers are operating in as noted above. Outward-focused local asset rededployability is then the weighted average

[6]TNIC2 industries are the text-based industry classification from HP2016 that is calibrated to be as granular as two-digit SIC industries. TNIC3 is finer and calibrated to be as granular as SIC-3. hence firms that are in TNIC2 but not TNIC3 are "distant peers" as they are still operating in nearby markets but not directly in the focal firm's current market.

[7]We use NAICS and not TNIC industries for this part of the calculation because BEA tables are directly linked to NAICS.

asset-complementarity (cosine similarity of the asset vectors for the two industries in a pair j,k) summed over the joint distribution of industry pairs spanned by the two sets of peers:

$$LocalAssetRedep._{i,t} = \sum_{j,ks.t.j \neq k \in NAICS-4} F_{i,t,j,near} F_{i,t,k,distant} < \frac{A_j}{A_j \cdot 1} \cdot \frac{A_k}{A_k \cdot 1} > \quad (4)$$

Importantly, the more the close and distant peers operate in the same NAICS-4 industries, the lower is the outward asset redeployability as there is less scope for outward scope expansion when all local firms are all in the same limited set of markets. The more they operate in different NAICS-4 industries, the more the weighted average of the redeployability scores of these pairs will increase the computed Local Asset Redeployability from the focal firm's perspective. Additionally, we note that the calculation does not depend on the focal firm itself and instead focuses on the industries served by peers that are more distant. This helps to reduce potential channels for violation of the exclusion requirement, as is reinforced by econometric theories of identification in network settings (see (Bramoulle, Djebbari, and Fortin, 2009) for example). Also see Cohen-Cole, Kirilenko, and Patacchini (2014) for a related application in finance. Importantly, when local asset redeployability is high, it indicates that the focal firm likely has many ways to increase scope that would be feasible with relatively low adjustment costs given the focal firm's likely asset composition. It thus is a shifter of the focal firm's scope-expansion strategy.

3.4 The Local Scope-Expansion Opportunity Set

Whereas our above instrument is based on incentives rooted in low adjustment costs to expanding scope, our second instrument is based on a measure of the quality of the outward-scope expansion opportunity set as seen from the focal firm's perspective. As was the case for our first instrument, we construct our second instrument by focusing on more distant peers and we do not use the characteristics of the focal firm itself to construct the instrument.

As above, we first identify distant peers for a given focal firm i in a given year t by identifying the rivals that are in the focal firm's TNIC-2 industry but are not in the focal firm's TNIC-3 industry. As above, we compute the distribution of NAICS-4 industries served by these distant peers ($F_{i,t,j,distant}$). To compute the local scope expansion opportunity set, we simply compute one minus the concentration ratio (HHI) based on this distribution:

$$LocalScopeExpansionOpp.Set_{i,t} = 1 - \sum_{j \in NAICS-4} F^2_{i,t,j,distant} \tag{5}$$

When this variable is high, it indicates that nearby peers serve a wide array of closely related product markets. From the focal firm's perspective, the firm thus faces a high quality opportunity set for scope-expansion. Because this measure is only a function of the firm's distant peers, as noted above, it is more likely to be first-order exogenous from the perspective of the focal firm's policies. Focal firms facing a higher value of this variable are likely to increase scope given the wider array of growth opportunities available.

3.5 R&D, Investment and Acquisitions

We examine four investment policies: R&D/assets, CAPX/assets, the decision to acquire assets, and dis-investment in the form of selling assets as a target. The R&D (XRD) and CAPX variables are from Compustat. We scale each by beginning of period total assets (AT). When R&D is missing, we assume it to be zero.[8] We obtain acquirer and target data using both full-firm and partial-firm asset acquisition data from SDC Platinum. SDC Acquirer is an indicator equal to one if the given firm acquires any assets from any seller (public or private) in the given year and is zero otherwise. Analogously, SDC Target is an indicator equal to one if the given firm sells any assets to any buyer (public or private) in the given year and is zero otherwise. Both variables include transactions involving parts of firms or whole firms.

We also consider four other outcome variables including sales growth and asset growth,

[8] If we exclude firms with missing R&D, we obtain similar results.

which are equal to the log of one plus the ratio of current sales to past-year sales and current assets to past-year assets), respectively. We compute firm a firm valuation ratio as its market value (market equity plus book assets minus book equity) scaled by total assets, and we compute profitability as operating income before depreciation scaled by total assets. Finally, we consider four financing policies including equity issuance, debt issuance, equity repurchases, and dividends, with all four being scaled by assets.

All accounting ratio variables are winsorized within each year at the 1%/99% level. Please see the complete variable description in the Appendix for more detail.

3.6 Summary Statistics and Correlations

Table 1 displays summary statistics for our 1989 to 2017 panel of 100,525 firm-year observations. The average value of our key FIC-scope and NAICS-scope variables are 6.9 and 6.3, respectively. This suggests that, using 2% granularity, the average firm in our sample is operating in markets that are related to roughly six well defined FIC or NAICS-4 industries, respectively. This is larger than the average number of Compustat Operating segments, which is just 1.4 in our sample. We measure scope in this relatively broad way to ensure there is adequate power to compare firms in the cross section, and because operating segments likely understate the true girth of the product portfolios offered by public firms in the United States. Notwithstanding that, we also note that our results are robust if we measure scope more narrowly using a 1% threshold or more broadly using a 5% threshold.

[Insert Table 1 Here]

We also note that our accounting variables have values that are similar to those in other studies. The average firm in our sample spends roughly 5.5% of its assets each on R&D and CAPX, and 29% of our sample firm-years are involved in an acquisition. The average firm's valuation ratio (market to book) is roughly 1.76, and the average firm spends roughly 1.6% of its assets on repurchases and 0.8% on dividend payments.

Table 2 displays Pearson correlation coefficients for our key variables and illustrates sensible relationships to key existing variables. For example, our two scope variables (FIC-scope and NAICS-scope) are about 20% correlated with the number of Compustat operating segments. This correlation is significant and positive as expected, but it is also far from unity illustrating why evaluating scope using segment counts alone is likely to miss much important variation. Both measures are also roughly 27% correlated with firm size as measured using log assets. This is intuitive and illustrates that larger firms serve a wider array of product markets. This finding also illustrates why controlling for variables such as size is important for our later inferences regarding investment policies. For example, both scope measures are also positively correlated with both the acquisition dummy and the target dummy. However, both dummies are even more positively correlated with firm size, as it is well known that larger firms are more active in restructuring. Hence, it is no surprising that when we run formal regression analysis, we find that scope is associated with more acquisitions but less divestitures (targets), which conforms to the intuition that firms with high incentives to increase scope are indeed net acquirers once size is held fixed.

[Insert Table 2 Here]

We also find that our control variables are only modestly correlated with our variables of interest and with each other. Multi-collinearity is thus unlikely to be a concern.

4 Relation to Traditional Scope Variables

In this section, we explore and validate the properties of our scope variables and compare them to the Compustat segments database and to firm size.

Before proceeding, we provide examples illstrating the nature of the underlying data for our scope measures. Table itbl:disney displays the sub-markets that Disney operates in for three representative years: 1990, 2003, and 2017. The results are based on the LDA-

based version of our scope measures as this approach additionally provides labels, which can illustrate the intuition of our measures. We remind the reader that our LDA model is based on 300 topics, and we fix the topic structure based on 1997 to be consistent with our other scope variables. The table shows that Disney operates in six potential sub-markets in 1990 including studio productions, sports, cable network programming, motion pictures, publishing and music. This increases to 10 sub-markets in 2003 and 11 sub-markets in 2017 illustrating Disney's increase in scope during our sample period. Online Appendix Table IA1 shows a similar report for Pfizer, whose scope has remained more stable over time.

4.1 Compustat Segments

The existing literature generally focuses on the Compustat segment tapes when exploring issues relating to scope and often takes the perspective that Conglomerate firms (those with more than one operating segment) have high levels of product scope but they are also diversified and tend to operate in relatively distant product markets. We take the perspective that the segment tapes are problematic for measuring scope, not only due to basic mismeasurement (see Villalonga 2004), but also because we expect modern firms to increase scope without increasing the actual number of rigid operating segments. In particular, modern firms are able to use innovation to increase product scope through more flexible production and by redeploying existing assets. A consequence is that scope is increasing but it would not be observed by plotting Compustat segments over time, which would be stable and not necessarily increasing.

We begin our analysis by computing basic summary statistics for subsamples of firms with different numbers of Compustat segments.

[Insert Table 4 Here]

Table 4 displays the results and shows that moving from one segment to two segments increases FIC-scope and NAICS-cope by roughly one unit. For example, FIC-scope increases

from 6.42 to 7.53. The table also shows that adding segments beyond two roughly adds one more unit to our scope measures. These results conform to intuition, and suggest that each additional operating segment adds one additional product market to our measures of scope. However, these expected positive relationships greatly under-state the true variation in our measures of scope, which have standard deviations ranging from five to seven, and hence most of the variation in our measures cannot be explained by the number of Compustat segments a given firm operates in.

4.2 Scope Trends

Figure 1 plots the average number of Compustat segments over time in the upper panel, and the average FIC-Scope and NAICS-Scope in the lower panel. The number of segments initially declines steadily from roughly 1.5 in 1989 to roughly 1.3 by 1997. This trend conforms to the intuition that older conglomerates, which might have been formed in the 1970s and 1980s, were gradually disbanding over time. However, from 1997 to 1999, we observe a major structural break and the number of segments suddenly increases to more than 1.5. The jump around 1997 can be explained by SFAS 131, in which FASB changed segment disclosure requirements for filings associated with fiscal years ending after December 15, 1997. In particular, this rule required that managers must report segments based on how managers themselves internally evaluate operating performance. Prior to this rule change, segment reporting was instead based on an industry approach. Yet we note that the rule change itself was precipitated by concerns by market participants that segments were being under-reported, perhaps for strategic reasons. We refer readers to Song (2020) for a more detailed summary of these important events.

[Insert Figure 1 Here]

The events leading up to SFAS 131, and the consequences of this rule change itself, suggest that readers should interpret any trend for Compustat segments in Figure 1 with

significant caution. It is unlikely to provide a clear indication of whether the scope of U.S. firms is increasing or not. For example, the alleged practice of under-reporting prior to the rule change calls the declining trend from 1989 to 1997 itself into question. After 1997, we observe a flat trend, but this too is questionable because segment counts are based on how managers internally evaluate performance and not how many product markets the firm actually operates in. For example, a major result we report later is that firms increasing scope choose to operate in industries that are closely related, not industries that are diversified. Intuitively, many managers might prefer to internally assess the performance of such related industry product lines together, and not separately. If so, the number of Compustat segments could strongly understate the increase in scope, as it is likely to only capture instances where firms operate in relatively unrelated product markets, where separate evaluation is more warranted.

The lower panel of Figure 1 displays the average FIC-scope and NAICS-scope over our sample. The coverage dating back to 1989 was made possible by the backward extension of the TNIC database to the late 1980s, which is also a contribution of the current study. The figure illustrates that scope was increasing during our entire sample, with the most rapid rate of increase appearing between 1997 and 2013. During this time, the average scope of firms in our sample increased by a full 50%. Notably, the upper panel shows that the number of Compustat segments did not change during this period. These results are consistent with the view that product market scope did increase materially, but the increases were mainly driven by firms serving multiple industries that are related (for example selling computers and cell phones) rather than diversified and unrelated (such as selling oil and cat food). Put together, our results are consistent with managers evaluating these highly related industry markets together, and hence we observe very few Compustat segments. Our evidence throughout the paper supports this view.

A final note on scope trends is that the increased scale and scope we report can also help to explain why the length of 10-Ks has also increased over time. The upper panel of

Figure 2 plots the average number of words in the 10-K Item 1 over time, which increased in the first half of our sample rather steadily until 2003. After this year, the size of the Item 1 has become relatively stable. This suggests that document size is related scope, but also different, as Figure 1 shows that scope has been increasing throughout our sample, even after 2003.

[Insert Figure 2 Here]

To further understand the evolution of Item 1 over time, we note that there are 3 sources of variation that might drive its length: (1) increased scope across product markets, (2) increased product variety within markets, and (3) increased boilerplate content. Regarding boilerplate content, our removal of stop words, or any word that appears in more than 25% of all filings in a given year, should greatly reduce the impact of boilerplate content on our measures. Regarding increased scope, as noted above, its time series is different from the trend in document size overall, which suggests that a shift in product variety might also have occurred in parts of our sample. The lower panel of Figure 2 supports this intuition, and reports the average time trend of the number of 10-K Item 1 words per product market the firm likely operates in. This is computed as the number of words in the given firm's Item 1 divided by FIC-scope (number of likely product markets). The figure suggests that within-market product variety has likely increased during the earlier part of our sample and thus can explain some of the increase in 10-K size. These findings motivate future research on this topic, as our study focuses on changes in scope across product markets and we do not examine within-market product variety further.

4.3 Scale and Scope

We now examine the role of increasing firm scale and its relation to firm scope. Figure 3 plots average firm size over time (based on book assets) both in nominal terms and in inflation-adjusted terms. The figure shows that average firm size has increased substantially

over time by both metrics. Using the conservative inflation adjusted metric, firm size has roughly tripled during our sample. This increase likely reflects the increases in firm scope we document above, but also increases in firm scale. We thus assess the relationship between scale and scope using sorts.

[Insert Figure 3 Here]

Table 5 reports average scale and scope statistics for size quintiles. Quintiles are formed by sorting on Compustat assets separately in each year. We report these statistics separately for the full sample and for firms that report just one Compustat operating segment.

[Insert Table 5 Here]

The table confirms that all measures of scope sort strongly with firm size. Even for Compustat segments, the smallest quintile firms have an average of 1.22 segments, which grows to 1.94 for the largest firms. Regarding FIC-scope, the interquartile range is from 5.65 product markets to 8.62 product markets. The range is larger for NAICS-scope at 4.02 to 9.17 markets. Yet the growth in scope by any measure across these quintiles pales in comparison to the range of firm size itself. Small quintile firms have about $23 million in assets, whereas the largest quintile firms average $11.7 billion. We conclude that some of the variation we see in firm size and its increase over time, likely is related to corresponding increases in firm scope. However, the sheer magnitude of the scale increase also suggests that the increases in firm size likely have other drivers beyond firm scope. In particular, it is likely that U.S. firms have achieved not only economies of scope, but also economies of scale.

We conclude this discussion with a note about single segment firms. The rightmost columns in Table 5 report the same statistics for the subset of single segment firms. Importantly, we see only modest reductions in the differences across the quintiles for this subsample. This reinforces further our conclusion that segments are not a reliable source of

information about firm scope. As we show at the end of this section, basic validation tests using orthogonal queries further reinforce that segment counts contain only a weak signal regarding scope, and our new measures of scope are much more strongly validated.

5 Scope but not Diversification

In this section, we examine if the high levels of scope we find are related to companies spanning distant and highly diversified product markets, or more proximate related product markets. Although older studies generally portray conglomerates as the former, recent studies suggest that modern firms are more like the latter (see theory by Crémer, Garicano, and Prat 2007 and empirical support in Hoberg and Phillips 2018). To examine this issue, we first compute the average product market distance between every permutation of pairs of FIC-300 industries. For a given pair of industries in a given year, this is computed as the average TNIC pairwise similarity (see HP2016) between all of the firms in the first industry relative to those in the second industry in the pair. We thus observe which pairs of industries are proximate and which are distant in the product space.

Next, we consider the firm-to-industry mapping created when computing the FIC-score. As we discussed in Section 3, this calculation first requires us to identify the set of FIC-300 industries that each firm likely operates in based on the given firm's coverage of the given industry's vocabulary in its 10-K item 1. Finally, we use firm configurations across industries to create a database of observed "operating pairs". A firm that maps to industry i and industry j is thus an observation of the operating pair ij. A firm that maps to three industries {i,j,k} is an observation of three operating pairs: {ij,ik,jk}. A firm that maps to just one industry does not have any observed operating pairs. We then tabulate the total number of operating pairs for each pair of industries in each year to compute the distribution of operating pairs for each year.

[Insert Table 6 Here]

In each year, we sort industry pairs into deciles based on the TNIC similarity of the pair. Table 6 then reports the fraction of all observed operating pairs that are in each decile. We report this distribution for all firms, and separately for single segment and multi-segment firms. The table shows that firms overwhelmingly operate in industry pairs that are close together in the product space. For the full sample and for the single and multi-segment firms individually, we find that almost 40% of all operating pairs are in the highest decile of TNIC industry pairwise similarity. An additional 13% to 15% are in the next decile. These results indicate that modern multi-industry firms are not the diversified conglomerates portrayed in the early corporate finance literature. The modern multi-industry firm operates in highly related industries, which are likely feasible to span without a complex conglomerate governance structure. Following results in Hoberg and Phillips (2010a) and Bena and Li (2014) for example, these related industries likely generate both product and operational synergies for these multi-industry firms, suggesting that this practice is value creating. Indeed we report later that scope-enhancement is rewarded with higher valuations and sales growth.

[Insert Table 7 Here]

We next examine the risk properties of our scope measures. Our central prediction is that firms that have operating segments that are far in the product space should be less risky due to the diversifying effects of operating in relatively unrelated markets. To examine this hypothesis, we divide our FIC-scope variable into two components, Near-Scope and Far-Scope, which are counts of how many spatially close and spatially distant markets firms operate in, respectively. To compute these quantities, we first use the text corresponding to each FIC-300 industry in the base year 1997 and compute pairwise cosine similarities for every pair of industries. We divide the industry pairs into near versus far groups based on whether the cosine similarity of the industry-pair's text is above or below the median, respectively. Finally, for each company in each year, we compute its pairwise permutations

of industry pairs based on our FIC-300 mapping as used to compute our FIC-Scope variable (see equation 2). Near Scope is then the number of pairs that are in the near group based on the first calculation, and Far Scope is the number of pairs that are in the far group.

Table 7 reports the results of regressions where we regress measures of firm risk on our scope variable. In order to examine whether different levels of scope reduce or increase risk, we separate out scope into terciles from "close scope" to"far scope". We also include controls for size, age, and year fixed effects. We additionally include firm fixed effects in Panels C and D. The first dependent variable Market Volatility is the standard deviation of the firm's daily stock returns in year t, and Cashflow Volatility is the standard deviation of a firm's quarterly operating income scaled by assets, computed over the 8 quarters of year t and $t+1$.

Panels A and C of Table 7 shows that firms with close operations and thus close scope are significantly more risky for stock volatility. These results are robust with or without firm fixed effects. Panels B and D show that cash flow volatility is also higher for firms with larger scope, with the coefficient being largest for near-scope firms. The results in Panel D show that the within firm relation between scope and cash flow volatility becomes insignificant for the close and far scope terciles when we additionally include firm fixed effects. These findings overall conform to our broader conclusion that diversification is unlikely to be a major motive driving firm-specific decisions. For example, our earlier results illustrate that firms over time operate less in distant markets. Rather, they focus on closely related markets where synergies are more likely. Because these expansions require increased innovative investment and because the markets firms operate in are quite related on average, a high scope strategy tends to associate with higher risk and little if any diversification.

5.1 Validation of Scope Measures

The results presented above provide support for the proposition that text-based measures of scope, which are backed by Regulation S-K which requires disclosure of the products sold by the firm in the given fiscal year, should have many advantages over using Compustat seg-

ments. Segment reporting, in contrast, is governed by SFAS 131, which is linked to internal performance evaluation rather than industry organization. In this section, we augment this evidence with a formal validation test that uses direct firm statements to evaluate candidate measures of scope.

We consider four queries of firm 10-Ks to identify direct statements indicating the firm offers a selection of products that has a high degree of scope. These queries are based on the following three lists:

List A: product lines, product categories

List B: product lines, product categories, service lines, service categories

List C: breadth, broad, broader, wide, multiple, numerous, diverse, categories, divisions

We use the metaHeuristica program to compute four variables of interest to validation. Our first "Product Breadth" is the number of paragraphs in each firm's overall 10-K that mentions a phrase in List A, scaled by the total number of paragraphs in the firm's 10-K. The variable "Product/Svc Breath" is analogously defined based on List B. Our second two variables are more specific. Our third variable "Product Breadth Detail" is the number of paragraphs that contain a phrase in List A and also a word from List C. Our final variable "Product/Svc Breadth Detail" is analogously defined using List B and List C. Intuitively, when these scores are higher, it is likely that the firm offers a wide-scope array of products and services. We also note that the latter two variables are quite stringent and are based on proximity searches. This anchor-phrase approach is more rigorous than are basic unconditional word counts as it would be less informative if words from List C appeared in different paragraphs than those where Lists A and B appear.

To validate our measures of scope and compare them to Compustat segments, we regress the four variables above on our scope measures. We additionally include controls for size, age, market to book, and the TNIC HHI, and we also include firm and year fixed effects in all specifications. For validation, a measure of scope should have a strong positive and

significant coefficient.

[Insert Table 6 Here]

Table 6 displays the results. The first four rows only include the controls as a baseline, and illustrate for example that size (log assets) is not surprisingly related to our direct statements of scope, and the t-statistic is between 3.5 to 4.0. Rows (5) to (8) add the number of Compustat segments to the regression. This variable is positive and significant for the first two broader validation variables (t-statistic of roughly 2.7) but is only significant at the 10% level for the more stringent variables. Rows (9) to (12) additionally add our new measure FIC-scope to the regression. We find that FIC-scope is much more positive and significant than both firm size and Compustat segments. Its t-statistic is roughly 8.5 for the broad validation measures and 6.5 for the strict validation measures. Additionally, including FIC scope reduces the significance of the Compustat segment variable by roughly one third. Rows (13) to (16) reproduce this test for the NAICS-scope variable, and we find similar but slightly weaker validation (t-statistics range from 5.3 to 6.2). We conclude that FIC-scope has the strongest support in this validation exercise, but NAICS-scope also performs quite well. However, Compustat segment counts are only very weakly validated.

6 Scope Incentives and Corporate Finance Policies

We now explore how firms seeking to increase scope modify their corporate finance policies. This question touches upon many issues of high importance for understanding corporate finance in general, and also issues of relevance to regulators. For example, is the increase in scope we report related to the high level of acquisition activity reported in the popular press over the past couple decades? Additionally, is innovation investment in R&D associated with increases in scope, or is it achieved instead through acquisitions and capital expenditures. We examine these potential mechanisms in this section using plausibly exogenous shifters

of the incentives firms have to increase scope. We also assess the link between scope and firm performance, and we explore how increases in scope are financed. These tests are not aimed at establishing full-fledged causality, which is not possible using available measures, but rather are aimed at examining whether the proposed scope increasing mechanisms are related to shifting corporate finance policies and firm outcomes.

6.1 First-Stage Analysis

We first examine the relation between our measures of scope incentives and our novel measures of scope. This analysis constitutes the first stage that we will ultimately use in our two-stage least squares analysis of the impact of scope incentives on ex-post investment, performance and financing in the next section. We use these instruments to assess the relevance of plausibly exogenous incentives to increase scope on various corporate finance outcomes. This is thus a test of mechanism relevance, and not a pure test of causality.

Our first ex-ante measure of scope incentives we label *Sectoral Redeployment Potential*, which we explain in detail in Section 3.3. This variable measures the extent to which the assets owned by a focal firm's close peers can be easily redeployed for use in the product markets covered by the focal firm's more distant peers. When this variable is high, it indicates that the focal firm likely has the ability to increase its scope outward at low cost, as its assets are likely redeployable to assist in production in these nearby product markets. Our second measure we label *Sectoral Opportunity Set Potential*, which is based on the supply of scope-expansion opportunities rather than the cost of executing them. This measure is one minus the concentration ratio of the distribution of industries spanned by the focal firm's more distant peers. When this quantity is high, it indicates that these peers span many related product markets. As a consequence, the focal firm likely sees a favorable distribution of industries to which it can increase its scope (a "thick" opportunity set). Importantly, both measures are computed without using the characteristics of the focal firm itself, and are weighted heavily on the more distant peers. The use of distant peers, as explained earlier,

is supported by econometric research as being moor plausibly exogenous due to the the second-degree (rather than first-degree) network linkages of these peers.

In our first stage analysis, we regress our measures of scope on both scope incentive variables and we include all control variables that are also included in our two stage models. Additionally, we include firm and year fixed effects in both stages. The results are displayed in Table 9.

[Insert Table 9 Here]

Row (1) shows that both scope incentive variables are positively related to FIC-scope. *Sectoral Redeployment Potential* is positive with a t-statistic of 4.3, and *Sectoral Opportunity Set Potential* has a positive t-statistic of 11.9. Results are similar for NAICS scope. For comparison, we run the same regression with the # of Compustat segments as the dependent variable and we find the results are much weaker. The first scope incentive variable is not significant, and the second is moderately significant with a t-statistic of 2.9. Overall these results indicate that our scope incentive variables are powerful regarding variation in FIC-scope and NAICS-scope, but not for the number of segments. Henceforth, we only consider FIC-scope and NAICS-scope in our second stage models.[9]

6.2 Corporate Finance Policies and Scope Expansion

We now consider the second stage regressions where we assess the impact of ex-ante scope increase incentives on ex-post investments, performance, and financing policies. We start with investments and consider ex post acquisitions, divestitures (target of acquisition), R&D, and CAPX. In particular, we consider two-stage least squares regressions where we instrument either FIC-scope or NAICS-scope using our two instruments based on ex-ante scope incentives. We also control for size, age, and firm and year fixed effects. We also consider a

[9] As expected in unreported tests, our results are weaker if we use the number of Compustat segments instead of FIC-scope or NAICS-scope.

specification that also controls for ex ante valuation (market to book) and the TNIC HHI.

[Insert Table 10 Here]

The results for investment policies are displayed in Table 10. In Panel A, we find that firms with high ex-ante incentives to increase scope are more likely to do an acquisition ($t - statistic$ of 4.7) and they are less likely to divest ($t - statistic$ of -2.3). These results indicate that acquisitions are a natural way to increase scope, and avoiding divestitures is also necessary to avoid losing any previous gains in scope. These results also suggest that increases in product scope are an important acquisition motive, and that scope increases might help to explain why acquisitions became so prevalent over the past two decades. These results can also inform regulatory debates given the more controversial link between acquisitions and market power suggested in the popular press.

A second finding is that firms with high incentives to increase scope also increase their R&D expenditures, but they do not increase capital expenditures. The increase in R&D is significant with a t-statistic of 3.9. This finding indicates that innovation likely facilitates scope expansion in tandem with acquisitions. For example, when assets can be redeployed across product markets, some innovation spending is likely synergistic as it can serve to improve productive efficiency and flexibility. In turn, this model likely facilitates the creation of multi-industry firms that do not need multiple operating segments. For example, firms might use R&D to develop more universal and flexible production sites. Hence the benefits of increased scope might be feasible in the 21st century without having to accept the dark side of negative governance externalities. Indeed our earlier results suggest that increases in scope were achieved during our sample with almost no change in the average number of Compustat operating segments.

Table 11 documents novel supplemental results based on running the tests in Table 10 separately within each major industry sector, as defined using the Fama-French-5 classification. Panel A shows that firms in the technology sector primarily increase scope by investing

in R&D and not in acquisitions. In contrast, firms in manufacturing sectors do the opposite and primarily invest in acquisitions but not in R&D. These results are intuitive given the focus on intangible assets in the tech industry and the focus on tangible assets in manufacturing. The other three sectors (consumer, health and miscellaneous) are consistent with both investment channels (R&D and net acquisitions) being relevant.

In Online Appendix Table IA2, we run the tests in Table 10 using a one-stage model where we regress ex post investments on the two ex ante scope-incentive measures directly. We find that increased R&D and reduced asset sales are significantly and positively related to the asset redeployability incentive, whereas increased acquisitions are most related to the opportunity set incentive. These results suggest that innovation spending indeed might be used to redeploy flexible assets to new localized product markets, thus also leading to a lower likelihood of asset sales. In contrast, acquisitions are more likely in less redeployable markets having numerous opportunities (redeployment is less feasible in these markets).

6.3 Ex-post Outcomes and Scope

Table 12 reports the results of analogous regressions for ex-post performance metrics. We consider ex-post valuations (market to book), sales growth, asset growth and return on assets. All right-hand-side variables are lagged one period and we use a two-stage least squares model with scope instrumented by our two ex ante scope incentive variables.

[Insert Table 12 Here]

The table shows that firms with high scope expansion incentives experience higher ex-post valuations, higher sales growth and higher asset growth.[10] However, we do not observe a significant coefficient for profitability measured as return on assets (ROA). Overall, the higher valuations suggest that scope expansion is a positive net present value investment

[10]Our results for valuation are robust if we use the Peters and Taylor (2017) measure of Q (which accounts for intangibles) as an alternative to market to book assets.

and that investors expect higher profits in the future. We also note that the non-result for ROA is consistent with the view that firms add new industries to their portfolio in an assortive way,[11] and focus on the most profitable markets first. This interpretation is consistent with all four of our findings on performance. Our valuation results - which show that firm market-to-book equity ratios increase with our scope measures - are in contrast to the historical conglomerate literature (Berger and Ofek (1995) and Lang and Stulz (1994)) that finds that firm market-to-book valuation measures go down with an increased number of reported Compustat segments. In Online Appendix Table IA3, we run these outcome tests in a one-stage model as before. The results suggest that value creation is strongest for scope expansions that are realized through the asset redeployability channel, but sales growth is highest for the opportunity set channel. These results are intuitive given our investment results, as they suggest that the return on investment is higher for organic investments such as R&D using existing redeployable assets. Consistent with the literature, valuation gains to acquisitions are lower by comparison, but acquisitions instead generate higher and more immediate sales growth (as acquisitions, unlike organic growth, typically entail the purchasing of an existing market presence in addition to the assets).

We next explore the importance of scope expansion to venture capital funded private firm entry and product market fluidity (the rate of change in product portfolios of existing public firms that operate in a focal firm's product markets) over time. We use two variables from Hoberg, Phillips, and Prabhala (2014) to measure both quantities. The first variable, *VC funding similarity* is the cosine similarity of the given focal firm's 10-K product description to the average vocabulary used by all startups in the given year (where the startup vocabulary is obtained from Venture Expert business descriptions of all startups receiving their first round of financing in the given year). The second variable *Product Market Fluidity* is the average market-wide change in the use of the given firm's 10-K product description vocabulary by

[11]The non-result for ROA is robust to alternative specifications such as (A) adding R&D back into operating income as it is not clear that R&D is an expense, (B) truncating ROA at zero when it is negative, or (C) scaling profitability by sales instead of assets.

all other firms. A high value indicates a large amount of product innovation by competing firms in the focal firm's product markets. We report these results in Table 13.

[Insert Table 13 Here]

The results are shown in Table 13, which shows that high venture capital related entry occurs into the focal firm's markets when the firm has scope increases, and fluidity also increases consistent with existing public firms also turning over their product portfolios more actively when scope incentives are strong. These results are particularly compelling when interpreted alongside our earlier-reported finding that high scope firms also do more acquisitions (see Table 10). Overall, these innovation and acquisition results are consistent with Phillips and Zhdanov (2013), who show that existing firms have strong incentives to purchase related start ups as their scope increases. This interpretation suggests that already-public firms tend to outsource scope-enhancing R&D and technology development to smaller startups (thus generating the higher levels of VC funding we observe) and later buy them (thus explaining the higher acquisitions we also observe).

[Insert Table 14 Here]

Table 14 reports the results of analogous regressions for ex-post financing policies. The question of interest is how do firms likely finance scope expansions? Our results suggest that equity is more commonly used than debt. Increased equity in the capital structure appears to accrue both through the issuance of new shares and through lower overall dividend payments. These results are consistent with innovation and asset redeployment being used to facilitate scope expansion, as neither creates a significant amount of new fixed collateral that is traditionally associated with debt financing. The one stage results in Online Appendix Table IA4 shows that our results for the financing variables are rather evenly spread across the two scope incentive variables.

As discussed in Section 3, we also consider an alternative measure of scope based on the Latent Dirichlet Allocation topic model. As we note in Online Appendix Tables IA5 to IA7, our results are fully robust to this alternative measure of scope.

6.4 Subsample Analysis: Extent of Scope Expansions and the Role of Scale

We next examine if our findings regarding scope-induced corporate policies and performance differ as firms become more spread out regarding the markets they serve, and whether these results differ based on firm scale. These issues are important as it is natural to ask whether the gains to scope become larger or smaller as firms advance in scale and scope. For example, if the gains to adding more scope are largest for firms that already achieved high scale and scope, it would suggest that the trend toward increased scope and fewer publicly traded firms is likely to continue. Alternatively, if the gains are largest for smaller firms, then this trend might focus more on smaller firms, and less on already-expanded firms.

As in our earlier analysis on risk profiles, we first split our sample into three terciles based on the type of scope firms have achieved ex ante. Firms with "near" scope are those with segments that are similar to each other in terms of product market spatial distance (these firms have a narrow market presence and operate in highly related markets). We also consider terciles for "mid" scope and "far" scope (firms that have achieved a high level of spatial coverage across spatially more distant U.S. markets). These subsamples are constructed in each year by sorting firms based on past-year scope-spread (the average spatial distance of the segments each firm covers) and hence we have near, mid and far scope subsamples. Our instrumented variable of interest, as in the prior subsection, is our measure of scope (FIC-Scope). For parsimony, we only report this variable's coefficient for each regression. Hence, in our table below, each coefficient we report is from a separate regression based on the three tercile subsamples as indicated in the column headers. We report these regressions across all of the dependent variables we considered in the prior subsection, and the dependent variable

for each model is indicated in the first column. All regressions include firm and year fixed effects as well as controls for size and age.

[Insert Table 15 Here]

Table 15 displays the results and shows that results are strongest for firms with near-scope on many dimensions. They do more acquisitions, R&D and they have higher valuations when scope-incentives are strong. These results support the predicted value gains to close-by scope as predicted by Panzar and Willig (1977). The strong results for innovation for these firms is further consistent with Teece (1980) and Henderson and Cockburn (1996), as firms especially invest in innovation when they are expanding across closer markets, where the gains associated with these theories are likely to be largest. The table also shows that there are essentially no valuation gains to increasing scope when firms are operating across product markets that are more spatially distant. This result suggests that there are diminishing gains to scope when firms increase scope too far. This finding is consistent with potential inefficiencies with excessive scope, as suggested by the early conglomerate literature focusing on excessively diversified firms. Further consistent with these views, we documented earlier that few firms actually choose to operate across markets that are spatially distant, especially in more recent years. Lastly, the the table shows that there is more VC backed entry and product market fluidity around firms with nearby scope, consistent with increases in innovation not only within the firm, but also external to the firm itself in these nearby scope markets. This further supports the confluence of the aforementioned works by Teece (1980) and Henderson and Cockburn (1996), alongside the outsourcing-of-innovation predictions of Phillips and Zhdanov (2013).

We next examine how our main results vary with firm scale, and we thus sort firms into annual terciles based on firm size using ex ante total assets. Table 16 displays the results using the same tercile-based format as Table 15. We thus report regression coefficients separately for large, mid-size and small firm subsamples. As before, our instrumented variable of interest

is a measure of scope (FIC-Scope), and for parsimony, we only report this coefficient for each regression. All regressions include firm and year fixed effects and controls for size and age.

[Insert Table 16 Here]

The results in Table 16 indicate that results are stronger for small firms. They do more acquisitions, more R&D, have higher sales growth and have higher valuations as scope increases. On the other hand, we see a negative effect (not quite significant) on valuation for the largest tercile firms, which is in sharp contrast to the significantly positive valuation result for smaller firms. This suggests diminishing returns to scope as scale increases, and suggests that scope increases might eventually reach a natural limit. Yet we note that these results are suggestive, and we believe further research examining whether an optimal scale exists (and what this optimal scale is) could be very fruitful. We also note that our results are regression-based and therefore give insights regarding the average firm. Any one individual firm might have unique capabilities that allow it to expand scope further (or less) than what is implied by the average.

We find that VC funding and product fluidity are significantly higher around smaller firms with high scope incentives, but this coefficient is still significantly positive for larger firms. This is consistent with the idea in Phillips and Zhdanov (2013) that large firms are perhaps ideal candidates to purchase outsourced innovation specifically from startups. Overall, our results in this section are consistent with the impact of scope on many policies being stronger for firms focused on nearby scope expansion and for smaller firms. The stock market also values scope expansion for these firms significantly more.

We conclude this section with a note on robustness. Readers might be concerned that our results are excessively driven by ultra-large companies such as Amazon, which are known to have experienced substantial growth in scope. Table IA8 thus considers a specification where we drop the 50 largest companies from the sample in each year based on lagged assets and our results are fully robust. We conclude that the impact of scope is much more broad-based

as it impacts firms of all sizes as documented above.

7 Increasing Concentration or Increasing Scope

Although our paper's primary objective is to document the rise in scope and examine the role of scope in corporate finance strategies and performance, we also examine the trend of increasing industry concentration documented in the literature (see Grullon, Larkin, and Michaely (2019) for example). Intuitively, if the number of firms in the economy were held fixed, and every firm expanded its scope to serve twice the number of product markets, it follows that pure horizontal competition would increase economy-wide as more and more firms would be serving each market and consumers would have twice as many options in each market. However, if these expanded firms are (incorrectly) assigned only to their historical industry classifications, industry concentration would not reflect the higher competition. This intuition is particularly clear in the extreme case, where all firms sell products in all markets. Here, all firms are direct competitors in all markets, and competition would be strong economy wide. This section examines if the magnitude of the increase in scope reported earlier is large enough to explain all or part of the apparent rise in horizontal concentration. The results could have important implications for the regulatory and academic debate surrounding this issue.

Existing industry classifications do not allow researchers to account for such increases in scope. Many earlier studies measure competition by computing HHIs based on SIC codes from Compustat. The key limitation is that each firm, regardless of its actual scope, is assigned to one and only one industry code. If scope was increasing, it would not be observable in these data structures. One remedy is to use the Compustat segment tapes (Hoberg and Phillips (2010b), Grullon, Larkin, and Michaely (2019)), which allow the researcher to assign firms to more than one industry. However, as we note earlier, SFAS 131 decoupled segment reporting from the actual industries firms operate in starting in 1997. Likely as a

consequence, Figure 1 shows that segments do not capture increases in scope. We consider two approaches to adjust concentration ratios for increasing scope.

One limitation of our study is that we only have scope data for U.S. publicly traded firms. Hence, we do not account for the competitive impact of private or foreign firms. The goal of this section is thus to illustrate that an alternative narrative should be considered, and to provide suggestive evidence on its economic magnitude. However, we also note that stylized facts suggest that accounting for the influence of foreign competitors and private firms would likely reinforce our finding that concentration is not increasing as sharply as suggested by prior studies. For example, globalization is increasing over time (see Hoberg and Moon (2017) for example) and accounting for foreign competition would likely further reduce the growth rate of concentration over time. Analogously, studies including Ewens and Farre-Mensa (forthcoming) suggest that larger firms are staying private longer, and accounting for the larger private firms (which are most material) might further reduce the measured growth rate of concentration. We advocate caution in drawing overly strong conclusions given these limitations, and future research accounting for them should be fruitful.

7.1 Broadening Scope of Businesses

The primary issue with existing classifications is they have fixed granularities, and as firms broaden scope of their operations, concentration in specific product markets cannot be computed using narrow industry assignments of firm sales data. Firms may produce in multiple 3-digit SIC codes and competition is mismeasured if researchers assign their sales to just a small subset of these SIC codes. The extent of this bias could be time-varying. For example, firms may produce in a just one 3-digit SIC industry code early in our sample, while later producing in multiple SIC codes - thus making one or even two 2-digit SIC codes more representative of its scope of production.

We first illustrate this point using a test that provides external validity of this idea. We intentionally avoid using the spatial TNIC representation of industries for this test and

instead consider annual OLS regressions where the intensity of managerial competition complaints is the dependent variable (see Li, Lundholm, and Minnis (2013)). We regress this variable on both one minus the Compustat SIC-3 HHI where each firm is assigned to the Compustat 3-digit SIC code it reports and one minus the Compustat SIC-2 HHI - using the 2-digit SIC code the firm reports. We flip the sign on the HHIs for convenience as (1-HHI) is a positive measure of competition. We also use the same sample selection criteria as Grullon, Larkin, and Michaely (2019) for consistency. The results are reported in Table 17.

The table illustrates an economically large trend toward increasing importance of coarser SIC-2 codes in understanding firm production and competition (reinforcing our conclusion that firms are operating in more markets over time). In the first year of this sample, 1997, only competition measured using the SIC-3 HHI predicts competition complaints. This early result indicates that 3-digit SIC codes well-represented the appropriate granularity of market boundaries at which competition among firms took place. However, throughout our sample, the relative importance of the HHI measured using 2-digit SIC codes increases and the relative importance of the SIC-3 digit HHI decreases. By the end of our sample, the coefficients for both HHIs are roughly equal in size, suggesting that competition is taking place across multiple 3-digit SIC codes and complaints are arising from multiple 3-digit level product markets. In the next section, we will show that market overlaps using our TNIC scope-based framework will indicate the same conclusion, and adjusting HHIs for broadening scope suggests that horizontal concentration is not rising materially in our sample.

7.2 Scope Adjustment via Market Overlap Analysis

We now develop an intuitive adjustment of HHIs for scope based on examining how market overlap varies with granularity. We define "Firm-Pair Market Overlap" for a pair of firms i and j using the FIC-300 classification and the firm-specific market definitions implied by equation (2). For example, suppose firm i operates in industry A and B, and j operates in A, C and D. Market Overlap for this pair is the true overlap in their markets, which is $\frac{1}{4}$, as

they intersect on just one industry but the union of industries they serve is four. We next define "Industry-Pair Market Overlap" for a pair of industries in any classification as the average Firm-Pair Market Overlap averaged over all permutations of pairs of firms i in the first industry and j in the second industry. If the two industries have high Industry Pair Market Overlap, it follows that the boundary between the two industries is not material and that competition plays out at a more coarse level of industry granularity.

[Insert Figure 4 Here]

To illustrate the impact of scope on industry boundaries and the role of granularity, the upper graph in Figure 4 plots the average Industry-Pair Market Overlap for all pairs of 4-digit SIC industries that have the same 3-digit SIC code, and also for all 4-digit SIC industries that have the same 2-digit SIC code but not the same 3-digit SIC code. Both statistics have been increasing rather dramatically throughout our sample. This illustrates that the aforementioned rise in scope is indeed rendering narrow industry boundaries less relevant over time, especially for more fine granularities such as three-digit SIC codes. The more important observation, however, is that the average market overlap for the SIC-2 pairs late in our sample is actually higher than the level of market overlap for SIC-3 pairs early in our sample. This indicates that industry boundaries are as strong today at the two-digit SIC level as they were at the three-digit SIC level 25 years ago.

Existing studies note 1997 as a pivotal year in which the rise in concentration began to accelerate. At the start of this year, SIC-2 market overlap was 4.04% and SIC-3 market overlap was 5.72%. By the end of our sample, SIC-2 market overlap rose to 4.88%, and this 0.84% rise is enough to close 50% of the ex-ante gap of 1.68% between SIC-2 and SIC-3. It follows that between 1997 and present day, the granularity at which competition takes place moved roughly one half of one level of granularity. To show the impact of such a shift on concentration levels, we plot three trend-lines for concentration in the lower graphic of Figure 4. These include the benchmark SIC-2 HHI and the SIC-3 HHI as computed in the

existing literature,[12] as well as a mixture of the two that starts at 100% SIC-3 HHI in 1997 and linearly moves to 50% SIC-3 HHI and 50% SIC-2 HHI at the end of our sample. Only the mixed HHI roughly holds market overlap fixed during the crucial post-1996 sample, and hence only this specification is a reasonable scope-adjusted HHI trend line.

The figure illustrates that horizontal concentration is not rising materially when we consider a scope-adjusted HHI. In contrast, we replicate the finding in the existing literature that concentration does appear to be rising dramatically if we do not adjust HHI measures for scope. The scope-adjusted HHI essentially allows granularity to shift with average scope whereas past studies hold granularity fixed over time. Adjusting granularity is necessary because increasing scope broadens industry boundaries, and competition thus occurs over increasingly coarse levels of granularity. The linear adjustment we employ in this section is highly simplified, and we reiterate that our goal here is to show intuition for how scope can impact competitive granularity, which in turn, can impact how competition is changing over time. In the next section, we adopt a more direct scope-adjusted measure of concentration based on our implicit modeling of the multiple industries firms operate in.

7.3 Scope Adjustment via Implied Multi-Industry Assignments

The construction of the FIC-scope variable assigns each firm to multiple industries when its Item 1 is similar to more than one industry. We now use this enhanced data structure to compute new HHIs at the FIC-300 industry level that use this multi-industry-assignment-classification directly. To do so, we first allocate each firm's total sales to the multiple industries it is assigned to using the basic similarity weights (see $Q_{i,j,t,FIC}$ in equation (1)) that were used to construct the classification itself. HHIs are then computed at the FIC industry level using these allocated sales where firms operate in multiple sectors. We then

[12] We compute baseline SIC-2 and SIC-3 HHIs following the sample and weighting scheme used by Grullon, Larkin, and Michaely (2019). We limit the sample to firms with CRSP exchange codes of 1 to 3, CRSP share codes 10 and 11, sales and assets greater than one million, and we exclude financials and utilities. We also compute HHIs based on assigning firms to more than one industry if indicated in the Compustat segment tapes. The annualized average HHIs are also weighted by sales.

aggregate these HHIs back to the firm level by computing weighted averages over the sectors each firm operates in (again using weights $Q_{i,j,t,FIC}$). Note that our results are similar if we use equal weights instead.

We then aggregate HHIs to the economy-wide annual level by computing a sales weighted average of the firm HHIs or an equal weighted average of the firm HHIs.[13] We then plot both estimates of the HHI faced by average firm in each year in the Figure 5. The figure illustrates, as was the case with the scope adjustment used in the previous section, that horizontal concentration levels are not rising materially after 1997.

The results in this section suggest that an extended narrative might be relevant to understand the rise in industry concentration reported in the literature. This extended narrative is that scope has been rising rapidly as companies merged and listings declined, and as a consequence, traditional HHIs measured without adjustment are increasing. Yet the rise in these HHIs might not indicate reductions in horizontal competition as they are based on overly rigid classifications that do not account for scope and that assign firms to single industry categories. We show that scope-adjusted horizontal concentration measures do not rise materially. Hence, future research might further examine the role of scope in generating the high levels of market power suggested in the literature. In particular, scope can also generate market power through channels such as anti-competitive product bundling strategies, increased market power within supply chains, increases in barriers to new entry, or it can induce kill zones in the market for innovation (see Kamepalli, Rajan, and Zingales (2020)). Firms achieving high levels of both scale and scope might realize particularly amplified levels of market power through these channels.

8 Conclusions

We use textual analysis of firm 10-Ks to compute novel measures of scope at the firm-year level. Using our new measures, we find that the scope of U.S. firms has increased dramatically

[13]The sales-weighted approach is used in Grullon, Larkin, and Michaely (2019).

during our sample period from 1989 to 2017. Our findings illustrate the rise of a new 21st century high-scope firm, which increases product scope using innovation and acquisitions. These firms are capable of servicing multiple product markets without increasing the number of operating segments. Indeed, analogous tests using the traditional Compustat segment tapes are generally uninformative regarding the scope of U.S. public firms. These findings support our thesis that modern firms can build multiple-industry related product portfolios while maintaining a simple single segment organizational form.

We find that firms increase scope by acquiring more, divesting less, and increasing innovation spending in R&D, but they do not increase CAPX. The increased innovation spending is consistent with developing increased flexibility in production. Firms increasing scope also realize higher valuations and higher sales growth. Scope expansion is financed using equity rather than debt, consistent with intangibles and asset redeployment not creating material amounts of new collateral. We document that related-markets scope expansion is also highly valued by the market, which illustrates the novelty of our results given the discount for conglomerates previously documented in the earlier conglomerate literature for unrelated business lines.

We conclude our analysis with evidence that the increase in scope we report might explain why other studies have documented a trend of increasing concentration over time. We compute adjusted HHIs that account for the fact that increased scope can increase competition as more firms operate in more overlapping markets. We find that these adjusted HHIs are essentially unchanging since 1997. These results suggest that an extended narrative that considers the growth in scope can help to contextualize the previous reports of increasing HHIs and the high levels of M&A activity. In particular, much M&A has been targeted at increasing scope, a business strategy that can produce positive net present value as our findings indicate. Yet these results must be interpreted with care, as increased scope can lead to significant antitrust concerns in the form of product bundling and increased bargaining power within supply chains or decreasing entry into new markets that larger already estab-

lished firms have moved into. We believe that future research examining scope and market power in detailed product areas could be particularly impactful given the importance of these issues to regulators and society at large.

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Appendix A. Variable definitions

Table A1: Variable definitions

Table A1

Variable	Definition	Source
FIC-Scope	The number of TNIC (see Hoberg and Phillips 2016) industries (using the FIC-300 classification based on 1997 industry clusters) that each firm's 10-K product description is similar to. The classification from firm to segments is based on a 2% granularity, and firm-segments similarities are deemed to be pairs for the 2% highest textual similarities between each firm and the text describing the 300 FIC industries.	
NAICS-Scope	This is computed in a similar way to the FIC-scope variable. The NAICS scope is based on the text describing NAICS industries (using the highly detailed 963 page 2017 NAICS manual) instead of TNIC FIC industries. The classification from firm to segments is based on a 2% granularity, and firm-segment similarities are deemed to be pairs for the 2% highest textual similarities between each firm and the text describing the 311 4-digit NAICS industries.	
Product Breadth	Using metaHeuristica queries, we count the number of paragraphs that mention "product lines" or "product categories". These phrases indicate high levels of product breadth. Product Breadth is this number of paragraphs scaled by the total number of paragraphs in the 10-K.	
Prod/Svc Breadth	This variable is computed analogous to Product Breadth, but we also count paragraphs that mention either "service lines" or "service categories".	
Product Breadth Detail	Same as Product Breadth, as described above, except that we only count paragraphs that additionally mention a specific clarifying term in the following list: {breadth, broad, broader, wide, multiple, numerous, diverse, categories, divisions}	
Prod/Svc Breadth Detail	Same as Product/Svc Breadth, as described above, except that we only count paragraphs that additionally mention a specific clarifying term in the following list: {breadth, broad, broader, wide, multiple, numerous, diverse, categories, divisions}	
Sectoral Redeployment Potential	This is an instrument indicating a shift in the incentives for firms to increase scope. The data draws from information in the Bureau of Economic Analysis, Compustat, and the research paper Kim and Kung (2017). This variable is the average cosine similarity between the asset utilization vector of the focal firm's NAICS industry and that of the NAICS industry of the focal firm's TNIC-2 peers that are not also TNIC-3 peers. This latter step ensures that the measure is based on product market peers that are close but a bit more distant in product space than are near peers, which further increases the extent of exogenous content in the measure. When this value is high, it indicates that expansion in scope for the focal firm is likely to have low cost regarding expansion into neighboring product markets in the given year.	
Sectoral Opportunity Set Potential	This variable is similar to the above except that it is based on product offerings rather than the inputs to production (asset vectors). This variable is computed as the HHI, or concentration ratio, of companies that are in the focal firm's TNIC-2 industry but not in the most proximate TNIC-3 industry. The HHI calculation is based on the NAICS codes of the firms in these near but slightly more distant product markets. When this value is high, it indicates high growth opportunities to scope expansion for the focal firm in the given year.	
Logassets	Natural logarithm of total assets of the firm Compustat	
Log Age	Natural logarithm of one plus the current year of observation minus the first year the firm appears in the Compustat database Compustat	
Valuation Ratio	This ratio is computed as the market value of the firm (book assets minus book equity plus market equity), all divided by book assets. Market equity is Compustat shares outstanding times the share price at the end of the fiscal year PRCC. Book equity is shareholders equity (Compustat SEQ), plus TXDITC minus preferred stock (PSTKRV, and if missing, then PSTKL, and if missing then UPSTK). Shareholders equity iS SEQ, but if missing, is Compustat CEQ plus UPSTK, and if missing, is assets less long term assets.	
10K Size	Natural logarithm of one plus the total number of paragraphs in the focal firm's 10-K report.	
TNIC HHI	The concentration ratio based on TNIC industries as computed in Hoberg and Phillips (2016).	
NAICS HHI	The concentration ratio based on NAICS industries as computed in Grullon, Michaely, and Larkin (2019).	

Variable	Definition
Acquirer Dummy	A dummy equal to one if the given firm had an acquisition become effective in the current year according to the SDC Platinum database.
Target Dummy	A dummy equal to one if the given firm had a sale of assets or a merger become effective in the current year according to the SDC Platinum database.
R&D/Assets	Compustat XRD divided by total assets AT, winsorized at the 1/99% level. This variable is set to zero if XRD is missing.
CAPX/Assets	Compustat CAPX divided by total assets AT, winsorized at the 1/99% level. This variable is set to zero if it is missing.
Sales Growth	Natural logarithm of total sales in the current year t divided by total sales in the previous year $t-1$.
Asset Growth	Natural logarithm of total assets in the current year t divided by total assets in the previous year $t-1$.
OI/Assets	Compustat OIBDP divided by total assets AT, winsorized at the 1/99% level.
Equity Issuance/Assets	Computed as Compustat (SSTK - PRSTKC) divided by total assets AT, winsorized at the 1/99% level.
Debt Issuance/Assets	Computed as Compustat DLTIS divided by total assets AT, winsorized at the 1/99% level.
Equity Repurchases/Assets	Computed as Compustat PRSTKC divided by total assets AT, winsorized at the 1/99% level.
Dividends/Assets	Computed as Compustat DVC divided by total assets AT, winsorized at the 1/99% level.

Additional stop words dropped from the NAICS manual vocabularies: THE, AND, OF, COMPANIES, IN, SERVICES, CLASSIFIED, OR, INCLUDES, EXCLUDES, PRODUCTS, PRIMARILY, INCLUDING, NOT, PROVIDING, DIVERSIFIED, OTHER, THAT, TO, ENGAGED, GAS, MANAGEMENT, OPERATORS, RELATED, OWNERS, A, PRODUCERS, CONSUMER, ELSEWHERE, PROVIDERS, ALSO, FOR, COMPONENTS, DEVELOPMENT, PRODUCTION, AS, BUT, CENTERS, WITH, ARE, PRODUCING, LARGE, NON, OPERATING, OPERATIONS, USING, FROM, IT, MULTI, EITHER, EMPLOYMENT, THREE, UNDER, WHOSE, ACTIVITY, CORPORATE, DO, END, HELD, HIGH, MORE, WHICH, THEIR, WIDE, ACROSS, ASSETS, AT, OPERATE, INDUSTRY, MANUFACTURING, ESTABLISHMENTS, THIS, COMPRISES, EXCEPT, CROSS, REFERENCES, MERCHANT, SUCH, GROUP, EXAMPLES, ALL, PRODUCT, ILLUSTRATIVE, THESE, ACTIVITIES, MAY, NEW, PURCHASED, TYPE, MADE, SUPPORT, SECTOR, ONE, SUBSECTOR, WITHOUT, BASIS, INCLUDED, WORK, KNOWN, PROCESSING, PROVIDE, DIRECT, ORGANIZATIONS, PREPARATION, SELLING, GROWING, INTO, OTHERS, FOLLOWING, BUSINESS, COMBINATION, MISCELLANEOUS, SALE, INDUSTRIES, USE, MAKING, ORDER, PROGRAMS, THEY, BENEFICIATING, SIMILAR, STOCK, CONTRACT, BASED

Table 1: Summary Statistics

Summary statistics are reported for our sample of 100,525 observations based on annual firm observations from 1988 to 2017. Our main variables of interest, TNIC-scope and NAICS-scope, are based on scoring each firm's Item 1 business description based on how similar it is to the product text of specific fixed industries. For FIC-scope, fixed industries are based on the TNIC FIC-300 industries (see Hoberg and Phillips 2016), and for NAICS-scope, it is based on 4-digit NAICS industries. All variables are described in detail in the variable list in Appendix A and in Section 3 of the paper.

Variable	Mean	Std. Dev.	Minimum	Median	Maximum	# Obs
Panel A: Scope and Segment Variables						
TNIC-Scope	6.923	5.482	0.000	6.000	30.000	100,525
NAICS-Scope	6.269	7.519	0.000	4.000	47.000	100,525
# Compsutat Segments	1.452	0.862	1.000	1.000	11.000	100,525
Panel B: Accounting Variables						
R&D/Assets	0.056	0.127	0.000	0.000	2.944	100,525
CAPX/Assets	0.058	0.070	-0.000	0.037	0.725	100,525
Acquisition Dummy	0.287	0.452	0.000	0.000	1.000	100,525
Target Dummy	0.126	0.332	0.000	0.000	1.000	100,525
Valuation (M/B)	1.758	2.156	0.064	1.204	203.313	99,938
Sales Growth	0.110	0.437	-6.177	0.076	9.383	100,112
Asset Growth	0.077	0.356	-4.294	0.050	5.529	100,494
Equity Issuance	0.051	0.152	-0.002	0.004	2.895	100,525
Debt Issuance	0.103	0.207	0.000	0.002	1.999	100,525
Dividends/Assets	0.008	0.028	0.000	0.000	1.248	100,424
Equity Repurchase	0.016	0.042	0.000	0.000	0.518	93,049
Log Assets	5.446	2.122	0.694	5.327	13.590	100,525
Log Age	2.622	0.766	0.693	2.565	4.220	100,525

Table 2: Pearson Correlation Coefficients

Pearson Correlation Coefficients are reported for our sample of 100,525 observations based on annual firm observations from 1988 to 2017. Our main variables of interest, TNIC-scope and NAICS-scope, are based on scoring each firm's Item 1 business description based on how similar it is to the product text of specific fixed industries. For FIC-scope, fixed industries are based on the TNIC FIC-300 industries (see Hoberg and Phillips 2016), and for NAICS-scope, it is based on 4-digit NAICS industries. All variables are described in detail in the variable list in Appendix A and in Section 3 of the paper.

Row	Variable	Fic-Scope	NAICS-Scope	# CS Segments	Log Assets	Log Age	R&D/ Assets	CAPX/ Assets	Acquisition Dummy	Target Dummy	Sales Growth
	NAICS-Scope	0.579									
	# Compsutat Segments	0.186	0.198								
	Log Assets	0.269	0.273	0.312							
	Log Age	0.038	-0.047	0.309	0.400						
	R&D/Assets	0.010	-0.039	-0.155	-0.250	-0.147					
	CAPX/assets	-0.016	0.045	-0.043	0.026	-0.097	-0.092				
	Acquisition Dummy	0.067	0.088	0.133	0.301	0.075	-0.089	-0.015			
	Target Dummy	0.054	0.057	0.167	0.248	0.168	-0.056	-0.006	0.156		
	Sales Growth	0.030	0.055	-0.032	-0.013	-0.166	0.032	0.099	0.104	-0.065	
	TNIC HHI	-0.133	-0.299	0.091	-0.182	0.171	-0.149	-0.124	-0.042	-0.011	-0.071

Table 3: Disney Scope vs Time

The table displays the LDA-based scope allocations of Disney in 1990 (Panel A), 2003 (Panel B), and 2017 (Panel C).

Year	Topic	Amount	Word List
			Panel A: Disney Scope Allocations in 1990
1990	296	275.0	series, production, warner, live, feature, studio, distribution, company, release, produced
1990	180	155.2	event, team, garden, super, champion, league, collectible, sporting, arena, concert
1990	100	128.4	programming, broadcast, network, cable, satellite, program, time, channel, broadcasting, household
1990	222	127.3	motion, picture, screen, movie, production, cinema, company, theater, creative, sound
1990	290	43.2	publishing, adult, company, publisher, toy, character, gift, imperial, english, preview
1990	122	41.9	music, audio, disc, theater, studio, content, videocassette, licensors, digital, consumer
			Panel B: Disney Scope Allocations in 2003
2003	100	745.3	programming, broadcast, network, cable, satellite, program, time, channel, broadcasting, household
2003	296	641.1	series, production, warner, live, feature, studio, distribution, company, release, produced
2003	180	448.8	event, team, garden, super, champion, league, collectible, sporting, arena, concert
2003	245	316.9	radio, market, broadcasting, broadcast, ownership, company, rule, interest, communication, local
2003	222	294.5	motion, picture, screen, movie, production, cinema, company, theater, creative, sound
2003	198	92.6	cable, system, service, regulation, local, rate, programming, television, authority, ownership
2003	127	88.3	resort, vacation, grand, valley, lift, ownership, white, company, located, owner
2003	167	86.3	company, food, guest, menu, quality, concept, location, service, beverage, item
2003	285	75.2	florida, development, resident, county, residential, company, alaska, residence, miami, area
2003	217	72.6	group, room, reservation, eagle, brand, leisure, travel, occupancy, company, service
			Panel C: Disney Scope Allocations in 2017
2017	100	736.4	programming, broadcast, network, cable, satellite, program, time, channel, broadcasting, household
2017	296	620.8	series, production, warner, live, feature, studio, distribution, company, release, produced
2017	180	416.7	event, team, garden, super, champion, league, collectible, sporting, arena, concert
2017	245	237.4	radio, market, broadcasting, broadcast, ownership, company, rule, interest, communication, local
2017	222	193.4	motion, picture, screen, movie, production, cinema, company, theater, creative, sound
2017	127	138.6	resort, vacation, grand, valley, lift, ownership, white, company, located, owner
2017	148	117.5	service, launch, satellite, programming, primestar, channel, system, echostar, company, directv
2017	190	115.3	cost, ferc, order, service, pipeline, settlement, restructuring, interstate, transportation, regulatory
2017	217	101.8	group, room, reservation, eagle, brand, leisure, travel, occupancy, company, service
2017	167	84.2	company, food, guest, menu, quality, concept, location, service, beverage, item
2017	290	62.2	publishing, adult, company, publisher, toy, character, gift, imperial, english, preview

Table 4: Scope Statistics vs Compustat Segment Counts

The table reports scale and scope statistics separately for firms based on how many operating segments the firm reports in the Compustat database. Our main variables of interest, TNIC-scope and NAICS-scope, are based on scoring each firm's Item 1 business description based on how similar it is to the product text of specific fixed industries. For FIC-scope, fixed industries are based on the TNIC FIC-300 industries (see Hoberg and Phillips 2016), and for NAICS-scope, it is based on 4-digit NAICS industries. Assets are from Compustat (variable AT).

# Segments	FIC-SCope	NAICS-Scope	Assets	# Obs.
1 segment	6.41	5.56	1365	71,575
2 segments	7.53	7.02	3255	17,939
3 segments	8.63	8.57	6192	7,447
4 segments	9.90	10.21	10084	2,353
5+ segments	12.21	15.17	30776	1,211

Table 5: Scope Statistics vs Firm Size

The table reports scale and scope statistics separately for firms sorted into size quintiles. Sorts are annual and are based on Compustat assets (variable AT). Our main variables of interest, FIC-scope and NAICS-scope, are based on scoring each firm's Item 1 business description based on how similar it is to the product text of specific fixed industries. For FIC-scope, fixed industries are based on the TNIC FIC-300 industries (see Hoberg and Phillips 2016), and for NAICS-scope, it is based on 4-digit NAICS industries. Assets are from Compustat (variable AT). We report statistics for the full sample and separately for single segment firms only (see column headers).

		All Firms					Single Segment Firms Only				
Row	Firm Size Quintile	# Segments	FIC-Scope	NAICS-Scope	Assets	# Obs.	# Segments	FIC-Scope	NAICS-Scope	Assets	# Obs.
	Small Firms	1.22	5.65	4.02	23	20,094	1	5.50	3.88	19	14,304
	Quintile 1	1.26	6.16	5.04	102	20,110	1	6.07	4.72	74	14,321
	Quintile 2	1.35	6.69	5.93	305	20,113	1	6.28	5.39	203	14,320
	Quintile 3	1.50	7.50	7.18	936	20,111	1	6.76	6.18	604	14,321
	Big Firms	1.94	8.62	9.17	11728	20,097	1	7.41	7.64	5926	14,309

Table 6: Scope Statistics vs Industry-Pair-Relatedness

The table reports the distribution of the industries spanned by single firms (scope) across all industry pairs, sorted by how similar are the industries in the given pair. For each pair of FIC-300 industries in each year, we first tabulate the number of firms that operate in both industries in the pair based on the FIC-scope variable's construction. A firm is thus designated as operating in both industries if the given firm's business description is highly similar to the text of both industries in the pair. The result is a panel database of industry-pair-years indicating the number of firms operating in each pair. We then sort industry pairs into deciles based on the average TNIC similarity score of all firms in the first industry relative to those in the second. Industries that score highly are spatially close in the TNIC space. Finally, we sum the firm-operating-pairs in each decile and report the fraction of operating pairs in each decile. We report this fraction for all firms, only for single segment firms and only for multi-segment firms. Finally, we report the average TNIC distance of the industry pairs in each decile and the number of industry pairs in each group in the final columns.

Industry-Pair Similarity Decile	Fraction Scope Pairs (All Firms)	Fraction Scope Pairs (Single-Seg)	Fraction Scope Pairs (Multi-seg)	Average TNIC-pair Similarity	# Obs.
Least Similar	0.036	0.038	0.030	0.001	828,872
Decile 2	0.043	0.046	0.035	0.002	829,542
Decile 3	0.041	0.043	0.036	0.003	829,012
Decile 4	0.052	0.056	0.043	0.004	829,145
Decile 5	0.053	0.053	0.054	0.006	829,064
Decile 6	0.067	0.067	0.068	0.008	829,462
Decile 7	0.086	0.086	0.086	0.010	828,756
Decile 8	0.096	0.091	0.107	0.014	829,414
Decile 9	0.132	0.125	0.147	0.020	828,926
Most Similar	0.393	0.393	0.395	0.047	829,422

Table 7: Risk Profile Regressions

The table reports the results of OLS regressions where measures of risk are regressed on measures of scope decomposed into components that are spatially near versus far from the focal firm. The first dependent variable is stock market risk used in Panels A and C, which is computed as the standard deviation of daily stock returns in year t. The second is cashflow volatility used in Panels B and D, which is computed as the standard deviation of a firm's quarterly operating income scaled by assets, computed over the 8 quarters of year t and $t+1$. We express both as percentages for ease of interpretation. All RHS variables are computed using data from year $t-1$. We report results for three tercile-based subsamples within each panel and as noted in the first column. The subsamples are constructed in each year by sorting firms based on the average product market distance of the FIC industry segments they are assigned to when constructing our FIC-scope variable (firms assigned to just one FIC segment have a distance of zero). Firms in the close-scope tercile subsample are operating across industries that are highly related, whereas firms in the far-scope tercile are operating across industries that are more distant in the product space. Our main variable of interest, FIC-scope, is based on scoring each firm's Item 1 business description based on how similar it is to the product text of specific fixed industries. The fixed industries are based on the TNIC FIC-300 industries (see Hoberg and Phillips 2016). All regressions include year fixed effects, and controls for firm size, and firm age. The regressions in Panels C and D additionally include firm fixed effects. t-statistics for both panels are clustered by firm and shown in parentheses.

Row	Dependent Variable	FIC-Scope	Log Assets	Log Age	ARSQ	# Obs
			Panel A: Dependent Variable is Stock Volatility (OLS with Year Fixed Effects)			
(1)	Close-Scope Tercile	0.018	–0.546	–0.519	0.36	34,781
		(2.970)	(–42.940)	(–16.930)		
(2)	Medium-Scope Tercile	0.014	–0.507	–0.351	0.39	27,413
		(4.220)	(–42.970)	(–13.340)		
(3)	Far-Scope Tercile	0.003	–0.550	–0.381	0.37	29,627
		(0.910)	(–42.280)	(–13.100)		
			Panel B: Dependent Variable is Cashflow Volatility (OLS with Year Fixed Effects)			
(4)	Close-Scope Tercile	0.039	–0.465	–0.277	0.17	33,781
		(4.820)	(–30.090)	(–8.440)		
(5)	Medium-Scope Tercile	0.025	–0.505	–0.233	0.19	26,798
		(5.650)	(–29.560)	(–6.910)		
(6)	Far-Scope Tercile	0.019	–0.484	–0.204	0.18	28,846
		(4.550)	(–28.820)	(–6.720)		
			Panel C: Dependent Variable is Stock Volatility (OLS with Firm and Year Fixed Effects)			
(7)	Close-Scope Tercile	0.024	–0.264	–0.306	0.66	34,781
		(3.040)	(–8.010)	(–3.500)		
(8)	Medium-Scope Tercile	0.008	–0.251	–0.467	0.67	27,413
		(1.660)	(–7.560)	(–5.410)		
(9)	Far-Scope Tercile	0.007	–0.230	–0.285	0.68	29,627
		(1.580)	(–6.450)	(–3.430)		
			Panel D: Dependent Variable is Cashflow Volatility (OLS with Firm and Year Fixed Effects)			
(10)	Close-Scope Tercile	–0.005	–0.322	–0.097	0.60	33,781
		(–0.610)	(–8.320)	(–1.080)		
(11)	Medium-Scope Tercile	0.012	–0.364	–0.169	0.63	26,798
		(2.190)	(–7.810)	(–1.850)		
(12)	Far-Scope Tercile	0.007	–0.400	–0.059	0.65	28,846
		(1.490)	(–8.540)	(–0.680)		

Table 8: High Product Breadth Validation Regressions

The table reports validation regressions in which the dependent variable is a direct text-based measure of companies indicating that their products are broad. We consider four query-based measures obtained using the metaHeuristica software platform, based on product and service breadth. "Product Breadth" is the number of 10-K paragraphs containing the phrases {product lines, product categories}. "Prod/Svc Breadth" is analogously defined based on the search phrases {product lines, product categories, service lines, service categories}. "Product Breadth Detail" runs the same query as "Product Breadth" but is more stringent and additionally requires that the paragraph include one word from the following list: {breadth, broad, broader, wide, multiple, numerous, diverse, categories, divisions}. "Prod/Svc Breadth Detail" is a parallel more stringent version of the baseline "Prod/Svc Breadth" query. All four variables are scaled by the number of paragraphs in the 10-K overall. All regressions include firm and year fixed effects, and controls for firm size, age, 10-K size, M/B, and the TNIC HHI. Results are robust to dropping any of the controls. All regressions include firm and year fixed effects, coefficients are multiplied by 100 for ease of viewing, and t-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	FIC-Scope	NAICS-Scope	# Segments	Log Assets	Log Age	Log 10K Size	M/B	TNIC HHI	# Obs
(1)	Product Breadth				1.650	0.400	–8.422	–0.209	–2.119	72,280
					(3.640)	(0.260)	(–7.300)	(–2.520)	(–1.760)	
(2)	Prod/Svc Breadth				1.774	0.642	–8.869	–0.209	–2.063	72,280
					(3.840)	(0.410)	(–7.470)	(–2.490)	(–1.680)	
(3)	Prod Breadth Detail				0.763	–1.124	–3.327	0.016	–1.558	72,280
					(3.820)	(–1.700)	(–7.270)	(0.500)	(–3.260)	
(4)	Prod/Svc Breadth Detail				0.791	–0.917	–3.459	0.017	–1.497	72,280
					(3.920)	(–1.370)	(–7.290)	(0.540)	(–3.070)	
(5)	Product Breadth			1.381	1.513	0.140	–8.501	–0.205	–2.124	72,280
				(2.800)	(3.320)	(0.090)	(–7.370)	(–2.470)	(–1.760)	
(6)	Prod/Svc Breadth			1.299	1.646	0.397	–8.943	–0.205	–2.068	72,280
				(2.570)	(3.550)	(0.260)	(–7.530)	(–2.440)	(–1.680)	
(7)	Prod Breadth Detail			0.430	0.720	–1.205	–3.352	0.017	–1.559	72,280
				(1.920)	(3.590)	(–1.820)	(–7.310)	(0.540)	(–3.260)	
(8)	Prod/Svc Breadth Detail			0.415	0.750	–0.996	–3.483	0.019	–1.498	72,280
				(1.820)	(3.700)	(–1.480)	(–7.330)	(0.580)	(–3.070)	
(9)	Product Breadth	0.640		0.959	1.075	0.569	–9.263	–0.224	–0.410	72,280
		(8.430)		(1.960)	(2.390)	(0.380)	(–7.980)	(–2.740)	(–0.340)	
(10)	Prod/Svc Breadth	0.663		0.861	1.192	0.841	–9.732	–0.225	–0.293	72,280
		(8.520)		(1.720)	(2.600)	(0.550)	(–8.150)	(–2.720)	(–0.240)	
(11)	Prod Breadth Detail	0.216		0.288	0.572	–1.060	–3.609	0.011	–0.981	72,280
		(6.360)		(1.300)	(2.910)	(–1.610)	(–7.810)	(0.340)	(–2.010)	
(12)	Prod/Svc Breadth Detail	0.228		0.265	0.594	–0.843	–3.754	0.012	–0.888	72,280
		(6.610)		(1.170)	(2.990)	(–1.260)	(–7.840)	(0.380)	(–1.780)	
(13)	Product Breadth		0.309	1.063	1.253	0.391	–9.075	–0.210	–0.700	72,280
			(6.020)	(2.150)	(2.770)	(0.260)	(–7.780)	(–2.530)	(–0.580)	
(14)	Prod/Svc Breadth		0.327	0.962	1.371	0.662	–9.550	–0.210	–0.562	72,280
			(6.240)	(1.900)	(2.970)	(0.430)	(–7.940)	(–2.500)	(–0.450)	
(15)	Prod Breadth Detail		0.132	0.294	0.609	–1.098	–3.596	0.015	–0.952	72,280
			(5.290)	(1.310)	(3.090)	(–1.660)	(–7.760)	(0.480)	(–1.960)	
(16)	Prod/Svc Breadth Detail		0.137	0.275	0.635	–0.884	–3.737	0.017	–0.867	72,280
			(5.360)	(1.200)	(3.190)	(–1.320)	(–7.770)	(0.520)	(–1.750)	

Table 9: First-Stage Regressions

The table reports the results of first-stage regressions where measures of scope (FIC-scope and NAICS-scope) are regressed on our two instruments in addition to all controls and fixed effects. Our first instrument is "Sectoral Redeployment Potential" which is a product market spatially localized version of the asset redeployability measure in Kim and Kung (2017). In particular, we use the BEA capital flows table and represent the assets of each 4-digit NAICS industry as a vector. For each focal's local product market, we compute the average redeployability between the focal firm's nearest peer NAICS industries and the focal firm's distant peer NAICS industries. Intuitively, when the assets of near peers are easily redeployed to the market of more distant peers, the focal firm faces a low cost to expanding its market outward in space (lower cost of increasing scope). The second instrument "Sectoral Opportunity Set Potential" is simply the concentraiton ratio of 4-digit NAICS industries that the moderately distant peers in the focal firm's product market reside in. When this concentration ratio is high, it indicates that the focal firm's peers all tend to operate in the same market, which in turn implies there are few opportunities for scope expansion by the focal firm (as there are fewer related product markets that are spatially close). For success in the first stage, we predict that the former measure will be positively related to our scope variables, and the second will be negatively related. All regressions include firm and year fixed effects, and controls for firm size, age, 10-K size, M/B, and the TNIC HHI. All regressions include firm and year fixed effects, and t-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	Sectoral Redeployment Potential	Sectoral Opportunity Set Potential	Log Assets	Log Age	# Obs
(1)	FIC-Scope	1.251	6.941	0.882	–0.830	99,506
		(4.330)	(11.910)	(19.290)	(–6.030)	
(2)	NAICS-Scope	1.074	12.772	1.279	–0.976	99,506
		(2.380)	(14.680)	(17.730)	(–5.060)	
(3)	# Segments	0.019	0.293	0.107	0.161	99,506
		(0.300)	(2.900)	(12.340)	(6.260)	

Table 10: Investment Regressions

The table reports the second stage results of 2-stage instrumental variable regressions where the dependent variable is a firm investment policy such as acquisitions, divestitures (target of an acquisition), R&D/assets or CAPX/assets. Our instrumented variable of interest is a measure of scope (FIC-Scope or NAICS-Scope) as indicated in the panel headers. The first-stage regressions are displayed in Table 9 and include two instruments for scope (explained in detail in Table 9). The first is a measure of the extent to which the broader product market surrounding a focal firm is characterized by a high degree of outward-directed asset redeployability indicating a low cost to scope expansion by existing firms. The second is a measure of the size of the focal firm's outward-expansion opportunity set. We also include controls for size, age, and in Panel C, we additionally include controls for market to book and the TNIC HHI. All regressions include firm and year fixed effects, and t-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	Scope Variable	Log Assets	Log Age	Mkt/Book	TNIC HHI	# Obs
			Panel A: FIC-Scope is Scope Variable				
(1)	Acquirer Dummy	0.026	–0.006	–0.029			98,196
		(4.660)	(–0.920)	(–2.710)			
(2)	Target Dummy	–0.009	0.038	0.039			98,196
		(–2.270)	(8.570)	(5.390)			
(3)	R&D/Assets	0.003	–0.016	0.009			98,196
		(3.900)	(–12.690)	(4.370)			
(4)	CAPX/Assets	0.000	–0.002	–0.014			98,196
		(0.450)	(–2.630)	(–9.820)			
			Panel B: NAICS-Scope is Scope Variable				
(5)	Acquirer Dummy	0.016	–0.003	–0.035			98,196
		(4.860)	(–0.580)	(–3.540)			
(6)	Target Dummy	–0.005	0.036	0.042			98,196
		(–2.060)	(9.060)	(6.240)			
(7)	R&D/Assets	0.001	–0.015	0.008			98,196
		(3.570)	(–12.860)	(3.980)			
(8)	CAPX/Assets	0.000	–0.002	–0.014			98,196
		(0.570)	(–2.870)	(–10.190)			
			Panel C: FIC-Scope is Scope Variable (extra controls added)				
(9)	Acquirer Dummy	0.036	–0.007	–0.017	0.009	0.107	97,624
		(4.360)	(–0.840)	(–1.500)	(9.180)	(4.560)	
(10)	Target Dummy	–0.012	0.039	0.036	–0.002	–0.028	97,624
		(–2.130)	(7.120)	(4.630)	(–3.400)	(–1.660)	
(11)	R&D/Assets	0.004	–0.017	0.009	–0.001	0.002	97,624
		(3.190)	(–11.910)	(4.190)	(–2.100)	(0.610)	
(12)	CAPX/Assets	0.000	–0.001	–0.013	0.002	–0.003	97,624
		(–0.480)	(–0.790)	(–8.720)	(9.090)	(–1.240)	

Table 11: Investment Regressions (by Fama-French-5 Major Sectors)

The table reports the second stage results of 2-stage instrumental variable regressions where the dependent variable is a firm investment policy such as acquisitions, divestitures (target of an acquisition), R&D/assets or CAPX/assets. These regressions use the same specification as in Table 10 except we now run them using 5 industry subsamples based on the Fama-French-5 industry groupings (see Panel headers). Our instrumented variable of interest is a measure of scope (FIC-Scope). The first-stage regressions are displayed in Table 9 and include two instruments for scope (explained in detail in Table 9). The first is a measure of the extent to which the broader product market surrounding a focal firm is characterized by a high degree of outward-directed asset redeployability indicating a low cost to scope expansion by existing firms. The second is a measure of the size of the focal firm's outward-expansion opportunity set. All regressions include firm and year fixed effects, and *t*-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	Scope Variable	Log Assets	Log Age	Mkt/Book	TNIC HHI	# Obs
			Panel A: FIC-Scope (Tech-Industry Subsample)				
(1)	Acquirer Dummy	0.000	0.045	–0.065	0.00	26,252	
		(–0.020)	(3.110)	(–2.220)			
(2)	Target Dummy	0.003	0.021	0.073	0.00	26,252	
		(0.180)	(2.120)	(3.660)			
(3)	R&D/Assets	0.009	–0.027	0.027	0.00	26,252	
		(2.250)	(–8.360)	(4.120)			
(4)	CAPX/Assets	0.000	0.000	–0.008	0.00	26,252	
		(–0.090)	(–0.330)	(–2.510)			
			Panel B: FIC-Scope (Manufacturing-Industry Subsample)				
(5)	Acquirer Dummy	0.034	–0.059	–0.042	0.00	20,519	
		(3.310)	(–3.490)	(–1.720)			
(6)	Target Dummy	–0.008	0.066	0.038	0.00	20,519	
		(–1.090)	(5.430)	(2.230)			
(7)	R&D/Assets	0.000	–0.002	0.005	0.00	20,519	
		(–0.510)	(–2.030)	(2.420)			
(8)	CAPX/Assets	0.000	–0.002	–0.012	0.00	20,519	
		(0.050)	(–0.970)	(–3.420)			
			Panel C: FIC-Scope (Consumer-Industry Subsample)				
(9)	Acquirer Dummy	0.032	–0.020	–0.028	0.00	21,432	
		(2.320)	(–1.260)	(–1.290)			
(10)	Target Dummy	–0.015	0.043	0.022	0.00	21,432	
		(–1.370)	(3.700)	(1.560)			
(11)	R&D/Assets	0.003	–0.004	0.001	0.00	21,432	
		(2.420)	(–2.920)	(0.370)			
(12)	CAPX/Assets	0.002	–0.007	–0.013	0.00	21,432	
		(1.510)	(–4.100)	(–4.500)			
			Panel D: FIC-Scope (Health-Industry Subsample)				
(13)	Acquirer Dummy	0.015	0.012	–0.030	0.00	12,528	
		(1.320)	(1.060)	(–0.990)			
(14)	Target Dummy	–0.032	0.043	–0.026	0.00	12,528	
		(–3.020)	(3.750)	(–1.100)			
(15)	R&D/Assets	0.013	–0.045	0.016	0.00	12,528	
		(2.110)	(–6.710)	(1.070)			
(16)	CAPX/Assets	–0.001	0.001	–0.010	0.00	12,528	
		(–0.460)	(0.580)	(–2.570)			
			Panel E: FIC-Scope (Misc-Industry Subsample)				
(17)	Acquirer Dummy	0.041	–0.052	–0.046	0.00	15,583	
		(2.750)	(–2.960)	(–1.540)			
(18)	Target Dummy	–0.001	0.027	0.068	0.00	15,583	
		(–0.160)	(2.430)	(4.240)			
(19)	R&D/Assets	0.001	–0.003	0.003	0.00	15,583	
		(1.920)	(–2.130)	(1.560)			
(20)	CAPX/Assets	0.002	–0.005	–0.023	0.00	15,583	
		(1.310)	(–2.200)	(–5.250)			

Table 12: Outcomes Regressions

The table reports the second stage results of 2-stage instrumental variable regressions where the dependent variable is a firm outcome variable such as the market to book ratio (market value of firm divided by total assets), sales growth, asset growth or profitability. Our instrumented variable of interest is a measure of scope (FIC-Scope or NAICS-Scope) as indicated in the panel headers. The first-stage regressions are displayed in Table 9 and include two instruments for scope (explained in detail in Table 9). The first is a measure of the extent to which the broader product market surrounding a focal firm is characterized by a high degree of outward-directed asset redeployability indicating a low cost to scope expansion by existing firms. The second is a measure of the size of the focal firm's outward-expansion opportunity set. We also include controls for size, age, and in Panel C, we additionally include controls for market to book and the TNIC HHI. All regressions include firm and year fixed effects, and t-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	Scope Variable	Log Assets	Log Age	Mkt/Book	TNIC HHI	# Obs
			Panel A: FIC-Scope is Scope Variable				
(1)	Valuation (M/B)	0.080	–0.532	–0.344			97,625
		(4.310)	(–17.410)	(–7.360)			
(2)	Sales Growth	0.031	–0.098	–0.182			97,825
		(5.790)	(–14.990)	(–17.860)			
(3)	Asset Growth	0.047	–0.206	–0.038			98,193
		(8.830)	(–30.220)	(–3.550)			
(4)	OI/Assets	–0.001	0.012	0.000			97,995
		(–0.540)	(3.510)	(0.010)			
			Panel B: NAICS-Scope is Scope Variable				
(5)	Valuation (M/B)	0.040	–0.512	–0.373			97,625
		(3.730)	(–17.880)	(–8.230)			
(6)	Sales Growth	0.018	–0.094	–0.191			97,825
		(5.960)	(–15.990)	(–20.450)			
(7)	Asset Growth	0.028	–0.200	–0.050			98,193
		(9.500)	(–33.210)	(–5.180)			
(8)	OI/Assets	–0.001	0.011	0.000			97,995
		(–0.490)	(3.650)	(0.100)			
			Panel C: FIC-Scope is Scope Variable (extra controls added)				
(9)	Valuation (M/B)	0.095	–0.448	–0.156	0.222	0.246	97,391
		(3.770)	(–14.290)	(–3.850)	(10.340)	(2.690)	
(10)	Sales Growth	0.042	–0.091	–0.150	0.032	0.129	97,267
		(5.460)	(–11.480)	(–13.030)	(12.100)	(5.740)	
(11)	Asset Growth	0.056	–0.192	0.002	0.044	0.137	97,624
		(7.140)	(–23.500)	(0.130)	(16.340)	(6.100)	
(12)	OI/Assets	–0.002	0.014	0.004	0.005	0.000	97,430
		(–0.470)	(3.800)	(0.690)	(4.780)	(0.030)	

Table 13: Venture Capital Funding Similarity and Fluidity Regressions

The table reports the second stage results of 2-stage instrumental variable regressions where the dependent variable is a measure of early-stage startup financing or innovative activity in the given firm's product market. Both dependent variables are developed in Hoberg, Phillips, and Prabhala (2014). VC funding similarity is the cosine similarity of the given focal firm's 10-K product description to the average vocabulary used by all startups in the given year (where the startup vocabulary is obtained from Venture Expert business descriptions of all startups receiving their first round of financing in the given year). Product market fluidity is the average market-wide change (fluidity) in the use of the given firm's 10-K product description vocabulary by all other firms. A high value indicates a large amount of product innovation by competing firms in the focal firm's product markets. Our instrumented variable of interest is a measure of scope (FIC-Scope or NAICS-Scope) as indicated in the panel headers. The first-stage regressions are displayed in Table 9 and include two instruments for scope (explained in detail in Table 9). The first is a measure of the extent to which the broader product market surrounding a focal firm is characterized by a high degree of outward-directed asset redeployability indicating a low cost to scope expansion by existing firms. The second is a measure of the size of the focal firm's outward-expansion opportunity set. We also include controls for size, age, and in Panel C, we additionally include controls for market to book and the TNIC HHI. All regressions include firm and year fixed effects, and t-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	Scope Variable	Log Assets	Log Age	Mkt/Book	TNIC HHI	# Obs
			Panel A: FIC-Scope is Scope Variable				
(1)	VC Funding Similarity	1.926	–1.170	0.824			98,186
		(15.040)	(–8.190)	(3.020)			
(2)	Product Market Fluidity	1.251	–0.773	0.262			97,090
		(14.640)	(–8.180)	(1.470)			
			Panel B: NAICS-Scope is Scope Variable				
(3)	VC Funding Similarity	1.093	–0.868	0.265			98,186
		(17.460)	(–7.920)	(1.240)			
(4)	Product Market Fluidity	0.750	–0.634	–0.077			97,090
		(20.240)	(–9.220)	(–0.580)			
			Panel C: FIC-Scope is Scope Variable (extra controls added)				
(5)	VC Funding Similarity	2.575	–1.588	1.115	–0.034	5.515	97,614
		(11.030)	(–7.130)	(3.010)	(–1.410)	(8.190)	
(6)	Product Market Fluidity	1.483	–0.900	0.329	–0.015	2.716	96,523
		(10.650)	(–6.770)	(1.520)	(–1.140)	(6.920)	

Table 14: Financing Regressions

The table reports the second stage results of 2-stage instrumental variable regressions where the dependent variable is a firm financing policy such as equity issuance, debt issuance, dividends, or equity repurchases. Our instrumented variable of interest is a measure of scope (FIC-Scope or NAICS-Scope) as indicated in the panel headers. The first-stage regressions are displayed in Table 9 and include two instruments for scope (explained in detail in Table 9). The first is a measure of the extent to which the broader product market surrounding a focal firm is characterized by a high degree of outward-directed asset redeployability indicating a low cost to scope expansion by existing firms. The second is a measure of the size of the focal firm's outward-expansion opportunity set. We also include controls for size, age, and in Panel C, we additionally include controls for market to book and the TNIC HHI. All regressions include firm and year fixed effects, and t-statistics are clustered by firm and shown in parentheses.

Row	Dependent Variable	Scope Variable	Log Assets	Log Age	Mkt/Book	TNIC HHI	# Obs
			Panel A: FIC-Scope is Scope Variable				
(1)	Equity Issuance	0.009	–0.050	–0.009			98,196
		(7.220)	(–25.060)	(–2.950)			
(2)	Debt Issuance	0.002	–0.011	0.010			98,196
		(0.760)	(–3.960)	(1.990)			
(3)	Dividends/Assets	–0.001	0.001	0.002			98,097
		(–2.870)	(1.900)	(2.440)			
(4)	Repurchases/Assets	–0.001	0.005	0.005			90,680
		(–1.460)	(7.430)	(5.070)			
			Panel B: NAICS-Scope is Scope Variable				
(5)	Equity Issuance	0.005	–0.049	–0.012			98,196
		(7.530)	(–26.340)	(–4.010)			
(6)	Debt Issuance	0.001	–0.011	0.010			98,196
		(0.970)	(–4.390)	(2.050)			
(7)	Dividends/Assets	–0.001	0.001	0.002			98,097
		(–2.710)	(1.520)	(3.300)			
(8)	Repurchases/Assets	0.000	0.004	0.006			90,680
		(–1.290)	(7.860)	(5.590)			
			Panel C: FIC-Scope is Scope Variable (extra controls added)				
(9)	Equity Issuance	0.010	–0.047	0.000	0.010	0.021	97,624
		(5.580)	(–21.180)	(–0.130)	(10.190)	(3.890)	
(10)	Debt Issuance	0.001	–0.010	0.010	0.001	–0.005	97,624
		(0.160)	(–2.930)	(1.840)	(1.990)	(–0.510)	
(11)	Dividends/Assets	–0.002	0.001	0.002	0.000	–0.004	97,528
		(–2.790)	(2.380)	(2.330)	(4.760)	(–1.990)	
(12)	Repurchases/Assets	–0.001	0.005	0.006	0.001	–0.001	90,146
		(–1.350)	(6.960)	(5.240)	(5.780)	(–0.660)	

Table 15: Near versus Far Scope Tercile Subsamples

The table reports the second stage results of 2-stage instrumental variable regressions for various dependent variables as noted in the first column. These regressions use the same IV specification as in earlier tables such as Table 10, except we now run these regressions using 3 scope-distance tercile subsamples as indicated in the column headers for columns two to four. The subsamples are constructed in each year by sorting firms based on the average product market distance of the FIC industry segments they are assigned to when constructing our FIC-scope variable (firms assigned to just one FIC segment have a distance of zero). Firms in the close-scope tercile subsample are operating across industries that are highly related, whereas firms in the far-scope tercile are operating across industries that are more distant in the product space. Our instrumented variable of interest is a measure of scope (FIC-Scope), and we only report this coefficient for each regression for parsimony. Hence each coefficient below is this coefficient for a separate regression based on the subsample indicated in the column header and the dependent variable indicated in the first column. All regressions include firm and year fixed effects, controls for size and age (not reported) and t-statistics for the FIC-scope coefficient are clustered by firm and are shown in parentheses.

Row	Dependent Variable	Near Scope Tercile Subsample	Middle Scope Tercile Subsample	Far Scope Tercile Subsample
(1)	Acquirer Dummy	0.050	0.041	0.039
		(2.060)	(2.570)	(3.810)
(2)	Target Dummy	-0.028	-0.024	-0.011
		(-1.540)	(-1.750)	(-1.280)
(3)	R&D/Assets	0.011	0.002	0.001
		(3.030)	(1.100)	(0.640)
(4)	CAPX/Assets	0.002	0.002	-0.001
		(0.970)	(1.060)	(-0.930)
(5)	Valuation (M/B)	0.249	0.114	-0.008
		(2.980)	(2.380)	(-0.290)
(6)	Sales Growth	0.069	0.062	0.036
		(2.780)	(4.140)	(3.680)
(7)	Asset Growth	0.131	0.070	0.051
		(5.340)	(4.690)	(5.220)
(8)	OI/Assets	-0.002	0.003	0.002
		(-0.190)	(0.490)	(0.640)
(9)	Equity Issuance	0.028	0.013	0.006
		(4.730)	(4.200)	(2.840)
(10)	Debt Issuance	0.003	0.013	0.003
		(0.340)	(1.630)	(0.770)
(11)	Dividends/Assets	-0.005	-0.001	-0.001
		(-2.210)	(-0.520)	(-1.830)
(12)	Repurchases/Assets	-0.002	-0.002	-0.001
		(-1.020)	(-0.870)	(-1.290)
(13)	VC Funding Score	3.163	1.743	1.179
		(6.950)	(7.910)	(8.280)
(14)	Prod Mkt Fluidity	5.515	2.479	1.830
		(8.280)	(8.190)	(8.200)

Table 16: Firm Size Tercile Subsamples

The table reports the second stage results of 2-stage instrumental variable regressions for various dependent variables as noted in the first column. These regressions use the same IV specification as in earlier tables such as Table 10, except we now run these regressions using 3 firm size tercile subsamples as indicated in the column headers for columns two to four. The subsamples are constructed in each year by sorting firms based on past-year assets and hence we have large, mid-size and small firm subsamples. Our instrumented variable of interest is a measure of scope (FIC-Scope), and we only report this coefficient for each regression for parsimony. Hence each coefficient below is this coefficient for a separate regression based on the subsample indicated in the column header and the dependent variable indicated in the first column. All regressions include firm and year fixed effects, controls for size and age (not reported) and t-statistics for the FIC-scope coefficient are clustered by firm and are shown in parentheses.

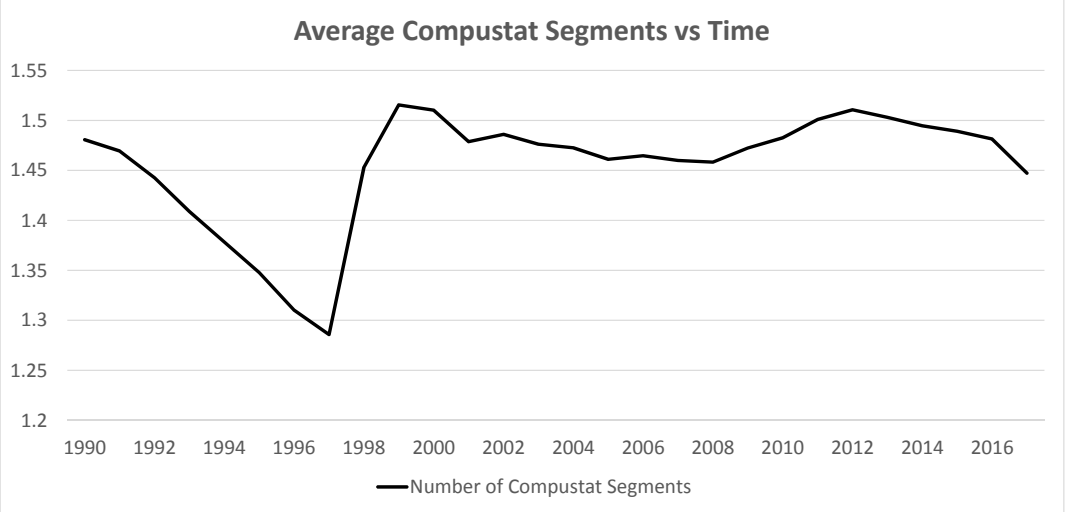
Row	Dependent Variable	Large-Firm Tercile Subsample	Mid-Size Tercile Subsample	Small-Firm Tercile Subsample
(1)	Acquirer Dummy	0.015	0.044	0.042
		(1.950)	(3.460)	(3.420)
(2)	Target Dummy	-0.008	-0.021	-0.007
		(-1.360)	(-2.240)	(-0.940)
(3)	R&D/Assets	0.000	0.003	0.005
		(-0.150)	(2.840)	(1.920)
(4)	CAPX/Assets	0.000	0.002	0.000
		(1.010)	(1.690)	(-0.260)
(5)	Valuation (M/B)	-0.022	0.108	0.202
		(-1.560)	(3.640)	(3.280)
(6)	Sales Growth	0.007	0.034	0.088
		(2.490)	(3.280)	(4.340)
(7)	Asset Growth	0.012	0.063	0.104
		(3.760)	(5.110)	(5.500)
(8)	OI/Assets	-0.001	0.004	-0.003
		(-0.670)	(1.160)	(-0.400)
(9)	Equity Issuance	0.000	0.007	0.022
		(1.200)	(3.900)	(4.530)
(10)	Debt Issuance	0.001	0.006	0.005
		(0.260)	(0.930)	(0.800)
(11)	Dividends/Assets	-0.001	0.000	-0.001
		(-3.610)	(0.090)	(-1.210)
(12)	Repurchases/Assets	-0.001	-0.001	-0.001
		(-0.830)	(-0.960)	(-0.880)
(13)	VC Funding Score	0.988	1.403	1.730
		(9.800)	(7.050)	(7.920)
(14)	Prod Mkt Fluidity	1.441	2.017	2.777
		(9.600)	(7.380)	(7.980)

Table 17: Competition Complaints vs HHIs and Granularity

The table reports annual cross sectional OLS descriptive regressions where the dependent variable is the intensity of the firm's competition complaints in its 10-K, which is computed as the number of 10-K paragraphs that mention competition divided by the total number of paragraphs in the 10-K. The two RHS variables are measures of concentration (with the sign reversed so they can be interpreted as positive measures of competition) at different granularities. In particular include the Compustat SIC-3 HHI and the Compustat SIC-2 HHI. Each is computed as the sales-based concentration among firms in the given SIC code defined based on three digit and two digit SIC codes, respectively. Finally, we report the fraction of 2-digit granularity as the (1 - SIC-2 HHI) coefficient divided by the sum of the coefficients for both HHIs (truncated at zero in the first three years). This indicates the fraction of total HHI weights that are attached to the more coarse granularity. A high fraction indicates that, in the given year, the economy is such that competition takes place mostly at the 2-digit granularity rather than at the 3-digit granularity. A low value for this fraction indicates the converse.

Year	One minus SIC-2 HHI	One minus SIC-3 HHI	Adj R^2	Fraction 2-digit Granularity	# Obs.
1997	-0.001	0.011	0.014	0.000	5,521
	(-0.46)	(8.15)			
1998	-0.003	0.011	0.012	0.000	5,297
	(-1.34)	(7.63)			
1999	-0.003	0.012	0.017	0.000	5,076
	(-1.24)	(8.66)			
2000	0.006	0.010	0.022	0.369	4,827
	(2.46)	(7.90)			
2001	0.007	0.010	0.019	0.401	4,359
	(2.37)	(6.74)			
2002	0.009	0.005	0.010	0.642	3,954
	(3.17)	(3.30)			
2003	0.009	0.006	0.007	0.600	3,631
	(2.34)	(2.90)			
2004	0.011	0.008	0.028	0.577	3,540
	(4.44)	(6.02)			
2005	0.011	0.007	0.023	0.604	3,465
	(4.25)	(5.11)			
2006	0.007	0.006	0.019	0.565	3,378
	(3.34)	(4.91)			
2007	0.008	0.004	0.016	0.661	3,305
	(3.85)	(3.80)			
2008	0.009	0.004	0.023	0.674	3,120
	(4.54)	(4.29)			
2009	0.008	0.005	0.024	0.636	3,006
	(4.21)	(4.78)			
2010	0.010	0.004	0.024	0.744	2,899
	(5.20)	(3.72)			
2011	0.013	0.003	0.029	0.825	2,755
	(6.47)	(2.91)			
2012	0.005	0.003	0.009	0.655	2,665
	(2.51)	(2.92)			
2013	0.004	0.004	0.014	0.516	2,654
	(2.10)	(4.23)			
2014	0.004	0.003	0.011	0.538	2,695
	(1.98)	(3.43)			
2015	0.003	0.004	0.016	0.445	2,643
	(1.82)	(4.57)			
2016	0.003	0.004	0.015	0.484	2,546
	(1.93)	(4.21)			
2017	0.005	0.003	0.017	0.619	2,453
	(2.96)	(3.67)			

Figure 1: Measures of scope versus time. The upper figure plots the average number of Compustat segments per firm over time. The lower figure plots the average values of FIC-scope and NAICS-scope over our sample period. TNIC-scope and NAICS-scope are based on scoring each firm's Item 1 business description based on how similar it is to the product text of specific fixed industries. For FIC-scope, fixed industries are based on the TNIC FIC-300 industries (see Hoberg and Phillips 2016), and for NAICS-scope, it is based on 4-digit NAICS industries.



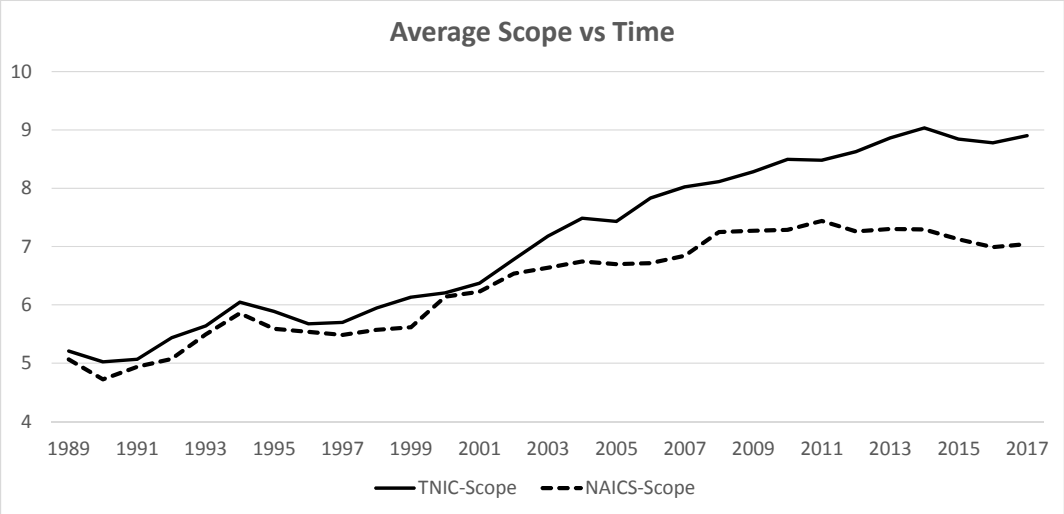
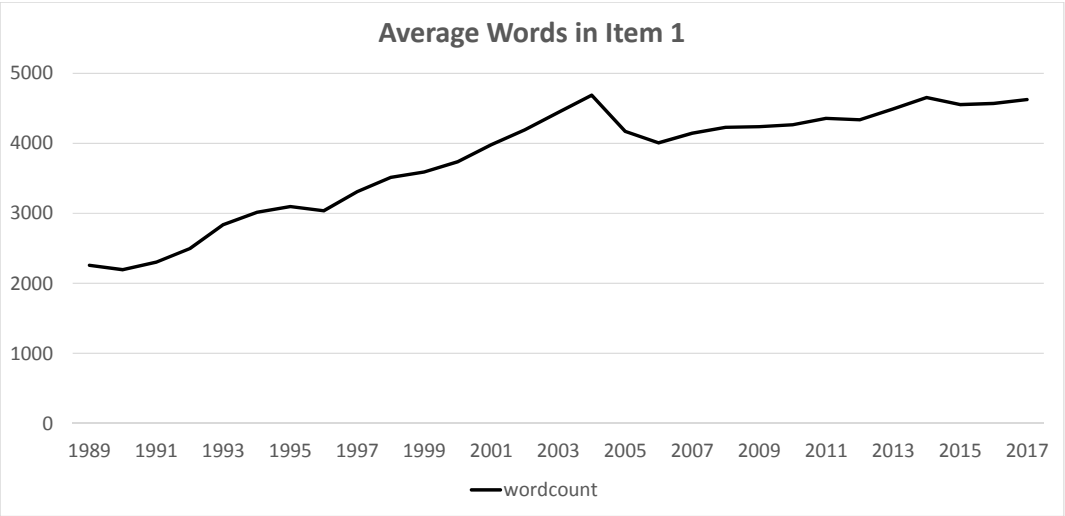


Figure 2: The upper figure reports the average number of words in the firm's 10-K Item 1 business description divided by the number of industries (FIC-based or NAICS-based scope) the firm likely operates in. The goal is to measure the average degree of product variety within industries over time. The lower figure displays the average size of the 10-K Item 1 over time.



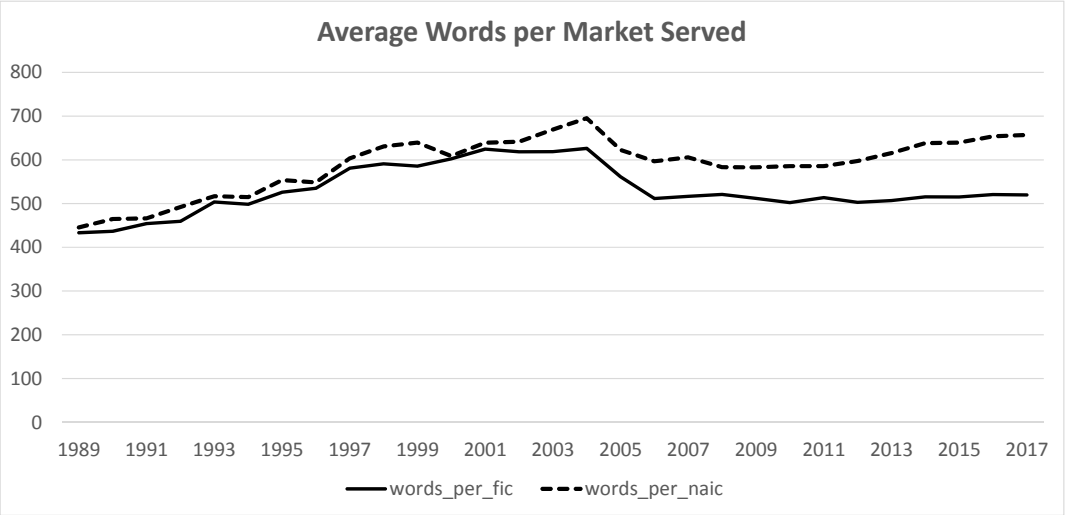


Figure 3: Firm size versus time. The figure displays firm size (measured as Compustat assets, both nominal and inflation adjusted) over time.

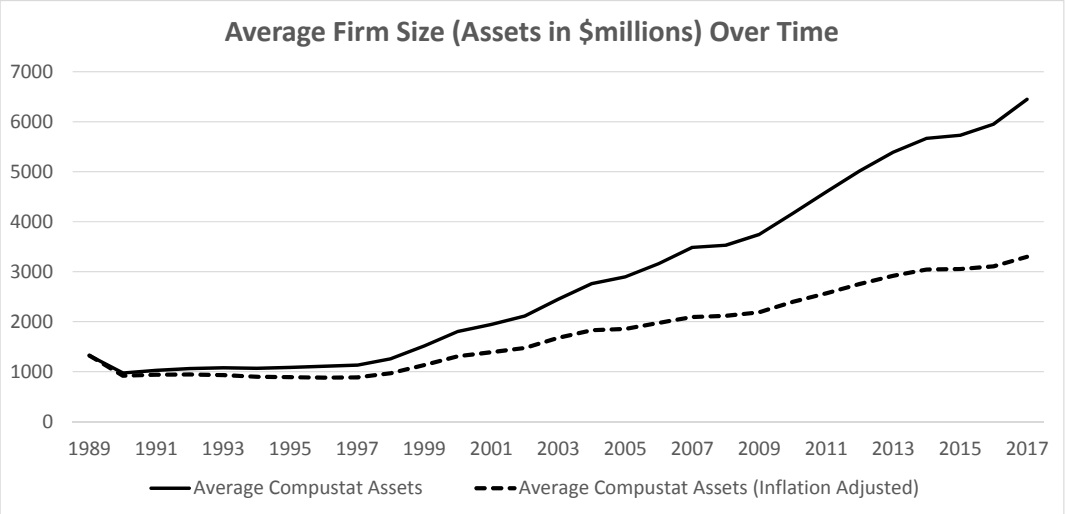
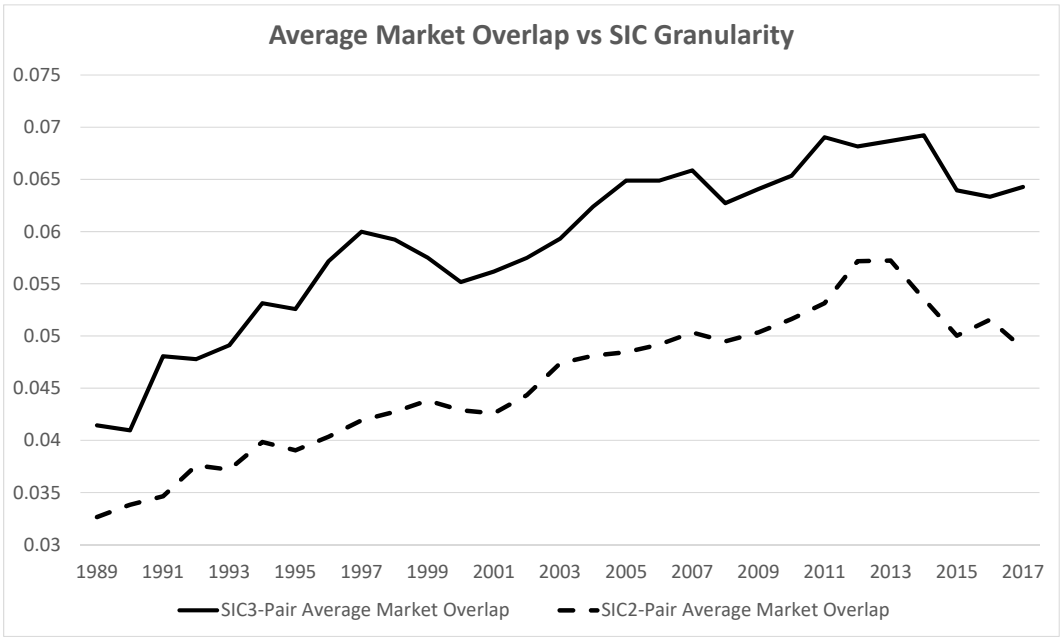


Figure 4: The upper figure reports the average market overlap of pairs of firms that are in the same SIC3 or SIC2 industries. Market overlap at the industry pair level is the average of firm-pair market overlap for all permutations of firms where one firm is in each of the industries being compared at the industry-pair level. Firm-pair overlap is the intersection of industries the two firms in the pair likely operate in divided by the union of industries they operate in (based on the industries assigned to each firm as indicated by the construction of the FIC-scope variable). This market overlap score ranges from zero to unity and is one if the firms operate in exactly the same industry and zero if they have no overlaps. The lower figure reports the two and three digit SIC HHI over time. The scope-adjusted HHI is the average the SIC2 and SIC3 HHI, where the weights start at zero in 1996 and grow linearly until they reach 50% by the end of our sample in 2017.



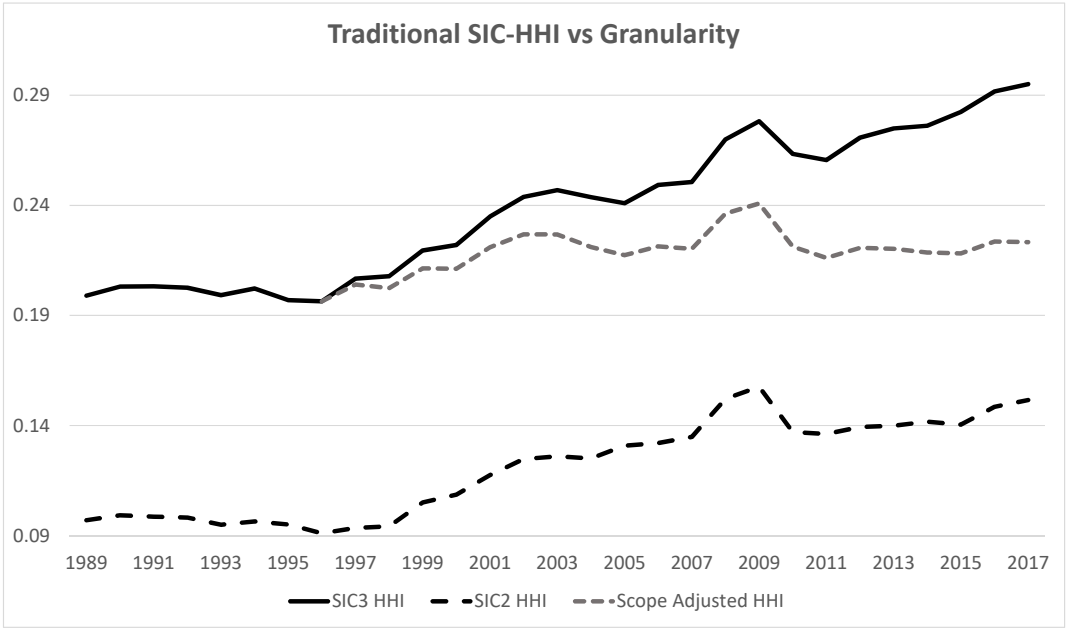


Figure 5: The FIC-Scope Implied HHI computes the HHI after allowing firms to have a presence in multiple industries, as is identified during the derivation of FIC-scope itself. Market shares are based on sales. Each firm's sales are allocated across the multiple sectors each firm is assigned to using similarity weights (similarity weights are defined as $Q_{i,j,t,FIC}$ in equation (1)). HHIs are then computed at the FIC industry level using these allocated sales where firms operate in multiple sectors. We then aggregate these HHIs back to the firm level by computing weighted averages over the sectors each firm operates in (again using weights $Q_{i,j,t,FIC}$). Note that our results are similar if we use equal weights instead. We then aggregate HHIs to the economy-wide annual level by computing a sales weighted average of the firm HHIs or an equal weighted average of the firm HHIs. The upper figure reports the sales-weighted average HHI over time and the lower figure reports the equal weighted average HHI over time.

