Peer Effects in Corporate Diversification

Abstract

A firm follows its industry peer rivals when undertaking corporate diversification. We show that there is an *active* dimension of peers' interactions to explain the cluster of corporate diversification, which complements the *passive* perspective in the prior literature. We carry out extensive tests to address endogeneity concerns, including a quasi-natural experiment based on the outcomes of mergers and acquisitions, time-varying industry and regional fixed effects, and an instrumental variable estimation based on the nontransitive characteristic of textual-network industry classification. Peer effects in corporate diversification are stronger in more competitive markets. We show that firms follow their rivals to diversify to maintain a competitive balance in internal financing.

Our paper aligns with the value-maximizing literature by incorporating peer effects into firms' diversification decision-making process.

JEL classification: D22; L22; L25

Keywords: Corporate diversification; Peer effects; Product market competition; Capital reallocation.

1. Introduction

How is the corporate diversification policy of a firm related to the actions or characteristics of its peers? The answer to this question **addresses** how resources are allocated since most resource allocation in the economy takes place within firms rather than markets (Matvos and Seru, 2014). Prior research documents that firms tend to diversify at similar times. However, most studies attribute the large commonality of corporate diversification policy (within industries) to exogenous industry shocks (Lang and Stulz, 1994; Campa and Kedia, 2002), and the role of peer firm behavior in affecting corporate diversification policy is often ignored.[1] Our paper fills this gap by exploring whether diversification made by industry peers affects a firm's diversification decisions.

Examining whether peer firm behavior matters for corporate diversification policy is crucial to uncover the origins of the extensive commonality observed within industries. While such commonality may arise either *passively*, as firms within the same peer group are exposed to similar fundamental shocks, or *actively*, implying complementarity where firms' diversification choices are influenced by their peers (Bustamante and Frésard, 2021). In contrast to the exposure to common shocks, the presence of an active corporate diversification policy amplifies the effects of firm specific or economy-wide shocks, thus significantly reshaping the allocation of capital both across and within industries.

Identifying peer effects in corporate diversification is challenging. The identification strategy requires overcoming the reflection problem, a specific form of endogeneity arising from the attempt to distinguish the peer action effect from the peer characteristic effect (Manski, 1993).[2] In our context, a firm's decision to diversify is caused by either the diversification

[1] For example, Santalo and Becerra (2008) shows that diversified firms enjoy a premium in those industries in which corporate diversification policy is preferred. Campa and Kedia (2002) finds that firms tend to diversify in industries with a large number of diversified firms. Although these studies document the large commonality of corporate diversification policy within industries, they explain this phenomenon with exogenous industry shocks such as changes in industry regulation or the introduction of new technology, and the interdependencies in corporate diversification policy are largely ignored.

[2] Manski (1993) argues that a standard peer effects model fails to differentiate between these two effects because the peer actions regressor is linearly dependent on other regressors, resulting in fewer equations than unknowns.

of its competitors (peer actions) or the specific characteristics shared among its peers (peer characteristics). The reflection problem becomes more pronounced when group members share identical peers, resulting in a constant peer actions regressor within the group, and therefore, fewer equations to isolate its effect (De Giorgi, Pellizzari, and Redaelli, 2010). To address the reflection issue, we define the peer groups based on Text-based Network Industry Classifications (TNIC), a *firm-specific* approach that allows the majority of firms to have *distinct*, yet partially overlapping peers (Hoberg and Phillips, 2016). Using the sample of U.S. firms from 1988 to 2019, we find that firms are more likely to diversify if their peers do so. In economic terms, a one-standard-deviation increase in the proportion of diversified peers leads to a 6% increase in the probability of firms engaging in diversification.

When firms from the same peer group face similar institutional environments or have similar characteristics correlated with their decision to diversify, an endogenous selection problem arises.[3] For example, firms from the same peer group may share similar organizational capabilities **that motivate them to diversify at the same time.** To mitigate the selection issue, we not only include a group of variables that previous research has found to be related to firms' propensity to diversify, but also explicitly control for firms' organizational capabilities.[4] In particular, we control for the organizational capabilities by including firms' asset redeployability (Kim and Kung, 2016), intangible organization capital (Peters and Taylor, 2017), and technical know-how.

We also employ a quasi-natural experiment to mitigate the selection issue. This approach uses the different status (complete or incomplete) and outcome (diversified or undiversified) of mergers and acquisitions. The setting has two desirable features. First, the difference between diversified and undiversified deals distinguishes between "peer diversification effect" and overall **firm expansion**. Second, whether a deal **is** complete or incomplete is largely

[3]The inability to accurately control these similarities of institutional environments and firm characteristics leave them into regression residual, and therefore bias our results.

[4]We include the firm fixed effects to control for any time-invariant firm-specific factors that affect corporate diversification. For example, firms from the same peer group may diversify together due to similar corporate culture.

influenced by peer firms' deal-specific considerations. Therefore, the outcome of the deal is exogenous to the focal firm. We find that the focal firm responds to peers' complete and diversified deals rather than incomplete and undiversified ones.

A selection issue may also arise if unobservable common shocks hit the group as a whole. For example, firms may diversify together in response to either a macroeconomic shock that increases financial market frictions (see Matvos, Seru, and Silva, 2018), or an industry shock that reduces the expected profit in the existing industry (see Campa and Kedia, 2002). We establish that unobservable common shocks are unlikely to drive our results through a wide variety of fixed effects. **We include a year fixed effect in baseline analysis to address macroeconomic shocks, while in the robustness check we include the time-varying industry (industry-by-year) fixed effect controls for common shocks impacting firms.**

To account for broader endogeneity and reverse causality concerns, we employ an instrumental variable based on partially overlapping peers in the Text-based Network Industry Classifications (Hoberg and Phillips, 2016). The group structure of partially overlapping peers lessens the reflection problem (Bramoullé, Djebbari, and Fortin, 2009), and more importantly, provides a large set of potential instruments, which are correlated with peers' actions through interactions but not directly correlated with individual focal firms' actions (De Giorgi et al., 2010; Aghamolla and Thakor, 2022). More specifically, we instrument for peer corporate diversification by using the corporate diversification of a firm that is a peer to the focal firm's peer but not a direct peer to the focal firm.[5] The results of the IV-2SLS regressions suggest a causal relationship between the focal firm's and its peers' corporate diversification.[6]

[5]Consider three firms: A, B, and C. Firm A is the focal firm. Firm B is the peer of firm A since they offer similar products in the product market (based on TNIC). Firm C is the peer of firm B but not the peer of firm A based on the similarity of their product offerings. Firm C could serve as an instrument to estimate the peer effects of firm B on firm A.

[6]Moreover, the existence of partially overlapping peers overcomes the reflection issue, which is a major identification challenge in estimating peer effects (De Giorgi et al., 2010; Aghamolla and Thakor, 2022). Partially overlapping peers means peer groups do not fully overlap, which makes it possible to identify all relevant parameters in linear models of peer effects (De Giorgi et al., 2010).

We next explore potential channels through which peer effects in corporate diversification could operate. The competition channel posits that firms may follow corporate diversification decisions to maintain a competitive balance with their rivals. Supporting this, we observe stronger peer effects for those firms facing intense competition. Additionally, we investigate whether peer effect in corporate diversification is driven by a learning channel, where firms acquire relevant information from their peers' corporate diversification, or a managerial channel, where managers follow peers' decisions to "share the blame" with their peers for unsuccessful diversification.[7] However, we fail to find support for either the learning or managerial channel.

If peer effects in corporate diversification operate through the competition channel, a remaining question is what specific competitive advantages do firms gain. The prior literature suggests that resource reallocation through an internal capital market is one of the key motivations for corporate diversification (Stein, 1997; Maksimovic and Phillips, 2013). We find that after following their peers by diversifying, firms decrease the cash flow correlation across divisions, suggesting that the diversification decision assists in internal capital reallocation (Matvos et al., 2018). Moreover, leveraging on both the time-series and cross-sectional heterogeneity, we find that peer effects in corporate diversification are more prevalent when an internal capital market is particularly valuable in maintaining a competitive balance. For time series variations, we show that peer effects are pronounced during times of high external capital market frictions and high macroeconomic uncertainty. For cross-sectional variations, we find more prevalent peer effects for firms that have difficulty raising funds externally, such as firms with less tangible assets and in a more innovative business.

We conduct several robustness checks. First, we explore whether the time and industry cluster of mergers and acquisitions (M&A waves) drive our results (Mitchell and Mulherin, 1996; Harford, 2005). Firms could engage in diversified M&As to achieve corporate diver-

[7] Scharfstein and Stein (1990) argue that firm managers are evaluated not only on their own performance but also on their rivals' performance. Managers have the motivations to follow their peers' agency-driven diversification and run away from unsuccessful diversification by "sharing the blame" with their peers (Duchin and Schmidt, 2013).

sification. If there is some overlap between the M&A waves and our sample, M&A waves might drive the peer effects in our sample. We show that our results still hold after excluding identified M&A waves from our sample period. Second, our results remain unchanged for various alternative proxies of corporate diversification (Herfindahl–Hirschman concentration index or total entropy) and definitions of industry (different digits of SIC or NAICS codes). Third, we explore the asymmetric peer effects of the scope change. The results indicate that peer effects are mainly from peers' decision to increase firm scope (diversification) rather than decrease firm scope (refocus). Fourth, our results sustain after including both the firm- and peer-level capital expenditure scaled by lagged fixed asset as controls, indicating that our finding is different with the "peer investment effect" as documented by Bustamante and Frésard (2021).

This paper makes multiple contributions to the literature. First, our work is most closely related to the literature highlighting the industry-driven differences in firms' decision to diversify. For example, Lang and Stulz (1994) find that firms are more likely to diversify in slow growing industries. Campa and Kedia (2002) show that firms tend to diversify in those industries that favor conglomerates.[8] Santalo and Becerra (2008) find that diversified firms enjoy a premium in those industries in which diversified firms are favored. Although these studies highlight the industry variation in explaining firms' decision to diversify, they only capture the interindustry variation from exogenous industry shocks (i.e., change in industry regulation or introduction of new technology) and ignore the interindustry differences driven by firms' within-industry interactions (peer effects in corporate behaviour).[9] In contrast, by

[8] Campa and Kedia (2002) measure the overall attractiveness of a given industry to conglomerates with the fraction of conglomerates and find that firms are more likely to diversify in industries dominated by a large number of conglomerates. Our findings are different from Campa and Kedia (2002) since our work captures interindustry variation driven by interdependencies in corporate diversification policy, while they capture interindustry differences from exogenous industry shocks such as change in industry regulation or introduction of new technology. After controlling these exogenous industry shocks (with $industry*year$ fixed effect in Table 9), our findings of interindustry variation in diversification still exists. Besides, we explicitly control the overall attractiveness of a given industry to conglomerates as Campa and Kedia (2002) in Panel B of Table B.5. Our results are qualitatively unchanged.

[9] Most previous studies on corporate diversification decision capture interindustry variation with industry fixed effects. Few exception, such as Campa and Kedia (2002), which explicitly investigates the industry effect on diversification, explains interindustry differences with exogenous industry shocks. In contrast, our

recognizing the importance of peer firms' diversification behavior in shaping industry environments, this paper explores how firms respond to this changing competitive environment by following their peers to diversify. Our study complements previous work by showing that the interindustry variation in diversification is accompanied by strong interdependencies in corporate diversification policy.

Our study is also related to an ongoing debate between the agency model and the value-maximizing model on the driving forces behind corporate diversification (Maksimovic and Phillips, 2013). The agency theory considers the multiple-industry structure an agency cost and argues that managers diversify their firms for private benefits such as power and social status (Jensen, 1986; Stulz, 1990), executive compensation (Jensen and Murphy, 1990), managerial entrenchment (Shleifer and Vishny, 1989), and future career prospects (Gibbons and Murphy, 1992).[10] In contrast, the value-maximizing model highlights the potential benefits of diversification and suggests that firms choose to diversify when the benefits of diversification outweigh the costs of diversification.[11] Our paper aligns with the value-maximizing literature by incorporating peer effects into firms' diversification decision-making process. We suggest that firms' optimal choice on diversification is not only based on firm-specific characteristics (Campa and Kedia, 2002), industry shocks (Lang and Stulz, 1994; Maksimovic and Phillips, 2002) or external market conditions (Kuppuswamy and Villalonga, 2016; Matvos et al., 2018), but also on behavior (diversification) of their peers. To the best of our knowledge, we are the first to show that firms' propensity to diversify is significantly related to the recent diversification of their peers.

work suggests that interdependencies in corporate diversification policy could also drive the interindustry variation in diversification.

[10]The agency explanations are motivated by diversification discount literature (Lang and Stulz, 1994; Berger and Ofek, 1995). However, more recent papers question whether the diversification discount is a real empirical phenomenon or an artifact of the measurement process (Villalonga, 2004; Hund, Monk, and Tice, 2012).

[11]For example, Maksimovic and Phillips (2002) argue that corporate diversification provides firms with flexibility in dealing with industrial shocks. Also, internal capital markets allow conglomerates to reallocate funds between different divisions to overcome imperfections in external capital markets (Stein, 1997).Several recent papers highlight the value of internal capital markets for resource reallocation in financial distress and argue that firms diversify in response to tight external capital markets (Kuppuswamy and Villalonga, 2016; Matvos et al., 2018).

Our paper adds to the rapidly growing literature on peer effects in corporate behaviors (Leary and Roberts, 2014; Grennan, 2019; Aghamolla and Thakor, 2022). Previous studies find the presence of peer effects in much corporate decision-making, such as corporate payout strategies (Kaustia and Rantala, 2015; Adhikari and Agrawal, 2018; Grennan, 2019), corporate investment decisions (Foucault and Fresard, 2014; Dessaint, Foucault, Frésard, and Matray, 2019), corporate cash holding (Hoberg, Phillips, and Prabhala, 2014), initial public offerings (IPOs) (Hsu, Reed, and Rocholl, 2010; Aghamolla and Thakor, 2022), and corporate governance practices (Foroughi, Marcus, Nguyen, and Tehranian, 2022). Our paper complements the above studies by extending the peer effects analysis to corporate diversification, a crucial decision relevant to firm stock risk, cost of capital, cash holding, and firm performance.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature and develops hypotheses. Section 3 describes the data sources and the construction of diversification measures and other variables. Section 4 presents baseline results, channels, and benefits of peer effect in corporate diversification. Section 5 deals with the endogeneity and robustness tests. Finally, Section 6 concludes the study.

2. Literature and Hypotheses Development

2.1. Peer Effects and Corporate Diversification

Several papers in corporate finance study the role of peer firms in shaping a number of corporate policies. For example, Leary and Roberts (2014) find that firms' capital structures are significantly influenced by their peers. A firm increases its leverage ratio when its peers do so. Similarly, peer effects are observed in several other corporate decision-making, such as payout strategies (Kaustia and Rantala, 2015; Adhikari and Agrawal, 2018; Grennan, 2019), investment decisions (Foucault and Fresard, 2014; Fracassi, 2017; Dessaint et al., 2019; Bustamante and Frésard, 2021), cash holding (Hoberg et al., 2014), corporate innovation

(Hsu, Huang, and Koedijk, 2023), IPOs (Hsu et al., 2010; Aghamolla and Thakor, 2022), governance practices (Foroughi et al., 2022), and corporate social responsibility (Cao, Liang, and Zhan, 2019; Li and Wang, 2022). Despite the growing attention in the corporate finance literature, the potential link between peer effects and corporate diversification is unexplored.

When making a decision, firm management weighs the costs and benefits about whether to diversify or stay stand-alone. Observing the diversification of product market peers could affect this tradeoff due to competitive, informational and managerial motivations (Duchin and Schmidt, 2013; Leary and Roberts, 2014; Aghamolla and Thakor, 2022). For example, corporate diversification may confer peer firms competitive advantages, such as providing an efficient internal capital market that overcomes imperfections in external capital markets (Stein, 1997; Matvos et al., 2018), improving flexibility in responding to industry shocks (Maksimovic and Phillips, 2001; Tate and Yang, 2015), and increasing debt capacity and tax shields from interest deductions (Lewellen, 1971). Consequently, firms may be compelled to diversify to neutralize their peers' competitive advantage (Lieberman and Asaba, 2006; Aghamolla and Thakor, 2022). Moreover, firms may follow their peers due to an informational incentive. The social learning theory suggests that the diversification of peer firms may reveal important information that a focal firm can include in its own decision-making, thus lowering the marginal costs of a focal firm to diversify (Leary and Roberts, 2014; Grennan, 2019). Except for competitive and learning channels, managerial-related motivations may also drive firms to mimic their peers' diversification decisions (Grieser, Hadlock, LeSage, and Zekhnini, 2022). Scharfstein and Stein (1990) argue that managers are evaluated not only on their own performance but also on their peers' performance. This relative evaluation incentives managers to follow their peers' diversification decisions, even when they consider diversification not optimal. Managers can shelter themselves from the consequence of these unsuccessful diversification by "sharing the blame" with their peers (Duchin and Schmidt, 2013). Based on the above arguments, we develop our first hypothesis as follows:

Hypothesis 1: Firms follow their peers' decisions of corporate diversification.

2.2. Why do Firms Imitate Each Other for Diversification Strategies?

Why do firms imitate each other's diversification strategies? The rivalry-based argument conjectures that corporate diversification confers firms competitive advantages in the product market (Cestone and Fumagalli, 2005; Boutin, Cestone, Fumagalli, Pica, and Serrano-Velarde, 2013), and hence their peers may imitate them to avoid falling behind the competition (Lieberman and Asaba, 2006; Aghamolla and Thakor, 2022). Prior literature advances various aspects of diversification that benefit firms in the competitive market. For example, the deep pockets theory suggests that internal capital markets allow conglomerates to reallocate funds among different divisions without relying on external financial markets (Stein, 1997; Khanna and Tice, 2001; Matvos and Seru, 2014), and therefore conglomerates can take actions and strategies that are not available to their stand-alone rivals due to financial constraints (Cestone and Fumagalli, 2005; Boutin et al., 2013).[12] The alleviation of financial constraints, for instance, enhances conglomerates' ability to fund R&D, advertising, and other capital expenditures that are central to the competitive race (Maksimovic and Phillips, 2008; Belenzon and Berkovitz, 2010; Boutin et al., 2013).

Moreover, corporate diversification provides firms with an advantage in responding to industry shocks (Maksimovic and Phillips, 2001; Tate and Yang, 2015). Maksimovic and Phillips (2001) show that firms dynamically adjust their industries through diversification strategies by exiting depressed industries and entering into promising ones. Tate and Yang (2015) find that diversification provides firms with an internal labor market to reallocate labor from divisions with weak prospects toward those with better opportunities. This restructuring of labor reduces the turnover rate of employees and saves the cost of compensation and re-recruitment, thus improving the labor productivity of firms. If corporate diversification brings firms a competitive edge, their rivals are forced to adopt similar strategies to avoid falling behind the competition (Lieberman and Asaba, 2006). Following the

[12] For example, Boutin et al. (2013) argue that, within multi-segment firms and business groups, investment capacity in one sector can as well be enhanced by cash generated in other sectors.

above literature on product market competition, we establish the following hypothesis:

Hypothesis 2A: Firms are more likely to follow their peers to diversify when they face more competitive pressure in the product market.

Firms may also follow their peers' diversification strategies due to the informational incentive. Free-riding in information acquisition suggests that managers learn relevant information from peer firms and update it to improve their decision-making (Foucault and Fresard, 2014; Leary and Roberts, 2014; Grennan, 2019). The peer-based information becomes more valuable when a firm's own signal is noisy and optimization is difficult, and in that case, managers may rationally put more weight on the decisions of others than on their own information (Leary and Roberts, 2014). Prior literature suggests that social learning is relevant to peer effects on several important corporate policies, such as capital structure (Leary and Roberts, 2014), corporate investment (Foucault and Fresard, 2014), dividend payouts (Grennan, 2019), and executive compensation design (Shue, 2013).

Corporate diversification is a critical and uncertain decision (Markides, 1997; Matsusaka, 2001). When managers are unsure whether a change in a firm's scope is optimal, they may infer the best choice from peer firms. Thus, we conjecture that peer effects in corporate diversification may be established through a learning channel. Leary and Roberts (2014) examine the learning mechanism with a leader-follower model in which "follower" (less successful firms) are sensitive to 'leaders" (more successful firms) but not the other way round. Based on the social learning argument, we posit our hypothesis as follows:

Hypothesis 2B: Followers follow the diversification decisions of leaders but not vice versa.

In addition to competitive and learning channels, prior work suggests the possibility of managerial-related motivations for peer effects in corporate diversification (Grieser et al., 2022). The agency theory argues that managers may diversify their firms for private benefits

(Jensen, 1986; Stulz, 1990; Shleifer and Vishny, 1989). These agency-driven diversifications would cost shareholders and are more likely to happen when the external monitoring is weak or the penalties for making such behavior are low. Scharfstein and Stein (1990) argue that managers are evaluated not only on their own performance but also on their peers' performance. This relative evaluation could motivate managers to follow their peers' agency-driven diversification as they are more likely to "get away with it" when their peers do so. In other words, managers may run away from the consequence of unsuccessful diversification by "sharing the blame" with their peers (Duchin and Schmidt, 2013). The "sharing the blame" argument is analogous to those studies in the crime literature that criminals are less likely to be caught during periods of high crime rates due to limited enforcement resources (Sah, 1991). The "sharing the blame" argument implies that the peer effects in corporate diversification are driven by agency problems. Therefore, we posit our hypothesis as follows:

Hypothesis 2C: Firms are more likely to follow their peers to diversify if there are more agency conflicts.

3. Data and Variable Construction

3.1. Data

Our sample builds upon several data sets over the period from 1988 to 2019. Our sample matches the availability of Text-based Network Industry Classification (TNIC) data. We collect segment-level data from Compustat Segment files and firm-level financial data from Compustat North America Industrial Annual files. Consistent with Matvos et al. (2018), we apply the following standard filters. First, we include only business segments and exclude segments with negative or missing values on assets, sales, or investments. Second, we exclude observations from firms in the heavily regulated utilities (SIC 4900 to 4999) and financial

(SIC 6000 to 6999) sectors.[13]

We define peer groups based on product market competition and collect TNIC data from the Hoberg and Phillips Data Library. We collect TED spread information from the Federal Reserve Bank of St. Louis. Economic uncertainty index is from Baker, Bloom, and Davis (2016). The G-index and E-index to measure corporate governance are from Gompers, Ishii, and Metrick (2003) and Bebchuk, Cohen, and Ferrell (2009), respectively. The asset redeployability measure and the organization capital measure are from Kim and Kung (2016) and Peters and Taylor (2017), respectively.[14] We collect mergers and acquisitions data from Refinitiv SDC. The detailed definitions for variables derived from those databases are in Table A.1.

3.2. *Measures of Corporate Diversification*

Following Mansi and Reeb (2002), we measure corporate diversification in our main analysis with two widely employed approaches. We use the segment-level three-digit SIC code to define the industry of a business segment.[15] The first proxy $\textit{Multisegment(0/1)}_{i,t}$ is a dummy variable that takes a value of one when a focal firm operates in multiple industries. The second proxy for corporate diversification $\textit{Number Divisions}_{i,t}$ is the number of business divisions in which a focal firm operates. We also construct several alternative measures

[13] When we exclude observations from those heavily regulated sectors, we define an industry with a firm-level Compustat historical SIC code since they are more accurate (see Kahle and Walkling (1996)). If a firm-level historical SIC code is missing, we use the corresponding CRSP SIC codes (see Belo, Gala, and Li (2013)).

[14] We thank Hoberg and Phillips (2016) for providing the comprehensive TNIC data set to the public. The website is `https://hobergphillips.tuck.dartmouth.edu/`. We thank Baker et al. (2016), Gompers et al. (2003), Bebchuk et al. (2009), Kim and Kung (2016) and Peters and Taylor (2017) for making the following data available: Macroeconomic uncertainty index is from `https://www.policyuncertainty.com/`. The G-index is collected from `https://faculty.som.yale.edu/andrewmetrick/data/`. The E-index is collected from `http://www.law.harvard.edu/faculty/bebchuk/data.shtml`. The asset redeployability is from `https://www.chicagofed.org/people/k/kim-hyunseob`. We extend the asset redeployability for the period from 2016 to 2019 to cover our sample. The organization capital is on Wharton Research Data Services (WRDS).

[15] We only tabulate the results based on three-digit SIC codes for brevity. We replicate the main empirical analysis using two-digit SIC codes, four-digit SIC codes, three-digit NAICS codes, four-digit NAICS codes, and five-digit NAICS codes as industry classifications. Our results are robust to all these different definitions of the business segment.

for corporate diversification in robustness checks: an asset-based inverse measure of the Herfindahl index (*1 - Focal HHI(Assets)*$_{i,t}$), a sales-based inverse measure of the Herfindahl index (*1 - Focal HHI(Sales)*$_{i,t}$), an asset-based entropy measure ($Focal\, EI(Assets)_{i,t}$), and a sales-based entropy measure ($Focal\, EI(Sales)_{i,t}$).

3.3. Peer Groups based on Product Market Competition

We define the peer reference groups based on TNIC because it better captures firms' competition in product markets than traditional fixed industry classifications (Hoberg and Phillips, 2016).[16] TNIC maps product market competition based on the degree of product similarity between a firm and its rivals. The calculation of product similarity is based on the text-based analysis of the firm's 10-K product description. Firms operating in the same markets tend to describe their products with a similar vocabulary in the 10-K business descriptions. In contrast, traditional fixed industry classifications (such as SIC or NAICS codes) define the industries based on the way the product is manufactured. Hoberg and Phillips (2016) find that TNIC is more informative in explaining profitability, sales growth, and market risk across different industries than fixed industry classifications. They also find that TNIC better explains the extent to which competitive pressures are felt by managers. Thus, TNIC is a better measure of product market competition, which is exactly the channel through which we expect the peer effects might operate.

Another important advantage to our approach is that TNIC allows the use of partially overlapping peers to lessens the reflection problem (i.e., simultaneity), a major identification challenge in estimating peer effects (De Giorgi et al., 2010). As Manski (1993) argues, the reflection problem arises when all members within a group share the *same* set of peers, and hence the regressor of peer actions does not vary among peers within the same group.[17] How-

[16] Prior research has adopted different ways to define peer groups. The most popular one is based on fixed industry classifications such as SIC or NAICS codes (Leary and Roberts, 2014; Grennan, 2019). Other ways to define peers include analyst coverage (Kaustia and Rantala, 2015), compensation contracts (Bizjak, Lemmon, and Naveen, 2008), geography peers (John, Knyazeva, and Knyazeva, 2011), and top executive's alumni network (Shue, 2013).

[17] A detailed explanation of this issue is presented in Section 4.1

ever, TNIC is a *firm-specific* approach that allows the majority of firms to have *distinct*, yet partially overlapping peers. The use of partially overlapping peers lessens the reflection problem (Bramoullé et al., 2009; De Giorgi et al., 2010; Aghamolla and Thakor, 2022). Moreover, the presence of partially overlapping peers provides a group of natural instruments—peers of peers—for instrumental variables estimation in addressing other endogeneity issues (i.e., unobservable common shocks or reverse causality).[18]

Our main variables of interest are diversification measures of peer firms based on TNIC. Following Hoberg and Phillips (2016), for any given firm i, we identify the firm j as i's peer if the degree of product similarity between firm i and j is above a 21.32% minimum similarity threshold in year t. Hoberg and Phillips (2016) argue that the minimum similarity threshold of 21.32% allows the TNIC-based industries to be comparable to three-digit SIC industries. We refer to peers identified with this method as *TNIC peers* throughout the paper. In our sample, a firm has a median of 31 TNIC peers each year. We use TNIC peers to construct peer-level diversification measures and peer control variables. For example, *Peer Multisegment(0/1)$_{-i,t-1}$* is the mean of the multi-segment dummy among firm i's TNIC peers (excluding firm i) in year $t-1$. *Peer Number Divisions$_{-i,t-1}$* is the mean number of business divisions among firm i's TNIC peers (excluding firm i) in year $t-1$.

3.4. Summary Statistics

Our sample contains 90,834 firm-year observations from 1988 to 2019.[19] Table 1 reports the summary statistics of our sample. Over our sample period, each firm on average has 1.30 business divisions. The minimum and the maximum number of business divisions are 1 and 10 in our sample, respectively. Diversified firms spanning multiple industries account for 19.41% (17,637/90,834) of the observations in our sample. The average number of business

[18] The detailed discussion on our instrumental variables approach is presented in Section 5.1.3.

[19] Our sample is comparable with the literature (Matvos et al., 2018). The difference between our sample and Matvos et al. (2018) is caused by several factors. The main reason is that the availability of TNIC peers reduces the size of our sample. Besides, different sample periods and model specifications further cause the difference. TNIC is only available since 1988. Before we apply the TNIC filter and limit our sample to the same sample period, our sample displays similar characteristics as the literature.

divisions in a diversified firm is 2.59. The mean and the median of the number of TNIC peers for each firm are 87 and 31, respectively, in our sample.

[Insert Table 1 about here.]

Our sample covers firms with different characteristics and in different development stages. As shown in Table 1, the mean leverage is 32.3% and the mean firm age is 7.96 in our sample. The average total assets in our sample are 159.65 million.[20] In Table B.1, we report the correlation matrix of our main variables on the benchmark regression. Neither *Peer Multisegment(0/1)*$_{\text{-}i,t\text{-}1}$ nor *Peer Number Divisions*$_{\text{-}i,t\text{-}1}$ is highly correlated with any of the control variables.

4. Empirical Methodology and Results

In this section, we first report the main empirical results. Then, we explore the economic forces that facilitate peer influence. We test the competition channel, the learning channel, and the managerial channel, separately. Finally, we explore the potential benefits of following the corporate diversification decisions of peer firms.

4.1. Peer Effects in Corporate Diversification

4.1.1. Model Specification

We test whether the propensity of a firm to diversify its businesses is affected by its product market peers' diversification decisions. Our estimation equation is as follows:

$$DIV_{i,t} = \alpha + \beta PeerDIV_{-i,t-1} + \gamma' \overline{X}_{-i,t-1} + \lambda' X_{i,t-1} + \delta_i + \nu_t + \epsilon_{i,t}, \tag{1}$$

where the dependent variable $DIV_{i,t}$ is, either a dummy variable (*Multisegment(0/1)*$_{i,t}$) or a continuous variable (*Number Divisions*$_{i,t}$), the measure of corporate diversification for firm

[20]The mean age corresponds to exp(2.074) as in Table 1. The average total assets corresponds to exp(5.073) as in Table 1.

i in year t. Our main variable of interest is $PeerDIV_{-i,t-1}$, which can be either *Peer Multisegment(0/1)$_{\text{-i,t-1}}$* or *Peer Number Divisions$_{\text{-i,t-1}}$* to match with the nature of the dependent variable. δ_i and ν_t denote firm and year fixed effects, respectively. The firm fixed effects control for any time-invariant firm-specific factors that relate to the corporate diversification of both a focal firm and its peers. The year fixed effects control for any time-varying macroeconomic factors affecting the diversification of all firms. $\epsilon_{i,t}$ is the error term. To control for potential serial correlation, we use robust standard errors clustered at the firm level.

We control for a host of peer average and firm-specific characteristics. First, firm's performance in the existing business might influence its decision to diversify. We include firm Tobin's Q ($Tobin\,Q_{i,t-1}$), book leverage ($Leverage_{i,t-1}$), and cash flow to assets ratio ($Cash\,Ratio_{i,t-1}$) as controls. Second, Matsusaka (2001) argues that firms are composed of organizational capabilities that can be profitable in multiple businesses, driving the firm to seek product diversification. Therefore, we explicitly control for asset redeployability, organization capital, and technical know-how. Specifically, we use the asset redeployability ($Redeployability_{i,t-1}$) from Kim and Kung (2016) to measure the useability of assets across industries. We include the organization capital measure ($Org.\,Capital_{i,t-1}$) developed by Peters and Taylor (2017) as control, which proxies for firms' investment in human capital, brand, customer relationships, and distribution systems. We account for the influence of firm's technical know-how by controlling for firm's R&D expenditures scaled by total assets ($R\&D_{i,t-1}$).[21] Third, firms' in various development phases and different industries have different tendency to diversify. We control for firm age ($Ln(Firm\,Age)_{i,t-1}$), firm size ($Ln(Total\,Assets)_{i,t-1}$), and industry's instability ($Instability_{i,t-1}$). Following Hoberg and Phillips (2018), industries with higher instability experience changes in its membership over time. The K-dimensional vectors $\overline{X}_{-i,t-1}$ and $X_{i,t-1}$ contain above-mentioned characteristics

[21] R&D expenditure measures the input of the innovation activity. In unreported results, we obtain qualitatively similar results when we use the number of applied patents (the output of the innovation activity) to proxy for firm's technical know-how.

at peer average and firm level, respectively.[22] The detailed definitions for these variables are provided in Table A.1 of the Appendix.

A major identification challenge in estimating peer effects is the reflection problem (Manski, 1993). It refers to a specific form of endogeneity arising from the attempt to distinguish between the different effects that may influence peer behavior. For example, in our context, a firm may diversify its businesses due to either the diversification of its rivals (peer actions) or some other characteristics of its peers (peer characteristics).[23] A standard peer effects model fails to distinguish the peer action effect from the peer characteristic effect since the regressor of peer actions is linearly dependent on other regressors, and hence fewer equations than unknowns exist (Manski, 1993). The reflection issue is manifested when all members within the same group share the *same* set of peers. Thus, the peer actions regressor does not change among peers within the same group, and fewer equations than unknowns are left to identify the peer actions effect from the other effects (De Giorgi et al., 2010).

As supported by Bramoullé et al. (2009), De Giorgi et al. (2010), and Aghamolla and Thakor (2022), the use of partially overlapping peers might lessen the reflection problem. The partially overlapping peers allow the peer action regressor to vary among peers within the same group, and hence there are enough equations to identify the peer action effect from the other effects. Our definition of peer groups is based on TNIC, a *firm-specific* industry classification that allows the majority of firms to have a group of *distinct*, yet partially overlapping peers. Thus, the reflection problem is eliminated in our specification.

4.1.2. Empirical Results

Table 2 reports estimation results of Equation (1), which investigates peer effects in corporate diversification. In columns (1) to (3), the dependent variable is $\mathit{Multisegment(0/1)}_{i,t}$.

[22]Augmenting the models with peer average characteristics could account for the contextual effect, which refers to the fact that the focal firm's diversification decision may be subject to the influence of other peer characteristics (Leary and Roberts, 2014). We exclude the firm i in the calculations of both peer averages of diversification measures and peer control characteristics to avoid the mechanical correlation.

[23]Manski (1993) refers to the response to peer actions as endogenous effects and the response to peer characteristics as exogenous effects (or contextual effects).

We find that the coefficients associated with *Peer Multisegment(0/1)*$_{\text{-}i,t\text{-}1}$ are positive and statistically significant at the 1% level. In columns (4) to (6), the dependent variable is *Number Divisions*$_{i,t}$. The coefficients associated with *Peer Number Divisions*$_{\text{-}i,t\text{-}1}$ are also positive and statistically significant at the 1% level. These results are consistent with Hypothesis 1, which states that the propensity of a firm to diversify its businesses is positively correlated with the corporate diversification behavior of its product market peers.

[Insert Table 2 about here.]

We next interpret the economic importance of our results.[24] In column (3), we find that a one-standard-deviation increase of *Peer Multisegment(0/1)*$_{\text{-}i,t\text{-}1}$ (0.241) will lead to a 0.011 ($0.241 * 0.045$) absolute increase in the focal firm's diversification, which is equivalent to a 6% (0.011/0.191) relative increase in the probability of firm changing scope. In column (6), we find that a one-standard-deviation increase in *Peer Number Divisions*$_{\text{-}i,t\text{-}1}$ (0.470) will lead to a 0.036 ($0.470 * 0.077$) absolute increase in the focal firm's divisions. Table 1 shows the mean segment is 1.304, indicating the diversified segments of the firms are 0.304 (1.304-1). To account for the fact that firms at least have one segment, an absolute increase of 0.036 is a 12% (0.036/0.304) change relative to the diversified segments of the firms.[25] The above results suggest that peer effects in corporate diversification are also economically meaningful.

[24] According to Leary and Roberts (2014), it is not accurate to use the partial derivative to measure the marginal effect of peer influence. Since the presence of externalities in the peer influence setting means changes to one firm will influence the outcomes at another firm. This amplification or spillover effect means the partial derivatives method we use here will possibly underestimate the true marginal effect of peer influence.

[25] This interpretation is equivalent to a model specification of regressing *Number Divisions*$_{i,t} - 1$ on *Peer Number Divisions*$_{\text{-}i,t\text{-}1} - 1$, which takes into account the fact that firms have at least one segment. In the untabulated results of this alternative specification, we confirm that the standard deviation and the coefficient of *Peer Number Divisions*$_{\text{-}i,t\text{-}1} - 1$ are still 0.470 and 0.077, respectively. The mean of *Number Divisions*$_{i,t} - 1$ is 0.304. We could reach the same 12% through the following calculation: $(0.470 * 0.077)/0.304$.

4.2. The Channels of Peer Effects in Corporate Diversification

4.2.1. Product Market Competition Channel

As discussed in Section 2, one of the potential channels is product market competition—firms may follow their peers in corporate diversification decisions to better compete with their rivals. For example, corporate diversification offers firms a competitive edge by building an effective internal capital market or internal labor market (Stein, 1997; Matvos and Seru, 2014; Tate and Yang, 2015), reducing the volatility of internal cash flow and increasing debt capacity (Lewellen, 1971; Campello, 2002; Franco, Urcan, and Vasvari, 2016), and providing flexibility to adapt to changes in the industry environment (Maksimovic and Phillips, 2001).

In this section, we explore the product market competition channel. If firms follow the diversification of their product market peers due to competitive reasons, we should see stronger peer effects for those firms facing greater competition. Prior literature suggests the relevancy of the competition channel on multiple corporate policies, such as trade credit policies (Gyimah, Machokoto, and Sikochi, 2020) and payout strategies (Adhikari and Agrawal, 2018). We examine whether peer effects in corporate diversification change with product market competition by using the interaction term between peer diversification measures and a group of proxies for product market competition.

Consistent with Hoberg and Phillips (2016), the first proxy $\textit{Total Similarity}_{i,t}$ is the sum of pairwise similarity scores between focal firm i and its TNIC peers in year t. The second proxy $\textit{1-Market-level HHI(Sales)}_{i,t}$ is the market-level Herfindahl-Hirshman concentration index based on firm sales. Since higher values of the Herfindahl index indicate lower levels of competition, we instead use the inverse measure (one minus Herfindahl-Hirshman Index) for ease of interpretation. The third proxy $\textit{Fluidity}_{i,t}$ is a measure of strategic interactions between a firm and its rivals. It measures the instability of the focal firm's product market environment caused by peer firms' moves. For all three proxies, a higher value indicates that a focal firm faces intense competition.

[Insert Table 3 about here.]

Table 3 reports the results of the competition channel. In columns (1) to (6), the interaction terms between peer diversification measures (*Peer Multisegment(0/1)*$_{-i,t-1}$ and *Peer Number Divisions*$_{-i,t-1}$) and product market competition measures (*Total Similarity*$_{i,t}$, *1-Market-level HHI(Sales)*$_{i,t}$, and *Fluidity*$_{i,t}$) are all positively and statistically significant at 1% in explaining *Multisegment(0/1)*$_{i,t}$ and *Number Divisions*$_{i,t}$. The above results suggest that peer effects in corporate diversification are more prevalent when the product market competition is intense. These findings support hypothesis 2A.

4.2.2. Peer Learning Channel

Another channel that firms may mimic one another is peer learning. As discussed in Section 2, free-riding in information acquisition allows managers to learn relevant information from their peers and to update it to improve their decision-making (Foucault and Fresard, 2014; Leary and Roberts, 2014; Grennan, 2019). This is particularly the case when a firm's own signal is noisy and an optimal decision is difficult to make (Leary and Roberts, 2014). Corporate diversification is an important corporate decision with a lot of uncertainty (Markides, 1997; Matsusaka, 2001). Thus, when a good model for decision-making is unavailable, managers may infer the best choice from their peers. This is especially likely when their peers are perceived as having greater expertise (Bikhchandani, Hirshleifer, and Welch, 1998).

[Insert Table 4 about here.]

Table 4 reports the results of the learning channel. We interact peer diversification with firm success proxies. In particular, we measure firm success with profitability ($Profitability_{i,t}$) margin and market share based on sales ($Market\,Share_{i,t}$). In all models, the interaction term between peer diversification measures (*Peer Multisegment(0/1)*$_{-i,t-1}$ and *Peer Number Divisions*$_{-i,t-1}$) and firm success measures ($Profitability_{i,t}$ and $Market\,Share_{i,t}$) are statistically not different from zero in explaining the focal firm's diversification decisions. Our findings do not support the learning channel as stated in hypothesis 2B.

4.2.3. Managerial Channel

In addition, managers may follow their peers to diversify for managerial-related motivations (Grieser et al., 2022). The theoretical work of Scharfstein and Stein (1990) argues that managers are evaluated not only on their own performance but also on their peers' performance. The relative evaluation may motivate managers to follow their peers' agency-driven diversification as they could justify their own behaviors with their peers' behaviors. This means that managers may get away with the consequence of unsuccessful diversifications by"sharing the blame" with their peers (Duchin and Schmidt, 2013).

[Insert Table 5 about here.]

In Table 5, we explore the managerial channel by using the interaction term between peer diversification measures and corporate governance proxies (E-index from Bebchuk et al. (2009) and G-index from Gompers et al. (2003)). The E-index (G-index) is constructed by adding one point if the firm has one provision within the 6 (24) provisions recorded in the IRRC database. In columns (1) to (4), we find that none of the coefficients associated with interaction terms is statistically significant. The above results do not support that agency problems are the underlying channel through which the peers influence corporate diversification, which does not support hypothesis 2C.

4.3. The Benefits of Following Peers to Diversify

We show that product market competition incentivizes firms to match up with their rivals. It remains unknown what specific competitive advantages a firm may get by following its peers to diversify. One of the major benefits of corporate diversification is access to an internal capital market, which allows managers to reallocate resources among different business divisions. The resource reallocation through an internal capital market helps firms avoid financing costs from external capital markets.[26] Thus, we investigate whether benefits from an internal capital market drive firms to follow their peers to diversify. We first test whether capital reallocation prospects improve if firms follow their peers to diversify. Second, based on time-series variations, we test whether peer effects in corporate diversification are more prevalent when an internal capital market is especially important, such as during times of high external capital market frictions or high macroeconomic uncertainty.[27] Third, leveraging on cross-sectional variations, we show that peer effect concentrates on focal firms that have difficulties to raise funds externally.

4.3.1. Peer Effects and Capital Reallocation Prospects

Through an internal capital market, firms can reallocate funds from divisions with extra cash flows to divisions without sufficient capital but with profitable projects. Matvos et al. (2018) argue that resource reallocation is more productive when cash flow across different divisions is less correlated. Consider a division with good investment opportunities but insufficient funds, if the cash flow among divisions is highly correlated, the cash flow of other divisions is low as well, providing little opportunity for reallocation. Consistent with Matvos et al. (2018), we measure the opportunities of internal capital reallocation with the cash flow correlation across divisions (see Appendix for the construction of cash flow correlation measure). If a firm follows its peers (to diversify) for internal capital reallocation purposes, we expect that a match up of diversification decision reduces the cash flow correlation.

[Insert Table 6 about here.]

In Table 6, we estimate how firms' cash flow correlation changes in response to corporate

[26] Without internal capital markets, firms must finance their investment projects through external capital markets. The external capital markets have less information about the value of investment projects than do managers. The informational asymmetry leads to higher financing costs from the external capital markets.

[27] The internal capital market provides conglomerates an option to avoid costly external financing in more states of the world. Aivazian, Rahaman, and Zhou (2019) argue that this real option is more valuable when macroeconomic uncertainty is higher.

diversification of their peers, and more importantly, whether this change is mainly driven through focal firms' diversification behavior. In columns (1) and (3) of Panel A, we regress the cash flow correlation measure ($Cashflow\ Correlation_{ft}$) on peer diversification measures (*Peer Multisegment(0/1)*$_{\text{-}i,t\text{-}1}$ and *Peer Number Divisions*$_{\text{-}i,t\text{-}1}$). The negative coefficient suggests that after observing their peers diversify, firms reduce the correlation in cash flow across divisions. In columns (2) and (4) of Panel A, we augment the model with the focal firms' diversification measures (*Multisegment(0/1)*$_{i,t}$ and *Number Divisions*$_{i,t}$), which, as expected, have a negative and significant association with the cash flow correlation (Matvos et al., 2018). The inclusion of focal firms' diversification measures largely reduces the estimated coefficients of peer diversification on cash flow correlation (from -0.041 to -0.01 for *Peer Multisegment(0/1)*$_{\text{-}i,t\text{-}1}$ and from -0.027 to -0.003 for *Peer Number Divisions*$_{\text{-}i,t\text{-}1}$), suggesting that the main effect of peer diversification on focal cash flow correlation is through focal diversification. In Panels B and C, we repeat the analysis with alternative measures of internal capital reallocation opportunities ($Investment\ Correlation_{ft}$ and $Selfsufficiency_{ft}$). The results are similar.[28]

4.3.2. Internal Capital Market and Time Series Heterogeneity

Matvos et al. (2018) highlight the value of the internal capital market in resource reallocation when external financing is more difficult or costly. They find that firms are more likely to diversify their business during times of high external capital market frictions. If firms follow their rivals (to diversify) to maintain a competitive balance in internal financing, peer effects should be more prevalent during periods of high external capital market frictions. Thus, we test whether firms are more closely following their peers in times of high financial frictions. We add the interaction term between the measure of external market frictions and peer diversification measures into the regression.

[28] In Table B.6, we perform an additional test to examine the benefit of following peers to diversify. We run 2SLS regressions to identify the change in capital reallocation prospects after following peers' decisions to diversify. The results are qualitatively unchanged.

In Table 7, Panel A, we report the influence of external market frictions on the peer effects of corporate diversification. Following Matvos et al. (2018), our proxy of external capital market frictions $TED\,Spread_t$ is defined as the difference between three-month LIBOR and three-month Treasury bill. In columns (1) and (2), The coefficients of the interaction term between market frictions measure and peer diversification measures are all positively significant at 5%, suggesting that firms are more likely to follow their peers to diversify when the external market frictions is high.

[Insert Table 7 about here.]

Matsusaka and Nanda (2002) conjecture that access to an internal capital market creates an option for the conglomerate to avoid costly external financing in more states of the world. This real option becomes particularly valuable in times of heightened macroeconomic uncertainty (Aivazian et al., 2019). Therefore, we expect that firms are more likely to follow their peers to diversify when macroeconomic uncertainty is high.

Panel A of Table 7 reports the influence of economic uncertainty on peer effects. Following Baker et al. (2016), we employ two measures of economic uncertainty. In columns (3) and (4), $Economic\ Uncertianty_t$ measures the overall economic policy uncertainty. It is a weighted index aggregating uncertainty information from news coverage, tax code expiration data, and economic forecaster disagreement. In columns (5) and (6), $Media\text{-}based\ Uncertianty_t$ is solely based on the news coverage about policy-related economic uncertainty. We find that the coefficients of the interactions between economic uncertainty and diversification measures are all positively significant, indicating that peer effects of corporate diversification are more pronounced during periods of high economic uncertainty.

4.3.3. Internal Capital Market and Cross-sectional heterogeneity

We further leverage on the firms' cross sectional differences to analyze the benefit of the internal capital market. Boutin et al. (2013) argues that the internal capital market is more important for firms with high financial constraints. Following Boutin et al.

(2013), we use two group of variables to measure firms' financial constraints. The first variable is asset tangibility. Follow Lei, Qiu, and Wan (2018), asset tangibility is defined as $0.715\times$receivables$+0.547\times$inventories$+0.535\times$fixed capital, deflated by book value of total assets net of cash. Firms with high tangibility are easy to raise money from the external finance market. The second group of variables measure how innovative a firm is. More innovative firms have high risks and information asymmetry, which faces high hurdle to raise money externally. We use both the market value and number of awarded patents to a focal firm to measure how innovative a firm is. The market value of patent is provided by Kogan, Papanikolaou, Seru, and Stoffman (2017). Therefore, we conjecture peer effects should be more pronounced for firms with low tangibility or more innovative.

Panel B of Table 7 reports the results of this cross-sectional test. In columns (1) and (2), the coefficient of the interaction term is negatively significant, indicating that firms with high asset tangibility are less subject to peer effect of corporate diversification. In columns (3) to (6), we find the interaction terms are all positively significant for firms that are more innovative. To sum up, this cross-sectional heterogeneity suggests that internal capital market are one key benefit to facilitate the peer effect in corporate diversification.

5. Endogeneity and Robustness Tests

5.1. Endogeneity

5.1.1. A Quasi-natural Experiment Based on Mergers and Acquisitions

The observed correlation between corporate diversification policy can be attributed to the endogenous selection of firms into peer groups. Firms from the same peer group are more likely to expand business together since they share similar characteristics or institutional environments correlated with their decision to expand. For example, firms from the same peer group may have similar organizational capabilities or production technologies that allow firms to expand together. Our previous specifications include asset redeployability, intangible organization capital, and technical know-how to explicitly control for these similarities of firm characteristics and institutional environments.

We further control for this endogeneity selection through a quasi-natural experiment leveraging on the different status (complete or incomplete) and outcomes (diversified or undiversified) of mergers and acquisitions (Savor and Lu, 2009; Seru, 2014).[29] We estimate the following regression:

$$\begin{aligned} Diversified\,Ratio_{i,t} =& \alpha + \beta_1 Peer\,MA\,Complete_{-i,t-1} + \beta_2 Peer\,MA\,Diversified_{-i,t-1} \\ &+ \beta_3 Peer\,MA\,Complete_{-i,t-1} * Peer\,MA\,Diversified_{-i,t-1} + \gamma' \overline{X}_{-i,t-1} \\ &+ \lambda' X_{i,t-1} + \delta_i + \nu_t + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where the dependent variable, *Diversified Ratio*$_{i,t}$, is the ratio of the number of complete and diversified M&As to the total number of M&As conducted by focal firm in year t. Our coefficient of interest is β_3. *Peer MA Complete*$_{-i,t-1}$ is a dummy variable that takes a value of one if the focal firm's closest peer (highest TNIC similarity score) has a complete M&A in year $t-1$, otherwise zero. [30] *Peer MA Diversified*$_{-i,t-1}$ is a dummy variable that takes a value of one (zero) if the deal is diversified (undiversified). Diversified deals are M&As with the acquirer and the target from two different three-digit SIC business divisions. The K-dimensional vectors $\overline{X}_{-i,t-1}$ and $X_{i,t-1}$ contain control variables from focal firm's closest peer and focal firm, respectively. δ_i and ν_t denote firm and year fixed effects, respectively.

This test has two desirable attributes. First, the contrast between diversified and undiversified deals could better differentiate between "peer diversification effect" and overall business expansion. Second, whether a deal could be complete or incomplete is largely influenced by peer firms' deal-specific considerations. Therefore, the outcome of the deal is exogenous to the focal firm. If peer effects are present, we expect that the focal firm should

[29] In tabulated results, we confirm that the peer effects in corporate diversification also exist in the sample of diversified mergers and acquisitions, supporting us to use this M&A-based quasi-natural experiment to ascertain the causality of peer effects in corporate diversification.

[30] If the deal is classified as "complete" or "unconditional" as recorded in SDC, we group it as complete mergers and acquisitions, otherwise as incomplete ones.

respond to peers' complete and diversified deals rather than incomplete and undiversified ones.

The detailed sample selection process is as follows: We assemble a group of complete and incomplete mergers and acquisitions from Refinitiv SDC. We start with all deals (diversified and undiversified) in which the control of the firm has changed (the acquirer owns less than 50% of the target before the deal and more than 50% after the deal) between 1988 and 2019. Similar to Matvos et al. (2018), diversified deals are M&As with the acquirer and the target from two different three-digit SIC business divisions. We focus on deals between US firms. The acquirer is a public firm but the target could either be a public or private firm. We use the deal status information to classify M&As into complete and incomplete deals.[31] We keep deals in which the acquirer serves as the closest peer for any focal firm based on the TNIC similarity score. We require focal firm's closest peer only has one type of MA deals out of four possible permutations between complete and incomplete and diversified and undiversified deals.[32] Focusing on focal firm's closet peer could avoid the scenario in which a focal firm has peers engage in different permutations of MA deals, which contaminates the inference of the quasi-natural experiment.

[Insert Table 8 about here.]

Table 8 shows the results of the quasi-natural experiment. The variable of interest is the interaction term between *Peer MA Complete*$_{-i,t-1}$ and *Peer MA Diversified*$_{-i,t-1}$. In columns (1) to (3), the coefficient of the variable of interest is positively significant. Those results indicate the focal firm only respond to peer's complete and diversified deals rather than incomplete and undiversified ones, which mitigates the endogeneity concern.

[31] If the deal is classified as "complete" or "unconditional" as recorded in SDC, we group it as complete mergers and acquisitions, otherwise as incomplete ones.

[32] For each deal, there are four different possible permutations for MA types. There are complete/diversified, complete/undiversified, incomplete/diversified, and incomplete/undiversified. If a focal firm's closest peer has engaged in two complete/diversified deals and one complete/undiversified deal in year $t-1$, we exclude it from our sample for that year. If a focal firm's closest peer has engaged in only two complete/diversified deals, we set *Peer MA Complete*$_{-i,t-1}$=1 and *Peer MA Diversified*$_{-i,t-1}$=1.

5.1.2. Unobservable Common Shocks

Endogeneity on peer effects may also arise if unobservable common shocks hit the group as a whole. In other words, when we observe a significant correlation in the corporate diversification strategy between a focal firm and its peers, it is hard to say whether this result is due to a true peer effect or a common response to an unobservable shock. There are two main sources of common shocks. First, firms may diversify together in response to macroeconomic shocks, such as an increase in financial market frictions (Matvos et al., 2018). Second, industry shocks (such as changes in industry regulation or innovation) could reduce the expected payoff in the existing industry, and therefore, drive firms to diversify together (Campa and Kedia, 2002).

The inclusion of year fixed effect (in the baseline regressions) alleviates potential concerns from macroeconomic shocks. Besides, we explicitly control for the previously-documented macroeconomic changes that may affect corporate diversification strategy. For example, Matvos et al. (2018) argue that, when frictions in the external capital market increase, capital allocation in internal capital markets become more attractive, leading firms to increase their scope. Consistent with this argument, Matvos et al. (2018) find that firms are more likely to diversify their scope during periods of high external capital market frictions.

[Insert Table 9 about here.]

In Panel A of Table 9, we re-estimate the baseline regressions by including a proxy for external capital market frictions. We confirm the results as documented in Matvos et al. (2018) that firms increase their scope during times of high external capital market frictions. More importantly, we find that the coefficients associated with $\textit{Peer Multisegment(0/1)}_{\textit{-i,t-1}}$ and $\textit{Peer Number Divisions}_{\textit{-i,t-1}}$ remain positive and statistically significant at 1% after controlling for $TED\ Spread_t$. This test, therefore, shows that our previous results are not driven by external capital market frictions.

We further saturate the main specification with a wide variety of time-varying industry and regional fixed effects. With these additional fixed effects, our empirical specifications thus specifically control for shocks in any particular year that are common to firms operating in a given industry or geographic group. The results with the inclusion of these additional fixed effects are reported in Panel B of Table 9. In columns (1) to (4), we find that the coefficients associated with *Peer Multisegment(0/1)*$_{\text{-}i,t\text{-}1}$ and *Peer Number Divisions*$_{\text{-}i,t\text{-}1}$ remain positive and statistically significant at 1%. Thus, our previous results are unlikely to be driven by common shocks that affect the industry and geographic groups.

5.1.3. Instrumental Variables Specification

Our construction of peer groups based on TNIC allows the use of partially overlapping peers to lessen the reflection problem (De Giorgi et al., 2010; Aghamolla and Thakor, 2022). Moreover, our previous findings suggest that endogenous selection of firms into peer groups and unobservable common shocks are unlikely to drive our results. To further address the endogeneity concerns, we re-estimate the baseline regressions with the instrumental variable two-stage least squares (IV-2SLS) approach.

The presence of partially overlapping peers provides a group of natural instruments for peer effects estimation, namely peers of peers who are not in the focal firm's peer group (De Giorgi et al., 2010). Specifically, we instrument for the corporate diversification of a focal firm's peer by using the corporate diversification of a firm that is a peer to the focal firm's peer, but not a peer to the focal firm. For example, consider three firms: A, B, and C. Firm A is the focal firm. Firm B is the peer of firm A since they offer similar products in the product market (based on TNIC). Firm C is the peer of firm B but not the peer of firm A based on the similarity of their product offerings.[33] Firm C could serve as an instrument to estimate the peer effects of firm B on firm A since it satisfies both the validity requirement and exclusivity restriction.[34] For the validity requirement, the corporate diversification of

[33]For example, Nike competes with Head in tennis and Callaway in golf, but there is no direct competition between Head and Callaway.

[34]De Giorgi et al. (2010) and Aghamolla and Thakor (2022) argue that peers of peers (based on partially overlapping peers) validates the exclusivity restriction since individual group shocks are being uncorrelated

firm C is strongly correlated with the corporate diversification of firm B (the regressor of peer action) due to the product market competition. For the exclusivity restriction, the corporate diversification of firm C is not directly correlated with the corporate diversification of firm A (the dependent variable) since firm C is not the peer of firm A.[35] In other words, firm C's corporate diversification behavior only affects firm A's corporate diversification behavior through its (peer) effect on firm B's corporate diversification behavior. This structure is guaranteed by the non-transitivity of TNIC. Figure 1 provides a graphical illustration of our identification strategy.

We estimate the following 2SLS regression. In the first stage, we instrument for the peer actions regressor $PeerDIV_{-i,t-1}$ by using $Peer'sPeerDIV_{-i,t-2}$, the measures of corporate diversification for peers of peers. $Peer'sPeerDIV_{-i,t-2}$ is defined as the group averages of corporate diversification measures in year $t-2$ for those firms who are peer to the focal firm's peers, but not peer to the focal firm. Our first stage estimation equation is as follows:

$$PeerDIV_{-i,t-1} = \kappa_0 + \kappa_1 Peer'sPeerDIV_{-i,t-2} + \kappa'\overline{X}_{-i,t-1} + \tau' X_{i,t-1} + \delta_i + \nu_t + \epsilon_{i,t}, \tag{3}$$

With $\widehat{PeerDIV}_{-i,t-1}$ (instrumented $PeerDIV_{-i,t-1}$), our second stage estimation equation is as follows:

$$DIV_{i,t} = \pi_0 + \pi_1 \widehat{PeerDIV}_{-i,t-1} + \pi'\overline{X}_{-i,t-1} + \theta' X_{i,t-1} + \delta_i + \nu_t + \epsilon_{i,t}. \tag{4}$$

Table 10 reports the results of IV-2SLS regressions. In columns (1) and (3), we estimate the first-stage regressions with a linear probability model where the dependent variable is either *Peer Multisegment(0/1)*$_{-i,t-1}$ or *Peer Number Divisions*$_{-i,t-1}$. We find that our instruments $Peer's\ Peer\ Multisegment(0/1)_{-i,t-2}$ and $Peer's\ Peer\ Number\ Divisions_{-i,t-2}$ satisfy the validity requirement since they are positive and statistically significant at the 1% level in explaining *Peer Multisegment(0/1)*$_{-i,t-1}$ and *Peer Number Divisions*$_{-i,t-1}$. The F statistics are also well above the rule-of-thumb value of 10, indicating that our results are

across peer groups, but peer performance is being correlated due to individual peer interactions.

[35] De Giorgi et al. (2010) argue that the exclusivity restriction even holds when firm C is allowed to directly interact with firm A as long as the strength of the interactions declines with distance in the network.

unlikely to be subject to weak-instrument bias.

[Insert Table 10 about here.]

In columns (2) and (4) of Table 10, we estimate the second-stage regressions where the dependent variables are $Multisegment(0/1)_{i,t}$ or $Number\ Divisions_{i,t}$. The indicators of peer actions ($Peer\ Multisegment(0/1)_{-i,t-1}$ or $Peer\ Number\ Divisions_{-i,t-1}$) are replaced by their instrumented values ($Peer\ Multi\widehat{segment}(0/1)_{-i,t-1}$ or $Peer\ Numb\widehat{er\ Di}visions_{-i,t-1}$) from the first-stage regressions. Results presented in columns (2) to (4) show that the coefficients associated with $Peer\ Multisegment(0/1)_{-i,t-1}$ and $Peer\ Number\ Divisions_{-i,t-1}$ are positive and statistically significant at the 1% level. The IV-2SLS approach supports our findings that firms adjust their scope as a response to the corporate diversification of their peers. In an unreported table, we instrument for each variable of interest ($Peer\ Multisegment(0/1)_{-i,t-1}$ or $Peer\ Number\ Divisions_{-i,t-1}$) by using two instrument variables (both $Peer's\ Peer\ Multisegment(0/1)_{-i,t-2}$ and $Peer's\ Peer\ \ Number\ Divisions_{-i,t-2}$) to conduct an over-identification test. The p-value of Hansen J statistic are all over 0.1. The Hansen over-identification test fails to reject the hypothesis that our instruments are exogenous.

To further warrant the exclusivity restriction, we re-estimate the IV-2SLS regressions with a stringent criterion for instrumental variables. Specifically, we further exclude industry peers (by three-digit SIC codes) and geographic peers (by the location of headquarter) of the focal firm when we construct $Peer'sPeerDIV_{-i,t-2}$. This additional restriction ensures that peers of peers' diversification decisions are unrelated to the focal firm from the industry and geographic dimensions. We report the results of this additional test in Table B.2 of the Appendix. Our results still hold to this more restrictive definition of peers of peers.

5.1.4. Placebo Tests Based on Pseudo Peers

We perform a placebo test to investigate whether peer effects still hold with a group of pseudo peers. This test serves two purposes. First, it tests whether the documented peer effects are caused by latent common factors. If some unobservable common factors, such as macro-economic environment, drive our results, the definition of peer group should not matter, and peer effects should hold for the pseudo peers (Grennan, 2019). Second, the placebo test further examines the competition channel. If product market competition is the channel through which peer effects operate, our results should not hold for pseudo peers that have less product market competition with the focal firm.

We use Propensity Score Matching (PSM) to identify pseudo peers that are comparable with TNIC peers in firm dimensions but without direct product market competition with the focal firm. Specifically, for each focal firm i in year t, we match each of its TNIC peers (treatment firms) with pseudo peers (control firms) from firms with scores below the median of the pairwise similarity scores distribution.[36] Treatment firms and control firms are matched by the following firm-level variables: $Tobin\,Q_{i,t-1}$, $Leverage_{i,t-1}$, $Cash\,Ratio_{i,t-1}$, $Redeployability_{i,t-1}$, $Org.\,Capital_{i,t-1}$, $R\&D_{i,t-1}$, $Ln(Firm\,Age)_{i,t-1}$, $Ln(Total\,Assets)_{i,t-1}$, and $Instability_{i,t-1}$. We run a logistic regression for each year and firm combination and require common support when implementing the matching process. We use the nearest neighbor method to choose the best match for each treatment firm. The matched firms are selected with replacement and the caliper is specified as 5%.

[Insert Table 11 about here.]

Table 11 displays the results of placebo tests based on pseudo peers. We find that peer effects in corporate diversification do not appear between the focal firm and its pseudo peers. In columns (1) and (2), the coefficients associated with peer diversification measures ($Peer\ Multisegment(0/1)_{-i,t-1}$ and $Peer\ Number\,Divisions_{-i,t-1}$) are statistically not different from zero in explaining the focal firm's diversification decisions ($Multisegment(0/1)_{i,t}$ and $Number\,Divisions_{i,t}$).

[36]Hoberg and Phillips provide datasets that contain the similarity scores for all possible pairs of firms in each year in its advanced database. Different from the standard TNIC database, this advanced database also includes firms that have similarity scores below 21.32%, which facilitates our placebo tests.

5.2. Robustness Tests

5.2.1. Exclude Merger and Acquisition Waves

The literature has referred to M&A waves to describe the phenomenon that mergers and acquisitions tend to cluster by time and industry (Mitchell and Mulherin, 1996; Harford, 2005). Firms could involve in diversified M&As to achieve corporate diversification. If there is some overlap between the M&A waves and our sample, M&A waves might drive the peer effects in our paper. However, several aspects set us apart from M&A waves. First, our results hold in a specification with an industry-by-year fixed effect (see Panel B of Table 9), which accounts for the influence of time-variant industry factors, including merger and acquisition waves. Second, the timing of peer effects in our paper differs from the timing of M&A waves. Most of the mergers and acquisitions concentrate on the "boom" period of the economy (Lambrecht, 2004; Rhodes-Kropf, Robinson, and Viswanathan, 2005; Bouwman, Fuller, and Nain, 2009). However, we show that peer effects in corporate diversification are more pronounced in times of high financial market frictions and high economic uncertainty (see Table 7).

[Insert Table 12 about here.]

We further empirically test whether M&A waves drive our results. Table 12 reports the results after excluding identified M&A waves from our baseline sample. M&A waves commonly last for two years and could start and end at any month in a year (see Appendix for the method to identify M&A waves). However, our dependent variable is measured annually. To align the frequency, we exclude focal firms from our sample if they fall between the starting and ending years of identified M&A waves. We essentially exclude the influence of M&A waves in a period of three years rather than two years, which further strengthens our test. The number of observations drops from 83,000 in the baseline analysis to 67,000 in this table, suggesting that 20% of observations might have been subject to the influence of M&A waves. In both columns (1) and (2), we find our results still hold after excluding the influence of M&A waves. These findings suggest that peer effects in corporate diversification are not driven by the M&A waves documented in the literature.

5.2.2. Alternative Measures of Corporate Diversification

In our previous analysis, we employ two main measures to define corporate diversification: a dummy variable for multi-division firms and the number of business divisions in which a firm operates. We further examine the robustness of our results with several alternative measures of corporate diversification. We change the definition of corporate diversification for both the firm-level dependent variable and the peer-level variable of interest.

The first group of alternative measures is the Herfindahl–Hirschman concentration index based on division assets (columns (1)) and division sales (columns (2)). Since higher values of the Herfindahl index indicate lower levels of diversification, we instead use the inverse measure (*1-HHI(Assets)* or *1-HHI(Sales)*) for ease of interpretation. The second group of alternative measures is total entropy based on division assets ($Focal\, EI(Assets)_{i,t}$ in columns (3)) or division sales ($Focal\, EI(Sales)_{i,t}$ in columns (4)). The total entropy equals zero for a single segment firm and it rises with the extent of corporate diversification. See Table A.1 for detailed definitions of these alternative measures of corporate diversification. In Table B.3, we re-estimate our baseline regression with alternative measures of corporate diversification and our results remain unchanged.

5.2.3. Diversification or Refocus

Our existing results support the existence of the peer effects of scope change. However, the results are silent on the direction of scope change. The focal firm could be subject to either peers' influence to increase (diversification) or decrease (refocus) their scope. Either direction could manifest as peer effects. In this subsection, we explore whether there exists the asymmetric peer effects of diversification and refocus.

Panel A of Table B.4 presents the results of testing responses to peers' decision of scope change, separating changes into increases (column (1)) and decreases (column (2)). We find that the peer effects concentrate on peers' decision to diversify rather than refocus. In column (1), we examine the peer effects of increasing firm scope. The coefficient of $\mathit{Fraction\,Diversification}_{\text{-}i,t\text{-}1}$ is positively significant at the 5% level. In column (2), we run a similar analysis to discern the peer effects of refocusing. The coefficient of the fraction of peers that have reduced its scope ($\mathit{Fraction\,Refocus}_{\text{-}i,t\text{-}1}$) is negative and insignificant.

After showing that the peer effects are mainly from the peer firms' decision to increase the firm scope, in Panel B Table B.4, we further discern which type of diversification change is more likely to be subject to peer effects.[37] We repeat the regression in Panel A but run separate regressions for single and multiple segment firms based on the focal firm's segment count in year $t-1$. We find the coefficient is only positively significant for firms that are single-segment firms (column (1)). This result suggests that the peer firms' decision to increase firm scope is more likely to influence single-segment firms.

5.2.4. Account for the Investment Effect and Overall Industry Attractiveness

Bustamante and Frésard (2021) show that firm's capital expenditure is influenced by their peers. It is possible that our results is simply another manifestation of the peer investment effect rather than the peer diversification effect. To rule out this possibility, we include both the firm- and peer-level capital expenditure scaled by lagged fixed asset (property, plant, and equipment) as control variables. Panel A of Table B.5 reports the regression of accounting for the peer investment effect. We find our results still maintain, which indicates our paper captures a different dimension of peer effect with Bustamante and Frésard (2021).

Campa and Kedia (2002) find that firms are more likely to diversify in industries dominated by a large number of conglomerates. Our findings are different from Campa and Kedia (2002) since our work captures interindustry variation driven by interdependencies in

[37] Focal firms' diversification could be classified into two types. The first one is the change from single-segment firms to multiple-segment firms. The alternative change is from multiple segment firms to firms with more segments.

corporate diversification policy, while they capture interindustry differences from exogenous industry shocks such as change in industry regulation or introduction of new technology. After controlling these exogenous industry shocks (with $industry * year$ fixed effect in Table 9), our findings of interindustry variation in diversification still exists. In this test, we explicitly control the overall attractiveness of a given industry to conglomerates. Following Campa and Kedia (2002), we add the ratio of diversified firms ($Diversified\,Ratio_{i,t-1}$) in the same industry as focal firm and the fraction of sales accounted for by diversified firms ($Sale\,Fraction_{i,t-1}$) in the same industry as focal firm into the regression. In Panel B of Table B.5, our results are qualitatively unchanged.

6. Conclusion

Prior research documents that firms tend to diversify at similar times. Regarding the cluster of corporate diversification, existing research tend to attribute it to firms' *passive* reactions to exogenous industry shocks. The role played by peers has been largely ignored in existing studies. Our study shows that firms *actively* respond to peer firms' corporate diversification, enriching the perspective to understand corporate diversification cluster.

In economic terms, if the proportion of peers that are diversified increases by one standard deviation, the probability of the firm engaging in diversification increases by 6%. To the best of our knowledge, our paper is the first to show that firms adjust their organizational structure as a strategic response to the corporate diversification decisions of their product market rivals. Therefore, we add to the rapidly growing literature on peer effects in corporate behaviors.

We conduct extensive tests to mitigate endogeneity issues arising from the selection issue and other broader endogeneity and reverse causality concerns. We employ explicit controls of firms' organizational capabilities, a quasi-natural experiment based on the outcomes of mergers and acquisitions, time-varying industry and regional fixed effects, placebo tests based on pseudo peers, and an instrument variable based on the non-transitivity characteristic of textual-network industry classification to show our results are robust to endogeneity concerns.

Product market competition is the channel underlying the peer effects. We find that the peer effects in corporate diversification become more prevalent when firms face stronger product market competition. This is consistent with the argument that corporate diversification confers to firms competitive advantages and their peers imitate them to avoid falling behind. We also demonstrate that peer effects in corporate diversification elevate the benefit of an internal capital market. we find that peer effects in corporate diversification are more prevalent when an internal capital market is particularly valuable, such as during times of high external capital market frictions and high macroeconomic uncertainty and for firms with less asset tangibility and in more innovative business.

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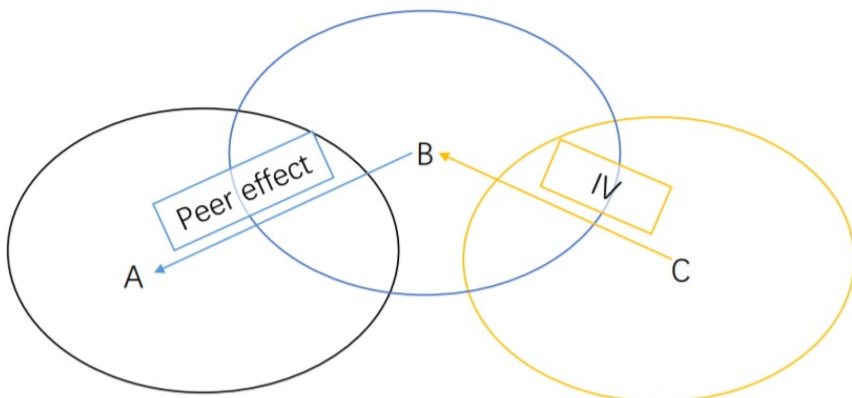

Fig. 1. **Graphical illustration of our identification strategy**
Consider three firms: A, B, and C. Firm A is the focal firm. Firm B is the peer of firm A since they offer similar products in the product market (based on TNIC). Firm C is the peer of firm B but not the peer of firm A based on the similarity of their product offerings. Firm C could serve as an instrument to estimate the peer effects of firm B on firm A.

Table 1: **Summary Statistics**

This table reports the summary statistics of the main variables used in our empirical analysis. The sample period is from 1988 to 2019. We exclude observations from firms in the heavily regulated utilities (SIC 4900 to 4999) and financial (SIC 6000 to 6999) sectors. The detailed variable descriptions are in Table A.1.

Variable	Obs	Mean	Std. Dev.	P25	P50	P75
Dependent variables:						
$Multisegment(0/1)_{i,t}$	90,834	0.191	0.393	0.000	0.000	0.000
$Number\ Divisions_{i,t}$	90,834	1.304	0.743	1.000	1.000	1.000
Variables of interest:						
$Peer\ Multisegment(0/1)_{-i,t-1}$	90,834	0.186	0.241	0.012	0.087	0.267
$Peer\ Number\ Divisions_{-i,t-1}$	90,834	1.303	0.470	1.013	1.111	1.400
Peer average characteristics:						
$Peer\ Tobin\ Q_{-i,t-1}$	90,834	2.346	1.180	1.476	1.973	3.016
$Peer\ Leverage_{-i,t-1}$	90,834	0.314	0.157	0.184	0.303	0.417
$Peer\ Cash\ Ratio_{-i,t-1}$	90,834	-0.032	0.178	-0.076	0.034	0.083
$Peer\ Redeoyloyability_{-i,t-1}$	90,834	0.379	0.094	0.334	0.397	0.436
$Peer\ Org.\ Capital_{-i,t-1}$	90,834	4.558	1.410	3.694	4.640	5.450
$Peer\ R\&D_{-i,t-1}$	90,834	0.077	0.097	0.000	0.025	0.137
$Peer\ Ln(Firm\ Age)_{-i,t-1}$	90,834	1.990	0.625	1.561	1.956	2.380
$Peer\ Ln(Total\ Assets)_{-i,t-1}$	90,834	5.214	1.377	4.311	5.029	6.116
$Peer\ Instability_{-i,t-1}$	90,834	0.093	0.067	0.05	0.079	0.121
Firm characteristics:						
$Tobin\ Q_{i,t-1}$	83,150	2.245	1.948	1.107	1.555	2.553
$Leverage_{i,t-1}$	83,150	0.323	0.239	0.119	0.273	0.488
$Cash\ Ratio_{i,t-1}$	83,150	-0.022	0.283	-0.034	0.067	0.120
$Redeployability_{i,t-1}$	83,150	0.384	0.127	0.347	0.414	0.458
$Org.\ Capital_{i,t-1}$	83,150	3.362	2.025	1.897	3.220	4.717
$R\&D_{i,t-1}$	83,150	0.067	0.121	0.000	0.003	0.084
$Ln(Firm\ Age)_{i,t-1}$	83,150	2.074	1.035	1.386	2.197	2.944
$Ln(Total\ Assets)_{i,t-1}$	83,150	5.073	2.086	3.575	4.943	6.478
$Instability_{i,t-1}$	83,150	0.094	0.102	0.029	0.069	0.129

Table 2: **Peer Effects in Corporate Diversification: Benchmark Results**

This table reports the benchmark results of regressing the focal firm's corporate diversification on peers' corporate diversification. In columns (1) to (3), *Multisegment(0/1)*$_{i,t}$ is a dummy variable that takes a value of one if the focal firm operates in more than one three-digit SIC business division in year t, and zero otherwise. In columns (4) to (6), *Number Divisions*$_{i,t}$ is the number of three-digit SIC business divisions that the focal firm operates in year t. Our main variables of interest, *Peer Multisegment(0/1)*$_{-i,t-1}$ and *Peer Number Divisions*$_{-i,t-1}$, are peer group averages (excluding firm i) of corporate diversification measures in year $t-1$. We control for a host of peer average and firm-specific characteristics. The coefficients of peer average characteristics are omitted for brevity. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Multisegment(0/1)$_{i,t}$			*Number Divisions*$_{i,t}$		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Peer Multisegment(0/1)$_{-i,t-1}$	0.043***	0.050***	0.045***			
	(3.84)	(4.49)	(3.98)			
Peer Number Divisions$_{-i,t-1}$				0.076***	0.085***	0.077***
				(5.41)	(6.05)	(5.36)
$Tobin\,Q_{i,t-1}$		0.001	0.001		0.003*	0.002
		(0.87)	(0.76)		(1.86)	(1.57)
$Leverage_{i,t-1}$		0.026*	0.027**		0.054**	0.056**
		(1.90)	(1.97)		(2.19)	(2.30)
$Cash\,Ratio_{i,t-1}$		-0.009	-0.009		-0.026**	-0.026**
		(-1.26)	(-1.33)		(-2.34)	(-2.41)
$Redeployability_{i,t-1}$		0.231***	0.237***		0.396***	0.399***
		(5.85)	(5.90)		(5.55)	(5.37)
$Org.\,Capital_{i,t-1}$		-0.005	-0.005		-0.009	-0.010
		(-1.02)	(-1.08)		(-0.86)	(-0.89)
$R\&D_{i,t-1}$		0.043**	0.040**		0.100***	0.097***
		(2.16)	(2.00)		(2.92)	(2.85)
$Ln(Firm\,Age)_{i,t-1}$		0.024***	0.024***		0.061***	0.061***
		(3.91)	(3.90)		(5.09)	(5.14)
$Ln(Total\,Assets)_{i,t-1}$		0.035***	0.035***		0.078***	0.076***
		(7.91)	(7.80)		(8.20)	(8.05)
$Instability_{i,t-1}$		-0.002	0.000		0.031	0.027
		(-0.16)	(0.01)		(1.22)	(0.97)
Peer average characteristics	Yes	No	Yes	Yes	No	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	90,834	83,150	83,150	90,834	83,150	83,150
R^2	0.735	0.743	0.743	0.759	0.767	0.767

Table 3: **Product Market Competition Channel**

This table tests the competition channel. We interact peer diversification measures with a group of proxies for product market competition. Consistent with Hoberg and Phillips (2016), we employ three proxies to measure product market competition. For all three proxies, a higher value indicates intense competition. The first proxy $\textit{Total Similarity}_{i,t}$ (columns (1) and (2)) is the sum of pairwise similarity scores between focal firm i and its TNIC peers in a given year. The second proxy $\textit{1-Market-level HHI(Sales)}_{i,t}$ (columns (3) and (4)) is the market-level Herfindahl-Hirshman concentration index based on firm sales. Since higher values of the Herfindahl index indicate lower levels of competition, we instead use the inverse measure for ease of interpretation. The third proxy $\textit{Fluidity}_{i,t}$ (columns (5) and (6)) is a proxy for strategic interactions between a firm and its rivals. It measures the instability of the focal firm's product market environment caused by peer firms' moves. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\textit{Multisegment(0/1)}_{i,t}$	$\textit{Number Divisions}_{i,t}$	$\textit{Multisegment(0/1)}_{i,t}$	$\textit{Number Divisions}_{i,t}$	$\textit{Multisegment(0/1)}_{i,t}$	$\textit{Number Divisions}_{i,t}$
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
$\textit{Peer Multisegment(0/1)}_{-i,t-1}$	0.032***		-0.003		-0.026	
	(2.73)		(-0.14)		(-1.26)	
$\textit{Peer Number Divisions}_{-i,t-1}$		0.051***		-0.024		-0.091***
		(3.48)		(-1.11)		(-3.25)
$\textit{Total Similarity}_{i,t}$	-0.016***	-0.225***				
	(-3.02)	(-4.20)				
$\textit{1-Market-level HHI(Sales)}_{i,t}$			-0.029**	-0.281***		
			(-2.25)	(-4.44)		
$\textit{Fluidity}_{i,t}$					0.001	-0.037***
					(0.79)	(-4.72)
$\textit{Total Similarity}_{i,t}\textit{*Peer Multisegment}(0/1)_{-i,t-1}$	0.092***					
	(3.92)					
$\textit{Total Similarity}_{i,t}\textit{*Peer Number Divisions}_{-i,t-1}$		0.177***				
		(3.94)				
$\textit{1-Market-level HHI(Sales)}_{i,t}\textit{*Peer Multisegment}(0/1)_{-i,t-1}$			0.095***			
			(2.78)			
$\textit{1-Market-level HHI(Sales)}_{i,t}\textit{*Peer Number Divisions}_{-i,t-1}$				0.203***		
				(4.18)		
$\textit{Fluidity}_{i,t}\textit{*Peer Multisegment}(0/1)_{-i,t-1}$					0.015***	
					(4.19)	
$\textit{Fluidity}_{i,t}\textit{*Peer Number Divisions}_{-i,t-1}$						0.034***
						(5.60)
Peer average characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	83,097	83,097	81,205	81,205	80,488	80,488
R^2	0.743	0.768	0.743	0.767	0.746	0.771

Table 4: **Learning channel**

This table tests the learning channel. We interact peer diversification measures with a group of proxies for learning. The first proxy $Profitability_{i,t}$ (columns (1) and (2)) is profitability margin. The second proxy (columns (3) and (4)) $Market\,Share_{i,t}$ is market share based on sales. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Multisegment(0/1)_{i,t}$	$Number\,Divisions_{i,t}$	$Multisegment(0/1)_{i,t}$	$Number\,Divisions_{i,t}$
VARIABLES	(1)	(2)	(3)	(4)
$Peer\ Multisegment(0/1)_{-i,t-1}$	0.045***		0.046***	
	(3.86)		(3.22)	
$Peer\ Number\,Divisions_{-i,t-1}$		0.079***		0.072***
		(5.13)		(4.12)
$Profitability_{i,t}$	0.004*	0.052		
	(1.82)	(1.60)		
$Market\,Share_{i,t}$			0.063***	0.127*
			(3.14)	(1.68)
$Profitability_{i,t}$*$Peer\ Multisegment(0/1)_{-i,t-1}$	-0.016			
	(-0.61)			
$Profitability_{i,t}$*$Peer\ Number\ Divisions_{-i,t-1}$		-0.048		
		(-1.50)		
$Market\,Share_{i,t}$*$Peer\ Multisegment(0/1)_{-i,t-1}$			-0.016	
			(-0.39)	
$Market\,Share_{i,t}$*$Peer\ Number\ Divisions_{-i,t-1}$				0.007
				(0.14)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	79,434	79,434	77,761	77,761
R^2	0.742	0.767	0.742	0.767

Table 5: **Managerial Channel**

This table tests the managerial channel. We explore the managerial channel by using the interaction term between peer diversification measures and corporate governance proxies. We use E-index (Bebchuk et al., 2009) and G-index (Gompers et al., 2003) to measure corporate governance. A higher value of both measures indicates worse corporate governance. The E-index (G-index) is constructed by adding one point if the firm has one provision within the 6 (24) provisions recorded in the IRRC database. Robust *t*-statistics clustered at the firm level are reported in brackets. The sample is from 1990 to 2006 given the availability of corporate governance measures. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Multisegment(0/1)$_{i,t}$	*Number Divisions*$_{i,t}$	*Multisegment(0/1)*$_{i,t}$	*Number Divisions*$_{i,t}$
VARIABLES	(1)	(2)	(3)	(4)
Peer Multisegment(0/1)$_{-i,t-1}$	0.008		-0.110	
	(0.12)		(-0.96)	
Peer Number Divisions$_{-i,t-1}$		0.018		-0.141
		(0.24)		(-1.17)
$E-index_{i,t}$	-0.005	-0.017		
	(-0.41)	(-0.37)		
$G-index_{i,t}$			-0.004	-0.037
			(-0.65)	(-1.54)
$E-index_{i,t}$*$Peer\ Multisegment(0/1)_{-i,t-1}$	0.009			
	(0.41)			
$E-index_{i,t}$*$Peer\ Number\ Divisions_{-i,t-1}$		0.020		
		(0.73)		
$G-index_{i,t}$*$Peer\ Multisegment(0/1)_{-i,t-1}$			0.015	
			(1.33)	
$G-index_{i,t}$*$Peer\ Number\ Divisions_{-i,t-1}$				0.021
				(1.58)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	6,708	6,708	6,708	6,708
R^2	0.824	0.836	0.825	0.836

Table 6: **Internal Capital Market as Benefit: Cash Flow Correlations**

This table reports the results of the change in capital reallocation prospects after following peers' decisions to diversify. The dependent variables are capital reallocation measures. Following Matvos et al. (2018), we construct three proxies to measure the capital reallocation prospects. For all three proxies, a smaller value indicates better capital allocation prospects. In Panel A, $Cashflow\ Correlation_{ft}$ measures the firm-level cash flow correlation across different divisions within the firm. In Panel B, $Investment\ Correlation_{ft}$ measures the correlation of investment opportunities. In Panel C, we construct the investment self-sufficiency variable ($Selfsufficiency_{ft}$) to measure the flexibility to use a firm's own capital to fund its own investment. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The Correlation of Cash Flow

	$Cashflow\ Correlation_{ft}$			
VARIABLES	(1)	(2)	(3)	(4)
Peer Multisegment(0/1) $_{-i,t-1}$	-0.041***	-0.010**		
	(-3.93)	(-2.39)		
Multisegment(0/1) $_{i,t}$		-0.768***		
		(-85.80)		
Peer Number Divisions $_{-i,t-1}$			-0.027***	-0.003
			(-4.66)	(-0.56)
Number Divisions $_{i,t}$				-0.310***
				(-29.53)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	78,299	78,299	78,299	78,299
R^2	0.758	0.961	0.758	0.870

Panel B: The Correlation of Investment Opportunities

	$Investment\ Correlation_{ft}$			
VARIABLES	(1)	(2)	(3)	(4)
Peer Multisegment(0/1) $_{-i,t-1}$	-0.035***	-0.011**		
	(-3.90)	(-2.55)		
Multisegment(0/1) $_{i,t}$		-0.569***		
		(-60.71)		
Peer Number Divisions $_{-i,t-1}$			-0.022***	-0.004
			(-4.48)	(-1.03)
Number Divisions $_{i,t}$				-0.231***
				(-26.92)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	78,299	78,299	78,299	78,299
R^2	0.767	0.935	0.767	0.861

Panel C: The Investment Self-sufficiency

	$Selfsufficiency_{ft}$			
VARIABLES	(1)	(2)	(3)	(4)
Peer Multisegment(0/1) $_{-i,t-1}$	-0.040***	-0.008**		
	(-3.81)	(-1.97)		
Multisegment(0/1) $_{i,t}$		-0.787***		
		(-93.88)		
Peer Number Divisions $_{-i,t-1}$			-0.027***	-0.002
			(-4.61)	(-0.46)
Number Divisions $_{i,t}$				-0.315***
				(-29.14)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	78,299	78,299	78,299	78,299
R^2	0.757	0.965	0.757	0.870

Table 7: **Internal Capital Market as Benefit: Time Series and Cross-sectional Heterogeneity**

This table substantiates the internal capital market as benefit of peer effect based on time series and cross-sectional heterogeneity, respectively. Panel A shows the results based on time series heterogeneity. In columns (1) and (2), following Matvos et al. (2018), our proxy of external capital market frictions $TED\,Spread_t$ is defined as the difference between three-month LIBOR and three month Treasury bill. We employ two proxies for economic uncertainty from Baker et al. (2016). For both proxies, a higher value indicates high macroeconomic uncertainty. In columns (3) and (4), *Economic Uncertianty$_t$* measures the overall economic policy uncertainty. It is a weighted index aggregating uncertainty information from news coverage, tax code expiration data, and economic forecaster disagreement. In columns (5) and (6), *Media-based Uncertianty$_t$* is solely based on the news coverage about policy-related economic uncertainty. Panel B shows the results based on cross-sectional heterogeneity. In columns (1) and (2), follow Lei et al. (2018), asset tangibility ($Tangibility_{i,t}$) is defined as 0.715×receivables (RECT)+0.547×inventories (INVT)+0.535×fixed capital (PPENT), deflated by book value of total assets (AT) net of cash (CHE). In columns (3) to (6), we use the dollar value ($Patent\,Value_{i,t}$) and number ($Patent\,Number_{i,t}$) of awarded patents to the focal firm by USPTO to measure how innovative the firm is. The market value of patent is provided by Kogan et al. (2017). Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Time Series Heterogeneity

	Multisegment(0/1)$_{i,t}$	*Number Divisions$_{i,t}$*	*Multisegment(0/1)$_{i,t}$*	*Number Divisions$_{i,t}$*	*Multisegment(0/1)$_{i,t}$*	*Number Divisions$_{i,t}$*
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Peer Multisegment(0/1)$_{-i,t-1}$	0.039**		-0.195**		-0.085	
	(2.55)		(-1.98)		(-1.24)	
Peer Number Divisions$_{-i,t-1}$		0.066***		-0.230**		-0.073
			(3.75)	(-2.06)		(-0.93)
$TED\,Spread_t$	0.006	-0.053*				
	(1.34)	(-1.74)				
Economic Uncertianty$_t$			-0.406***	-1.310***		
			(-4.67)	(-6.56)		
Media-based Uncertianty$_t$					-0.168***	-0.542***
					(-4.75)	(-6.71)
$TED\,Spread_t{*}Peer\,Multisegment(0/1)_{-i,t-1}$	0.037**					
	(2.20)					
$TED\,Spread_t{*}Peer\,Number\,Divisions_{-i,t-1}$		0.065***				
		(2.64)				
$Economic\,Uncertianty_t{*}Peer\,Multisegment(0/1)_{-i,t-1}$			0.052**			
			(2.41)			
$Economic\,Uncertianty_t{*}Peer\,Number\,Divisions_{-i,t-1}$				0.066***		
				(2.71)		
$Media-based\,Uncertianty_t{*}Peer\,Multisegment(0/1)_{-i,t-1}$					0.028*	
					(1.87)	
$Media-based\,Uncertianty_t{*}Peer\,Number\,Divisions_{-i,t-1}$						0.032*
						(1.88)
Peer average characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	83,150	83,150	83,150	83,150	83,150	83,150
R^2	0.741	0.764	0.743	0.767	0.743	0.767

Panel B: Cross-sectional Heterogeneity

	Multisegment(0/1)$_{i,t}$	*Number Divisions$_{i,t}$*	*Multisegment(0/1)$_{i,t}$*	*Number Divisions$_{i,t}$*	*Multisegment(0/1)$_{i,t}$*	*Number Divisions$_{i,t}$*
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Peer Multisegment(0/1)$_{-i,t-1}$	0.208***		0.027**		0.043***	
	(5.44)		(2.31)		(3.77)	
Peer Number Divisions$_{-i,t-1}$		0.251***		0.043***		0.067***
		(5.51)		(3.09)		(4.95)
$Tangibility_{i,t}$	0.028	0.460***				
	(1.31)	(4.33)				
$Patent\,Value_{i,t}$			0.001	-0.028**		
			(0.48)	(-2.33)		
$Patent\,Number_{i,t}$					0.000	-0.001*
					(0.96)	(-1.76)
$Tangibility_{i,t}$*$Peer\,Multisegment(0/1)_{-i,t-1}$	-0.380***					
	(-4.63)					
$Tangibility_{i,t}$*$Peer\,Number\,Divisions_{-i,t-1}$		-0.413***				
		(-4.22)				
$Patent\,Value_{i,t}$*$Peer\,Multisegment(0/1)_{-i,t-1}$			0.020***			
			(3.02)			
$Patent\,Value_{i,t}$*$Peer\,Number\,Divisions_{-i,t-1}$				0.029***		
				(3.07)		
$Patent\,Number_{i,t}$*$Peer\,Multisegment(0/1)_{-i,t-1}$					0.000*	
					(1.67)	
$Patent\,Number_{i,t}$*$Peer\,Number\,Divisions_{-i,t-1}$						0.001**
						(2.46)
Peer average characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	83,105	83,105	83,112	83,112	83,112	83,112
R^2	0.744	0.768	0.743	0.768	0.743	0.768

Table 8: **Endogeneity: A Quasi-natural Experiment**

This table reports the results of a quasi-natural experiment leveraging on the different status (complete or incomplete) and outcomes (diversified or undiversified) of mergers and acquisitions. The dependent variable, $\textit{Diversified Ratio}_{i,t}$, is the ratio of the number of complete and diversified M&As to the total number of M&As conducted by focal firm in year t. Our variable of interest is the interaction term between $\textit{Peer MA Complete}_{-i,t-1}$ and $\textit{Peer MA Diversified}_{-i,t-1}$, which measures MA deal attributes of the focal firm's closest peer with the highest TNIC similarity score. $\textit{Peer MA Complete}_{-i,t-1}$ is a dummy variable that takes a value of one (zero) if the focal firm's closest peer has a complete (an incomplete) M&A in year $t-1$. If the deal is classified as "complete" or 'unconditional" as recorded in SDC, we group it as complete mergers and acquisitions, otherwise as incomplete ones. $\textit{Peer MA Diversified}_{-i,t-1}$ is a dummy variable that takes a value of one (zero) if the deal is diversified (undiversified). Diversified deals are M&As with the acquirer and the target from two different three-digit SIC business divisions. To exclude the influence of other confounding factors, we require focal firm's closest peer only has one type of MA deals out of four permutations between complete and incomplete and diversified and undiversified deals. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) $\textit{Diversified Ratio}_{i,t}$	(2) $\textit{Diversified Ratio}_{i,t}$	(3) $\textit{Diversified Ratio}_{i,t}$
$\textit{Peer MA Complete}_{-i,t-1} * \textit{Peer MA Diversified}_{-i,t-1}$	0.029**	0.030**	0.031**
	(2.26)	(2.34)	(2.37)
$\textit{Peer MA Complete}_{-i,t-1}$	-0.009	-0.009	-0.010
	(-1.02)	(-1.06)	(-1.21)
$\textit{Peer MA Diversified}_{-i,t-1}$	-0.023**	-0.024**	-0.024**
	(-2.00)	(-2.12)	(-2.12)
$Tobin\, Q_{i,t-1}$		0.002	0.001
		(0.62)	(0.29)
$Leverage_{i,t-1}$		-0.138***	-0.142***
		(-5.39)	(-5.49)
$Cash\, Ratio_{i,t-1}$		0.048**	0.045**
		(2.34)	(2.19)
$Redeployability_{i,t-1}$		-0.014	0.002
		(-0.29)	(0.04)
$Org.\, Capital_{i,t-1}$		-0.002	-0.002
		(-0.37)	(-0.39)
$R\&D_{i,t-1}$		-0.039	-0.039
		(-0.56)	(-0.55)
$Ln(Firm\, Age)_{i,t-1}$		-0.003	-0.003
		(-0.34)	(-0.36)
$Ln(Total\, Assets)_{i,t-1}$		0.000	0.000
		(0.05)	(0.00)
$Instability_{i,t-1}$		0.000	0.016
		(0.01)	(0.38)
Peer characteristics	Yes	No	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes
Observations	22,440	22,319	22,319
R^2	0.374	0.378	0.378

Table 9: **Endogeneity: Peer Effects in Diversification, Controlling Unobservable Common Shocks**

This table reports the robustness of results to common shocks. In Panel A, we re-estimate the benchmark regressions by controlling for external capital market frictions. Following Matvos et al. (2018), our proxy of external capital market frictions $TED\,Spread_t$ is defined as the difference between three-month LIBOR and three month Treasury bill. In Panel B, we saturate our main specification with a wide variety of time-varying industry and regional fixed effects, controlling for any correlated information arrival or common shock that influences the corporate diversification decisions of firms within a given industry or geographic group. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: TED

	$Multisegment(0/1)_{i,t}$	$Number\,Divisions_{i,t}$
VARIABLES	(1)	(2)
$TED\,Spread_t$	0.014***	0.035***
	(3.62)	(4.86)
$Peer\ Multisegment(0/1)_{-i,t-1}$	0.061***	
	(5.22)	
$Peer\ Number\,Divisions_{-i,t-1}$		0.105***
		(6.84)
Peer average characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Firm effects	Yes	Yes
Observations	83,150	83,150
R^2	0.741	0.764

Panel B: Industry-by-year and Region-by-year Fixed Effects

	$Multisegment(0/1)_{i,t}$		$Number\,Divisions_{i,t}$	
VARIABLES	(1)	(2)	(3)	(4)
$Peer\ Multisegment(0/1)_{-i,t-1}$	0.107***	0.305***		
	(6.47)	(18.16)		
$Peer\ Number\,Divisions_{-i,t-1}$			0.197***	0.387***
			(8.98)	(15.92)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Firm effects	No	No	No	No
Industry*Year effects	Yes	No	Yes	No
State*Year effects	No	Yes	No	Yes
Observations	83,150	81,623	83,150	81,623
R^2	0.326	0.227	0.374	0.250

Table 10: **Endogeneity: Peer Effects in Diversification, IV-2SLS Specification**

This table reports the results of IV-2SLS regression. In the first stage regression in column (1) (column (3)), we instrument the peer actions regressor *Peer Multisegment(0/1)*$_{-i,t-1}$ (*Peer Number Divisions*$_{-i,t-1}$) by using the measures of corporate diversification for peers of peers $Peer's\, Peer\, Multisegment(0/1)_{-i,t-2}$ ($Peer's\, Peer\, Number\, Divisions_{-i,t-2}$), which are defined as the group averages of corporate diversification measures in year $t-2$ for those firms who are peer to the focal firm's peers, but not peer to the focal firm. In the second stage, $Peer\, Multi\widehat{segment}(0/1)_{-i,t-1}$ and $Peer\, Number\, \widehat{Divisions}_{-i,t-1}$ are the instrumented values from the first stage. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Peer Multisegment(0/1)$_{-i,t-1}$	*Multisegment(0/1)*$_{i,t}$	*Peer Number Divisions*$_{-i,t-1}$	*Number Divisions*$_{i,t}$
VARIABLES	(1) First stage	(2) Second stage	(3) First stage	(4) Second stage
$Peer's\, Peer\, Multisegment(0/1)_{-i,t-2}$	0.149***			
	(11.01)			
$Peer\, Multi\widehat{segment}(0/1)_{-i,t-1}$		0.281***		
		(2.71)		
$Peer's\, Peer\, Number\, Divisions_{-i,t-2}$			0.170***	
			(11.42)	
$Peer\, Number\, \widehat{Divisions}_{-i,t-1}$				0.246***
				(2.80)
$Tobin\, Q_{i,t-1}$	0.000	0.001	0.000	0.002*
	(0.70)	(0.82)	(0.17)	(1.82)
$Leverage_{i,t-1}$	-0.006	0.030**	-0.019	0.063***
	(-1.04)	(2.33)	(-1.53)	(2.75)
$Cash\, Ratio_{i,t-1}$	-0.003	-0.009	-0.005	-0.025**
	(-0.90)	(-1.32)	(-0.83)	(-2.42)
$Redeployability_{i,t-1}$	-0.029**	0.243***	-0.051**	0.408***
	(-2.44)	(6.52)	(-2.12)	(5.93)
$Org.\, Capital_{i,t-1}$	-0.003	-0.005	-0.002	-0.009
	(-1.52)	(-1.01)	(-0.72)	(-0.90)
$R\&D_{i,t-1}$	-0.007	0.041**	-0.012	0.099***
	(-0.85)	(2.19)	(-0.80)	(3.14)
$Ln(Firm\, Age)_{i,t-1}$	0.002	0.023***	0.010**	0.058***
	(0.94)	(4.01)	(2.10)	(5.24)
$Ln(Total\, Assets)_{i,t-1}$	0.001	0.035***	0.003	0.076***
	(0.45)	(8.34)	(0.82)	(8.67)
$Instability_{i,t-1}$	-0.002	0.001	-0.029	0.036
	(-0.26)	(0.11)	(-1.50)	(1.33)
First-stage F test statistics	121.24		130.50	
Peer average characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	82,455	80,625	82,455	80,625

Table 11: **Endogeneity: Peer Effects in Diversification, Pseudo Peer Groups**

This table reports the results of the placebo tests based on pseudo peers. To construct a pseudo peers group for each focal firm i in year t, we use propensity score matching (PSM) to identify matched firms that are comparable with TNIC peers in firm dimensions but without direct product market competition with the focal firm. Specifically, for each focal firm i in year t, we match each of its TNIC peers (treatment firms) with pseudo peers (control firms) from firms with scores below the median of the pairwise similarity scores distribution. Treatment firms and control firms are matched by the following variables: $Tobin\,Q_{i,t-1}$, $Leverage_{i,t-1}$, $Cash\,Ratio_{i,t-1}$, $Redeployability_{i,t-1}$, $Org.Capital_{i,t-1}$, $R\&D_{i,t-1}$, $Ln(Firm\,Age)_{i,t-1}$, $Ln(Total\,Assets)_{i,t-1}$, and $Instability_{i,t-1}$. We run a logistic regression for each year and firm combination to construct pseudo peers, then re-run the baseline analysis using those pseudo peers. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	$Multisegment(0/1)_{i,t}$	$Number\,Divisions_{i,t}$
VARIABLES	(1)	(2)
$Peer\ Multisegment(0/1)_{-i,t-1}$	-0.009	
	(-1.05)	
$Peer\ Number\,Divisions_{-i,t-1}$		-0.003
		(-0.31)
Peer average characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes
Observations	72,205	72,205
R^2	0.751	0.774

Table 12: **Robustness: Peer Effects in Diversification, Exclude Merger and Acquisition Waves**

This table reports the results after excluding merger and acquisition waves. We use the identified M&A waves in Harford (2005) for 1988 to 2000 and extend the wave sample to 2019 based on the same methodology. Specifically, we exclude observations from our sample if they fall between the starting and ending years of identified M&A waves. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\textit{Multisegment(0/1)}_{i,t}$	$\textit{Number Divisions}_{i,t}$
VARIABLES	(1)	(2)
$\textit{Peer Multisegment(0/1)}_{-i,t-1}$	0.038***	
	(3.17)	
$\textit{Peer Number Divisions}_{-i,t-1}$		0.072***
		(4.89)
Peer average characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes
Observations	67,246	67,246
R^2	0.760	0.784

Appendix

Table A.1: **Definitions of Variables**

Variable	Definition
Dependent Variables	
Multisegment(0/1)$_{i,t}$	A dummy variable that takes a value of one if the focal firm operates in more than one three-digit SIC business division in year t, and zero otherwise. We use the primary SIC code (Compustat item **SICS1**) to define the industry of a business division.
Number Divisions$_{i,t}$	The number of distinct three-digit SIC business divisions that the focal firm operates in year t.
1 - Focal HHI(Assets)$_{i,t}$	This variable is defined as one minus the Herfindahl-Hirshman Index of division assets of the focal firm in year t. The Herfindahl-Hirshman Index of division assets is defined as $HHI(Assets)_{it} = \sum_{j \in Jit} \left(\frac{A_{jit}}{\sum_{j \in Jit} A_{jit}} \right)^2$, where A_{jit} represents the assets of division j of firm i in year t and Jit is the set of divisions of firm i in year t.
1 - Focal HHI(Sales)$_{i,t}$	This variable is defined as one minus the Herfindahl-Hirshman Index of division sales of the focal firm in year t. The Herfindahl-Hirshman Index of division sales is defined as $HHI(Sales)_{it} = \sum_{j \in Jit} \left(\frac{S_{jit}}{\sum_{j \in Jit} S_{jit}} \right)^2$, where S_{jit} represents the sales of division j of firm i in year t and Jit is the set of divisions of firm i in year t.
Focal $EI(Assets)_{i,t}$	This variable is defined as the total entropy of division assets of the focal firm in year t. The total entropy of division assets is defined as $EI(Assets)_{it} = \sum_{j \in Jit} \left(\frac{A_{jit}}{\sum_{j \in Jit} A_{jit}} \times \ln(\frac{\sum_{j \in Jit} A_{jit}}{A_{jit}}) \right)$, where A_{jit} represents the assets of division j of firm i in year t and Jit is the set of divisions of firm i in year t.
Focal $EI(Sales)_{i,t}$	This variable is defined as the total entropy of division sales of the focal firm in year t. The total entropy of division sales is defined as $EI(Sales)_{it} = \sum_{j \in Jit} \left(\frac{S_{jit}}{\sum_{j \in Jit} S_{jit}} \times \ln(\frac{\sum_{j \in Jit} S_{jit}}{S_{jit}}) \right)$, where S_{jit} represents the sales of division j of firm i in year t and Jit is the set of divisions of firm i in year t.
Diversification Dummy$_{i,t}$	This dummy is set as one if the focal firm has increased its number of segments from year $t-1$ to t, otherwise zero.
Refocus Dummy$_{i,t}$	This dummy is set as one if the focal firm has reduced its number of segments from year $t-1$ to t, otherwise zero.
Peer-level Variables	
Peer Multisegment(0/1)$_{-i,t-1}$	This variable is defined as the mean of the multi-segment dummy among firm i's TNIC peers (excluding firm i) in year $t-1$. The multi-segment dummy takes a value of one if a peer firm operates in more than one three-digit SIC business division in year $t-1$, and zero otherwise.
Peer Number Divisions$_{-i,t-1}$	The mean number of three-digit SIC business divisions that peer firms (excluding firm i) operate in year $t-1$.
1 - Peer HHI(Assets)$_{-i,t-1}$	This variable is defined as the means of one minus the Herfindahl-Hirshman Index of division assets of the peer firms (excluding firm i) in year $t-1$. The definition of the Herfindahl-Hirshman Index of division assets sees above.
1 - Peer HHI(Sales)$_{-i,t-1}$	This variable is defined as the means of one minus the Herfindahl-Hirshman Index of division sales of the peer firms (excluding firm i) in year $t-1$. The definition of the Herfindahl-Hirshman Index of division sales sees above.
Peer EI(Assets)$_{-i,t-1}$	This variable is defined as the mean of the total entropy of division assets of the peer firms (excluding firm i) in year $t-1$. The definition of the total entropy of division assets sees above.
Peer EI(Sales)$_{-i,t-1}$	This variable is defined as the mean of the total entropy of division sales of the peer firms (excluding firm i) in year $t-1$. The definition of the total entropy of division sales sees above.
Fraction Diversification$_{-i,t-1}$	This variable is defined as the number of firms that have increased their number of segments from year $t-2$ to $t-1$ divided by the number of focal firm i's peers.
Fraction Refocus$_{-i,t-1}$	This variable is defined as the number of firms that have reduced their number of segments from year $t-2$ to $t-1$ divided by the number of focal firm i's peers.

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Table A.1 – continued from previous page

Variable	Definition
Peer Tobin Q$_{-i,t-1}$	The mean of Tobin's Q of peer firms (excluding firm i) in year $t-1$. Tobin's Q is defined as the market value of assets divided by the book value of assets. Our construction of both market value of assets and book value of assets is the same as that in Matvos et al. (2018). Winsorized at the 1% and 99% level.
Peer Leverage$_{-i,t-1}$	The mean of book leverage of peer firms (excluding firm i) in year $t-1$. Book leverage is defined as the book value of debt divided by the market value of assets. Our construction of both book value of debt and market value of assets is the same as that in Matvos et al. (2018). Winsorized at the 1% and 99% level.
Peer Cash Ratio$_{-i,t-1}$	This variable is the mean of Cash-flow to assets ratio of peer firms (excluding firm i) in year $t-1$. The Cash-flow to assets ratio is defined as $Cash\,Ratio = \frac{\mathbf{cshpri}*\mathbf{epspx}+\mathbf{dp}}{\mathbf{at}}$, where **cshpri** represents common shares used to calculate earnings per share, **epspx** represents earnings per share excluding extraordinary items, **dp** represents depreciation and amortization, and **at** represents book total assets. Winsorized at the 1% and 99% level.
$Peer\ Redeoyloyability_{-i,t-1}$	This variable is the mean of firm-level asset redeployability of peer firms (excluding firm i) in year $t-1$. Following Kim and Kung (2016), asset redeployability measures the useability of firm assets across industry.
$Peer\ Org.\,Capital_{-i,t-1}$	This variable is the mean of organization capital of peer firms (excluding firm i) in year $t-1$. Following Peters and Taylor (2017), organization capital accumulates a fraction of past SG&A spending using the perpetual inventory method.
$Peer\ R\&D_{-i,t-1}$	This variable is the mean of R&D expenditure of peer firms (excluding firm i) in year $t-1$. R&D expenditure is the R&D expenditure divided by total assets.
Peer Ln(Firm Age)$_{-i,t-1}$	The mean of the natural logarithm of firm age of peer firms (excluding firm i) in year $t-1$. The firm age is defined as the current year minus the first year in which the firm appeared in Compustat.
Peer Ln(Total Assets)$_{-i,t-1}$	The mean of the natural logarithm of total assets (Compustat item **at**) of peer firms (excluding firm i) in year $t-1$. Winsorized at the 1% and 99% level.
$Peer\ Instability_{-i,t-1}$	This variable is the mean of industry instability of peer firms (excluding firm i) in year $t-1$. Following Hoberg and Phillips (2018), industry instability the absolute value of the natural logarithm of the number of firms in the industry t in which firm i belongs to, scaled by the number of firms in the same industry in year $t-1$.
$Peer\ Investment_{-i,t-1}$	This variable is the mean of investment of peer firms (excluding firm i) in year $t-1$. following Bustamante and Frésard (2021), investment is defined as capital expenditure scaled by lagged fixed asset (property, plant, and equipment).
Firm-level Variables	
$Tobin\,Q_{i,t-1}$	Tobin's Q of the focal firm in year $t-1$. Tobin's Q is defined as the market value of assets divided by the book value of assets. Our construction of both market value of assets and book value of assets is the same as that in Matvos et al. (2018). Winsorized at the 1% and 99% level.
$Cash\,Ratio_{i,t-1}$	This variable is the Cash-flow to assets ratio of the focal firm in year $t-1$. The Cash-flow to assets ratio is defined as $Cash\,Ratio = \frac{\mathbf{cshpri}*\mathbf{epspx}+\mathbf{dp}}{\mathbf{at}}$, where **cshpri** represents common shares used to calculate earnings per share, **epspx** represents earnings per share excluding extraordinary items, **dp** represents depreciation and amortization, and **at** represents book total assets. Winsorized at the 1% and 99% level.
$Leverage_{i,t-1}$	The book leverage of the focal firm in year $t-1$. Book leverage is defined as the book value of debt divided by the market value of assets. Our construction of both book value of debt and market value of assets is the same as that in Matvos et al. (2018). Winsorized at the 1% and 99% level.
$Redeployability_{i,t-1}$	This variable measures the firm-level useability of firm assets across industry. Following Kim and Kung (2016), this measure is based on the economic link reflected in the 1997 Bereau of Economic Analysis (BEA) capital flow table. The asset redeployability is from `https://www.chicagofed.org/people/k/kim-hyunseob`. We extend it for the period from 2016 to 2019 to cover our sample.
$Org.\,Capital_{i,t-1}$	Following Peters and Taylor (2017), this variable accumulates a fraction of past SG&A spending using the perpetual inventory method. At least part of SG&A measures the investment in employment training, advertising, and spending on distribution systems, which are essential components of organization capital. The organization capital is collected from Wharton Research Data Services (WRDS).

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Table A.1 – continued from previous page

Variable	Definition
$R\&D_{i,t-1}$	This variable is the R&D expenditure divided by total assets of firm i in year $t-1$.
$Ln(Firm\ Age)_{i,t-1}$	The natural logarithm of firm age of the focal firm in year $t-1$. The firm age is defined as the current year minus the first year in which the firm appeared in Compustat.
$Ln(Total\ Assets)_{i,t-1}$	The natural logarithm of total assets (Compustat item **at**) for the focal firm in year $t-1$. Winsorized at the 1% and 99% level.
$Instability_{i,t-1}$	Following Hoberg and Phillips (2018), this variable is the absolute value of the natural logarithm of the number of firms in the industry in which firm i belongs to in year t, scaled by the number of firms in the same industry in year $t-1$.
$Investment_{i,t-1}$	To account for investment effect, following Bustamante and Frésard (2021), investment is defined as capital expenditure scaled by lagged fixed asset (property, plant, and equipment).
$Diversified\ Ratio_{i,t-1}$	This variable is the ratio of diversified firms in firm i's industry in year $t-1$ as in Campa and Kedia (2002).
$Sale\ Fraction_{i,t-1}$	This variable is the fraction of sales accounted for by diversified firms in firm i's industry in year $t-1$ as in Campa and Kedia (2002).
$Total\ Similarity_{i,t}$	This variable captures the intensity of product market competition that the focal firm is facing in year t. Following Hoberg and Phillips (2016), we measure the competition pressure a firm faces from the product market by the total similarity score of this firm. The total similarity score is defined as the sum of the pairwise similarities between the given firm and all other firms in the sample in the given year. The total similarity score data is collected from `https://hobergphillips.tuck.dartmouth.edu/`.
1-Market-level HHI(Sales)$_{i,t}$	This variable measures the market power of firm i in year t based on firm-level sales. Following Hoberg and Phillips (2016), we measure the market power of a firm as one minus the Herfindahl-Hirshman Index of firm-level sales of the peer firms in year t. The data is collected from `https://hobergphillips.tuck.dartmouth.edu/`.
$Fluidity_{i,t}$	This variable measures the instability of the focal firm's product market environment caused by peer firms' moves, which captures the strategic interactions between the focal firm and peer firms. Follow Hoberg and Phillips (2016), the data is collected from `https://hobergphillips.tuck.dartmouth.edu/`.
$Profitability_{i,t}$	This variable is defined as the EBITDA divided by total assets of the focal firm i in year t.
$Market\ Share_{i,t}$	This variable is defined as the focal firm's firm-level sales as a fraction of all sales of the focal firm's TNIC peers (including firm i) in year t.
$E-index_{i,t}$	This variable measures the corporate governance of the firm. The E-index is constructed by adding one point if the firm has one provision within the 6 provisions recorded in the IRRC database and used in Bebchuk et al. (2009). The E-index is collected from `http://www.law.harvard.edu/faculty/bebchuk/data.shtml`.
$G-index_{i,t}$	This variable measures the corporate governance of the firm. The G-index is constructed by adding one point if the firm has one provision within the 24 provisions recorded in the IRRC database and used in Gompers et al. (2003). The G-index is collected from `https://faculty.som.yale.edu/andrewmetrick/data/`.
$Cashflow\ Correlation_{ft}$	First, we calculate the time-invariant correlation of the cash flow across three-digit SIC industries. Cash flow is defined as common shares used to calculate earnings per share basic (Compustat item **cshpri**) times earnings per share (basic) - excluding extraordinary items (Compustat item **epspx**) plus depreciation and amortization (Compustat item **dp**) divided by total assets (Compustat item **at**). We only include the single-segment firms to construct the average cash flow series for each three-digit SIC industry. The pairwise correlation is calculated based on the constructed average cash flow and is calculated over the entirety of the sample. Second, we use the segment assets as weights to calculate the firm-level correlation of cash flow. The formula is as follows: $\frac{\sum_{hj\in[\Omega]^2_{ft}}(A_{hft}+A_{jft})\times CF\text{ Correlation }_{hj}}{\sum_{hj\in[\Omega]^2_{ft}}(A_{hft}+A_{jft})}$, where A_{hft} is the asset of business division h of firm f in year t. A_{jft} is the asset of business division j of firm f in year t. CF Correlation $_{hj}$ is the correlation of the three-digit SIC industry-level cash flow between industry h and j. $[\Omega]^2_{ft}$ is the set that contains all pairs permutations of business division hj of firm f in year t. For example, if firm i has three business divisions: A, B, and C, then $[\Omega_{ft}]^2 = \{A,B;A,C;B,C\}$.

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Variable	Definition
$Investment\ Correlation_{ft}$	First, we calculate the time-invariant correlation of the investment needs across three-digit SIC industries. The investment is defined as capital expenditures/total assets (Compustat items **capx** and **at**). We only include the single-segment firms to construct the average investment series for each three-digit SIC industry. The pairwise correlation is calculated based on the constructed average investment series and is calculated over the entirety of the sample. Second, we use the segment assets as weights to calculate the firm-level correlation of investment needs. The formula is as follows: $\frac{\sum_{hj\in[\Omega]^2_{ft}}(A_{hft}+A_{jft})\times \text{ Investment Correlation }_{hj}}{\sum_{hj\in[\Omega]^2_{ft}}(A_{hft}+A_{jft})}$. The definitions of corresponding variables are similar to $Cashflow\ Correlation_{ft}$.
$Selfsufficiency_{ft}$	First, we calculate the time-invariant correlation of the excess cash flow (cash flow minus investment) across three-digit SIC industries. Cash flow is defined as common shares used to calculate earnings per share basic (Compustat item **cshpri**) times earnings per share (basic) - excluding extraordinary items (Compustat item **epspx**) plus depreciation and amortization (Compustat item **dp**) divided by total assets (Compustat item **at**). Investment is defined as capital expenditures (Compustat items **capx**) divided by total assets (Compustat items **at**). We only include the single-segment firms to construct the average excess cash flow series for each three-digit SIC industry. The pairwise correlation is calculated based on the constructed average excess cash flow and is calculated over the entirety of the sample. Second, we use the segment assets as weights to calculate the firm-level correlation of excess cash flow. The formula is as follows: $\frac{\sum_{hj\in[\Omega]^2_{ft}}(A_{hft}+A_{jft})\times CF-Selfsufficiency \text{ Correlation }_{hj}}{\sum_{hj\in[\Omega]^2_{ft}}(A_{hft}+A_{jft})}$. The definitions of corresponding variables are similar to $Cashflow\ Correlation_{ft}$.
$Tangibility_{i,t}$	Follow Lei et al. (2018), asset tangibility is defined as 0.715×receivables (RECT)+0.547×inventories (INVT)+0.535×fixed capital (PPENT), deflated by book value of total assets (AT) net of cash (CHE).
$Patent\ Value_{i,t}$	It is defined as the market value of awarded patents by USPTO to the focal firm. The market value of patent is provided by Kogan et al. (2017).
$Patent\ Number_{i,t}$	It is defined as the number of awarded patents by USPTO to the focal firm.
Other Variables	
$TED\ Spread_t$	TED spread is defined as the difference between three month LIBOR based on US dollars and three month Treasury bill. We take the mean of the daily TED spread as TED spread in year t.
Economic Uncertianty$_t$	This variable measures the overall economic policy uncertainty. It is a weighted uncertainty index from the following areas: news coverage about policy-related economic uncertainty, tax code expiration data, and economic forecaster disagreement. We use the year-end value of the original monthly series from the last year. The data is from `https://www.policyuncertainty.com/`.
Media-based Uncertianty$_t$	This variable is solely based on the news coverage about policy-related economic uncertainty. We use the year-end value of the original monthly series from the last year. The data is from `https://www.policyuncertainty.com/`.

Internet Appendix

(Not for Journal Publication)

Peer Effects in Corporate Diversification

The Correlation of Cash Flow and Investment

Consistent with Matvos et al. (2018), we construct three proxies to measure the capital reallocation prospects. The first proxy $Cashflow\ Correlation_{ft}$ measures the firm-level cash flow correlation across different divisions within the firm. Capital reallocation would be more efficient if cash flow across divisions is less correlated. Consider a division with good investment opportunities but insufficient funds. If the cash flow among divisions is highly correlated, the cash flow of other divisions is low as well, providing little opportunity for reallocation. The second measure is based on the correlation of investment opportunities ($Investment\ Correlation_{ft}$). Capital reallocation would be productive if the cost of reducing investment in one business division is smaller than the benefit of adding investment in another division. A lower investment correlation will enable this capital reallocation process (Matvos et al., 2018). Our third measure of capital reallocation prospects ($Selfsufficiency_{ft}$) is based on the correlation in the excess cash flow (cash flow − investment). This investment self-sufficiency variable measures the flexibility of a firm to use its own capital to fund its investment.

We employ a two-step procedure to construct a firm-level proxy for cash flow correlation across divisions ($Cashflow\ Correlation_{ft}$). First, we calculate the pairwise correlation of average cash flow across different three-digit SIC industries. The pairwise correlation between industries h and j, $Cashflow\ Correlation_{hj}$, is based on the constructed average cash flow of industries h and j and calculated over the entirety of the sample. This provides us with a long time series to more accurately calculate the correlation across industries, which is consistent with Matvos et al. (2018). Second, we use the segment assets as weights to calculate the firm-level cash flow correlation. The formula is as follows:

$$Firm\ Cashflow\ Correlation_{ft} = \frac{\sum_{hj\in[\Omega]^2_{ft}} (A_{hft} + A_{jft}) \times Cashflow\ Correlation_{hj}}{\sum_{hj\in[\Omega]^2_{ft}} (A_{hft} + A_{jft})}, \quad (5)$$

where A_{hft} is the asset of business division h of firm f in year t. A_{jft} is the asset of business division j of firm f in year t. $[\Omega]^2_{ft}$ is the set that contains all pairs permutations of business divisions of firm f in year t. For example, if firm i has three business divisions: A, B, and C, then $[\Omega_{ft}]^2 = \{A, B; A, C; B, C\}$. We follow a similar procedure to calculate the correlation in investment opportunities ($Investment\ Correlation_{ft}$) and cash flow self-sufficiency ($Selfsufficiency_{ft}$). The detailed definitions of these three measures see Table A.1 of the Appendix.

The Method to Identify M&A Waves

Our mergers and acquisition data are from SDC. All mergers or tender offer bids from 1988 to 2019 are included in the initial sample. Following Harford (2005) and Garfinkel and Hankins (2011), we impose the following data requirement: (1) the deal value, as reported in SDC, was at least 50 million US dollars; (2) the targets are from the US; (3) the acquirer owned less than 50% of the target before the announcement and obtains 100% of the target share after the transaction; (4) the deal is classified as successful or unconditional; (5) multiple bids for a single target within two months are regarded as a single bid; (6) we assign the target and the acquirer into one of Fama-French 48 industry groups based on their SIC codes. If the target and the acquirer are in the same Fama-French 48 industries, the bid will count once. If the target is in industry X and the acquirer is in industry Y, the bid will count for industry X and industry Y separately.

We use the identified M&A waves in Harford (2005) for 1988 to 2000 and extend the wave sample to 2019 based on the same methodology. The methodology to identify a potential wave in one specific industry is as follows: for each Fama-French 48 industry in each decade, the 24 months of the highest concentration of mergers and acquisitions is first identified as the potential merger wave. The actual concentration ratio of this potential wave is defined as the total number of mergers and acquisitions in the 24 months divided by the total number of mergers and acquisitions in the decade. To test the statistical significance of each potential merger wave, we compare the actual concentration ratio with the simulated distribution of the concentration ratio of 1000 simulations. If the actual concentration ratio exceeds the 95th percentile of the simulated distribution of concentration ratio, the potential wave is considered a true wave. In each simulation, we assume the total number of mergers and acquisitions in each industry will equally occur in any month within a decade. Following Harford (2005) and Duchin and Schmidt (2013), we allow each industry to have only one wave per decade. We define the decade as 2000 to 2009 and 2010 to 2019. Besides, each wave at least should contain ten mergers and acquisition events.

Table B.1: **Correlation Table**

This table reports the correlation of the main variables used in our empirical analysis.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1) $Multisegment(0/1)_{i,t}$	1.00																					
(2) $Number\,Divisions_{i,t}$	0.84	1.00																				
(3) $Peer\ Multisegment(0/1)_{-i,t-1}$	0.34	0.35	1.00																			
(4) $Peer\ Number\,Divisions_{-i,t-1}$	0.34	0.37	0.89	1.00																		
(5) $Peer\ Tobin\,Q_{-i,t-1}$	-0.21	-0.19	-0.38	-0.34	1.00																	
(6) $Peer\ Leverage_{-i,t-1}$	0.21	0.20	0.40	0.37	-0.73	1.00																
(7) $Peer\ Cash\,Ratio_{-i,t-1}$	0.19	0.18	0.33	0.29	-0.58	0.39	1.00															
(8) $Peer\ Redeoyloyability_{-i,t-1}$	0.03	0.02	0.05	0.05	0.07	0.00	-0.01	1.00														
(9) $Peer\,Org.\,Capital_{-i,t-1}$	0.14	0.15	0.26	0.27	-0.17	0.19	0.23	0.04	1.00													
(10) $Peer\ R\&D_{-i,t-1}$	-0.23	-0.21	-0.40	-0.35	0.67	-0.61	-0.81	-0.01	-0.18	1.00												
(11) $Peer\ Ln(Firm\,Age)_{-i,t-1}$	0.24	0.23	0.46	0.42	-0.42	0.33	0.36	-0.03	0.46	-0.32	1.00											
(12) $Peer\ Ln(Total\,Assets)_{-i,t-1}$	0.24	0.25	0.45	0.44	-0.36	0.37	0.40	-0.12	0.74	-0.40	0.54	1.00										
(13) $Peer\ Instability_{-i,t-1}$	0.03	0.04	0.07	0.08	-0.01	0.06	0.07	0.16	-0.08	-0.13	-0.16	-0.06	1.00									
(14) $Tobin\,Q_{i,t-1}$	-0.17	-0.15	-0.20	-0.18	0.47	-0.37	-0.33	0.03	-0.11	0.37	-0.24	-0.21	-0.00	1.00								
(15) $Leverage_{i,t-1}$	0.20	0.19	0.24	0.22	-0.42	0.50	0.29	0.01	0.13	-0.39	0.21	0.25	0.04	-0.52	1.00							
(16) $Cash\,Ratio_{i,t-1}$	0.14	0.13	0.19	0.17	-0.34	0.26	0.51	0.01	0.16	-0.46	0.21	0.23	0.03	-0.34	0.08	1.00						
(17) $Redeployability_{i,t-1}$	0.09	0.08	0.04	0.04	0.04	0.01	0.00	0.69	0.02	-0.02	-0.03	-0.08	0.12	0.02	0.02	0.02	1.00					
(18) $Org.\,Capital_{i,t-1}$	0.25	0.26	0.21	0.20	-0.23	0.20	0.31	0.05	0.55	-0.28	0.37	0.52	-0.04	-0.19	0.22	0.32	0.07	1.00				
(19) $R\&D_{i,t-1}$	-0.20	-0.18	-0.29	-0.25	0.48	-0.44	-0.58	-0.01	-0.12	0.72	-0.23	-0.29	-0.09	0.41	-0.31	-0.64	-0.02	-0.30	1.00			
(20) $Ln(Firm\ Age)_{i,t-1}$	0.27	0.26	0.22	0.20	-0.22	0.16	0.20	-0.02	0.26	-0.17	0.46	0.30	-0.10	-0.22	0.20	0.21	0.00	0.44	-0.16	1.00		
(21) $Ln(Total\ Assets)_{i,t-1}$	0.27	0.30	0.26	0.26	-0.22	0.24	0.23	-0.07	0.51	-0.24	0.34	0.61	-0.05	-0.22	0.22	0.36	-0.04	0.76	-0.29	0.37	1.00	
(22) $Instability_{i,t-1}$	0.04	0.05	0.05	0.05	-0.02	0.05	0.05	0.10	-0.05	-0.10	-0.09	-0.03	0.48	-0.01	0.04	0.03	0.12	-0.03	-0.08	-0.09	-0.03	1.00

Table B.2: **Robustness Check of IV Regression: Excluding Industry and Geography Peers**

This table reports the robustness check for IV-2SLS regression. To further warrant the exclusion restriction, we re-estimate the IV-2SLS regressions with a stringent criterion to define peers of peers. Specifically, we further exclude industry peers (by three-digit SIC codes) and geographic peers (by the location of headquarters) of the focal firm when we construct $Peer'sPeerDIV_{-i,t-2}$. This additional restriction ensures that peers of peers' diversification decisions are unrelated to the focal firm from the industry and geographic dimensions. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	Peer Multisegment(0/1)$_{-i,t-1}$	*Multisegment(0/1)*$_{i,t}$	*Peer Number Divisions*$_{-i,t-1}$	*Number Divisions*$_{i,t}$
	(1)	(2)	(3)	(4)
VARIABLES	First stage	Second stage	First stage	Second stage
$Peer's\,Peer\,Multisegment(0/1)_{-i,t-2}$	0.114***			
	(9.66)			
$Peer\,\widehat{Multisegment}(0/1)_{-i,t-1}$		0.196*		
		(1.65)		
$Peer's\,Peer\,Number\,Divisions_{-i,t-2}$			0.128***	
			(10.01)	
$Peer\,\widehat{Number\,Divisions}_{-i,t-1}$				0.210**
				(2.09)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	82,144	80,302	82,144	80,302

Table B.3: **Robustness: Alternative Measures of Diversification**

This table reports the results of employing alternative measures of corporate diversification. The first group of alternative measures is the Herfindahl–Hirschman concentration index based on division assets (*1 - Focal HHI(Assets)*$_{i,t}$ in columns (1)) and division sales (*1 - Focal HHI(Sales)*$_{i,t}$ in columns (2)). Since higher values of the Herfindahl index indicate lower levels of diversification, we instead use the inverse measure for ease of interpretation. The second group of alternative measures is total entropy based on division assets ($Focal\ EI(Assets)_{i,t}$ in columns (3)) or division sales ($Focal\ EI(Sales)_{i,t}$ in columns (4)). The total entropy equals zero for a single segment firm and it rises with the extent of corporate diversification. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

	1 - Focal HHI(Assets)$_{i,t}$	*1 - Focal HHI(Sales)*$_{i,t}$	$Focal\ EI(Assets)_{i,t}$	$Focal\ EI(Sales)_{i,t}$
VARIABLES	(1)	(2)	(3)	(4)
1 - Peer HHI(Assets)$_{-i,t-1}$	0.065***			
	(5.58)			
1 - Peer HHI(Sales)$_{-i,t-1}$		0.039***		
		(3.08)		
Peer EI(Assets)$_{-i,t-1}$			0.073***	
			(6.06)	
Peer EI(Sales)$_{-i,t-1}$				0.056***
				(4.74)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	83,150	83,150	83,150	83,150
R^2	0.746	0.711	0.767	0.772

Table B.4: **Robustness: Asymmetric Peer Effects of Diversification or Refocus**

This table reports the asymmetric peer effects of diversification and refocus. Panel A presents the results of testing responses to peers' decisions to change the scope, separating changes into diversify (column (1)) and refocus (column (2)). Following Grennan (2019), we use the direction of the segment count change as the criteria to explore asymmetric peer effects. In column (1) ((2)), the dependent variable, $\textit{Diversification Dummy}_{i,t}$ ($\textit{Refocus Dummy}_{i,t}$), is defined as one if the focal firms increase (decrease) its segment number from year $t-1$ to year t, otherwise zero. The variables of interest, $\textit{Fraction Diversification}_{\textit{-i,t-1}}$ ($\textit{Fraction Refocus}_{\textit{-i,t-1}}$), is the fraction of focal firms' peers that has increased (decreased) its number of segments from $t-2$ to year $t-1$. In Panel B, we are further interested to discern which type of corporate diversification is more likely to be subject to peer effects. We repeat the regression in Panel A but run separate regressions for single (column (1)) and multiple segment (columns (2) and (3)) firms based on the focal firm's segment count in year $t-1$. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Diversification or Refocus

	$\textit{Diversification Dummy}_{i,t}$	$\textit{Refocus Dummy}_{i,t}$
VARIABLES	(1)	(2)
$\textit{Fraction Diversification}_{\textit{-i,t-1}}$	0.044**	
	(2.19)	
$\textit{Fraction Refocus}_{\textit{-i,t-1}}$		-0.002
		(-0.11)
Peer average characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes
Observations	75,529	75,529
R^2	0.180	0.168

Panel B: Subsample Analysis Based on Segment Count in Year $t-1$

	=1 segment $\textit{Diversification Dummy}_{i,t}$	>1 segment $\textit{Diversification Dummy}_{i,t}$	>1 segment $\textit{Refocus Dummy}_{i,t}$
VARIABLES	(1)	(2)	(3)
$\textit{Fraction Diversification}_{\textit{-i,t-1}}$	0.055**	0.010	
	(2.31)	(0.26)	
$\textit{Fraction Refocus}_{\textit{-i,t-1}}$			-0.021
			(-0.42)
Peer average characteristics	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes
Observations	60,882	14,647	14,647
R^2	0.334	0.167	0.277

Table B.5: **Robustness: Account for the Investment Effect and Overall Attractiveness of A Given Industry**

This table reports the results of controlling for the investment effect and overall attractiveness of a given industry to conglomerates. In Panel A, to rule out the investment effect, we further include both the firm- and peer-level capital expenditure scaled by lagged fixed asset (property, plant, and equipment) as control variables. In Panel B, we explicitly include two variables that proxy for the overall attractiveness of a given industry to conglomerates into the baseline regression. Following Campa and Kedia (2002), we add the ratio of diversified firms ($Diversified\,Ratio_{i,t-1}$) in the same industry as focal firm and the fraction of sales accounted for by diversified firms ($Sale\,Fraction_{i,t-1}$) in the same industry as focal firm into the regression. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Account for the Investment Effect

	Multisegment(0/1)$_{i,t}$	$Number\,Divisions_{i,t}$
VARIABLES	(1)	(2)
Peer Multisegment(0/1)$_{-i,t-1}$	0.047***	
	(3.95)	
$Peer\,Number\,Divisions_{-i,t-1}$		0.078***
		(5.19)
$Investment_{i,t-1}$	-0.000	0.002
	(-0.16)	(0.42)
$Peer\,Investment_{-i,t-1}$	-0.015	-0.048
	(-0.76)	(-1.37)
Peer average characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes
Observations	74,573	74,573
R^2	0.747	0.771

Panel A: Account for Overall Attractiveness of A Given Industry

	Multisegment(0/1)$_{i,t}$	$Number\,Divisions_{i,t}$
VARIABLES	(1)	(2)
Peer Multisegment(0/1)$_{-i,t-1}$	0.038***	
	(3.386)	
$Peer\,Number\,Divisions_{-i,t-1}$		0.071***
		(4.872)
$Diversified\,Ratio_{i,t-1}$	0.320***	0.720***
	(5.691)	(4.634)
$Sale\,Fraction_{i,t-1}$	0.029	-0.013
	(1.456)	(-0.306)
Peer average characteristics	Yes	Yes
Firm characteristics	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes
Observations	83,150	83,150
R^2	0.703	0.731

Table B.6: **Robustness Check to Show Internal Capital Market as Benefit: Cash Flow Correlations with 2SLS**

This table further shows the benefits of following peers to diversify. We run 2SLS regressions to identify the change in capital reallocation prospects after following peers' decisions to diversify. Panel A (B) uses *Peer Multisegment(0/1)$_{\text{-}i,t\text{-}1}$* (*Peer Number Divisions$_{\text{-}i,t\text{-}1}$*) as the instrument for three proxies for capital reallocation prospects. Following Matvos et al. (2018), we construct three proxies to measure the capital reallocation prospects. For all three proxies, a smaller value indicates better capital allocation prospects. The first measure is based on the correlation of cash flow ($Cashflow\ Correlation_{ft}$). The second proxy $Investment\ Correlation_{ft}$ measures the correlation of investment opportunities. Third, we construct the investment self-sufficiency variable ($Selfsufficiency_{ft}$) to measure the flexibility to use a firm's own capital to fund its own investment. Robust t-statistics clustered at the firm level are reported in brackets. *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *Peer Multisegment(0/1)$_{\text{-}i,t\text{-}1}$* as the instrument

	Multisegment(0/1)$_{i,t}$	$Cashflow\ Correlation_{ft}$	$Investment\ Correlation_{ft}$	$Selfsufficiency_{ft}$
	(1)	(2)	(3)	(4)
VARIABLES	First stage	Second stage	Second stage	Second stage
Peer Multisegment(0/1)$_{\text{-}i,t\text{-}1}$	0.041***			
	(3.78)			
Fitted Mutlisegment		-1.001***	-0.843***	-0.977***
		(-10.06)	(-7.83)	(-10.22)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	78,333	76,534	76,534	76,534
R^2	0.022	0.766	0.563	0.810

Panel B: *Peer Number Divisions$_{\text{-}i,t\text{-}1}$* as the instrument

	Number Divisions$_{i,t}$	$Cashflow\ Correlation_{ft}$	$Investment\ Correlation_{ft}$	$Selfsufficiency_{ft}$
	(1)	(2)	(3)	(4)
VARIABLES	First stage	Second stage	Second stage	Second stage
Peer Number Divisions$_{\text{-}i,t\text{-}1}$	0.077***			
	(5.40)			
Fitted segmentcount		-0.345***	-0.286***	-0.343***
		(-5.62)	(-5.32)	(-5.67)
Peer average characteristics	Yes	Yes	Yes	Yes
Firm characteristics	Yes	Yes	Yes	Yes
Year/Firm effects	Yes/Yes	Yes/Yes	Yes/Yes	Yes/Yes
Observations	78,333	76,534	76,534	76,534
R^2	0.031	0.471	0.393	0.475