Shopping for Information? Diversification and the Network of Industries*

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Abstract

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 inter-industry 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.

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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, Scharfstein, and Stein, 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 (...)*".[2] 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.

[1] This is illustrated in the following quote from Hargadon (2003): "*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] Source: `http://usatoday30.usatoday.com/money/general/2002/01/28/ge.htm`

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 inter-industry customer-supplier links, which is consistent with much existing research.[3] If information flows through customer-supplier relationships, then depending on the overall inter-industry 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 non-redundant 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, 2013). 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

[3] McEvily and Marcus (2005) argue that knowledge sharing between customers and suppliers leads to the acquisition of competitive capabilities; Powell, Koput, and Smith-Doerr (1996) find evidence that inter-firm networks influence biotech innovation productivity; Gulati (1999) claims that information percolating through inter-firm 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, Moore, and Spires (2003) present evidence that US-based firms transmitted "best practices" to UK suppliers; and Robertson, Swan, and Newell (1998) find that firms selecting a Computer-Aided Production Management (CAPM) technology draw on their inter-firm connections to make a choice.

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.

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 due to 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.[4] Third, we construct various alternative specifications of network variables and excess value.[5] Fourth, we show that our results are not driven by industry concentration, systematic risk,[6]

[4] 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, Baghai, and Subramanian (2014), Bradley, Kim, and Tian (2014), and Custódio, Ferreira, and Matos (2014).

[5] Results are very similar, both economically and statistically, if we change our definition of excess value using a goodwill adjustment (Custódio, 2013), if we exclude industries with fewer than 5 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 section 5.3 and in the online appendix.

[6] Ahern (2013) argues that there is a associations between network position and systematic risk.

or just by conglomerates that participate in highly central industries.[7]

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 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, Jaffe, and Trajtenberg (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

[7] These results are presented in section 5.3 and in the online appendix.

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,[8] 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).[9] Two recent examples of such an approach in finance are Hochberg, Ljungqvist, and Lu (2007) and Ozsoylev, Walden, Yavuz, and Bildik (2013).[10]

The remainder of the 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. An appendix contains variable definitions and further details about our dataset construction and assumptions. Ad-

[8] See, among others, Lang and Stulz (1994), Berger and Ofek (1995), Maksimovic and Phillips (2002), Graham, Lemmon, and Wolf (2002), Schoar (2002), and Villalonga (2004).

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

[10] Hochberg, Ljungqvist, and Lu (2007) analyze how the network position of venture capitalists affects their investments' performance. Ozsoylev, Walden, Yavuz, and Bildik (2013) 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.

ditional robustness checks mentioned in the text are included in an online appendix, available from the authors' websites.

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*. Second, we describe the empirical implementation using an industry network based on input-output 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 inter-industry (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.[11]

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 share information internally without frictions.[12] If this infor-

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

[12]We provide a more detailed explanation of the key assumptions in light of the existing theories of the firm in section D of the appendix.

mation 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 in order 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

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

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 frictionlessly 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

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

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):

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

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

The construction of our main variable of interest, excess centrality, implies some assumptions which may or may not hold in data. For example, it is possible that a minimum level of participation in an industry is required in order 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.[13] This argument notwithstanding, later in the paper we employ an approach that allows for tractable use of alternative centrality measures (see section 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 network.

Our data comes from two sources: (i) input-output tables for the construction of the inter-industry network; and (ii) data from COMPUSTAT, COMPUSTAT Segment and 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

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

are aggregated into 470 industries, a similar level of aggregation as the 4-digit SIC code. We use such industry classification, rather than more conventional classifications such as SIC or NAICS, because the input-output tables reporting the flow of goods and services between industries come from the Bureau of Economic Analysis. Detailed input-output tables are prepared by the BEA every 5 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 5 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 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 section 5.3 we replicate the main analysis with the 2002 network, and we find very similar results. In section 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 when we use the detailed industry classification (61 industries vs 470 industries).

The first step in constructing our network variables is to create a square matrix of inter-industry flows. We use flows from the 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 section 5.3.

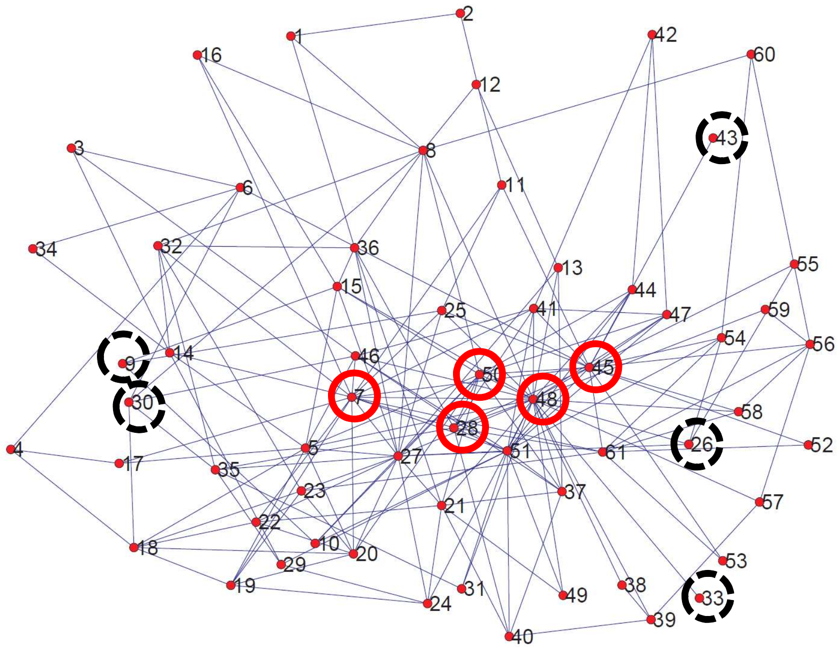

Figure 1: The figure shows the industry network using the 3-digit Input-Output Tables Industry Classification system level. Solid red (dashed black) circles represent the top (bottom) 5 industries in the centrality ranking. The top centrality industries are "Construction", "Miscellaneous professional, 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.

The second step in constructing the network variables is to compute the average flow for industry pair (i, j); denote this flow by $\overline{f}_{i,j}$. 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:

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

With the adjacent distances we can now construct an industry network, which is a weighted undirected graph.[14] Figure 1 illustrates the industry network, as well as the top 5 and bottom 5 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).[15] 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 in order to access the information at that node. To address this concern, section 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" (IO code 325180) and "AC, refrigeration, and forced air heating" (IO 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

[14] 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.

[15] These network measures were computed using MATLAB BGL routines (available at `http://www.mathworks.nl/matlabcentral/fileexchange/10922`), namely the dijkstra algorithm for minimal travel costs.

follows that the excess centrality of LSB for 2008, according to equation (4), is

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

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, section 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.

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. In order 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.[16] 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 section 3.2.2 by employing econometric specifications where excess centrality is driven *uniquely* by changes in the overall network structure.

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 dataset covers the period from 1990 to 2011, because we requires 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 Segment reports the NAICS code of each segment, and BEA provides a map-

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

ping between these NAICS codes and the 6-digit Input-Output Codes. In section B 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, 2013): 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 discount in our sample (-0.29) is larger , relative to the discount found in Berger and Ofek (1995) (-0.16). This is probably due to the difference in sample periods (1990-2011 vs 1986-1991) and to the different industry classification (I-O vs 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 1 about here]

Table 2 presents 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 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,[17] and to allow a direct comparison of coefficients across variables and specifications under reasonable distribution assumptions.

[Table 2 about here]

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), in order 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

[17] 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.

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 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

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

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 $\pm$ 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 2- and 3-segment conglomerates, as tabulated in the online appendix. Therefore, for the average 2-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. In order 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 due to 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. While 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):

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

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.[18]

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 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 about here]

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.

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

[18] 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 section 5.3.

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 (section 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 which cannot be credibly conveyed to outsiders, such as external capital markets (Stein, 2002; Faure-Grimaud, Laffont, and Martimort, 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.

[Table 4 about here]

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)).

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 non-public information.

[Table 5 about here]

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 dataset). 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.

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 (section 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 section D 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 R&D productivity is also used by Seru (2010) to study the innovation performance of diversified firms. We collect the patent data from the National Bureau of Economic Research, created by Hall, Jaffe, and Trajtenberg (2001) for the fiscal years 1990 to 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.[19] Summary statistics are presented in panel B of table 1. Consistent with the results in Seru (2010), conglomerates produce fewer patents (-5.3%) and receive less citations (-21.1%) than 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, Jaffe, and Trajtenberg (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 pro-

[19] We winsorize the patents and citations variables at the 1% and 99%. 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.

duce patents. We use the same control variables as in previous tables: vertical relatedness, number of segments, number of related segments, and financial characteristics.

[Table 6 about here]

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 leads to an additional of about 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 section 3.3.1.

[Table 7 about here]

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, Jaffe, and Trajtenberg (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 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, Hagedoorn, and Jaffe (2006), who study patterns of cross-industry patent citations in inter-corporate alliances. The authors argue that their findings suggest that knowledge flows more easily within alliances than across non-allied 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 dataset used for the patents and citations analysis in section 4.1, and the 3-digit Input-Output industry classification. First, we assemble a dataset containing all patents produced by public companies, and we assign each patent to one or more related I-O industries.[20] 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 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 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 C in the appendix provides a detailed example of how the cross-industry

[20]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 sub-classes, while 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 4-digit 1997 NAICS, and thus I-O industries.

citations measure is computed.

[Table 8 about here]

Table 8 shows the results of a student's t-test comparing the cross-citations pattern of conglomerates and the cross-citations 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.

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 section 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 informational advantages (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 75-th 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%.

[Table 9 about here]

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 section 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.

5.2 Controlling for co-insurance 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, Ogneva, and Ozbas (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.[21]

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.

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

where as before $\mathcal{I}$ 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 about here]

Table 10 shows that the coefficient on cross-segments correlation is negative, which is consistent with the presence of a coinsurance effect. However, our results on excess centrality remain significant, statistically and economically, in all specifications.

[21]See for example Manso (2011), Acharya, Baghai, and Subramanian (2014), Bradley, Kim, and Tian (2014), and Custódio, Ferreira, and Matos (2014).

5.3 Additional robustness checks

First, as we noted in section 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, B, and 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 about here]

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),[22] 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 thats "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

[22]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.

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 (2013) (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 5 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 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, Caskey, and Ozel (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 which 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 inter-industry 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 inter-industry 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 inter-firm and inter-industry informational asymmetries. Our paper thus adds to the literature by proposing a novel unifying framework for some of the bright sides of corporate diversification.

APPENDIX

A. 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*: Dummy variable equal to 1 if the firm simultaneously participates in core and peripheral segments, with thresholds defined as the 75-th and the 25-th 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 & Administrative Expenses minus Depreciation and Amortization (Source: EBIT variable in COMPUSTAT).
- *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 Segment 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 Segment 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 Segment 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 Centrality (Equally-Weighted)*: 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).

- *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 due to 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 Dataset, 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 Segment 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 Dataset, 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 Dataset, 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 due to 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 Dataset, 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*: $\frac{N_i}{N_i-1}\left(1-\sum_{j=1}^{M} s_{ij}^2\right)$, 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. (Source: NBER Patent 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).

- *Market 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).

- *Number 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).

- *Number of Segments*: The number of unique segments of a conglomerate using the detailed Input-Output industry classification system (Source: COMPUSTAT SEGMENTS and BEA).

- *Originality*: $\frac{N_i}{N_i-1}\left(1-\sum_{j=1}^{M} s_{ij}^2\right)$, 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 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 3-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).
- *Vertical Relatedness*: Constructed following Fan and Lang (2000). Measures the average input-output flow intensity between each of the conglomerate's non-primary segments and the conglomerate's primary segment; averaged across all non-primary segments. (Source: COMPUSTAT SEGMENTS, BEA, and Authors' Calculations).

B. Sample Selection

The original source for the main dataset 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 dataset has 315,173 segment-level observations. We drop firms that cannot be found on Compustat Fundamental 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 dataset has 237,392 observations.

We then match NAICS codes to the Input-Output detailed industry classification using the BEA concordance tables.[23] Using the IO industry codes, we aggregate all divisions within the same industry, resulting in 206,609 unique IO-code-industry segments. We split the data into a dataset of 119,606 specialized firms, and a dataset of 87,003 conglomerates divisions. We use the specialized firms dataset to construct the benchmark portfolio: we drop firms whose Tobin's Q is below the 1-st or above the 99-th percentile, or whose total assets reported in Compustat Segments differ more than 5% from the total assets reported on Compustat Fundamental 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 IO industry. The final specialized firm dataset has 7,319 industry-year observations (438 industries and 22 years).

We then work on the conglomerates dataset: First, we drop firms whose Tobin's Q is below the 1-st or above the 99-th percentile. Then for each division, we merge in the respective

[23] The concordance tables can be found on the BEA website at http://www.bea.gov/scb/pdf/2002/12December/1202I-OAccounts2.pdf.

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 dataset 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.

C. 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 8 patents related to 6 I-O industries. These 8 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 8 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 8 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%.

D. 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) 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 in order 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 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 in order 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 towards 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.

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Table 1: Summary Statistics. 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.

Panel A: Specialized Firms

Variable	Mean	Std. Dev.	Min.	Max.	N. Obs.
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
N. Patents	2.555	30	0	1,891	91,114
N. 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

Variable	Mean	Std. Dev.	Min.	Max.	N. Obs.
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 Dummy	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	-1018	12.14	21,829
Excess Assets	0.023	2.302	-10.861	10.459	22425
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
Number of Citations	85.998	699.281	0	20,722.5	16,002
Number of Analysts SS	3.023	2.21	0	22	22,425
Number of Patents	15.218	101.472	0	2,467	16,002
Number 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
Vertical Relatedness	47.101	163.855	0	1,697.34	22,425

Continued on next page

Table 1 – continued from previous page

Panel C: Conglomerates - Time-Varying Network

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N. Obs.**
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	-1018	12.14	19,094
Excess Centrality (Equally-Weighted)	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
Number 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
Vertical Relatedness	2.441	4.698	0	93.047	19,615

Table 2: Excess Value and Excess Centrality in Conglomerates. 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(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)
N. 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 FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes
R^2	0.024	0.026	0.037	0.026
N. of Observations	22,425	22,425	21,516	21,516

Table 3: Excess Value and Excess Centrality – Time-Varying Network. 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) to (3) use the full sample. Specification (4) uses only the sub-sample 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 (3-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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(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)
N. 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 FE	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Firm-Cohort FE	No	No	Yes	No
R^2	0.046	0.059	0.058	0.059
N. of Observations	11,374	11,374	9,906	5,300

Table 4: Industry Composition and Excess Centrality. 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(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)
Exc. Centrality * Mkt. Share SS				-0.956***	-1.003***	-0.691**
				-0.104	-0.108	-0.075
				(-3.62)	(-3.62)	(-2.50)
N. 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 FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	No	No	Yes
R^2	0.045	0.053	0.033	0.048	0.056	0.034
N. of Observations	22,395	21,516	21,516	22,395	21,516	21,516

Table 5: Analyst Coverage and Excess Centrality. 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. N. 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(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)
N. 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)
Exc. Centrality * N. 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)
N. 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 FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes
R^2	0.030	0.031	0.042	0.031
N. of Observations	22,398	22,398	21,516	21,516

Table 6: Excess Innovation and Excess Centrality in Conglomerates. In the first (last) four specifications, the dependent variable is Excess Patents (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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	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)
N. 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 FE	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
N. of Observations	4,326	4,172	3,282	3,159	3,762	3,635	2,875	2,774

Table 7: Excess Innovation and Excess Centrality: Originality and Generality. In the first (last) two specifications, the dependent variable is Excess Generality (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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	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)
N. 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 FE	Yes	Yes	Yes	Yes
R^2	0.038	0.052	0.043	0.049
N. of Observations	3,134	3,041	4,058	3,920

Table 8: Cross-Industry Citations. 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 parenthesis). The cross-industry citations (Patent Weighted) of a conglomerate is the percentage of citations made by patents produced by a conglomerate's division which 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 which 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

Panel A: Cross-Industry Citations (Patent Weighted)

	Obs.	Mean	St.Dev.
Cross-Industry Citations - Conglomerates	5,038	0.0276	0.0011
Cross-Industry Citations - Portfolio of Specialized Firms	5,038	0.0213	0.0006
Cross-Industry Citations - Difference	5,038	0.0063***	0.0010
		(6.44)	

Panel B: Cross-Industry Citations (Industry Weighted)

	Obs.	Mean	St.Dev.
Cross-Industry Citations - Conglomerates	5,038	0.0313	0.0744
Cross-Industry Citations - Portfolio of Specialized Firms	5,038	0.0210	0.0393
Cross-Industry Citations - Difference	5,038	0.0103***	0.0009
		(10.92)	

Table 9: Excess Value and Core-Periphery Strategies. 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(1)	(2)	(3)
Core-Periphery	0.063**	0.061**	0.063**
	0.029	0.028	0.029
	(2.09)	(1.97)	(2.02)
N. 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 FE	Yes	Yes	Yes
R^2	0.014	0.017	0.029
N. of Observations	22,425	22,425	21,516

Table 10: Excess Value, Excess Centrality, and Cross-Segments Correlation. 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(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)
N. 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 FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	Yes
R^2	0.033	0.034	0.041	0.038
N. of Observations	20,648	20,648	19,809	19,809

Table 11: Summary of Robustness Checks. 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. Significance at 10%, 5%, and 1%, is indicated by *, **, and ***.

	(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 Exc. 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. 5 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 FE	Yes	Yes	Yes	Yes
Diversification controls	No	Yes	Yes	Yes
Financial controls	No	No	No	Yes
Firm FE	No	No	No	Yes