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Shopping for Information? Diversification and the Network of Industries

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We propose and test a view of corporate diversification as a strategy that exploits internal information markets, by bringing together information that is scattered across the economy. First, we construct an interindustry network using input-output data, to proxy for the economy's information structure. Second, we introduce a new measure of conglomerate informational advantage, named "excess centrality," which captures how much more central conglomerates are relative to specialized firms operating in the same industries. We find that high-excess-centrality conglomerates have greater value, and produce more and better patents. Consistent with the internal-information-markets view, we also show that excess centrality has a greater effect in industries covered by fewer analysts and in industries where soft information is important.

Keywords: corporate diversification; networks; innovation; input-output tables
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1. Introduction

Much finance literature on conglomerates emphasizes the role of internal capital markets. According to this view, one of the key benefits of corporate diversification is the ability to reallocate capital across segments more efficiently than if the segments were separate entities (Gertner et al. 1994, Khanna and Tice 2002, Hubbard and Palia 2002). Also in this spirit, recent work proposes the existence of internal labor markets, where conglomerates allow for a more efficient cross-industry reallocation of workers (Tate and Yang 2014). The advantages of internal capital and labor markets can plausibly be driven by information flowing more easily inside firms than across firms, which would minimize frictions such as adverse selection and moral hazard. Furthermore, there are other instances where within-firm information transmission may prove economically useful. For example, the innovation literature also emphasizes the role of the diversified firm as an information broker.[1]

Our paper espouses and generalizes the above views about conglomerates, and we argue that the bright sides of corporate diversification are driven by *internal information markets*, by which we mean that diversified firms have an easier access to much business-relevant information in the economy, relative to specialized firms. For example, a General Electric quote from 2002 mentions that "(...) [the] plastics business [is used] as a guide to wider economic performance in the future, because plastics use pervades industry (...)" (Laidlaw and Lawsky 2002). Being better informed about the overall state of the economy may thus be one dimension of conglomerate informational advantage. Also, previous literature has identified settings where within-conglomerate information sharing can generate value: Massa and Rehman (2008) find that mutual funds operated by financial conglomerates post superior performance, arguably because of information shared by the banking division.

To test the internal-information-market hypothesis we use the network of industries as a proxy for the economy's information structure. In this approach, information is assumed to flow across the economy via interindustry customer–supplier links, which is consistent with much existing research.[2] If information

[1] This is illustrated in the following quote from Hargadon (2003, p. 13): "By working in a range of different industries or markets, firms are in a better position to see when the people, ideas, and objects of one world can be combined in new ways to solve the problems of another."

[2] McEvily and Marcus (2005) argue that knowledge sharing between customers and suppliers leads to the acquisition of competitive capabilities; Powell et al. (1996) find evidence that interfirm networks influence biotech innovation productivity; Gulati (1999) claims that information percolating through interfirm networks is used to select appropriate alliance partners; and several papers find evidence that customer–supplier relationships are an important determinant for the adoption of technologies and management practices: Mol and Birkinshaw (2009) show that the adoption of new management practices is influenced by customer–supplier relationships; Potter et al. (2003) present evidence that

flows through customer–supplier relationships, then depending on the overall interindustry network structure, some industries will possess more information than others. In particular, one would expect more central industries in the network to be rich in information, since they are exposed to many nonredundant sources.

We extend the concept of centrality to conglomerates, by assuming that these firms create informational shortcuts across industries. We thus construct our key explanatory variable, *excess centrality*, defined as the log-difference between the network centrality of a conglomerate and the centrality of a similar portfolio of specialized firms. We argue that excess centrality is a proxy for the amount of information available to a diversified firm, in excess of information already available to specialized companies operating in the same industries as the conglomerate. Excess centrality is high whenever the conglomerate creates a meaningful shortcut in the industry network. This occurs if segments are distant from one another, or if the conglomerate simultaneously combines core industries (information rich) and peripheral industries (information poor).

To test our main hypothesis, we investigate whether excess centrality explains conglomerate excess value, a standard measure in corporate-diversification research (Berger and Ofek 1995, Villalonga 2004, Santalo and Becerra 2008, Custódio 2014). Excess value is defined as the log-difference between the Tobin's Q of the conglomerate and the Tobin's Q of a comparable portfolio of specialized firms. It is important to emphasize that our analysis does not simply focus on whether conglomerates are present in more or less central industries, since such an approach could lead to spurious results. For example, low information in peripheral industries could lead to entry/exit barriers, which affect equilibrium competition, profitability, and hence value. To control for unobserved industry heterogeneity, we thus compare excess centrality and excess value, which are defined as relative to a benchmark portfolio of specialized firms operating in the same industries.

Using a large sample of conglomerates from 1990 to 2011, we find that excess centrality is positively related to excess value, even after controlling for other conglomerate characteristics: a one-standard-deviation increase in excess centrality leads to about 6%–9% greater value for the average conglomerate. Our results hold even if we add conglomerate fixed effects to our regressions: conglomerates that increase their excess centrality over time experience an economically and statistically significant increase in market value.

U.S.-based firms transmitted "best practices" to UK suppliers; and Robertson et al. (1998) find that firms selecting a computer-aided production management technology draw on their interfirm connections to make a choice.

We acknowledge that the association between excess centrality and excess value could be endogenous. Therefore, we perform a series of additional tests, where we find results consistent with our arguments: First, we develop an econometric specification where excess centrality is only driven by the overall structure of the network, which because of its macro nature can be considered as exogenous to an individual firm. Second, we add a proxy for coinsurance effects to our main specification, since coinsurance effects could be an alternative explanation for our findings. For example, if high-excess-centrality conglomerates had a lower likelihood of default/distress, this could affect worker incentives and thus firm performance.[3] Third, we construct various alternative specifications of network variables and excess value.[4] Fourth, we show that our results are not driven by industry concentration, systematic risk,[5] or just by conglomerates that participate in highly central industries.[6]

Our main analysis shows an association between a conglomerate's network position and its value. We interpret this as evidence of an informational-advantage effect, but a concern is that we never actually measure information directly. To make the case that excess centrality is indeed a proxy for information, we analyze how excess centrality affects the production of innovation. If excess centrality truly is a measure of having access to information from disparate sources, then this should allow firms to innovate more and to come up with better innovations. Such an association between information and innovation is consistent with literature on management and organizations (Burt 2004, 2005).

Following the above hypothesis, we test whether high-excess-centrality conglomerates produce more patents and receive more patent citations than low-excess-centrality conglomerates, as compared with portfolios of specialized firms. We find that a one-standard-deviation increase in excess centrality corresponds to an increase in innovation productivity in the order of 10%–20% for the average

[3] If the firm is more unlikely to collapse, workers know that they can be easily reallocated to other divisions, and thus are appropriately incentivized. See, for example, Manso (2011), Acharya et al. (2013), Bradley et al. (2014), and Custódio et al. (2014).

[4] Results are very similar, both economically and statistically, if we change our definition of excess value using a goodwill adjustment (Custódio 2014), if we exclude industries with fewer than five companies (Berger and Ofek 1995), if we use coarser industry definitions, and under various alternative ways of computing links and network variables. These results are presented in §5.3 and in the online appendix.

[5] Ahern (2013) argues that there are associations between network position and systematic risk.

[6] These results are presented in §5.3 and in the online appendix.

conglomerate, consistent with the order of magnitude found in the excess-value analysis. Furthermore, high-excess-centrality conglomerates produce more original and more general patents, using the measures in Hall et al. (2001).

Consistent with our internal-information-markets view, we also find that patents produced by conglomerates in a given industry tend to cite patents related to the other industries where the conglomerate also operates, compared to the patent-citing behavior of specialized firms.

We complement our study of how excess centrality affects excess value with three additional analyses. First, we show that excess centrality has a more pronounced effect on excess value in industries where soft information is important (using the proxy of Santalo and Becerra 2008), which is consistent with the notion that excess centrality is a proxy for the quantity of soft information available to conglomerates. Second, we show that the excess centrality effect is weaker for conglomerates that participate in industries with high analyst coverage. This is consistent with informational advantages being less present whenever much industry-level information becomes public via intense external scrutiny. Third, we construct a simple and more intuitive variable as an alternative to excess centrality that presumably also captures a conglomerate's informational advantage, namely, a dummy indicating whether the firm simultaneously participates in core and peripheral segments. We find that conglomerates with core-periphery combinations have a higher excess value.

Our paper uncovers an important economic role for the diversified firm, namely, acting as an information aggregator. This expands on previous literature on diversification,[7] which emphasized mostly the effects of focus and technological relatedness. Our empirical results suggest a trade-off between increasing the firm's information set and losing focus and attention, since as in previous diversification studies we find that excess value decreases with both the number of segments and how unrelated they are.

Our paper also contributes to a growing literature on the economic role of information diffusion across networks and the returns to network position (e.g., Granovetter 1973; Burt 1992, 2004).[8] Two recent examples of such an approach in finance are Hochberg et al. (2007) and Ozsoylev et al. (2014).[9]

The remainder of this paper is organized as follows. Section 2 develops the conceptual framework of an industry-networks approach to conglomerate informational advantage. Section 3 develops our identification strategy and shows how excess centrality is associated with higher value. Section 4 studies how a conglomerate's network position affects its ability to innovate. Section 5 contains robustness checks. Section 6 concludes. The appendix contains variable definitions and further details about our data set construction and assumptions. Additional robustness checks mentioned in the text are included in the online appendix, available as supplemental material at http://dx.doi.org/10.1287/mnsc.2014.2060.

2. A Measure of Conglomerate Informational Advantage

In this section we first propose a measure for a conglomerate's informational advantage that is based on its network position, which we term *excess centrality*. We then describe the empirical implementation using an industry network based on input-output (I-O) flows.

2.1. The Excess-Centrality Concept

As argued in the introduction, we assume that customer–supplier connections allow for the transmission of economically relevant information about various topics: the state of the macroeconomy, managerial practices, technologies, etc. Taking this argument one step further, one would expect information to diffuse throughout the overall interindustry (trade) network. Therefore, network position should correlate with the amount of information available at the industry level. A standard network statistic that captures the notion of one single industry receiving a higher quantity of information is *closeness centrality*, a measure of how far a node is from any other node in the network. Formally, it is defined as

$$CC_i = \left(\frac{\sum_{j \neq i} l_{ij}}{N-1} \right)^{-1}, \tag{1}$$

where N is the number of nodes in the network and l_{ij} is the length of the shortest path between nodes i and j.[10]

Consider now that the economy comprises not only specialized firms but also conglomerates, which in a network sense are collections of disparate nodes (i.e., industries). Further assume that conglomerates

[7] See, among others, Lang and Stulz (1994), Berger and Ofek (1995), Maksimovic and Phillips (2002), Graham et al. (2002), Schoar (2002), and Villalonga (2004).

[8] See Burt (2005) for a textbook coverage of this topic.

[9] Hochberg et al. (2007) analyze how the network position of venture capitalists affects their investments' performance. Ozsoylev et al. (2014) infer the structure of investor social networks from patterns of trade. In both these papers centrality is shown to be positively associated with economic performance.

[10] For a reference about standard network statistics, see, for example, Jackson (2008).

share information internally without frictions.[11] If this information is valuable for business decisions, then conglomerates will possess an *informational advantage* with respect to specialized firms. The informational advantage will be higher whenever conglomerates combine information that single-segment firms have difficult access to. For example, when conglomerates simultaneously participate in core and peripheral industries, the conglomerate can leverage the information "collected" in the core segment to enhance the operations of the peripheral segment, which given its network position is informationally constrained. More generally, one can extend the concept of closeness centrality to conglomerates. Denoting the set of participated industries of a conglomerate by $\mathcal{I}$, we define conglomerate centrality as

$$CC_{\text{cong}} := \left(\frac{\sum_{j \notin \mathcal{I}} \min_{i \in \mathcal{I}} \{l_{ij}\}}{N} \right)^{-1}. \tag{2}$$

Equation (2) is very similar to the centrality expression from Equation (1), except (i) distances to industries where the conglomerate participates are set to zero; and (ii) we define the distance of the conglomerate to industry j by considering the segment i that is closest to j, following the assumption that information flows without friction within the conglomerate (hence the min operator). Therefore, the informational advantage of a conglomerate present in industry i, relative to specialized firms in the same industry, can be proxied by the difference

$$CC_{\text{cong}} - CC_i, \tag{3}$$

where, as before, CC_i is the closeness centrality of industry i. Integrating over all of the conglomerate's segments and normalizing, the conglomerate's total (or average) informational advantage is then proxied by what we term *excess centrality* (EC):

$$\text{EC} := \log\left(\frac{CC_{\text{cong}}}{\sum_{i \in \mathcal{I}} w_i CC_i} \right) \approx \frac{CC_{\text{cong}} - \sum_{i \in \mathcal{I}} w_i CC_i}{\sum_{i \in \mathcal{I}} w_i CC_i}, \tag{4}$$

where w_i is the asset weight for industry i' segment.

The construction of our main variable of interest, excess centrality, implies some assumptions that may or may not hold in data. For example, it is possible that a minimum level of participation in an industry is required to access its information. We defer these discussions to later sections, but we do wish to make clear that we address many of these concerns (as the one exemplified), and that our results are robust across specifications.

One might also wonder why we focus on closeness centrality, instead of other popular measures, such as degree or eigenvector centrality. Equation (2) shows that closeness centrality at the conglomerate level is the average distance between the conglomerate and any other industry. Thus we only have to construct one single network, and take the shortest path between any node and the closest conglomerate segment. This is not as straightforward with other centrality measures. For example, to implement a similar approach with eigenvector centrality, we would have to construct a specific network and compute the associated centrality measure *for each firm-year* (collapsing the industries where the conglomerate operates), which would be computationally cumbersome.[12] This argument notwithstanding, later in the paper we employ an approach that allows for tractable use of alternative centrality measures (see §5.1).

2.2. Empirical Implementation

Now we turn to the empirical implementation of excess centrality. First we describe how we construct the industry network. Second we show how to compute excess centrality in such a network.

Our data comes from two sources: (i) input-output tables for the construction of the interindustry network; and (ii) data from COMPUSTAT, COMPUSTAT Segments, and the Center for Research in Security Prices (CRSP), which is used to compute firm-level variables. As our main network, we use the benchmark input-output table for the year 1997 at the detailed level. The industry and commodity flows are aggregated into 470 industries, a similar level of aggregation as the four-digit Standard Industrial Classification (SIC) code. We use such industry classification, rather than more conventional classifications such as SIC or North American Industry Classification System (NAICS), because the input-output tables reporting the flow of goods and services between industries come from the Bureau of Economic Analysis (BEA). Detailed input-output tables are prepared by the BEA every five years and are released with substantial lag.

For the main analysis we decided to use the 1997 industry network, for which the release date—i.e., the time at which this information becomes public—corresponds roughly to the midpoint of our data period. We use a constant network, rather than a network that changes every five years with the release of new input-output tables, because at the detailed level industries are reclassified over time, making comparisons difficult. To illustrate the importance of reclassification at the detailed level, we note that there are 409 industries in 2002, versus 470 in 1997. In a

[11] We provide a more detailed explanation of the key assumptions in light of the existing theories of the firm in §A.4 of the appendix.

[12] This problem is further compounded by the fact that we explore alternative specifications of the interindustry network: different levels of aggregation, different years, excluding industries, etc.

recent paper on industry links and merger propagation, Ahern and Harford (2014) also base their main specifications using only the 1997 input-output data, claiming as we do that reclassification makes comparisons difficult. However, the results presented in the main section are robust to choosing input-output tables of different years. In §5.3 we replicate the main analysis with the 2002 network, and we find very similar results. In §3.2.2, we also employ input-output tables that change every year, but have a stable industry classification for the period 1998–2011. The drawbacks of working with these tables are that the sample period is shorter, and the level of aggregation is much coarser than when we use the detailed industry classification (61 industries versus 470 industries).

The first step in constructing our network variables is to create a square matrix of interindustry flows. We employ flows from the I-O-use tables, which report a dollar flow from commodity i to industry j, and where each industry has an assigned primary commodity; we denote this flow by f_{ij}. It is not obvious how to map these flows to a proxy for information transmission across industries, which is the relevant construct for our research question. Our main specification employs flows f_{ij} directly, which implicitly assumes that the amount of information transmitted is proportional to dollar flows. Notwithstanding our main link-size specification, we show that our results are robust to using various other reasonable specifications, an issue we discuss in §5.3.

The second step in constructing the network variables is to compute the average flow for industry pair (i, j); denote this flow by $\bar{f}_{i,j}$. This operation generates a symmetric square matrix of flows across industries. We employ a symmetric approach for simplicity and also because there is no clear way of assigning direction, in the sense that we do not expect \$1 in purchases to be associated with more or less information transmission than \$1 in sales. Next we define an adjacent distance measure for an industry pair, by taking the inverse of the average flow:

$$d_{ij} = \frac{1}{\bar{f}_{ij}}. \tag{5}$$

With the adjacent distances we can now construct an industry network, which is a weighted undirected graph.[13] Figure 1 illustrates the industry network, as well as the top five and bottom five industries in the centrality ranking. For visualization purposes, the figure represents input-output flows at the annual level (61 industries instead of 470), and uses unweighted links. The figure shows how some industries are more central in the economy, whereas others are more peripheral. This is relevant for our main idea, since core-periphery combinations, as argued previously, are potentially associated with a conglomerate having a greater informational advantage relative to specialized firms.

Given the industry network, we compute the weighted shortest path (one can think of distance as a cost) between any two industries by determining the total distance of the optimal path (i.e., the one that minimizes total distance or cost).[14] Denoting these shortest-path lengths for industry pairs as l_{ij}, we can now compute centrality for any industry as in Equation (1), as well as conglomerate excess centrality using formula (4).

A potential concern with our excess centrality variable is that it implies that a conglomerate only requires a minimal participation in any one industry to access the information at that node. To address this concern, §5.3 shows that our results are robust when we consider only segments with a minimum relative size threshold of 5% or 10% of total assets.

To illustrate how excess centrality is computed, consider a real firm from our sample, "LSB Industries" (LSB), an industrial company with two segments in 2008: "Other basic inorganic chemical manufacturing" (I-O code 325180) and "AC, refrigeration, and forced air heating" (I-O code 333415). The first segment has an asset weight of 55%. The conglomerate centrality of LSB is 1.44, using Equation (2), whereas the closeness centrality for each of the industries in which it is present is 1.22 and 1.43, respectively, using Equation (1). It thus follows that the excess centrality of LSB for 2008, according to Equation (4), is

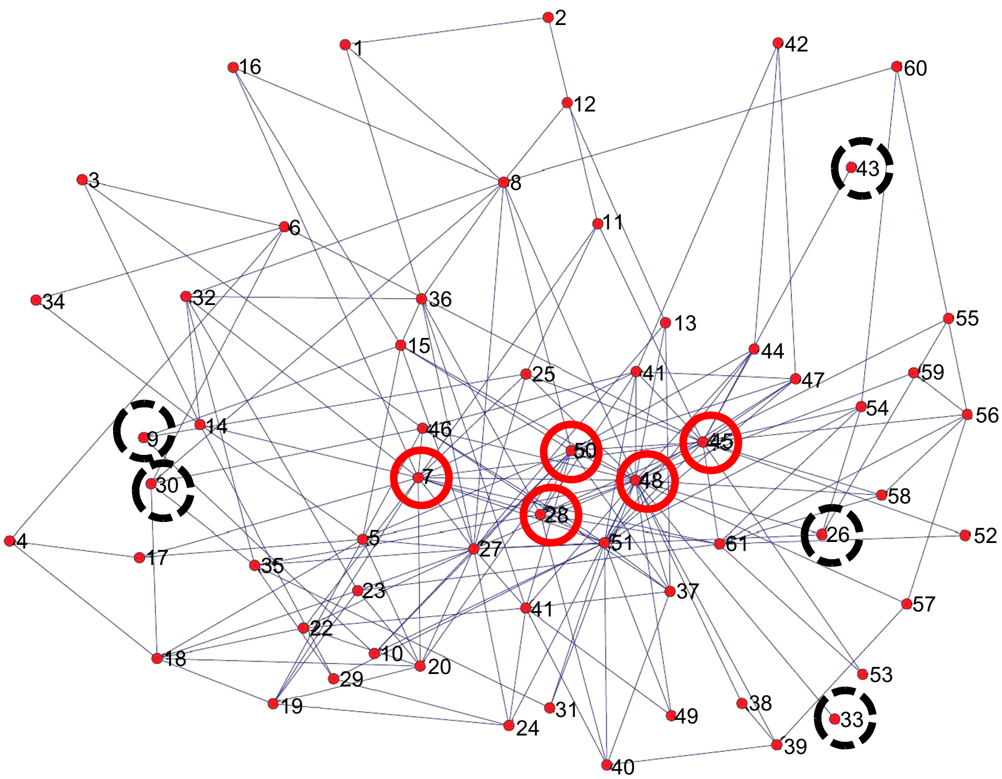
$$\mathrm{EC}_{\mathrm{LSB},\,2008} = \log\left(\frac{1.44}{0.55 \times 1.22 + 0.45 \times 1.43}\right) \approx 0.09.$$

Note how in this case the conglomerate centrality (1.44) is very close to the closeness centrality of the most central segment (1.43). This means, according to our framework, that most informational gains would accrue to the peripheral segment, which is contributing only marginally to the overall ability of the conglomerate to extract information/knowledge that is scattered across the economy. Indeed, §5.1 shows that we find similar results if we replace excess centrality with a simple measure indicating whether the conglomerate simultaneously participates in peripheral and core segments.

[13] Binary networks do not exploit information that we believe is relevant (namely, information transmission being more likely for stronger ties), and also they require the definition of a somewhat arbitrary threshold for the link strength after which a tie is classified to exist.

[14] These network measures were computed using MatlabBGL routines (available at http://www.mathworks.com/matlabcentral/fileexchange/10922-matlabbgl, accessed November 19, 2014), namely the Dijkstra algorithm for minimal travel costs.

Figure 1 **(Color online) Industry Network Using the Three-Digit Input-Output Tables Industry Classification System Level**



Notes. Solid (dashed) circles represent the top (bottom) five industries in the centrality ranking. The top centrality industries are "construction," "miscellaneous professional, scientific, and technical services," "retail trade," "management of companies and enterprises," and "real estate"; the bottom centrality industries are "miscellaneous manufacturing," "rail transportation," "textile mills and textile product mills," "transit and ground passenger transportation," and "insurance carriers and related activities." For visualization purposes, we use unweighted links.

3. Excess Centrality and Conglomerate Value

This section contains our main empirical analysis, where we test whether excess centrality, intended to proxy for a conglomerate's informational advantage, affects conglomerate value.

3.1. Identification Strategy

In our main empirical investigation we analyze whether variation in excess centrality can explain variation in conglomerate valuation. However, several endogeneity concerns need to be addressed when comparing network position to firm value. First, firm value, as measured by Tobin's Q, can be influenced by unobserved industry characteristics. To address this concern, we follow most of the literature on corporate diversification, and compute an industry-adjusted value measure, commonly termed *excess value*. Excess value is the log-difference between the conglomerate's Tobin's Q and the Tobin's Q of a similar portfolio of specialized firms. Using this approach, we isolate variation in conglomerate value that is not driven by time-invariant unobserved industry-level factors, at least those factors that affect the value of diversified and specialized firms similarly.

Unfortunately, the industry-adjustment strategy used in the conglomerate discount literature suffers from further omitted variable problems, as pointed out recently by Gormley and Matsa (2014). A solution to this problem is to adjust all the independent variables in the same way as the dependent variable, i.e., using the same benchmark portfolio of specialized firms.[15] This is the approach we take in our main specification.

Additional endogeneity concerns arise with respect to firm-level quality. To control for observable characteristics and time-invariant unobservable heterogeneity, we employ econometric specifications, which include firm-level variables and firm fixed effects. A harder endogeneity concern is related to time-varying unobserved firm-level characteristics: changes in a firm's industry portfolio could be associated with important changes to the firm, since a firm's industry portfolio is (partly) endogenous. We tackle this issue in §3.2.2 by employing econometric specifications where excess centrality is driven *uniquely* by changes in the overall network structure.

[15] For comparability with the standard literature on the conglomerate discount, we present the results without adjusting the control variables in the online appendix. Results are unchanged.

3.2. Excess-Value Analysis

3.2.1. Static-Network Approach. In this section we investigate how the position of conglomerates in the industry network influences their value. We expect conglomerates with high excess centrality to have a valuation premium, relative to conglomerates with low excess centrality.

We use the business segment data from COMPUSTAT Segments for division-level data, COMPUSTAT for accounting data, and CRSP for stock prices and market values. Our data set covers the period from 1990 to 2011, because we require NAICS codes at the segment level, which are reported only starting in 1990. We exclude conglomerates whose main segment (i.e., the one with largest asset weight) belongs to the financial industry. COMPUSTAT Segments reports the NAICS code of each segment, and BEA provides a mapping between these NAICS codes and the six-digit input-output codes. In §A.2 of the appendix, we describe in great detail the sample selection and the database construction. The key dependent variable in our empirical analysis is excess value—an industry-adjusted value measure—which is computed as in studies about the diversification discount (Berger and Ofek 1995, Villalonga 2004, Santalo and Becerra 2008, Custódio 2014): we take the log-difference of the conglomerate's Tobin's Q with respect to the average Tobin's Q of a benchmark portfolio of specialized firms, using the asset weights of the conglomerate's segments to compute the Tobin's Q of the benchmark.

Table 1 presents the summary statistics of the data we use for the excess value analysis. Panel A refers to the specialized firms we use to construct the benchmark portfolio. Panel B refers to conglomerates using the 1997 static network. Finally, panel C refers to conglomerates using the aggregated time-varying network from 1998 to 2011. Consistent with papers on the diversification discount, the average conglomerate excess value is negative. The magnitude of the excess value measure in our sample (−0.29) is smaller, relative to the excess value found in Berger and Ofek (1995) (−0.16). This is probably due to the difference in sample periods (1990–2011 versus 1986–1991) and to the different industry classification (I-O versus SIC). Also consistent with the literature on the conglomerate discount, we find that the median conglomerate has two unrelated segments, and conglomerates are larger than single-segment firms, with lower Tobin's Q.

Table 2 presents ordinary least squares (OLS) regression coefficients of excess value on excess centrality—our proxy for informational advantage—and other control variables. As mentioned before, by focusing on excess value and excess centrality we control for industry characteristics using specialized firms as benchmarks. We adjust for time-series correlation of the error term by clustering the standard errors at the conglomerate level. All specifications include year fixed effects to control for simultaneous macroeconomic shocks to the variables, and to control for the major change in reporting requirements from the Statement of Financial Accounting Standards (SFAS) 14 to SFAS 131 occurred in 1997 (see Sanzhar 2006 for more details about the rule changes). The only departure from the approach illustrated in Berger and Ofek (1995) is the adjustment of the financial control variables using the benchmark portfolio of specialized firms, to control for the omitted variable bias induced by the industry adjustment (see Gormley and Matsa 2014 for more details). We do not adjust the other control variables because the normalization factor is the same for all conglomerates. For robustness and comparability with previous studies, we also present the main results using unadjusted control variables in the online appendix. In addition to the OLS coefficients and the t-statistics, we also present the beta coefficients to provide a more immediate measure of the order of magnitude of the results,[16] and to allow a direct comparison of coefficients across variables and specifications under reasonable distribution assumptions.

Specification (1) shows a positive association between excess centrality and excess value without controlling for firm characteristics. Specification (2) controls for the main determinants of conglomerate excess value suggested by previous literature, namely, the number of segments in the conglomerate, and the number of related segments, following Berger and Ofek (1995). We also include a vertical-relatedness variable, following Fan and Lang (2000), to account for effects associated with vertical integration. All variables are defined in detail in the appendix.

Consistent with prior literature, we find that the higher the number of segments and the more unrelated the segments are, the lower is the value of the conglomerate. This is also consistent with Hoberg and Phillips (2010), who find that synergies are greater when firms merge with others operating in similar product markets. Specification (2) shows that the excess centrality coefficient is still positive and significant after accounting for these operational characteristics of conglomerates. The fact that excess centrality has a positive effect, whereas the number of segments and the number of unrelated segments have a negative effect, suggests a trade-off faced by diversified firms: on the one hand, diversification increases the

[16] A beta coefficient shows the change in fraction of standard deviation of the dependent variable upon a one-standard-deviation change in the independent variable.

Table 1 Summary Statistics

Variable	Mean	Std. dev.	Min	Max	No. of obs.
		Panel A. Specialized firms			
Assets	1,875	23,402	0.001	3,221,972	119,588
Capex/Sales	1.18	46.111	−693.222	7,826.2	117,656
EBIT/Sales	−6.41	165.942	−28,838.199	5,638.247	111,441
No._of_patents	2.555	30	0	1,891	91,114
No._of_citations	22.482	299.176	0	18,940.5	91,114
Tobin's_Q	2.572	3.271	0.499	35.193	98,564
		Panel B. Conglomerates—1997 industry network			
Acquisition_ratio	0.023	0.066	−0.445	3.206	22,425
Assets	5,195	16,199	0.081	340,647	22,425
Capex/Sales	0.096	0.298	−0.940	13.602	22,166
Core-periphery	0.101	0.301	0	1	22,425
Cross-segments_correlation	0.386	0.232	−0.626	0.975	20,541
EBIT/Sales	−0.094	7.4	−1,018	12.14	21,829
Excess_assets	0.023	2.302	−10.861	10.459	22,425
Excess_capex/sales	−0.753	6.274	−282.498	12.405	22,162
Excess_centrality	0.149	0.169	0.002	2.047	22,425
Excess_citations (scaled by assets)	−0.211	2.202	−5.652	6.166	3,762
Excess_citations (scaled by R&D)	0.031	1.964	−4.984	5.394	2,875
Excess_EBIT/sales	2.915	14.298	−1,017.863	362.275	21,818
Excess_generality	0.416	0.977	−3.279	7.261	3,134
Excess_originality	0.397	0.836	−2.871	5.663	4,058
Excess_patents (scaled by assets)	−0.053	2.008	−4.965	6.189	4,326
Excess_patents (scaled by R&D)	0.182	1.824	−4.658	5.269	3,282
Excess_value	−0.294	0.659	−3.062	6.816	22,425
Mkt._share_single_segments	0.333	0.217	0	0.988	22,425
No._of_citations	85.998	699.281	0	20,722.5	16,002
No._of_analysts SS	3.023	2.21	0	22	22,425
No._of_patents	15.218	101.472	0	2,467	16,002
No._of_segments	2.651	0.955	2	10	22,425
Related_segments	0.363	0.654	0	6	22,425
Sales	4,237	13,938	0.003	458,361	22,425
Tobin's_Q	1.63	1.487	0.499	35.156	22,425
Vert._relatedness	47.101	163.855	0	1,697.34	22,425
		Panel C. Conglomerates—Time-varying network			
Assets	5,351	16,977	0.081	340,647	19,615
Capex/Sales	0.098	0.291	−0.940	13.602	19,381
EBIT/Sales	−0.103	7.865	−1,018	12.14	19,094
Equally-weighted_excess_centrality	0.207	0.115	0.026	0.859	19,615
Excess_assets	−0.488	2.234	−9.109	6.828	19,615
Excess_EBIT/sales	4.385	13.666	−1,017.866	284.082	19,094
Excess_capex/sales	−1.021	6.627	−282.499	12.657	19,381
Excess_value	−0.466	0.504	−2.271	3.027	19,615
No._of_segments	2.478	0.779	2	10	19,615
Related_segments	0.58	0.724	0	6	19,615
Tobin's_Q	1.63	1.495	0.499	35.156	19,615
Vert._relatedness	2.441	4.698	0	93.047	19,615

Notes. The table presents means, standard deviations, minimum and maximum values, and the number of observations for each variable. All variables are defined in detail in the appendix.

firm's information set, but on the other hand, diversification may reduce managerial attention and focus, as well as exacerbate agency problems.

Specification (3) includes other control variables used by Berger and Ofek (1995) and Santalo and Becerra (2008), but industry-adjusted, to control for size, current profitability, and growth opportunities. However, the excess centrality coefficient is still positive and statistically significant, changing little in magnitude. Finally, in specification (4) we add conglomerate fixed effects, to control for unobserved time-invariant firm characteristics. The coefficient of excess centrality is still positive and significant, although the magnitude drops about 30%.

According to specifications (1)–(3), a one-standard-deviation increase in excess centrality translates into an increase of around 0.1 standard deviations in excess value. Given the standard deviation of excess value in our sample, approximately 0.66, this corresponds to an increase of about 0.066 in excess value. Excess value is approximately equal to

$$\frac{Q_{\text{conglomerate}} - Q_{\text{benchmark}}}{Q_{\text{benchmark}}},$$

Table 2 Excess Value and Excess Centrality in Conglomerates

	(1)	(2)	(3)	(4)
Excess_centrality	0.400***	0.406***	0.380***	0.259**
	0.103	0.104	0.098	0.067
	(6.06)	(5.87)	(5.51)	(2.49)
No._of_Segments		−0.031***	−0.037***	−0.038***
		−0.045	−0.055	−0.056
		(−2.99)	(−3.44)	(−3.49)
Related_segments		0.037**	0.030*	0.004
		0.037	0.030	0.004
		(2.02)	(1.68)	(0.19)
Vert._relatedness		−0.000	−0.000	0.000
		−0.009	−0.013	0.003
		(−0.86)	(−1.17)	(0.07)
Excess_assets			0.015***	−0.015
			0.054	−0.053
			(2.70)	(−1.35)
Excess_EBIT/sales			−0.005***	−0.001***
			−0.089	−0.026
			(−8.93)	(−2.68)
Excess_capex/sales			0.001**	0.003***
			0.013	0.029
			(2.50)	(8.68)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes
R^2	0.024	0.026	0.037	0.026
No. of observations	22,425	22,425	21,516	21,516

Notes. The dependent variable is *Excess_value*, defined as the log-difference between the Tobin's Q of a conglomerate and the Tobin's Q of a similar portfolio of specialized firms. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the closeness centrality of a similar portfolio of specialized firms. All network variables use the 1997 BEA input–output network. The independent variables are lagged one year. All variables are defined in detail in the appendix. A constant is included in each specification but not reported in the table.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

and on average the Tobin's Q of conglomerates is approximately 29% lower than that of the (specialized-firm) benchmark. Therefore, an increase of 0.066 in excess value corresponds to an additional $0.066/0.71 \approx 9.3\%$ in firm value for the average conglomerate. Specification (4), with firm fixed effects, implies a lower magnitude for the excess-centrality effect, of about 6.2% in firm value. Also, the beta coefficient of excess centrality has a similar magnitude relative to the beta coefficient of related segments across all specifications, suggesting that information effects are as economically significant as agency effects.

To obtain a more intuitive grasp for the magnitude of the effects, the online appendix shows examples of conglomerates that have representative levels of excess centrality (average, and ± one standard deviation). Also, about one-third of variation in excess centrality (total standard deviation of 0.17) comes from within-firm variation (standard deviation of 0.05). This within-firm variation is roughly equal to the difference in average excess centrality between two- and three-segment conglomerates, as tabulated in the online appendix. Therefore, for the average two-segment conglomerate, adding one segment generates approximately a one-standard-deviation increase in excess centrality.

3.2.2. Time-Varying Network Approach. In our main analysis we use the detailed 1997 input-output tables to construct a static industry network. However, time-varying unobservable firm characteristics may correlate both with excess centrality and excess value. To address this endogeneity concern and focus on the most exogenous source of variation in conglomerate network position, we use the aggregated annual input-output tables from 1998 to 2011. The advantage of these tables is that they use the same industry classification, and thus we can construct a time-varying network to study the effects on excess value of exogenous changes to excess centrality. The drawbacks are that it is a much coarser representation of the economy (61 industries instead of 470) and that it is a shorter sample period.

Excess centrality can change because of three main drivers: (i) conglomerates differ cross-sectionally in their diversification strategy in the network of industries; (ii) conglomerates change their industry portfolio over time by changing the relative size of their divisions, or by outright adding/subtracting divisions; and finally (iii) the overall network changes its structure. Whereas the first two sources of variation are partly endogenously determined, we consider overall changes to the network architecture to be exogenous to an individual firm. Cross-sectional differences in diversification can be controlled with firm fixed effects. To control for within-conglomerate changes in diversification due to changes in the relative size of the divisions, we define a slightly different measure of excess centrality, that we call *equally-weighted excess centrality* (EWEC):

$$\mathrm{EWEC} := \log\left(\frac{CC_{\mathrm{cong}}}{\sum_{i\in\mathcal{I}} \frac{1}{M} CC_i}\right), \tag{6}$$

with M the number of segments in the conglomerate. By equally weighting the benchmark industries, we develop a measure of excess centrality that is invariant to changes in the relative size of divisions within a conglomerate. The correlation between this new measure and the original excess centrality is 0.75.[17]

Finally, we control for outright addition of new divisions or sales of old divisions by using firm-cohort fixed effects, where a cohort is defined as a

[17] Our main results from Table 2 are very similar if we replace the original excess centrality variable with its equally-weighted version, as shown in §5.3.

sequence of adjacent years for which the firm did not change its industry portfolio. With this approach, any effects of excess centrality on excess value arising from changing segments are absorbed by the firm-cohort dummies. Using the equally-weighted excess centrality and firm-cohort fixed effects, we are left with a measure of centrality that is only influenced by the change in industry flows at the overall network level.

Table 3 contains the results of OLS regressions of excess value on equally-weighted excess centrality and other variables. First, we shut down changes in excess centrality arising from conglomerates changing weights over time by using the new excess centrality variable in Equation (6). We then replicate the cross-sectional results in Table 2 including controls for several firm characteristics. The effect of equally-weighted excess centrality on excess value is statistically and economically similar to the one found in the main analysis. Specification (2) adds firm fixed effects to model (1) and we find similar results.

Table 3 Excess Value and Excess Centrality—Time-Varying Network

	(1)	(2)	(3)	(4)
Equally-weighted_ excess_centrality	0.537***	0.379***	0.432**	0.482**
	0.118	0.083	0.095	0.095
	(4.95)	(3.27)	(2.19)	(1.99)
No._of_segments	−0.033**	−0.028*		
	−0.048	−0.041		
	(−2.17)	(−1.83)		
Related_segments	−0.025	−0.009		−0.006
	−0.035	−0.012		−0.006
	(−1.62)	(−0.45)		(−0.06)
Vert._relatedness	0.000	0.000	0.000	−0.004*
	0.001	0.005	0.001	−0.039
	(0.05)	(0.26)	(0.02)	(−1.81)
Excess_assets	−0.024***	−0.116***	−0.124***	−0.127***
	−0.105	−0.507	−0.540	−0.523
	(−4.04)	(−10.71)	(−9.12)	(−7.86)
Excess_EBIT/sales	−0.005***	−0.001**	−0.000	0.000
	−0.116	−0.018	−0.011	0.004
	(−7.96)	(−2.19)	(−1.32)	(0.35)
Excess_capex/sales	0.000	0.003***	0.003***	0.003***
	0.004	0.049	0.051	0.052
	(0.43)	(16.09)	(15.73)	(10.55)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	No	Yes
Firm-cohort fixed effects	No	No	Yes	No
R^2	0.046	0.059	0.058	0.059
No. of observations	11,374	11,374	9,906	5,300

Notes. The dependent variable is *Excess_value*, defined as the log-difference between the Tobin's Q of a conglomerate and the Tobin's Q of a similar portfolio of specialized firms. Specifications (1)–(3) use the full sample. Specification (4) uses only the subsample of firms that do not change the number of segments over the entire sample period. The table presents OLS coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Equally-weighted_excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the one of a similar equally-weighted portfolio of specialized firms using the annual (three-digit) 1998–2011 BEA input-output networks. A firm-cohort is defined as a sequence of adjacent years during which the firm did not change its number of segments. The independent variables are lagged one year. All variables are defined in detail in the appendix. A constant is included in each specification but not reported in the table.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Specification (3) contains the key result of this analysis. In this specification, we turn off any variation in excess centrality that is associated with conglomerates changing their industry portfolios over time by including firm-cohort dummies in the regression. The excess centrality coefficient is positive and significant, and the magnitude actually increases compared to model (2). According to specification (3), a one-standard-deviation increase in excess centrality leads to about 0.095 standard deviations increase in excess value. The standard deviation of excess value under this industry classification is about 0.5, and on average the Tobin's Q of diversified firms is about 46% lower than that their specialized benchmarks (see Table 1). Therefore, a one-standard-deviation increase in excess centrality corresponds to about $0.095 \times 0.5/0.54 = 9\%$ more in value for the average conglomerate, a magnitude that is similar to what we have found in our main analysis in the previous section. Alternatively, as shown in specification (4), we can drop from the sample all conglomerates that either add or delete a segment throughout the period 1997–2011. In this specification firm-cohort fixed effects are no longer necessary. The coefficient of excess centrality remains positive and significant, with a magnitude that is close to that of specification (3).

Overall, we find that the position of a conglomerate in the network of industries (i.e., excess centrality) is a critical determinant of value even when we consider only variations due to changes in the overall network structure. This confers further plausibility to our idea that network position leads to value creation, although we acknowledge that it is possible that conglomerates are responding to industry-network changes by taking actions—beyond adding or dropping segments, or shifting assets weights—that could affect value.

3.3. Excess Centrality and Industry Characteristics

3.3.1. Industry Composition. One possible explanation for our findings is that excess centrality is simply correlated with unobserved heterogeneity in industry characteristics that give conglomerates a competitive advantage, i.e., the existence of self-selection of conglomerates into specific industries. Whereas this concern is significantly mitigated with the analysis using exogenous variation in excess centrality (§3.2.2), we provide further evidence that unobserved industry-level heterogeneity does not drive our results.

To address this issue, we adopt the view on industry composition in Santalo and Becerra (2008), who interpret the pervasiveness of conglomerates in an industry as a "sufficient statistic" for whether conglomerates have a natural advantage. The authors conjecture that such competitive advantage is a function of the importance of *soft* information, that is, information that cannot be credibly conveyed to outsiders, such as external capital markets (Stein 2002, Faure-Grimaud et al. 2003). The importance of soft information has been suggested as a potential source of conglomerate advantage, via internal capital markets (Shleifer and Vishny 1991, Servaes 1996). As in Santalo and Becerra (2008), we measure industry composition using the market share of all single segments in a given industry: the greater the market share of specialized firms in an industry, i.e., the less prevalent conglomerates are, the less advantage conglomerates have relative to single segments. For each conglomerate, we then average this industry composition variable across participated segments. We include such conglomerate industry-composition variable as a control in our excess value regressions and observe whether the excess-centrality effect disappears. Results are presented in Table 4.

Consistent with Santalo and Becerra (2008), we find that industry composition significantly influences conglomerate value. However, the inclusion of this variable does not change our main results. Specification (1) includes the market share of specialized firms in addition to the other variables that drive excess value; the coefficient of excess centrality remains statistically significant, and the economic magnitude of the coefficient is just slightly smaller relative to specification (2) in Table 2. Specification (2) adds financial characteristics, and results are also similar. The same is true if we add firm fixed effects (specification (3)).

Table 4 Industry Composition and Excess Centrality

	(1)	(2)	(3)	(4)	(5)	(6)
Excess_centrality	0.339***	0.328***	0.237**	0.645***	0.646***	0.431***
	0.087	0.085	0.061	0.166	0.167	0.111
	(5.09)	(4.85)	(2.33)	(5.47)	(5.37)	(2.88)
Mkt._share_SS	−0.435***	−0.429***	−0.365***	−0.292***	−0.284***	−0.253***
	−0.143	−0.140	−0.120	−0.096	−0.093	−0.083
	(−9.72)	(−9.42)	(−6.50)	(−5.50)	(−5.32)	(−4.06)
Excess_centrality × *Mkt._share_SS*				−0.956***	−1.003***	−0.691**
				−0.104	−0.108	−0.075
				(−3.62)	(−3.62)	(−2.50)
No._of_segments	−0.038***	−0.037***	−0.038***	−0.038***	−0.037***	−0.037***
	−0.056	−0.055	−0.055	−0.056	−0.055	−0.054
	(−3.71)	(−3.50)	(−3.46)	(−3.73)	(−3.49)	(−3.44)
Related_segments	0.020	0.022	0.006	0.018	0.021	0.004
	0.020	0.022	0.006	0.018	0.021	0.004
	(1.13)	(1.26)	(0.30)	(1.01)	(1.16)	(0.22)
Vert._relatedness	−0.000	−0.000	0.000	−0.000	−0.000	0.000
	−0.015	−0.014	0.002	−0.013	−0.013	0.001
	(−1.42)	(−1.31)	(0.06)	(−1.29)	(−1.16)	(0.02)
Excess_assets		−0.000	−0.037***		−0.001	−0.038***
		−0.000	−0.127		−0.003	−0.130
		(−0.02)	(−3.03)		(−0.16)	(−3.11)
Excess_EBIT/sales		−0.005***	−0.001***		−0.005***	−0.001***
		−0.085	−0.025		−0.085	−0.026
		(−8.75)	(−2.66)		(−8.93)	(−2.73)
Excess_capex/sales		0.001**	0.003***		0.001**	0.003***
		0.012	0.030		0.012	0.030
		(2.45)	(9.20)		(2.39)	(9.11)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	No	No	Yes
R^2	0.045	0.053	0.033	0.048	0.056	0.034
No. of observations	22,395	21,516	21,516	22,395	21,516	21,516

Notes. The dependent variable is *Excess_value*, defined as the log-difference between the Tobin's Q of a conglomerate and the Tobin's Q of a similar portfolio of specialized firms. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the one of a similar portfolio of specialized firms. *Mkt._share_SS* is the assets-weighted average of the market share of single-segment competitors in each of the detailed input-output industries in which the conglomerate firm is active. All network variables use the 1997 BEA input-output network. The independent variables are lagged one year. All variables are defined in the appendix. A constant is included but not reported.

** and *** indicate statistical significance at the 5% and 1% levels, respectively.

We finally conduct an additional analysis using the approach from Santalo and Becerra (2008). Our measure of excess centrality can be interpreted as a proxy for the *quantity* of soft information available to a conglomerate, relative to its specialized counterparts. If one of the industry characteristics that determines the natural advantage of conglomerates is the importance of soft information, then one should expect the access to more information—via excess centrality, as we argue—to be particularly important in these industries. Specifications (4)–(6) in Table 4 add an interaction term of excess centrality and the market share of specialized firms to specifications (1)–(3). Assuming industry composition proxies for the irrelevance of soft information, then an interaction term with excess centrality should have a negative coefficient. In all three specifications (4)–(6), the interaction term is negative and statistically significant. The position of a conglomerate in the industry network influences its value, and this is especially true in industries where specialized firms are less prevalent.

3.3.2. Analyst Coverage. An alternative to the proxy suggested by Santalo and Becerra (2008) as a measure of soft information is the extent of *analyst coverage*. The idea is that for industries that are more heavily scrutinized by analysts, much information becomes public. Therefore, one would expect the excess centrality effect to be lower for conglomerates that operate in such industries, if excess centrality is measuring access to nonpublic information.

We start by computing a measure for public availability of information at the industry level, which averages the number of analysts that cover single-segment firms in each industry (from the IBES data set). Next, we compute the (asset-weighted) average analyst coverage across all industries where the conglomerate is present. Table 5 shows OLS regressions of excess value on excess centrality as in our main analysis (Table 2), which now include the new analyst-coverage variable and an interaction between analyst coverage and excess centrality. In all specifications the interaction coefficient is negative and statistically significant, as expected. In short, this analysis is consistent with conglomerates being less able to extract informational rents if they operate in industries where much information becomes public.

Table 5 **Analyst Coverage and Excess Centrality**

	(1)	(2)	(3)	(4)
Excess_centrality	0.673***	0.670***	0.629***	0.399***
	0.173	0.173	0.162	0.103
	(6.43)	(6.33)	(5.95)	(3.07)
No._of_analysts SS	0.006	0.006	0.006	−0.013***
	0.021	0.022	0.021	−0.045
	(1.34)	(1.37)	(1.31)	(−2.76)
Excess_centrality × *No._of_analysts_SS*	−0.134***	−0.132***	−0.124***	−0.074***
	−0.107	−0.106	−0.100	−0.059
	(−4.97)	(−4.93)	(−4.67)	(−2.81)
No._of_segments		−0.026**	−0.033***	−0.037***
		−0.039	−0.048	−0.054
		(−2.57)	(−3.03)	(−3.42)
Related_segments		0.035*	0.030*	0.007
		0.035	0.030	0.007
		(1.91)	(1.65)	(0.36)
Vert._relatedness		−0.000	−0.000	0.000
		−0.012	−0.016	0.004
		(−1.16)	(−1.40)	(0.12)
Excess_assets			0.014**	−0.031***
			0.047	−0.107
			(2.36)	(−2.74)
Excess_EBIT/sales			−0.005***	−0.001***
			−0.089	−0.027
			(−8.88)	(−2.74)
Excess_capex/sales			0.001**	0.003***
			0.012	0.028
			(2.50)	(8.44)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes
R^2	0.030	0.031	0.042	0.031
No. of observations	22,398	22,398	21,516	21,516

Notes. The dependent variable is *Excess_value*, defined as the log-difference between the Tobin's Q of a conglomerate and the Tobin's Q of a similar portfolio of specialized firms. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the one of a similar portfolio of specialized firms. *No._of_analysts_SS* is the assets-weighted average of the number of equity analysts covering single-segment competitors in each of the detailed input-output industries in which the conglomerate firm is active. All network variables use the 1997 BEA input-output network. The independent variables are lagged one year. All variables are defined in the appendix. A constant is included but not reported.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4. Mechanism: Innovation Production

In the previous section we have shown evidence tying a conglomerate's informational advantage—as measured by excess centrality—to its ability to create value (Tobin's Q). This section investigates whether excess centrality is also a main driver of innovation production, which would be further evidence that excess centrality is indeed a proxy for information advantage.

As explained in the introduction, previous ideas from the innovation and networks literatures suggest that access to a broad knowledge base is a key determinant of innovation production. We use patent production, citations, generality, and originality as a measure of innovation quantity and quality, and we test if high-excess-centrality conglomerates are able to produce relatively more and better patents. Our identification strategy is similar to the one used in the excess-value analysis (§3.2), except that we replace the dependent variable with innovation-related proxies.

In this section we also provide a more direct test of our key assumption that diversified firms exchange information internally more easily than specialized firms across their boundaries, using cross-industry citations. In particular, we test whether patents produced by a conglomerate in a given industry often cite patents in other industries in which the conglomerate is also present, as compared to a benchmark portfolio of specialized firms. One might argue that patents are hard information that is publicly available to all, which would invalidate the rationale for our cross-industry citations analysis. However, we believe that interpreting and making use of scientific knowledge is not the same as having access to a patent. In §A.4 of the appendix, we elaborate more about knowledge flow and the boundaries of the firm.

4.1. Excess Centrality and Patents

We first investigate the association between excess centrality and patent production. This proxy for research and development (R&D) productivity is also used by Seru (2014) to study the innovation performance of diversified firms. We collect the patent data from the National Bureau of Economic Research (NBER), created by Hall et al. (2001) for the fiscal years 1990–2005. Our main variables of interest are the number of patent applications by a conglomerate in a given year, and the number of citations a patent receives in subsequent years, scaled by assets, or R&D expenses. The number of patents represents the raw innovation production of a firm. The number of citations received represents both the innovation quantity, as well as the innovation quality generated by the firm.

In keeping with our previous excess-value approach in the measurement of relative conglomerate performance, we construct two variables termed *excess patents* and *excess citations*, which correspond to the log-difference between the number of (scaled) patents and citations produced by a conglomerate, relative to a comparable portfolio of single-segment firms.[18] Summary statistics are presented in panel B of Table 1. Consistent with the results in Seru (2014), conglomerates produce fewer patents (−5.3%) and receive less citations (−21.1%) than benchmark-portfolio of specialized firms, when we scale patents and citations by total assets.

We then perform OLS regressions of the excess-innovation variables on excess centrality and other controls; Table 6 reports the results. Standard errors are clustered at the conglomerate level. In all specifications, we add year dummies not only to control for macroeconomic shocks, but also to control for truncation in the patent registration process, and citation count, as suggested by Hall et al. (2001), and to control for the 1997 change in segment reporting requirements. The number of observations drops significantly relative to the excess value analysis because of the smaller sample period, and because excess patents and citations ratios are not well defined when the benchmark portfolio does not produce patents. We use the same control variables as in previous tables: vertical relatedness, number of segments, number of related segments, and financial characteristics.

The dependent variable in specifications (1) and (2) in Table 6 is the excess number of patents produced by a conglomerate, where the scaling factor is the same as in the excess value analysis, total assets. The coefficient on excess centrality is statistically and economically significant. According to specifications (1) and (2), a one-standard-deviation increase in excess centrality corresponds to an increase of about 0.06 standard deviations in excess patents. Since the standard deviation of excess patents is about 2 and the average conglomerate produces about 5% fewer patents than the specialized-firm benchmark (see panel A of Table 1), this increase is roughly $0.06 \times 2/0.95 \approx 13\%$, relative to the average conglomerate.

Specifications (3) and (4) still consider excess patents as the dependent variable, but now patents are normalized by R&D expenditures, instead of assets. This analysis thus measures innovation production as a return per R&D dollar spent, which proxy for innovation-specific investment. However, we note that using R&D expenditures as a scaling variable can be problematic, because many firms do not report R&D expenses as there is accounting discretion on what exactly constitutes R&D, and this could introduce sample selection biases. This concern notwithstanding, the coefficient on excess centrality is positive and statistically significant in both specifications. The economic magnitudes are comparable to specifications (1) and (2). According to specifications (3) and (4), a one-standard-deviation increase in excess centrality is associated with an increase in scaled patent production of about 9% $(0.06 \times 1.82/1.18)$ relative to the average conglomerate.

Specifications (5)–(8) replicate the analysis from specifications (1)–(4), only replacing patents by number of citations received. This measure is considered a proxy for the quality of innovation. As before, excess centrality has a positive coefficient, and it is significant across models. In terms of economic magnitudes, if we take specifications (5) and (6) (asset scaling), a one-standard-deviation increase in excess centrality

[18] We winsorize the patents and citations variables at the 1% and 99% levels. However, we find very similar results, tabulated in the online appendix, without winsorization, or if we truncate the variables at the 1% and 99% levels.

Table 6 Excess Innovation and Excess Centrality in Conglomerates

	Excess_patents				*Excess_ citations*			
	Scaled by assets		Scaled by R&D		Scaled by assets		Scaled by R&D	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Excess_centrality	0.701***	0.694***	0.642**	0.633**	0.784***	0.703**	0.665**	0.542*
	0.063	0.062	0.063	0.062	0.064	0.058	0.061	0.050
	(2.75)	(2.76)	(2.26)	(2.28)	(2.80)	(2.57)	(2.19)	(1.79)
No._of_segments	−0.221***	−0.095	−0.196***	−0.095	−0.230***	−0.128*	−0.195***	−0.126*
	−0.122	−0.053	−0.120	−0.058	−0.118	−0.066	−0.113	−0.073
	(−3.76)	(−1.64)	(−3.19)	(−1.50)	(−3.39)	(−1.89)	(−2.86)	(−1.79)
Related_segments	−0.197**	−0.146*	−0.212***	−0.178**	−0.181*	−0.130	−0.192**	−0.161
	−0.076	−0.056	−0.093	−0.078	−0.065	−0.046	−0.079	−0.066
	(−2.44)	(−1.83)	(−2.60)	(−2.14)	(−1.93)	(−1.41)	(−2.01)	(−1.64)
Vert._relatedness	−0.001***	−0.001**	−0.000	0.000	−0.001	−0.001	−0.000	−0.000
	−0.069	−0.055	−0.012	0.001	−0.048	−0.042	−0.015	−0.011
	(−2.62)	(−2.21)	(−0.33)	(0.03)	(−1.51)	(−1.37)	(−0.40)	(−0.28)
Excess_assets		−0.242***		−0.173***		−0.210***		−0.118***
		−0.239		−0.192		−0.187		−0.120
		(−9.33)		(−6.27)		(−7.26)		(−4.00)
Excess_EBIT/sales		−0.011		0.001		−0.028***		−0.011
		−0.053		0.003		−0.086		−0.038
		(−1.43)		(0.11)		(−3.36)		(−1.16)
Excess_capex/sales		0.032		0.093**		0.026		0.091*
		0.031		0.064		0.021		0.057
		(1.22)		(2.22)		(0.76)		(1.73)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.056	0.113	0.048	0.072	0.049	0.090	0.058	0.048
No. of observations	4,326	4,172	3,282	3,159	3,762	3,635	2,875	2,774

Notes. In the first (last) four specifications, the dependent variable is *Excess_patents* (*Excess_citations*), defined as the log-difference between the number of patents (citations) produced by a conglomerate and the number of patents (citations) produced by a similar portfolio of specialized firms. In the odd columns, the number of patents (citations) is scaled by total firm assets, and in the even columns it is scaled by R&D. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the one of a similar portfolio of specialized firms. All network variables use the 1997 BEA input-output network. The independent variables are lagged one year. All variables are defined in detail in the appendix. A constant is included in each specification but not reported in the table.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

leads to an additional 0.06 standard deviations in excess citations. Since the average conglomerate has approximately 21% fewer citations than the benchmark with a standard deviation of 2.2, this increase is about $0.08 \times 2.2/0.79 \approx 22\%$ more citations relative to the average conglomerate. Specifications (7) and (8) use R&D expenditures as a scaling factor, where once again conglomerates perform on average better than the benchmark, by about 3%. According to these specifications, a one-standard-deviation increase in excess centrality corresponds to an increase of approximately 12% ($0.061 \times 1.96/1.03$) and 10% ($0.05 \times 1.96/1.03$) in scaled citations relative to the average conglomerate, respectively.

Overall, we find that conglomerates with high excess centrality not only exhibit greater value, but also produce more and better-cited patents. Moreover, in the online appendix we show that excess centrality effects on innovation seem stronger when specialized firms are less prevalent, in keeping with the excess-value analysis from §3.3.1.

Next we extend the analysis of how excess centrality affects innovation, by looking at two popular outputs: *patent originality* and *patent generality*. According to our main story, conglomerates that have access to a larger information set should produce innovation that is more general (i.e., that is relevant for many industries) and more original (i.e., that builds on patents from many other industries). Following Hall et al. (2001), patent generality is computed as follows:

$$\frac{N_i}{N_i - 1}\left(1 - \sum_{j=1}^{M} s_{ij}^2\right),$$

where s_{ij} is the percentage of citations received by patent i from patents that belong to patent class j, and where there are a total of M patent classes and patent i received a total of N_i citations. Intuitively, if a patent receives most of its citations from just one patent class, then the above measure converges to 0 (the lower bound). The measure of patent originality is computed similarly, except replacing citations received by citations made.

After computing patent-level measures of generality and originality, we create conglomerate-level measures of *excess* generality and originality. These

Table 7 Excess Innovation and Excess Centrality: Originality and Generality

	Excess_generality		*Excess_originality*	
	(1)	(2)	(3)	(4)
Excess_centrality	0.463***	0.418***	0.637***	0.623***
	0.083	0.076	0.135	0.133
	(3.27)	(3.02)	(4.91)	(4.84)
No._of_segments	0.069***	0.075***	0.091***	0.079***
	0.081	0.088	0.122	0.107
	(2.89)	(3.04)	(4.17)	(3.59)
Related_segments	−0.135***	−0.119***	−0.102***	−0.106***
	−0.109	−0.096	−0.095	−0.099
	(−3.50)	(−3.06)	(−3.21)	(−3.23)
Vert._relatedness	0.000	0.000	−0.000***	−0.000***
	0.018	0.019	−0.053	−0.062
	(1.07)	(1.04)	(−3.65)	(−4.11)
Excess_assets		−0.020		0.023**
		−0.041		0.054
		(−1.50)		(2.02)
Excess_EBIT/sales		−0.015***		−0.004
		−0.105		−0.052
		(−3.44)		(−1.01)
Excess_capex/sales		−0.008		−0.007
		−0.014		−0.017
		(−0.60)		(−0.71)
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.038	0.052	0.043	0.049
No. of observations	3,134	3,041	4,058	3,920

Notes. In the first (last) two specifications, the dependent variable is *Excess_generality* (*Excess_originality*), defined as the log-difference between the generality (originality) of the patents produced by a conglomerate and the generality (originality) of the patents produced by a similar portfolio of specialized firms. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the one of a similar portfolio of specialized firms. All network variables use the 1997 BEA input-output network. The independent variables are lagged one year. All variables are defined in detail in the appendix. A constant is included in each specification but not reported in the table.

** and *** indicate statistical significance at the 5% and 1% levels, respectively.

measures correspond to the log-difference between the average generality (originality) of a conglomerate's patents and the average generality (originality) of patents produced by a portfolio of comparable single-segment firms. Table 7 reports the output of OLS regressions of excess generality and originality on excess centrality and other control variables. Excess centrality is found to be a determinant of both excess generality and originality, as expected, with a similar economic magnitude as in previous tests.

The evidence above suggests that conglomerates that are strategically diversified in the network of industries can more efficiently gather information that is scattered across the economy and use it to produce superior innovation, and thus create value. However, this argument hinges on the critical assumption that information flows more directly inside a conglomerate than externally across specialized firms. We test this assumption below.

4.2. Cross-Industry Citations

One way to test the information flow assumption is to examine the citations made by all patents produced by a conglomerate in a given industry, and count how many of them refer to other industries where the conglomerate is also present. This measure of conglomerate cross-industry citations can then be compared to a similar measure of cross-industry citations for patents produced by single-segment firms. If information and knowledge flow more easily inside a conglomerate, we would observe a greater number of cross-industry citations in conglomerates, relative to a similar portfolio of specialized firms. Our approach is close to Gomes-Casseres et al. (2006), who study patterns of cross-industry patent citations in intercorporate alliances. The authors argue that their findings suggest that knowledge flows more easily within alliances than across nonallied firms, a claim very similar to ours with respect to conglomerates.

To construct the measure of cross-industry citations, we use the same NBER patent data set used for the patents and citations analysis in §4.1, and the three-digit input-output industry classification. First, we assemble a data set containing all patents produced by public companies, and we assign each patent to one or more related I-O industries.[19] We also consider all citations that are contained in these patents, and we assign each citation to one or more I-O industries of the cited patent. Thus, for each firm we have a matrix of citing industry/cited industry where each pair of citing patent-cited patent occupies one or more cells.

Second, for each conglomerate, we consider all possible division pairs. For each pair, we define our measure of cross-industry citations as the percentage of citations made by the conglomerate's patents in the industry of the first division citing a patent (not necessarily a patent of the conglomerate, but any patent) in the industry of the second division, or vice versa. Then we average this cross-industry citations measure across all possible division pairs within a conglomerate. Since patents can be related to several industries, there are two different ways to aggregate patent citations by firms: (1) Each patent receives a weight of one, and when multiple industries are related to a patent, each industry receives a fraction of the

[19] Each patent is classified by the United States Patent and Trademark Office (USPTO) into one or more United States Patent Classification (USPC) industry classes and subclasses, whereas our main analysis is done using the input-output industry classification system. The USPTO also offers a concordance between the USPC and 30 fields based on the four-digit 1997 NAICS, and thus I-O industries.

weight. The cross-industry citations are thus weighted by patent. (2) Each related industry receives a weight of one, regardless of how many industries are related to a single patent. In such a way, we weight citations by industry. The former approach gives more weight to patents with a lower number of related industries, and the latter gives more weight to patents with a greater number of related industries. Because both approaches seem equally valid, we construct and use both measures of cross-industry citations in our tests. Finally, we compare this cross-industry citations index with the one of a similar portfolio of specialized firms. Section A.3 in the appendix provides a detailed example of how the cross-industry citations measure is computed.

Table 8 shows the results of a student's t-test comparing the cross-industry-citation pattern of conglomerates and the cross-industry-citation pattern of benchmark portfolios of specialized firms, using both industry-weighted and patent-weighted measures. On average, between 2.8% and 3.1% of citations of a conglomerate refer to an industry where the conglomerate also has a division. This is between 30% and 49% greater than cross-industry citations of a similar portfolio of specialized firms. The difference in cross-industry citations is statistically significant at the 1% level. This result means that patents produced in one division of a conglomerate have a greater likelihood of citing patents produced in an industry where the conglomerate is also present, relative to a similar portfolio of single-segment firms.

Table 8 Cross-Industry Citations

	No. of obs.	Mean	Std. dev.
Panel A. *Cross_industry_citations* (*patent_weighted*)			
Conglomerates	5,038	0.0276	0.0011
Portfolio of specialized firms	5,038	0.0213	0.0006
Difference	5,038	0.0063*** (6.44)	0.0010
Panel B. *Cross_industry_citations* (*industry_weighted*)			
Conglomerates	5,038	0.0313	0.0744
Portfolio of specialized firms	5,038	0.0210	0.0393
Difference	5,038	0.0103*** (10.92)	0.0009

Notes. The table presents means and standard deviations of the cross-industry citations measure, both for conglomerates and for a similar portfolio of single-segment firms. The last line in each panel shows the p-value of a student's t-test comparing the two means (in parentheses). The cross-industry citations (*patent_weighted*) of a conglomerate is the percentage of citations made by patents produced by a conglomerate's division that cite patents in industries where the conglomerate is also present, and where each patent receives a weight of one. The cross-industry citations (*industry_weighted*) of a conglomerate is the percentage of citations made by patents produced by a conglomerate's division that cite patents in industries where the conglomerate is also present and where each related industry has a weight of one. The construction of the cross-industry citations measures is explained in more detail in the appendix.

***Indicates statistical significance at the 1% level.

These findings provide supporting evidence to our assumption that information and knowledge flows with fewer frictions within a conglomerate than in the external market between single-segment firms.

5. Robustness Checks

5.1. Core-Periphery Analysis

In §2 we explain how it might be advantageous for a conglomerate to simultaneously be present in core industries and peripheral industries. The idea is that the firm can use the information from its more central segment in a way that is advantageous for the operation of its more peripheral low-information division. In this section we conduct a robustness check where we replace the excess-centrality variable with a dummy that takes the value of one if the conglomerate's industry portfolio exhibits this core-periphery characteristic. The value-added of this approach is that the core-periphery dummy is a simpler and more intuitive construct than excess centrality, albeit coarser and more limited as a proxy for different sources of informational advantage (beyond core-periphery combinations).

First, we classify each industry as either core, neutral, or peripheral. An industry is considered peripheral if its closeness centrality in the industry network is below the first quartile of the cross-sectional industry-centrality distribution. On the other hand, an industry is considered core if its centrality is above the 75th percentile. Second, a conglomerate exhibits the core-periphery characteristic if at least one of its segments is in a core industry and at least one other segment is in a peripheral industry. The correlation between excess centrality and the core-periphery dummy is 46%.

The results of our analysis are displayed in Table 9. The three specifications correspond to the first three specifications of our main table (Table 2); we do not have a specification with firm fixed effects because there is very little within-firm variation in core-periphery dummies. The table shows, across specifications, that a conglomerate with the core-periphery style has an excess value that is on average 6% higher than a conglomerate not pursuing a core-periphery strategy. Since the Tobin's Q of the average conglomerate is about 30% smaller than the Tobin's Q of a similar portfolio of specialized firm, this corresponds to about $6\%/0.7 \approx 8.5\%$ in firm value for the average conglomerate.

The core-periphery approach also allows us to test the robustness of our results to alternative definitions of centrality (see discussion at the end of §2). In the online appendix we report regressions that parallel those of Table 9, but using degree and eigenvector centrality, instead of closeness centrality. We find similar results using these other centrality measures.

Table 9 **Excess Value and Core-Periphery Strategies**

	(1)	(2)	(3)
Core-periphery	0.063**	0.061**	0.063**
	0.029	0.028	0.029
	(2.09)	(1.97)	(2.02)
No._of_segments		−0.022**	−0.031***
		−0.033	−0.045
		(−2.17)	(−2.82)
Related_segments		0.039**	0.031*
		0.039	0.030
		(2.09)	(1.68)
Vert._relatedness		−0.000**	−0.000***
		−0.026	−0.029
		(−2.50)	(−2.63)
Excess_assets			0.018***
			0.061
			(3.05)
Excess_EBIT/sales			−0.005***
			−0.091
			(−9.18)
Excess_capex/sales			0.002***
			0.014
			(2.89)
Year fixed effects	Yes	Yes	Yes
R^2	0.014	0.017	0.029
No. of observations	22,425	22,425	21,516

Notes. The dependent variable is *Excess_value*, defined as the log-difference between the Tobin's Q of a conglomerate and the Tobin's Q of a similar portfolio of specialized firms. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Core-periphery* is a dummy variable equal to 1 if the firm simultaneously participates in core and peripheral segments. All network variables use the 1997 BEA input-output network. The independent variables are lagged one year. All variables are defined in detail in the appendix. A constant is included but not reported in the table.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5.2. Controlling for Coinsurance Effects

An alternative explanation of our results is that our measure of excess centrality captures the positive benefits of diversification driven by coinsurance effects as shown by Hann et al. (2013), rather than by information diffusion within a conglomerate. One would expect conglomerates that participate in more distant segments to experience larger coinsurance gains from business diversification because of higher debt capacity and concomitant tax shields, or because of lower systematic risk through the avoidance of countercyclical deadweight costs. Also, if the firm is more unlikely to collapse, workers know that they can be easily reallocated to other divisions, and thus are appropriately incentivized. In turn, this could materially affect firm performance.[20]

To address the above concern, we construct a measure for the average industry return correlation among segments in a conglomerate. We first compute the weekly value-weighted industry stock return averaging the weekly stock return of each single segment firm in a BEA industry. Then for each year we compute the return correlation for each industry pair. Finally, for each conglomerate we define cross-segments correlation as the average correlation among all possible industry pairs in which the conglomerate is present.

$$\text{Cross-Segments Correlation} = \frac{\sum_{i\in\mathcal{J}}\sum_{j>i\wedge i\in\mathcal{J}}\mathrm{Corr}_{ij}}{M(M-1)/2}, \tag{7}$$

where, as before, $\mathcal{J}$ denotes the set of industries in which the conglomerate participates, M is the size of this set, and Corr_{ij} is the annual return correlation between industries i and j.

Table 10 shows that the coefficient on cross-segments correlation is negative, which is consistent with the presence of a coinsurance effect. However,

Table 10 **Excess Value, Excess Centrality, and Cross-Segments Correlation**

	(1)	(2)	(3)	(4)
Excess_centrality	0.240***	0.235***	0.228***	0.167**
	0.066	0.064	0.063	0.046
	(3.88)	(3.67)	(3.48)	(1.99)
Cross-segments_correlation	−0.221***	−0.217***	−0.217***	−0.040
	−0.085	−0.083	−0.083	−0.015
	(−6.06)	(−5.94)	(−5.88)	(−1.39)
No._of_segments		−0.002	0.002	−0.020*
		−0.004	0.003	−0.033
		(−0.26)	(0.16)	(−1.94)
Related_segments		0.021	0.027	0.014
		0.023	0.030	0.016
		(1.26)	(1.63)	(0.79)
Vert._relatedness		0.000	0.000	0.000
		0.004	0.007	0.022
		(0.35)	(0.58)	(1.02)
Excess_assets			−0.007	−0.059***
			−0.026	−0.223
			(−1.45)	(−6.26)
Excess_EBIT/sales			−0.004***	−0.001**
			−0.078	−0.015
			(−7.25)	(−2.37)
Excess_capex/sales			0.001**	0.003***
			0.014	0.031
			(2.27)	(10.11)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	No	Yes
R^2	0.033	0.034	0.041	0.038
No. of observations	20,648	20,648	19,809	19,809

Notes. The dependent variable is *Excess_value*, defined as the log-difference between the Tobin's Q of a conglomerate and the Tobin's Q of a similar portfolio of specialized firms. The table presents OLS regression coefficients, beta coefficients, and robust t-statistics clustered at the conglomerate level. *Excess_centrality* is defined as the log-difference between the closeness centrality of a conglomerate and the one of a similar portfolio of specialized firms. All network variables use the 1997 BEA input-output network. The independent variables are lagged one year. All variables are defined in the appendix. A constant is included but not reported.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[20] See, for example, Manso (2011), Acharya et al. (2013), Bradley et al. (2014), and Custódio et al. (2014).

our results on excess centrality remain significant, statistically and economically, in all specifications.

5.3. Additional Robustness Checks

First, as we noted in §2.2, many assumptions go into the definition of excess centrality and excess value. Even though all assumptions we made are theoretically justified and consistent with prior literature, one might wonder how the results look like if we make different choices in defining the variables of interest. Panels A–C in Table 11 summarize results when we use alternative definitions of excess value and excess centrality. Detailed tables with these results are presented in the online appendix.

Table 11 Summary of Robustness Checks

	(1)	(2)	(3)	(4)
1. *Main_specification*	0.400***	0.406***	0.380***	0.259**
Panel A. Alternative excess centrality measures				
2. *Min_5%_segment_size*	0.389***	0.391***	0.372***	0.274***
3. *Min_10%_segment_size*	0.392***	0.392***	0.380***	0.206**
4. *Max_of_industry_flows*	0.379***	0.387***	0.361***	0.277***
5. *Industry-to-commodity_flows*	0.465***	0.464***	0.444***	0.340***
6. *Normalized_industry_flows*	0.206**	0.345***	0.311***	0.432**
7. *2002_I-O_network*	0.296***	0.307***	0.280***	0.193**
8. *Equally-weighted_excess_centrality*	0.438***	0.454***	0.430***	0.182
9. *Using_sales_weights*	0.351***	0.358***	0.340***	0.109
10. *Using_capex_weights*	0.292***	0.293***	0.269***	0.089
Panel B. Alternative excess value measures				
11. *Goodwill_adjustment*	0.476***	0.456***	0.423***	0.265**
12. *Assets_match*	0.387***	0.376***	0.352***	0.311**
13. *Min._five_specialized_firms per_industry*	0.379***	0.392***	0.370***	0.272***
Panel C. Other robustness checks				
14. *Unadjusted_control_variables*	0.400***	0.406***	0.397***	0.271***
15. *Excl._retail_and_wholesale*	0.335***	0.344***	0.315***	0.236**
16. *Excl._prof.,_sci.,_and_tech._(1)*	0.415***	0.416***	0.388***	0.305***
17. *Excl._prof.,_sci.,_and_tech._(2)*	0.416***	0.417***	0.389***	0.318***
18. *Excl._conc._industries_(1)*	0.373***	0.379***	0.355***	0.236**
19. *Excl._conc._industries_(2)*	0.279***	0.288***	0.267***	0.184*
20. *Excl._M&A-active_congs.*	0.360***	0.363***	0.342***	0.273**
21. *Control_for_syst._risk*	0.406***	0.413***	0.373***	0.252**
22. *Control_for_excess_syst._risk*	0.358***	0.370***	0.346***	0.250**
Year fixed effects	Yes	Yes	Yes	Yes
Diversification controls	No	Yes	Yes	Yes
Financial controls	No	No	No	Yes
Firm fixed effects	No	No	No	Yes

Notes. In panel A, the dependent variable is *Excess_value*, defined as the log-difference between the Tobin's *Q* of a conglomerate and the Tobin's *Q* of a similar portfolio of specialized firms, following Berger and Ofek (1995), and each row presents the coefficient of excess centrality for a particular type of network construction. In panel B, the dependent variables are alternative definitions of the excess value measure, and each row presents the coefficient of excess centrality for a particular definition of excess value. Each column refers to different specifications in terms of control variables, which are indicated at the bottom of the table. "Diversification controls" refers to the following controls: vertical relatedness, number of segments, and related segments. "Financial controls" refers to the following controls: excess assets, excess EBIT/sales, and excess capex/sales. All variables are defined in detail in the appendix. The full set of results is reported in the online appendix. Standard errors are clustered at the conglomerate level.

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11 shows the excess centrality coefficients for several specifications using alternative definitions of industry network and excess value. In the first row, we report the main results of Table 2 for comparison purposes. Panel A presents results using alternative methods of network construction. In our main analysis we assume that even a minimal participation in an industry is enough to access the information at that node. To address concerns about this assumption, in rows 2 and 3 we present results when we consider only segments whose size is at least 5% or 10% of total assets, respectively. It is also not obvious how to map input-output flows to a proxy for information transmission across industries. Information transmission from industry A to industry B could be driven by the maximum of flows between the two industries (row 4), by a directional measure such as industry-to-commodity flows (row 5),[21] or by a flow scaled by the total flow to industries A and B (row 6). We note that the results using industry-to-commodity flows, which focus on how much an industry is selling to another industry, are stronger than the results of the main specification. This suggests that "sell flows" are more important for information diffusion and is consistent with the GE quote we present in the introduction, where the company claims that it obtained relevant information about the macroeconomic environment from its plastics division (which supplies a broad industry base). We also test whether results are similar when we use the 2002 input-output tables, instead of the 1997 ones (row 7), when we use equal weights to construct the centrality of the benchmark portfolio of specialized firms (row 8), and when we use sales or capex weights (rows 9 and 10) instead of asset weights. In almost all specifications, results are very similar to the ones found in the main table.

There is also some discretion in how we define our main dependent variable, excess value. Results are robust even when we control for the goodwill adjustment proposed by Custódio (2014) (row 11), when we restrict the sample to conglomerates whose total assets stated in COMPUSTAT Segments differ at most by 5% from the total assets stated in COMPUSTAT Fundamentals (row 12), and when we consider only industries where there are at least five specialized firms (row 13).

We ran additional robustness checks for the excess-value analysis, presented in panel C of Table 11. We find similar results if we use the same financial

[21] The network is disconnected when we consider flows in the other direction, i.e., commodity-to-industry, thus we could not replicate our analysis with this approach.

controls as in Berger and Ofek (1995), without the industry adjustment recommended by Gormley and Matsa (2014) (row 14); if we exclude from the analysis highly central industries (retail and wholesale trade; professional, scientific, and technical services) (rows 15–17); if we exclude from the analysis conglomerates that participate in highly concentrated industries (top decile or quintile of sales-based Herfindahl index) (rows 18–19); and if we drop from the sample conglomerates that engage significantly in M&A (row 20). Furthermore, we conduct a robustness check to make sure our results are not driven by systematic risk. Aobdia et al. (2014) and Ahern (2013) argue that industry size and network position are correlated with proxies for systematic risk; and Shin and Stulz (2000) suggest that Tobin's Q is positively related to systematic risk. To address these concerns, we add to our main regressions controls for conglomerate beta and also conglomerate excess beta, which is differenced out with respect to the beta of a similar portfolio of single-segment firms. Our results remain essentially unchanged (rows 21 and 22).

Finally, in other results tabulated in the online appendix, we present additional specifications using alternative definitions of excess patents and excess citations.

6. Conclusion

Our paper studies the diversification strategy of conglomerates within the network of industries. We view diversified firms as creating informational shortcuts that link otherwise distant industries in the economy. We hypothesize that these connections give conglomerates an informational advantage, allowing these firms to overcome the informational frictions that limit the trading and contracting opportunities available to specialized companies. Our empirical analysis tests this hypothesis using a networks approach. We postulate that interindustry trade flows are conduits for business-relevant information, and we accordingly use the network induced by these flows as a proxy for the economy's information structure. Using the interindustry network, we find that conglomerates with a high centrality relative to comparable portfolios of specialized firms command high value. Furthermore, and consistent with our information story, these same conglomerates innovate at a higher rate, producing more and better patents. Finally, we also show that the pattern of cross-industry citations for conglomerate-produced patents is consistent with conglomerates being able to effectively combine cross-industry knowledge, as compared to their single-segment counterparts. Our view of diversified firms, centered in the notion of internal information markets, is also a generalization of earlier research on conglomerates, since the benefits of internal capital or labor markets are predicated on interfirm and interindustry informational asymmetries. Our paper thus adds to the literature by proposing a novel unifying framework for some of the bright sides of corporate diversification.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2014.2060.

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Appendix

A.1. Variable Definitions

- *Acquisition_ratio*. The ratio between the acquisition activity (AQC) and the total assets of a company (source: COMPUSTAT).
- *Assets*. The total assets of a company (source: AT variable in COMPUSTAT).
- *Capex*. Funds used for additions to PP&E, excluding amounts arising from acquisitions (source: CAPEX variable in COMPUSTAT).
- *Core-periphery*. Dummy variable equal to 1 if the firm simultaneously participates in core and peripheral segments, with thresholds defined as the 75th and the 25th percentile of industry centrality (source: COMPUSTAT, COMPUSTAT Segments, BEA, and authors' calculations).
- *Cross-industry_citations*. The proportion of citations made by a patent produced in a given industry that refer to patents from another industry. To obtain the measure at the conglomerate and benchmark-portfolio level, this number is averaged across all possible industry pairs where the conglomerate is present.
- *Cross-segments_correlation*. We first compute the weekly value-weighted industry stock return averaging the weekly return of each single-segment firm in a BEA industry. Then for each year we compute the return correlation for each industry pair, if there are at least 10 weekly return observations for each industry year. Finally, for each conglomerate we define cross-segments correlation as the average return

correlation for all possible industry pairs where the conglomerate is present (source: CRSP, COMPUSTAT Segments, BEA, and authors' calculations).

- *EBIT* (*earnings before interest and taxes*). Net sales, minus cost of goods sold minus selling, general and administrative expenses minus depreciation and amortization (source: EBIT variable in COMPUSTAT).
- *Equally-weighted_excess_centrality*. The log-difference between the closeness centrality of a conglomerate and the equally-weighted closeness centrality of a similar portfolio of specialized firms, using the detailed input-output industry classification system (source: COMPUSTAT, COMPUSTAT Segments, BEA, and authors' calculations).
- *Equity_beta*. The equity beta of a company, computed with a daily return regression over the calendar year using the NYSE/NASDAQ market portfolio (source: BETAV variable in CRSP).
- *Excess_assets*. The log-difference between the assets of a conglomerate and the assets of a similar portfolio of specialized firms (source: COMPUSTAT Segments and authors' calculations).
- *Excess_equity_beta*. The difference between the equity beta of a conglomerate and the equity beta of a similar portfolio of specialized firms. We did not take the log difference as in other excess measures because in a few cases the equity beta is negative (source: CRSP, COMPUSTAT Segments, and authors' calculations).
- *Excess_capex/sales*. The difference between the capex/sales of a conglomerate and the capex/sales of a similar portfolio of specialized firms. We did not take the log difference as in other excess measures because in a few cases capex/sales is negative (source: COMPUSTAT Segments, and authors' calculations).
- *Excess_centrality*. The log-difference between the closeness centrality of a conglomerate and the assets-weighted closeness centrality of a similar portfolio of specialized firms, using the detailed input-output industry classification system (source: COMPUSTAT, COMPUSTAT Segments, BEA, and authors' calculations).
- *Excess_citations*. The log difference between the asset (or R&D)-scaled number of subsequent citations received by all patents produced by a conglomerate in a given fiscal year, and the asset (or R&D)-scaled number of subsequent citations received by all patents produced in a given year by a similar portfolio of specialized firms (constructed with conglomerate asset weights), using the detailed input-output industry classification system; the top and bottom 1% of observations were winsorized because of the presence of outliers, but results are robust to alternative outliers methods (truncation) and windows. We exclude observations where the comparable portfolio of specialized firms has zero patents produced (source: CRSP, COMPUSTAT Segments, COMPUSTAT, BEA, NBER patent data set, and authors' calculations).
- *Excess_EBIT/sales*. The difference between the EBIT/sales of a conglomerate and the EBIT/sales of a similar portfolio of specialized firms. We did not take the log difference as in other excess measures because in many cases EBIT/sales is negative (source: COMPUSTAT Segments and authors' calculations).
- *Excess_generality*. The log difference between the average generality of the patents produced by a conglomerate in a given fiscal year, and the average generality of patents produced in a given year by a similar portfolio of specialized firms (constructed with conglomerate asset weights), using the detailed input-output industry classification system; we exclude observations where the comparable portfolio of specialized firms has zero patents produced (source: CRSP, COMPUSTAT Segments, COMPUSTAT, BEA, NBER patent data set, and authors' calculations).
- *Excess_originality*. The log difference between the average originality of the patents produced by a conglomerate in a given fiscal year, and the average originality of patents produced in a given year by a similar portfolio of specialized firms (constructed with conglomerate asset weights), using the detailed input-output industry classification system; we exclude observations where the comparable portfolio of specialized firms has zero patents produced (source: CRSP, COMPUSTAT Segments, COMPUSTAT, BEA, NBER patent data set, and authors' calculations).
- *Excess_patents*. The log difference between the asset (or R&D)-scaled number of patents produced by a conglomerate in a given fiscal year, and the asset (or R&D)-scaled number of patents produced in a given year by a similar portfolio of specialized firms (constructed with conglomerate asset weights), using the detailed input-output industry classification system; the top and bottom 1% of observations were winsorized because of the presence of outliers, but results are robust to alternative outliers methods (truncation) and windows. We exclude observations where the comparable portfolio of specialized firms has zero patents produced (source: CRSP, COMPUSTAT Segments, COMPUSTAT, BEA, NBER patent data set, and authors' calculations).
- *Excess_value*. The log-difference between the Tobin's Q of a conglomerate and the assets-weighted Tobin's Q of a similar portfolio of specialized firms, using the detailed input-output industry classification system (source: CRSP, COMPUSTAT, BEA, and authors' calculations).
- *Generality*. $(N_i/(N_i-1))(1-\sum_{j=1}^{M} s_{ij}^2)$, where s_{ij} is the percentage of citations received by patent i from patents that belong to patent class j; and where there are a total of M patent classes and patent i received a total of N_i citations (source: NBER patent data set and authors' calculations).
- *Industry_centrality*. The closeness centrality of an industry, using the detailed input-output industry classification system. Closeness centrality is defined as the inverse of the average distance between the industry and all other industries in the network, as shown in Equation (1) (source: BEA and authors' calculations).
- *Mkt._share_single_segment*. The assets-weighted average of the market share of specialized (single-segment) competitors in each of the detailed input-output industries in which the conglomerate firm is active (source: COMPUSTAT, COMPUSTAT Segments, BEA, and authors' calculations).
- *No._of_analysts_SS*. The assets-weighted average of the number of equity analysts covering single-segment competitors in each of the detailed input-output industries in which the conglomerate firm is active (source: COMPUSTAT, COMPUSTAT Segments, BEA, IBES, and authors' calculations).

- *No._of_segments*. The number of unique segments of a conglomerate using the detailed input-output industry classification system (source: COMPUSTAT Segments and BEA).
- *Originality*. $(N_i/(N_i-1))(1-\sum_{j=1}^{M} s_{ij}^2)$, where s_{ij} is the percentage of citations made by patent i of patents that belong to patent class j; and where there are a total of M patent classes and patent i made a total of N_i citations (source: NBER patent data set and authors' calculations).
- *Related_segments*. The number of unique segments of a conglomerate using the detailed input-output industry classification system, minus the number of unique segments of a conglomerate using the three-digit input-output industry classification system, following Berger and Ofek (1995) (source: COMPUSTAT Segments and BEA).
- *Sales*. Gross sales reduced by cash discounts, trade discounts, and returned sales (source: SALE variable in COMPUSTAT).
- *Tobin's_Q*. The sum of total assets (AT) minus the book value of equity (BE) plus the market capitalization (stock price at the end of the year (PRCC_F) times the number of shares outstanding (CSHO)), divided by the total assets (AT) (source: COMPUSTAT).
- *Vert._relatedness*. Constructed following Fan and Lang (2000). Measures the average input-output flow intensity between each of the conglomerate's nonprimary segments and the conglomerate's primary segment; averaged across all nonprimary segments (source: COMPUSTAT Segments, BEA, and authors' calculations).

A.2. Sample Selection

The original source for the main data set is COMPUSTAT Segments. In 71% of the observations multiple source documents exists for each reported year segment, because companies retroactively update segment data over time. To avoid look-ahead biases, for each fiscal year we use only data from the first available source year. We start selecting the business segmentation, and downloading financial data on conglomerates and specialized firms from fiscal year 1989 until 2011. The starting data set has 315,173 segment-level observations. We drop firms that cannot be found on COMPUSTAT Fundamentals annuals, the United States Postal Service (GVKEY 61994) and any segment with no assets or sales (16% of the sample). In rare cases (1.3% of the sample) in which a segment has no NAICS industry code, we look for a segment of the same firm in previous or following years with the same name to fill up the missing information. We also drop segments where no NAICS code is available (< 1% of the sample). The resulting data set has 237,392 observations.

We then match NAICS codes to the input-output detailed industry classification using the BEA concordance tables.[22] Using the I-O industry codes, we aggregate all divisions within the same industry, resulting in 206,609 unique I-O-code-industry segments. We split the data into a data set of 119,606 specialized firms, and a data set of 87,003 conglomerates divisions. We use the specialized firms data set to construct the benchmark portfolio: we drop firms whose Tobin's Q is below the first or above the 99th percentile, or whose total assets reported in COMPUSTAT Segments differ more than 5% from the total assets reported on COMPUSTAT Fundamentals annuals. We then take the average Tobin's Q, assets, capex/sales, EBIT/sales, ROA, and number of patents and citations among all firms in each I-O industry. The final specialized firm data set has 7,319 industry-year observations (438 industries and 22 years).

We then work on the conglomerates data set: First, we drop firms whose Tobin's Q is below the first or above the 99th percentile. Then for each division, we merge in the respective specialized firm's data, and compute the asset-weighted measure of Tobin's Q, total assets, capex/sales, EBIT/sales, ROA, and number of patents and citations for the benchmark portfolio. Finally, we define the excess measures of Tobin's Q, assets, and number of patents and citations as the log-difference between the variable of interest for the conglomerate and the one for the benchmark portfolio of specialized firms, and the excess measures of capex/sales, EBIT/sales, and ROA as the difference between the variable of interest for the conglomerate and the one for the benchmark portfolio of specialized firms. We also apply our final filter, dropping conglomerates whose largest division by assets is in the financial industry (input-output industry code 52).

The final data set has 27,544 conglomerate-year observations. Given that the independent variables are lagged one year, there are only 22,425 observations in the main baseline regressions.

A.3. Cross-Industry Citations: Computation Example

Let us consider United Dominion Industries, a conglomerate that in fiscal year 1995 had two divisions in the prefabricated metal buildings (NAICS 332311) and air conditioning (NAICS 333415) industries. In 1995, the conglomerate applied for eight patents related to six I-O industries. These eight patents cited 1,045 patents related to 11 I-O industries. The conglomerate cross-industry citations measure is the percentage of citations made by these eight patents related to the industry of the first division that cite a patent from the industry of the second division, or vice versa. In our data, 13.3% of citations made by the eight patents produced by United Dominion Industries in 1995 originate in the metal buildings industry, and cite a patent from the air conditioning industry, or vice versa. We then construct a similar portfolio of specialized firms, and compute a similar measure of cross-industry citations. On average, specialized firms in the metal buildings industry cite a patent from the air conditioning industry (or vice versa) only 4.2% of the time. This means that United Dominion Industry has an excess cross-industry citations index of $13.3\% - 4.2\% = 9.1\%$.

A.4. Knowledge Exchange and the Boundaries of the Firm

This section briefly discusses our key assumption in light of the existing theories of the firm. In particular, why is it the case that integration—forming a conglomerate in our case—is required in order for firms to materialize the synergies that accrue from combining cross-industry information and knowledge, and the same cannot be achieved by an inter-firm contract? Most theories of the firm invoke transaction costs (e.g., Coase 1937, Williamson 1975) or incomplete contracting (Grossman and Hart 1986, Hart and Moore 1990)

[22] The concordance tables can be found at Lawson et al. (2002).

as the determinants of the integration decision. Many of these theories appeal explicitly to ex post opportunistic behavior arising as a consequence of relationship-specific investments.

To illustrate this argument in our setting, assume that to understand/assimilate industry B's practices, a firm in industry A needs to collaborate with a specific firm in industry B, which can be thought of as a "translator." In this example, the translator, given its special relationship with a firm in industry A, could well realize the importance B's technology plays there. As a consequence, the translator could decide to enter industry A, and it may be unable to commit not to do so ex ante in a world of incomplete contracts. In the presence of two separate firms, this increase in ex post competition may thus deter the firm in industry A from investing in learning about B's technology; such a problem is mitigated in a conglomerate.

Other theories of the firm focus on tensions internal to the firm (Robinson 2008, Mathews and Robinson 2008). It can be the case that to commit enough resources ex ante to the exploration of new processes/technologies at the intersection of two industries, it is necessary for the firm to be present in both businesses; perhaps because otherwise resources end up always being diverted ex post toward more pressing projects.

Finally, our key argument is in the spirit of Lindsey (2008), who shows that venture capitalists are instrumental in facilitating the formation of strategic alliances (which bring together knowledge and information). In a way, one could view the headquarters of a conglomerate firm as providing a similar service.

References

Acharya V, Baghai R, Subramanian K (2013) Labor laws and innovation. *J. Law Econom.* 56:997–1037.

Ahern KR (2013) Network centrality and the cross section of stock returns. Working paper, University of Southern California, Los Angeles.

Ahern KR, Harford J (2014) The importance of industry links in merger waves. *J. Finance* 69:527–576.

Aobdia D, Caskey J, Ozel NB (2014) Inter-industry network structure and the cross-predictability of earnings and stock returns. *Rev. Accounting Stud.* 19:1191–1224.

Berger PG, Ofek E (1995) Diversification's effect on firm value. *J. Financial Econom.* 37:39–65.

Bradley DJ, Kim I, Tian X (2014) Do unions affect innovation? Working paper, University of South Florida, Tampa.

Burt RS (1992) *Structural Holes: The Social Structure of Competition* (Harvard University Press, Cambridge, MA).

Burt RS (2004) Structural holes and good ideas. *Amer. J. Sociology* 110:349–399.

Burt RS (2005) *An Introduction to Social Capital* (Oxford University Press, Oxford, UK).

Coase R (1937) The nature of the firm. *Economica* 4:386–405.

Custódio C (2014) Mergers and acquisitions accounting and the diversification discount. *J. Finance* 69:219–240.

Custódio C, Ferreira MA, Matos PP (2014) Do general managerial skills spur innovation? Working paper, Arizona State University, Phoenix.

Fan J, Lang L (2000) The measurement of relatedness: An application to corporate diversification. *J. Bus.* 73:629–660.

Faure-Grimaud A, Laffont JJ, Martimort D (2003) Collusion, delegation and supervision with soft information. *Rev. Econom. Stud.* 70:253–279.

Gertner RH, Scharfstein DS, Stein JC (1994) Internal versus external capital markets. *Quart. J. Econom.* 109:1211–1230.

Gomes-Casseres B, Hagedoorn J, Jaffe AB (2006) Do alliances promote knowledge flows? *J. Financial Econom.* 80:5–33.

Gormley TA, Matsa DA (2014) Common errors: How to (and not to) control for unobserved heterogeneity. *Rev. Financial Stud.* 27:617–661.

Graham JR, Lemmon ML, Wolf JG (2002) Does corporate diversification destroy value? *J. Finance* 57:695–719.

Granovetter M (1973) The strength of weak ties. *Amer. J. Sociology* 78:1360–1380.

Grossman SJ, Hart OD (1986) The costs and benefits of ownership: A theory of vertical and lateral integration. *J. Political Econom.* 55:691–719.

Gulati R (1999) Network location and learning: The influence of network resources and firm capabilities on alliance formation. *Strategic Management J.* 20:397–420.

Hall B, Jaffe A, Trajtenberg M (2001) The NBER patent citations data file: Lessons, insights and methodological tools. NBER Working Paper 8498l, National Bureau of Economic Research, Cambridge, MA.

Hann R, Ogneva M, Ozbas O (2013) Corporate diversification and the cost of capital. *J. Finance* 68:1961–1999.

Hargadon A (2003) *How Breakthroughs Happen* (Harvard Business School Press, Boston).

Hart OD, Moore J (1990) Property rights and the nature of the firm. *J. Political Econom.* 98:1119–1158.

Hoberg G, Phillips G (2010) Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Rev. Financial Stud.* 23(10):3773–3811.

Hochberg YV, Ljungqvist A, Lu Y (2007) Whom you know matters: Venture capital networks and investment performance. *J. Finance* 62:251–301.

Hubbard RG, Palia D (2002) A reexamination of the conglomerate merger wave in the 1960s: An internal capital markets view. *J. Finance* 54:1131–1152.

Jackson MO (2008) *Social and Economic Networks* (Princeton University Press, Princeton, NJ).

Khanna N, Tice S (2002) The bright side of internal capital markets. *J. Finance* 56:1489–1528.

Laidlaw J, Lawsky D (2002) GE's Immelt sees no sign of U.S. upturn till 2003. *USA Today* (January 28), http://usatoday30.usatoday.com/money/general/2002/01/28/ge.htm.

Lang LHP, Stulz RM (1994) Tobin's *q*, corporate diversification, and firm performance. *J. Political Econom.* 102:1248–1280.

Lawson AM, Bersani KS, Fahim-Nader M, Guo J (2002) Benchmark input-output accounts of the United States, 1997. *Survey of Current Business* (December):19–109.

Lindsey L (2008) Blurring firm boundaries: The role of venture capital in strategic alliances. *J. Finance* 63:1137–1168.

Maksimovic V, Phillips G (2002) Do conglomerate firms allocate resources inefficiently? *J. Finance* 57:721–767.

Manso G (2011) Motivating innovation. *J. Finance* 66:1823–1869.

Massa M, Rehman Z (2008) Information flows within financial conglomerates: Evidence from the banks-mutual funds relation. *J. Financial Econom.* 89:288–306.

Mathews RD, Robinson DT (2008) Market structure, internal capital markets, and the boundaries of the firm. *J. Finance* 63:2703–2736.

McEvily B, Marcus A (2005) Embedded ties and the acquisition of competitive capabilities. *Strategic Management J.* 26:1033–1055.

Mol MJ, Birkinshaw J (2009) The sources of management innovation: When firms introduce new management practices. *J. Bus. Res.* 62:1269–1280.

Ozsoylev H, Walden J, Yavuz MD, Bildik R (2014) Investor networks in the stock market. *Rev. Financial Stud.* 27:1323–1366.

Potter J, Moore B, Spires R (2003) Foreign manufacturing investment in the United Kingdom and the upgrading of supplier practices. *Regional Stud.* 37:41–60.

Powell WW, Koput KW, Smith-Doerr L (1996) Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Admin. Sci. Quart.* 41:116–145.

Robertson M, Swan J, Newell S (1998) The role of networks in the diffusion of technological innovation. *J. Management Stud.* 33:333–359.

Robinson DT (2008) Strategic alliances and the boundaries of the firm. *Rev. Financial Stud.* 21:649–681.

Santalo J, Becerra M (2008) Competition from specialized firms and the diversification-performance linkage. *J. Finance* 63: 851–883.

Sanzhar SV (2006) Discounted but not diversified: Organizational structure and conglomerate discount. Working paper, University of North Carolina at Chapel Hill, Chapel Hill.

Schoar A (2002) Effects of corporate diversification on productivity. *J. Finance* 57:2379–2403.

Seru A (2014) Firm boundaries matter: Evidence from conglomerates and R&D activity. *J. Financial Econom.* 111:381–405.

Servaes H (1996) The value of diversification during the conglomerate merger wave. *J. Finance* 51:1201–1255.

Shin HH, Stulz R (2000) Firm value, risk, and growth opportunities. Working paper, Ohio State University, Columbus.

Shleifer A, Vishny RW (1991) Takovers in 60s and 80s: Evidence and implications. *Strategic Management J.* 12:51–59.

Stein JC (2002) Information production and capital allocation: Decentralized versus hierarchical firms. *J. Finance* 57:1891–1921.

Tate G, Yang L (2014) The bright side of corporate diversification: Evidence from internal labor markets. Working paper, University of North Carolina at Chapel Hill, Chapel Hill.

Villalonga B (2004) Diversification discount or premium? New evidence from the business information tracking series. *J. Finance* 59:479–506.

Williamson O (1975) *Markets and Hierarchies: Analysis and Antitrust Implications* (Free Press, New York).