Innovation Activities and the Incentives for Vertical Acquisitions and Integration

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ABSTRACT

We examine the incentives for firms to vertically integrate through acquisitions and production. We develop a new firm-specific measure of vertical relatedness and integration using 10-K product text. We find that firms in high R&D industries are less likely to become targets in vertical acquisitions or to vertically integrate. These findings are consistent with the idea that firms with unrealized innovation avoid integration to maintain *ex ante* incentives to invest in intangible assets and to keep residual rights of control as in Grossman and Hart (1986). In contrast, firms in high patenting industries with mature product markets are more likely to vertically integrate, consistent with control rights being obtained by firms to facilitate commercialization of already realized innovation.

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The scope of firm boundaries and whether to organize transactions within the firm (integration) or by using external purchasing is of major interest in understanding why firms exist. Williamson (1971), Williamson (1979) and Klein, Crawford, and Alchian (1978) pioneered this area through their theory of transaction cost economics and ex post holdup given contractual incompleteness. Firms choose the organizational form that minimizes transaction costs and ex post holdup. Grossman and Hart (1986) in their property rights theory of the firm show that control rights are key to understanding firm boundaries and their influence on ex ante investment. They show that ex ante incentives for a firm to invest in relationship-specific assets are reduced under vertical integration for the firm that gives up its residual rights of control to the other contracting firm. Holmstrom and Milgrom (1991) and Holmstrom and Milgrom (1994) also emphasize the role of incentives in firm structure.[1]

In this paper, we show that the costs and benefits of vertical integration are related to the stage of development of innovation. We focus on the distinction between unrealized innovation in the form of R&D and realized innovation characterized by legally enforceable patents. We construct a new firm-specific measure of vertical relatedness using text-based analysis of firm 10-K product descriptions filed with the Securities and Exchange Commission (SEC), and vertically-linked product descriptions from the Bureau of Economic Analysis (BEA) Input-Output tables. This allows us to determine vertical relatedness across firm pairs and hence identify which mergers and acquisitions are vertically related. Moreover, we develop a new measure of within-firm vertical integration at the firm-level based on whether firms use product vocabulary that spans vertically related markets.

This novel approach enables us to analyze vertical relatedness dynamically, as firm 10-Ks are updated annually. We relate firm organizational structures to the stage of their innovation activities (R&D in progress versus patented innovation) broadly across industries, narrowly through within-firm variation, and in industries

[1] Gibbons (2005) summarizes the large literature and highlights that the costs and benefits of vertical integration depend on transactions costs, rent seeking, contractual incompleteness, and the specificity of the assets involved in transactions.

where firms rely more on patents or on secrecy to protect innovation.[2] We use variation in R&D tax credits across states to control for endogeneity.

Using a sample of almost 7,000 publicly-traded firms over the 1996-2008 period, we find strong evidence that firms in R&D intensive industries are less likely to be acquired in vertical transactions. In contrast, firms in patent intensive industries are more likely to be targeted in vertical transactions. In addition, we show that vertical acquisitions tend to occur at times when target firms have accumulated more patents, in contrast to non-vertical acquisitions which typically take place after a slower accumulation of patents. Our framework linking vertical acquisitions and intangible assets is distinct from other motives for acquisitions including neoclassical theories, agency theories, and horizontal theories.[3]

The distinction between unrealized and realized innovation also matters in explaining firm-level vertical integration. We find strong evidence that firms in R&D intensive industries are less likely to be vertically integrated. In sharp contrast, we find that firms in industries characterized by high patenting intensity are more likely to be vertically organized. The distinction between unrealized and realized innovation is economically large: In our baseline specification, firms' vertical integration decreases by 10% in response to a one-standard deviation increase in R&D intensity, and increases by 7% following a one-standard deviation increase in patenting intensity.

Following Bloom, Schankerman, and van Reenen (2013), we exploit variation in R&D tax credits across U.S. states as an instrument for firms' R&D expenditures. Consistent with our baseline results, our instrumental variables framework indicates that an increase in industry R&D significantly lowers the likelihood that a firm will be acquired in a vertical acquisition transaction. Also, higher R&D intensity leads

[2]Many studies in industrial organization take the single-industry approach. Earlier studies include Monteverde and Teece (1982) focusing on automobile manufacturing, Masten (1984) focusing on airplane manufacturing, and Joskow (1987) focusing on coal markets. More recent studies include Lerner and Merges (1998) focusing on biotechnology, Baker and Hubbard (2003) focusing on trucking, or Hortacsu and Syverson (2007) focusing on the cement industry.

[3]See Maksimovic and Phillips (2001), Jovanovic and Rousseau (2002), and Harford (2005) for neoclassical and q theories and Morck, Shleifer, and Vishny (1990) for an agency motivation for acquisitions, and Phillips and Zhdanov (2013) for a recent horizontal theory of acquisitions.

to significantly less within-firm vertical integration.

Our results highlight that firms' vertical organization is related to the stage of development of *intangible* assets. These findings are complementary to the recent findings by Atalay, Hortascu, and Syverson (2014). Using comprehensive data on ownership structure, production, and shipment patterns, they report that upstream units ship only small shares of their outputs to own-firm downstream plants. They show suggestive evidence in support of intangible capital being important in vertical integration. Specifically, they show a relative decline in non-production workers in acquired establishments that are vertically related. They also show an increase in products that were made by the acquiring firm previously in the acquired firms' establishments. Our results complement theirs by providing direct evidence that intangible assets created through innovation activities are relevant determinants of vertical integration.

We propose a simple incomplete contracting model that links R&D and patent intensity to vertical integration and acquisitions. The decision of two firms to integrate vertically depends on the stage of development of the specific asset exchanged in their relationship. The model predicts that when the asset is still in the form of R&D (unrealized innovation), firms optimally will not integrate.[4] Separation maintains ex ante incentives for the upstream firm to invest in product development, and to maintain residual rights of control. In contrast, when the asset is more fully developed and its features are protected by a patent, the owner of the realized innovation has more legally enforceable residual rights of control as in Grossman and Hart (1986). At this time, R&D incentives for ongoing separation decline because the product is more mature. Integration optimally allocates the residual rights of control to the downstream firm that will use the realized innovation and commercialize it.

This distinction between high R&D and patents is empirically nontrivial. High

[4] Acemoglu (1996) argues that technological investments are partner-specific, thus creating relationship-specific assets that are difficult to contract on. Allen and Phillips (2000) and Kale and Shahrur (2007) show that R&D increases with interaction between alliance partners, consistent with the needed R&D incentives to develop relationship-specific assets.

R&D does not necessarily lead to high patenting rates. There are also cross-sectional differences in patenting across industries. As reported by Cohen, Nelson, and Walsh (2000) in their survey of 1,478 R&D labs, high R&D may not lead to patents due to concerns about appropriability. Their survey points to the ability of others to work around patents using information conveyed by the patent application, causing managers not to patent in many industries. Consistent with the importance of property rights, we find that the link between patents and vertical integration is only present in industries where patents are effective at protecting innovation.

Two recent examples of the effects we document for acquisitions are Microsoft's recent purchases of Skype and Nokia. Skype specialized in making VoIP phone and video calls over the Internet. After purchasing Skype, Microsoft integrated Skype into Windows and also into Windows phones. Regarding Nokia in 2013, one insider indicated that the deal between the two companies would help to bring the "hardware closer to the operating system and achieve a tighter integration." Buying firms to gain control of their realized innovations facilitates commercialization either through reduced ex post hold-up or increased commercialization incentives.[5]

An industry that exemplifies our findings regarding the dynamics of vertical integration is the network equipment industry, which includes Cisco, Broadcom, Citrix, Juniper, Novell, Sycamore, and Utstarcom. During our sample, and using our measures, we find that firms in this industry jointly experienced (A) levels of R&D that peaked and began to decline, (B) levels of patenting activity that rose four to five fold, and (C) levels of vertical integration that also rose four to five fold. The conversion of unrealized innovation into realized patented innovation reduced the incentives for relationship-specific investment by these firms, and also increased the incentives to vertically integrate in order to transfer control rights to the party commercializing the patents.[6]

We also consider the role of supply chain stability and maturity. For example,

[5]See http://www.businessinsider.com/why-microsoft-bought-skype-an-insider-explains-2011-5.

[6]The 2014 IBISWORLD industry report on the Telecommunication Networking Equipment Manufacturing confirms the trend towards more integration in this market. Players in this industry seek to offer "end-to-end" and "all-in-one" solutions.

assuming the benefits of integration derive from ongoing operations, an unstable supply chain can reduce the horizon during which benefits are realized. Because reorganization typically entails a high level of fixed costs, firms in unstable supply chains should thus be less willing to vertically integrate as the duration of gains may not be adequate to cover the high fixed costs. We find empirical support for the proposed positive link between maturity and vertical integration. In particular, both vertical acquisitions and vertical integration are positively related to maturity as captured by firm age, lower market-to-book ratio, and more tangible assets.

Overall our paper reconciles some of the tension between the *ex post* hold-up literature of Klein, Crawford, and Alchian (1978) and Williamson (1979), and the *ex ante* incentive to assign residual rights of control as in Grossman and Hart (1986). We find that ex ante effects occur when unrealized innovation is important. High R&D firms are more likely to remain separate and not sell out. We then find that ex post effects occur when integration is realized, and integration minimizes the potential for hold up and ex post bargaining over the already patented product that can be commercialized by the downstream firm. To the best of our knowledge, we are the first to explore if the stage of innovation can be a pivotal determinant of vertical firm boundaries, and to demonstrate empirically that R&D and patenting intensity have distinct effects on vertical organization. We contribute to a large literature examining the determinants of vertical integration (as surveyed by Lafontaine and Slade (2007) and Bresnahan and Levin (2012)), and more specifically to recent papers linking vertical integration to technological innovation such as Acemoglu, Aghion, Griffith, and Zilbotti (2010).[7]

Our paper also adds to the literature on vertical acquisitions. Fan and Goyal (2006) examine stock market reactions to vertical deals where vertical integration is identified at the industry level through links between SIC codes and the Input-Output tables. Kedia, Ravid, and Pons (2011) show that vertical mergers create

[7] These authors show that, in a sample of UK manufacturing firms, the intensity of backward integration is positively related to the R&D intensity of the downstream industry, and negatively related to the R&D intensity of the upstream industry. Our approach is complementary to theirs as we focus on the stage of innovation, and look at (backward and forward) vertical acquisitions and within-firm integration in a wide sample of the US economy.

more value in imperfectly competitive markets. Ahern (2012) shows that division of stock-market gains in mergers is determined in part by customer or supplier bargaining power. Ahern and Harford (2013) examine the extent to which shocks in the supply chain translate into vertical merger waves. Our results also complement Bena and Li (2013), who examine the impact of mergers on ex post innovation rates, and Phillips and Zhdanov (2013) who examine how anticipated mergers affect R&D.

Our last contribution is methodological. We demonstrate that our new text-based firm-specific measure of vertical relatedness have significant advantages over existing measures based on coarser industry definitions, such as SIC or NAICS codes. By linking the vocabulary of firms' business descriptions to that of the commodities in the Input-Output tables, we are able to identify vertical relatedness more directly at the firm level, and in a dynamic way. NAICS or SIC not only do not provide measures of vertical relatedness at the firm level, but links from BEA are only observed in five year intervals, and they are further problematic because they are based on production processes and not the products themselves.[8] Our new measures of vertical relationships also do not rely on the quality of the Compustat segment tapes, nor the quality of the NAICS classification.[9] Our focus on vertical links extends the work of Hoberg and Phillips (2015), who examine horizontal links and product differentiation between firms using 10-K text.

The remainder of this paper is organized as follows. Section II develops a simple model of vertical integration. Section III presents the data and develops our new measure of vertical relatedness between firms. Section IV examines the effect of innovation activities on vertical transactions. Section V examines vertical integration within the firm, and Section VI concludes.

[8] See http://www.naics.com/info.htm. The Census Department states "NAICS was developed to classify units according to their production function. NAICS results in industries that group units undertaking similar activities using similar resources but does not necessarily group all similar products or outputs."

[9] Hyland (1999) and Villalonga (2004) show that the Compustat segment database has serious reporting biases. Note that measures of vertical integration using SIC or NAICS rely heavily on the quality of the segment tapes.

II A Simple Model of Integration

In this section we develop a simple incomplete contracting model of the timing of integration. In the spirit of Grossman and Hart (1986), we assume that R&D is non-contractible and non-verifiable, as are commercialization and integration expenditures by the downstream firm. The party that is purchased in a vertical transaction loses control rights and thus will make no relationship-specific investment. If an upstream firm is acquired by a downstream firm, it thus has no incentives to further invest in R&D. Incentives for ongoing separate innovation thus decrease with integration, while the incentives of the downstream firm to commercialize the product and integrate any product extensions are higher under integration.

There are two firms in the economy, an upstream supplier and a downstream firm. At each time period t, they are cooperating to produce a product, with a base price P_t^b. The final price P_t, which we define later, further depends on the level of commercialization and product integration expenditures chosen by the downstream firm. These expenditures can include marketing the product, building a new factory, and hiring sales people. The upstream supplier chooses an x_t amount of R&D research effort that can result in new patentable features and extensions that can increase the price consumers are willing to pay for the product with a cost $k_t = c(x_t) = Sx_t^g$. We assume x_t is the non-contractible portion of R&D effort. Thus, if the downstream firm purchases the upstream supplier, x_t will be equal to zero.[10] The producer chooses an amount y_t of commercialization and integration activities that can also boost the price of the product with a cost $m_t = c(y_t) = Ry_t^h$. We assume that both $g > 1$ and $h > 1$ so that costs are convex. The discount rate is r.

The base price P_t^b takes a value in the set $\{P_0, P_1, \dots P_N\}$, with $P_s < P_{s+1}$ $(0 \leq s \leq N-1)$ and $P_{s+1} - P_s < P_s - P_{s-1}$ $(0 \leq s \leq N-1)$. A success in R&D research at time t results in new features and product enhancements. These product enhancements result in a patent, and boost the base price from P_s to P_{s+1}

[10]The contractible portion of R&D effort need not be equal to zero. For simplicity, we focus on the non-contractible portion.

($0 \leq s \leq N-1$). Additional product features and extensions have a positive but decreasing effect on prices. We use X_t to denote the result of R&D research which is realized and observed by both parties at the end of time period t, such that $X_t = 1$ corresponds to a success and $X_t = 0$ to a failure. The probability of success is determined by the R&D expenditure $p(X_t = 1) = x_t$.

For simplicity, we assume that the increase in price resulting from commercialization and integration expenditures is deterministic, and it increases the base price P_t^b by an amount y_t if the firms are separate, and $\rho(y_t)$ if the firms are integrated. Both the level of price impact and the marginal product of commercialization and integration expenditures are higher under integration, such that $\rho(y_t) > y_t$ and $\rho'(y_t) > 1$.

The bargaining power of the upstream supplier is α (and the downstream producer $1-\alpha$) in both ex-ante negotiation for integration and ex-post renegotiation for splitting total surplus. The timing of events are summarized in Figure 1. At each time period t, given the outcome of the R&D expenses at the end of last time period X_{t-1}, we have:

1. The downstream producer decides whether to integrate and negotiates with the upstream supplier if it decides to integrate.

2. R&D expenditures x_t and commercialization and integration expenditures y_t are decided by firms as ex-ante investments.[11]

3. Renegotiation occurs if firms are separated.

4. By the end of the period, the success of R&D efforts is realized, so that at the beginning of next period $t+1$, both firms observe the value of X_t.

The realization of R&D and the grant of a patent is key to determining when firms will integrate. Since we make the assumption that X_t is realized at the end of each

[11] We could equivalently consider the case where the upstream firm buys the downstream firm. This would occur if the downstream firm does the R&D and the upstream firm customizes the product features before supplying the product. Although the model can thus be applied in either direction, we focus on the case of the downstream firm buying the upstream firm for simplicity.

period, the final price charged on consumers is equal to $P_t = P_t^b(1 + y_t)$ under separation and $P_t = P_t^b(1 + \rho(y_t))$ under integration, with the base price $P_t^b = P_N$ if the last period base price is $P_{t-1}^b = P_N$ or $P_t^b = P_s + (P_{s+1} - P_s)X_{t-1}$ if the last period base price is $P_{t-1}^b = P_s < P_N$. Note that the base price is a contingent variable given the last-period R&D result X_{t-1}.

We model integration as a real option that, when exercised, is costly to reverse. Thus, firms do not integrate until the marginal benefit of staying separate decreases and becomes lower than that of integrating. Because product enhancements are cumulative and accrue over time, integration will also be positively linked to firm maturity.

We now present a sequence of propositions. All proofs of these propositions are contained in Appendix 1.

Proposition 1

Firms spending more on R&D are likely to be separate. Firms spending more on commercialization and customization of realized innovation are more likely to be integrated.

Proposition 2

If $P_t^b = P_N$, then both firms prefer to integrate. Hence, where V is the value function, we have $V(P_N) = V(P_N; I = 1) > V(P_N; I = 0)$.

Our next proposition, Proposition 3, gives our key result. As innovation becomes realized and more mature, it is optimal for firms to integrate. It is the key proposition that we empirically test.

Proposition 3

There exists a state s^* such that $V(P_s) = V(P_s; I = 1) \geq V(P_s; I = 0)$ for any $s \geq s^*$, and $V(P_s) = V(P_s; I = 1) < V(P_s; I = 0)$ for any $s < s^*$. The state s^*

would then be the triggering state for integration.

This proposition is illustrated in Figure 2. Intuitively, separation is optimal when further incentives for product development (x) benefit the overall relationship. In that case, separation maintains ex ante incentives for the upstream firm to invest in R&D, and maintains residual rights of control. In contrast, when the asset is more fully developed and its features are protected by a patent, R&D incentives for ongoing separation decline. At the same time, incentives to spend on commercialization and integration (y) increase. Integration optimally allocates the residual rights of control to the downstream firm that commercializes the product to reduce ex post holdup. We formally test this proposition using new a text-based measure of vertical integration and acquisitions, and by examining the distinct role played by R&D and patenting activity in explaining firms' vertical organizational form.

III Data and Methodology

We draw from multiple data sources to create our sample and our key variables. These include: 10-K business descriptions, the Input-Output (IO) tables from the Bureau of Economic Analysis (BEA), COMPUSTAT, the SEC Edgar database, SDC Platinum for transactions, and data on announcement returns from CRSP.

A Data from 10-K Business Descriptions

We start with the COMPUSTAT sample of firm-years from 1996 to 2008 with sales of at least $1 million and positive assets. We then use the Edgar database to extract text in the Business Description section of annual firm 10-Ks. We thus require that a given observation has a 10-K filed on the SEC Edgar website with a machine readable business description. The methodology we use to extract and process 10-K text follows Hoberg and Phillips (2015). The first step is to use web crawling and text parsing algorithms to construct a database of business descriptions from 10-K annual filings on the SEC Edgar website from 1996 to 2008. We search the Edgar database for filings that appear as "10-K," "10-K405," "10-KSB," or "10-KSB40."

The business descriptions appear as Item 1 or Item 1A in most 10-Ks. The document is then processed using APL to extract the business description text and a company identifier, CIK.[12] Business descriptions are legally required to be accurate, as Item 101 of Regulation S-K requires firms to describe the significant products they offer, and these descriptions must be updated and representative of the current fiscal year of the 10-K. There are 74,379 firm-years in the Compustat/Edgar universe.

B Data from the Input-Output Tables

We use both commodity text and numerical data from the Input-Output (IO) tables from the BEA. The IO tables account for the dollar flows between all producers and purchasers in the U.S. economy (including households, the government, and foreign buyers of U.S. exports). Relevant to our analysis, these tables are based on two primitive concepts: 'commodity' outputs (defined by the Commodity IO Code), and producing 'industries' (defined by the Industry IO Code). A commodity is any good or service that is produced. The 'Make' table reports the dollar value of each commodity produced by a given industry, and in the 2002 IO tables, there are 424 distinct commodities and 426 industries in the Make table. An industry can produce more than one commodity.[13]

The 'Use' table reports the dollar value of each commodity that is purchased by each industry or by final end-user.[14] There are 431 commodities in the Use table purchased by 439 industries or final end-users.[15] We describe three data structures we compute from the IO Tables, which we refer to later: (1) Commodity-to-commodity

[12]We use the SEC Analytics database from the Wharton Research Data Service (WRDS) to obtain a historical mapping of SEC CIK to COMPUSTAT gvkey, as the base CIK variable in COMPUSTAT only contains the most recent link.

[13]In the 2002 IO edition, the average (median) number of commodities produced per industry is 18 (13). The output of an industry tends to be rather concentrated: The average (median) commodity concentration ratio per industry is 0.78 (0.81).

[14]While costs are reported in both purchaser prices and producer costs, we use producers' prices.

[15]There are seven commodities in the Use table that are not in the Make table: non-comparable imports, used and second hand goods, rest of the world adjustment to final uses, compensation of employees, indirect business tax and nontax liability, and other value added. There are thirteen 'industries' in the Use table that are not in the Make table. These correspond to 'end users' and include personal consumption expenditures, private fixed investment, change in private inventories, exports and imports, and federal and state government expenditures.

(upstream to downstream) correspondence matrix (V), (2) Commodity-to-word correspondence matrix (CW), and (3) Commodity-to-'exit' (supply chain) correspondence matrix (E).

In addition to the numerical values in the BEA data, we use an often overlooked resource: the detailed verbal item descriptions for each commodity, which is critical to our identification of vertically related firms. The 'Detailed Item Output' table decomposes each commodity (i.e. each IO Commodity Code) into sub-commodities (labeled by 'IO Item Code'). For each sub-commodity, the BEA provides a verbal description and provides the dollar value of its total production. A commodity's total production as reported in the Input-Output Table is thus the sum of the production of its sub-commodities.[16] Each sub-commodities' verbal description uses between 1 to 25 distinct words (the average is 8) that summarize the nature of the good or service provided.[17] Table I contains an example of product text for the BEA 'photographic and photocopying equipment' commodity. We extract the verbal descriptions of sub-commodities to form the sets of words associated with each commodity. We label these sets 'commodity words'.

[Insert Table I Here]

We do not include all words in our analysis. We start with the convention in Hoberg and Phillips (2015) and we only consider nouns and proper nouns. We then apply four additional screens to ensure our identification of vertical links is conservative. First, because commodity vocabularies identify a stand-alone product market, we discard from the commodity vocabularies any expressions that indicate a vertical relation such as 'used in', 'made for' or 'sold to'. Second, we remove any expressions that indicate exceptions to what is sold in the given product market (e.g, we drop phrases beginning with 'except' or 'excluding'). Third, we discard common words that appear in large numbers of commodity vocabularies, as such

[16] There are 5,459 sub-commodities in the 'Detailed Item Output' table associated with 427 commodities. The average number of sub-commodities per commodity is 12, the minimum is 1 and the maximum is 154.

[17] For instance, the commodity 'Footwear Manufacturing' (IO Commodity Code #316100) has 15 sub-commodities, such as IO Item Code #316211 described as 'rubber and plastics footwear', or IO Item Code #316212 described as 'house slippers'.

words are not discriminating.[18]

Finally, we remove from each commodity vocabulary, any words that do not frequently co-appear with other words in the given commodity vocabulary. This further ensures that horizontal links or links capturing horizontal asset complementarities are not mislabeled as vertical links. We identify these broad words by examining the fraction of times each word in a given IO commodity co-appears with other words in the same IO commodity when the given word appears in a 10-K business description. We use all 10-Ks from 1997 to compute this fraction for each word in each commodity, and we then discard words in the bottom tercile (the broad words). For example, if there are 21 words in an IO commodity description, we would discard 7 of the 21 words using this method.[19] In all, we are left with 7,735 remaining commodity words that uniquely identify vertically related product markets in tight word clusters.

The information from the 'Detailed Item Output' table also enables us to determine the economic importance of each word for a given commodity's output. To obtain it, we compute the *relative* economic contribution of a given sub-commodity (ω) as the dollar value of its production relative to its commodity's total production. Each word in the sub-commodity's textual description is then assigned the same ω. Because a word can appear in the text of several sub-commodities within a commodity, we sum its ω's by commodity. Hence, a given commodity word is economically more important if it is used in the text of sub-commodities that account for a larger share of the commodity's output. We then define the commodity-word correspondence matrix (CW) as a three-column matrix having the first column being a given commodity, the second column being an associated commodity word, and the third being its economic importance.

Because the textual description in the Detailed Item Output table relates to commodities (and not industries), we focus on the intensity of vertical relatedness

[18]There are 250 such words including accessories, air, attachment, commercial, component. See the Internet Appendix for a full list.

[19]This approach (and our use of terciles) is based on Hoberg and Phillips (2010), who also focus on the local subset of words after discarding the tercile of most broad words.

between pairs of commodities and we construct the sparse square matrix V based on the extent to which a given commodity is vertically linked (upstream or downstream) to another commodity in the supply chain. To do this, from the Make Table, we create $SHARE$, an $I \times C$ matrix (Industry $\times$ Commodity) that contains the percentage of commodity c produced by a given industry i. The USE matrix is a $C \times I$ matrix that records the dollar value of industry i's purchase of commodity c as an input. The $CFLOW$ matrix is then given by $USE \times SHARE$, and is the $C \times C$ matrix of dollar flows from an upstream commodity c to a downstream commodity d. Similar to Fan and Goyal (2006), we define the $SUPP$ matrix as $CFLOW$ divided by the total production of the downstream commodity d. $SUPP$ records the fraction of commodity c that is used as an input to produce commodity d. Similarly, the matrix $CUST$ is given by $CFLOW$ divided by the total production of the upstream commodities c and records the fraction of commodity c's total production that is used to produce commodity d. The V matrix is then defined as the average of $SUPP$ and $CUST$. A larger element in V indicates a stronger vertical relationship between commodities c and d.[20] Note that V is sparse (i.e., most commodities are not vertically related in the supply chain) and is non-symmetric as it features distinct downstream ($V_{c,d}$) and upstream ($V_{d,c}$) directions.

Finally, we create an exit correspondence matrix E to account for the production that flows out of the U.S. supply chain. To do so, we use the industries that are present in the Use table but *not* in the Make table. These correspond to 'final users'. E is a one-column matrix where one row represents a commodity and the column-vector contains the fraction of each commodity's output that flows to users outside the U.S. supply chain.

C Text-based Vertical Relatedness

We identify vertical relatedness between firms by jointly using the vocabulary in firm 10-Ks and the vocabulary defining the BEA IO commodities. We link each

[20] Alternatively, we consider in unreported tests the maximum between $SUPP$ and $CUST$, and also $SUPP$, or $CUST$ alone, to define vertical relatedness. Our results are robust.

firm in our Compustat/Edgar universe to the IO commodities by computing the similarity between the given firm's business description and the textual description of each BEA commodity. Because vertical relatedness is observed from BEA at the IO commodity level (see description of the matrix V above), we can score every pair of firms i and j based on the extent to which they are upstream or downstream by (1) mapping i's and j's text to the subset of IO commodities it provides, and (2) determining i and j's vertical relatedness using the relatedness matrix V.

When computing all textual similarities, we limit attention to words that appear in the Hoberg and Phillips (2015) post-processed universe. We also note that we only use text from 10-Ks to identify the product market each firm operates in (vertical links between vocabularies are then identified using BEA data as discussed above). Although uncommon, a firm will sometimes mention its customers or suppliers in its 10-K. For example, a coal manufacturer might mention in passing that its products are "sold to" the steel industry. To ensure that our firm-product market vectors are not contaminated by such vertical links, we remove any mentions of customers and suppliers using 81 phrases listed in the Internet Appendix.[21]

Ultimately, we represent both firm vocabularies and the commodity vocabularies from BEA as vectors with length 60,507, which is the number of nouns and proper nouns appearing in 10-K business descriptions in Hoberg and Phillips (2015). Each element of these vectors corresponds to a single word. If a given firm or commodity does not use a given word, the corresponding element in its vector will be set to zero. By representing BEA commodities and firm vocabularies as vectors in the same space, we are able to assess firm and commodity relatedness using cosine similarities.

Our next step is to compute the 'firm to IO commodity correspondence matrix' B. This matrix has dimension $M \times C$, where C is the number of IO commodities, and M is the number of firms. An entry $B_{m,c}$ (row m, column c) is the cosine similarity of the text in the given IO commodity c, and the text in firm m's business description. In this cosine similarity calculation, commodity word vector weights are assigned based on the words' economic importance from the CW matrix (see

[21] Although we feel this step is important, our results are robust if we exclude this step.

above), and firm word vectors are equally-weighted following the TNIC construction used in Hoberg and Phillips (2015). We use the cosine similarity method because it naturally controls for document length and is a well-established method for computing document similarities (see Sebastiani (2002)). The cosine similarity is the normalized dot product (see Hoberg and Phillips (2015)) of the word-distribution vectors of the two vocabularies being compared. Cosine similarities are bounded in [0,1], and a value close to one indicates that firm i's product market vocabulary is a close match to IO commodity c's product market vocabulary. Hence, the matrix B indicates which IO commodity a given firm's products is most similar to. Most elements of B are zero or close to zero.

We then measure the extent to which firm i is upstream relative to firm j:

$$UP_{ij} = [B \cdot V \cdot B']_{i,j}. \tag{1}$$

The triple product $(B \cdot V \cdot B')$ is an $M \times M$ matrix of unadjusted upstream-to-downstream links between all firms i to firms j. Note that direction is important, and this matrix is not symmetric. Upstream relatedness of i to j is thus the i'th row and j'th column of this matrix. Firm-pairs receiving the highest scores for vertical relatedness are those having vocabulary that maps most strongly to IO commodities that are vertically related according to the matrix V (constructed only using BEA relatedness data), and those having vocabularies that overlap non-trivially with the vocabularies that are present in the IO commodity dictionary according to the matrix B. Thus, firm i is located upstream from firm j when i's business description is strongly associated with commodities that are used to produce other commodities whose description resembles firm j's product description.

Downstream relatedness is simply the mirror image of upstream relatedness, $DOWN_{ij} = UP_{ji}$. By repeating this procedure for every year in our sample (1996-2008), the matrices UP and $DOWN$ provide a time-varying network of vertical links among individual firms.

D NAICS-based Vertical Relatedness

Given we are proposing a new way to compute vertical relatedness between firms, we compare the properties of our text-based vertical network to those of the NAICS-based measure used in previous research, which we describe now. One critical difference is that the NAICS-based vertical network is computed using the BEA industry space, and not the BEA commodity space. This is by necessity because the links to NAICS are at the level of BEA industries. Avoiding the need to link to BEA industries is one advantage of the textual vertical network. More generally, the compounding of imperfections in BEA industries and NAICS industries may result in horizontal contaminations, especially when firms are in markets that do not cleanly map to NAICS industries. In particular, the Census Department states "NAICS was developed to classify units according to their production function. NAICS results in industries that group units undertaking similar activities using similar resources but does not necessarily group all similar products or outputs."

To compute the NAICS-based network, we use methods that parallel those discussed above for the BEA commodity space (matrix V), but we focus on the BEA industry space and construct an analogous matrix Z. We first compute the BEA industry matrix $IFLOW$ as $SHARE \times USE$, which is the dollar flow from industry i to industry j. We then obtain $ISUPP$ and $ICUST$ by dividing $IFLOW$ by the total production of industry j and i respectively (using parallel notation as was used to describe the construction of V). The matrix Z is simply the average between $ICUST$ and $ISUPP$.

Following common practice in the literature (see for example Fan and Goyal (2006)), we use two numerical thresholds to identify meaningful relatedness using the NAICS-based vertical network: 1% and 5%. A given industry i is then upstream (downstream) relative to industry j when Z_{ij} (Z_{ji}) is larger than this 1% or 5% threshold. Finally, we use the correspondence table to map IO industries to NAICS industries. We label the two resulting vertical networks as 'NAICS-10%' and 'NAICS-1%', respectively. Although these are based on 1% and 5% vertical flow cutoffs, the 10% and 1% figures reflect approximate granularities, which are 9.48% and 1.37% respectively. That is, 9.48% of all possible firm-pairs (in the Compustat/Edgar universe) are deemed to be vertically related when using the NAICS-10% network.

To ensure our textual networks are comparable, we thus choose two similar granularity levels: 10% and 1%. These two text-based vertical networks define firm pairs as vertically related when they are among the top 10% and top 1% most vertically related firm-pairs using the textual scores. We label these networks as 'Vertical Text-10%' and 'Vertical Text-1%'. Note that the textual networks generate a set of vertically related peers that is customized to each firm's unique product offerings. These firm level links provide considerably more information than is possible using broad industry links such as those based on NAICS.

E Vertical Network Statistics

We compare the properties of five key relatedness networks: Vertical Text-10%, Vertical Text-1%, NAICS-10%, NAICS-1%, and the TNIC-3 network developed by Hoberg and Phillips (2015). The first four networks are intended to capture vertical relatedness, and the TNIC-3 network is calibrated to be as granular as are three-digit SIC industries, and is intended to capture horizontal relatedness.

[Insert Table II Here]

The first row of Panel A in Table II presents the level of granularity of each network. The NAICS-10% and NAICS-1% networks have granularity levels of 9.48% and 1.37% respectively. The 'Vertical Text-10%' and 'Vertical Text-1%' networks have 10% granularity and 1% granularity, respectively. Finally, the TNIC-3 network has a granularity of 2.33%. The Vertical Text-1% network and the NAICS-1% network are thus twice as fine as SIC-3.

Reassuringly, the second to fourth rows in Panel A show that the four vertical networks exhibit low overlap with the horizontal TNIC-3 network, SIC and NAICS networks. Hence, none of the vertical networks are severely contaminated by known horizontal links. Despite this, the fifth and sixth rows illustrate that the vertical networks are quite different. Only 10.48% of firm-pairs in the NAICS-10% network are also present in the Vertical Text-10% network. Similarly, only 1.21% of firm-pairs are in both the Vertical Text-1% and NAICS-1% networks.

The eighth row reports the fraction of firm-pairs that includes at least one financial firm (SIC code ranging between 6000 and 6999). The presence of financial firms is quite low in the text-based vertical networks, at 9.20% and 1.80% of linked pairs, respectively. In contrast, financial firms account for a surprisingly large 48.44% and 34.31% of firm-pairs in the NAICS-based vertical networks. These results illustrate that treatment of financials is a first-order dimension upon which these networks disagree. When we discard financial firms, the overlap between our text-based network and NAICS-based network roughly doubles (e.g. 19.90% of non-financial firm-pairs in the NAICS-10% network are also present in the Vertical Text-10% network). As theories of vertical relatedness and integration often focus on non-financial concepts such as relationship-specific investment and ownership of assets, these results support the use of the text-based vertical network as covering more relevant industries.

Although we do not report full details here to conserve space, we conduct two validation tests in the online appendix to this paper. The goal is to compare the ability of the text-based and NAICS-based vertical networks to identify actual instances of vertical relatedness from orthogonal data sources. In the first test, we search all firm 10-Ks to identify direct verbal statements indicating the firm is vertically integrated. We find that the text-based network is roughly three times stronger in predicting these direct 10-K statements than is the NAICS-based network. In a second validation test, we examine related party trade data from the U.S. Census Bureau, and examine which network better predicts vertical integration through offshore activities. Once again, we find strong evidence that the text-based network better predicts vertical integration. Overall, both tests strongly support the conclusion that the text-based network is substantially more informative about vertical linkages than is the NAICS based network.

IV Vertical Acquisitions

We now use our text-based vertical network to provide evidence on the relations between innovation activities and vertical organization. We start by studying vertical acquisitions, as these transactions represent a direct way firms can alter their boundaries and modify their degree of integration. To test our main hypothesis and assess theoretical predictions in the literature (e.g., Grossman and Hart (1986)), we concentrate on targets (the sellers of assets) as they are the party that loses control rights due to the transaction, and for which the trade-off between ex ante investment incentives and ex post hold-up should be important. We thus examine how R&D and patenting intensity are related to the likelihood of being a target in vertical or non-vertical transactions.

A Transactions Sample

Our sample of transactions is from the Securities Data Corporation SDC Platinum database. We consider all announced and completed U.S. transactions with announcement dates between January 1, 1996 and December 31, 2008 that are coded as a merger, an acquisition of majority interest, or an acquisition of assets. As we are interested in situations where the ownership of assets changes hands, we only consider acquisitions that give acquirers majority stakes. To be able to distinguish between vertical and non-vertical transactions, we further require that both the acquirer and the target have available Compustat and 10-K data.

Table III displays summary statistics of our transactions sample. Following the convention in the literature, we limit attention to publicly traded acquirers and targets, and we exclude transactions that involve financial firms and utilities (SIC codes between 6000 and 6999 and between 4000 and 4999). Panel A shows that the sample consists of 3,460 transactions. Panel A further reports how many of these transactions are classified as vertical using the Vertical Text-10% and the NAICS-10% network.

[Insert Table III Here]

Given that the Vertical Text-10% and NAICS-10% vertical networks are designed to have similar granularity levels, it is perhaps surprising that the networks disagree sharply regarding the fraction of transactions that are vertically related. For our primary sample excluding financials, we observe that 39% are vertically related using the Vertical Text-10% network. Using the NAICS-10% network, we observe that just 13% are vertically related. For any network with a granularity of 10%, if transactions are random, we expect to see 10% of transactions belonging to this network. The fact that we find 39% is strong evidence that many transactions occur between vertically related parties. The results also suggest that the accumulated noise associated with NAICS greatly reduces the ability to identify vertically related transactions. We also note that with both networks, vertical deals are almost evenly split between upstream and downstream transactions.[22]

Panel B of Table III displays the average abnormal announcement returns (in percent) of combined acquirers and targets in vertical and non-vertical transactions. We present these results mainly to compare with previous research (based on either SIC or NAICS codes). Confirming existing evidence, the combined returns across all transactions are positive and range from 0.49% to 0.94%. Notably, when vertical transactions are identified using our text-based measure, the combined returns also appear to be larger in vertical transactions than in non-vertical transactions. This is in line with the idea that vertical deals are value-creating on average (as in Fan and Goyal (2006)). Yet, the differences in announcement returns between vertical and non-vertical transactions are not significant when vertical relatedness is identified using the NAICS-based network.

[22]We also find that transactions classified as vertical are followed by an increase in our firm-level measure of vertical integration (VI). Using the Vertical Text-10% network, acquirers in vertical transactions experience an increase of 6% in VI from one year prior to one year after the acquisition. In contrast, acquirers in non-vertical transactions experience a decrease of 0.70% in VI. In contrast, when we use the NAICS-10% network to identify vertical mergers, vertical acquirers see a negligible increase of 0.30% in VI.

B Profile of Targets in Vertical Transactions

Table IV presents the R&D and patenting profile of targets in vertical and non-vertical deals. We focus on all transactions and we use our text-based network (10%) to identify vertical deals. We consider both industry- (i.e. TNIC-3) and firm-level measures of R&D and patenting activity. We measure R&D intensity as R&D divided by sales, and patenting intensity as the number of patents divided by assets. We describe all variables used in the paper and display summary statistics in Appendix 2. In Panel A, we observe a large difference between targets in vertical and non-vertical deals. When compared to benchmark firms that never participate in any takeover transactions over the sample period (labeled as non-merging firms), vertical targets exhibit lower levels of R&D and hold more patents. In contrast, targets in non-vertical deals are more R&D intensive, and display lower patenting intensity.

[Insert Table IV Here]

To formally test these differences, we account for the fact that targets in vertical and non-vertical deals can differ on dimensions other than their R&D and patent profile. In Panels B and C, each actual target (vertical and non-vertical) is directly compared to a matched target with similar characteristics. For every actual transaction (i.e. any actual acquirer-target pair), we select matched targets from the subset of firms that did not participate in any transaction over the three years that precede the actual transaction. Matched targets are the nearest neighbors from a propensity score estimation. In panel B, we obtain matched targets based on industry (defined using the Fixed Industry Classification (FIC) of Hoberg and Phillips (2015))) and size. In panel C, we obtain matched targets based on FIC industries, size, age, market-to-book ratio, PPE/Assets, the fraction of End Users from the BEA data, and the number of segments.

The results in Table IV are consistent with our main hypothesis. High R&D firms remain separate to preserve strong ex ante incentives to create new innovation consistent with Grossman and Hart (1986). In contrast target firms have higher patenting activity consistent with acquirers buying high patent firms to reduce ex post hold-up that may occur when firms are attempting to commercialize the innovation.

[Insert Figure 3 Here]

These patterns are confirmed in Figure 3 when we look at the average patenting and R&D intensity of target firms *prior* to their acquisition. Strikingly, vertical acquisitions tend to occur after targets experience a period of increased patenting activity (either measured with *log(1+#Patents)* or *#Patents/assets*). The realization of successful innovation (i.e. the grant of patents) marks a time of increased firm maturity, and may indicate the end of the innovation cycle. As the marginal product of additional R&D investment declines, we observe increased integration at this time. The mirror image appears true for non-vertical acquisitions, which tend to cluster after a period of lower patenting activity. Although the dynamics are less clear-cut, Figure 3 confirms that there are large differences in R&D intensity between the firms that are acquired in vertical and non-vertical deals. Non-vertical targets have much higher R&D intensity than vertical targets.

C Multivariate Analysis

We complement the above univariate tests by estimating logistic regressions to examine how R&D and patenting intensity affect the likelihood of becoming a target. The dependent variable is an indicator variable indicating whether a given firm is a target in a vertical or a non-vertical transaction, as noted in the column headers, in a given year. We consider our text-based network when identifying which transactions are vertically related (Vertical Text-10%). Our sample covers the period 1996-2008 and excludes regulated utilities and financial firms. We further require observations to have non-missing values for each variable we use in the estimations. We have 45,198 firm-year observations corresponding to 6,924 distinct firms.

For the explanatory variables of interest (in particular R&D and patent intensity), we consider equally-weighted averages across TNIC-3 industries (instead of own-firm variables).[23] This choice is driven by two considerations. First, focusing on industry measures lessens endogeneity concerns as they apply to both vertical and non-vertical transactions (see Acemoglu, Aghion, Griffith, and Zilbotti (2010)). Indeed, while a firm directly chooses its degree of vertical integration, it has little choice regarding its industry's overall level of R&D or patenting activities. Second, the theoretical incentives to vertically integrate should be driven mostly by the characteristics of product markets, rather than firm-specific attributes. For instance, as in Acemoglu, Johnson, and Mitton (2009), the incentives to invest in intangibles are primarily determined by the specific product being exchanged between firms.

[Insert Table V Here]

Table V displays the results of these logistics regressions.[24] We first focus on the columns (1) to (4). We find strong differences between the types of firms targeted in vertical and non-vertical deals. In particular, column (1) indicates that even after we control for other factors, firms in high R&D industries are less likely to be a target in a vertical transaction. In contrast, column (2) shows that firms in these same R&D intensive industries are in fact more likely to be targets in non-vertical transactions. This is consistent with Phillips and Zhdanov (2013), who document that horizontally related high R&D firms are likely to integrate to internalize R&D competition.

We next focus on the level of patenting activity. Consistent with our hypothesis that ex post successful innovation indicates maturity and lowers the returns from separate R&D investment, we find that vertical targets are more likely to be firms in industries with more patenting activity. The opposite is true for non-vertical acquisitions, where firms in high patenting industries are less likely to be acquired in restructuring transactions.

Table V provides strong and robust evidence that R&D and patenting activities have opposite effects on the vertical transactions. Yet, as R&D and patenting

[23]We note, however, that our conclusion is qualitatively unchanged if we use own-firm R&D and patent variables instead of industry-level variables. The results are presented in the Internet Appendix (IA.IV.1).

[24]Note that we cluster standard errors at the industry (using the FIC data from Hoberg and Phillips (2015)) and year level.

activities are positively related, some industries with high levels of R&D activities also display high levels of patenting.[25] To account for this possibility, we introduce an interaction term between R&D and patenting activities and report the results in columns (3) and (4). The coefficient on this interaction is only significant for non-vertical transactions, which further confirms the differences across these types of transactions. The positive coefficient for industry patenting activity also remains robust for vertical acquisitions. [26]

Table V also supports our hypothesis that maturity is an important positive determinant of vertical transactions. For instance, column (1) indicates that firms with lower market-to-book ratios and older firms are more likely to be targets of vertical deals. In contrast, targets in non-vertical deals are more likely to be young and are in less capital intensive industries. These findings are consistent with the following interpretation of the U-shaped relationship between firm maturity and restructuring activity noted in Arikan and Stulz (2011). Younger firms engage in non-vertical transactions likely to capitalize on asset complementarities, while more mature firms increase their acquisition activity as their focus turns to vertical acquisitions.

D State R&D Tax Credit as Instrument

While our baseline results indicate that R&D and patenting intensity are related to firms' propensity to integrate vertically via acquisitions, our interpretation could still be threatened by the presence of omitted factors that correlate with both firms' vertical acquisitions and their innovation activities. To mitigate this concern, we follow Bloom, Schankerman, and van Reenen (2013) and rely on state-specific R&D tax credits as an instrument for firms' R&D expenditures. State R&D tax credits

[25] In our sample, R&D and patenting activity are not perfectly correlated. This correlation is 0.33 across firms, and 0.58 across industries.

[26] In additional tests that we present in the Internet Appendix for brevity, we show that the results hold when we use lagged values of the independent variables (Table IA.IV.2), when we use sales-weighted industry measures instead of equally-weighted measures (Table IA.IV.3), when we focus solely on industry R&D and patent intensity and exclude the additional control variables (Table IA.IV.4), when we include industry R&D and patent intensity separately (Table IA.IV.5). We also consider the NAICS-based measure of vertical relatedness to define vertical acquisitions (NAICS-10%) and report the results in the Internet Appendix (Table IA.IV.6). Overall, the results are much weaker.

offer firms credits against state income tax liability based on the amount of qualified research done within the state.[27] In practice, different states have different levels of R&D tax credits, rendering the cost of R&D dependent on firm locations. As discussed in Bloom, Schankerman, and van Reenen (2013), the existing literature suggests a large degree of randomness regarding the introduction and level of R&D tax credits. Therefore, we exploit differences in R&D tax credits across U.S. states to isolate variation in R&D expenditures that is purely driven by tax rules. This variation is plausibly unrelated to firms' organizational choices.

We gather data on statutory tax credit rates for each state-year between 1996 and 2008. We collect the rates reported in Wilson (2009) as a starting point, and then adjust for changes in the rates as reported in Falato and Sim (2014). Because our variable of interest is industry-level R&D, we compute for each firm the (equally-weighted) average statutory tax credit across TNIC-3 industries, and use this measure as an instrument for industry $R\&D/sales$.[28] During our sample period, there is relatively little within-state variation in tax credit rates, in contrast to a large heterogeneity across states. For this reason, we focus on within-industry specifications.

Columns (5) to (7) of Table V report results from instrumental variable estimations, where we use state R&D tax credits as an instrument for industry R&D expenditures.[29] Column (5) presents the first stage estimation. We observe a positive and highly significant coefficient on state-level tax credit rates, confirming that tax credits are positively related to R&D spending. This result also indicates that

[27] Note that firms can also benefit from Federal R&D tax credits. We ignore these credits as there is no variation across firm-year observations. As detailed in Wilson (2009), state and federal tax credits are based on the amount of qualified research within the state or country. States generally follow the Federal Internal Revenue Code (IRC) definition of qualified research: the wages, material expenses, and rental costs of certain property and equipment incurred in performing research"undertaken to discover information" that is "technological in nature" for a new or improved business purpose. Because we do not know the state location of each firm's R&D spending, we assume that all R&D activities are performed in the firm headquarter's state.

[28] Note that we obtain virtually identical results if we first use the instrument to predict firm-level R&D, and then compute the industry average of the instrumented R&D in the second stage estimation.

[29] Due to the binary nature of the dependent variable, we estimate instrumental variable probit regressions using Maximum Likelihood.

the tax instrument is strong. We continue to observe in column (6) a negative and significant effect for R&D in vertical deals, as well as a positive effect for patenting intensity. These results confirm that a higher R&D intensity significantly decreases the likelihood that a firm will be targeted in a vertical transaction. Remarkably, neither R&D nor patents are related to the incidence of non-vertical transactions in the instrumental variables estimation reported in column (7). For non-vertical horizontal and unrelated deals, other motives including market power, costs, and diversification are likely more relevant.

E Sub-sample Tests

Next, we examine if our results are different in industries with high versus low "secrecy". High R&D does not necessarily lead to high patenting rates because some inventions are better protected with secrecy than with patents. Based on the Carnegie Mellon Survey (CMS) on industrial R&D in the manufacturing sector, Cohen, Nelson, and Walsh (2000) report large differences across industries in the use of patents to protect inventions. In many cases, inventors indeed rely on secrecy to limit rivals from using information in the patent application. We use data from the CMS to separate manufacturing industries into 'Low' and 'High' secrecy subsamples.[30] The first four columns of Table VI present the results. Consistent with the importance of property rights, we observe that patenting intensity is positively and significantly associated with vertical transactions in low secrecy industries where patents are effective at protecting innovation. Vertical acquisitions are largely unrelated to patenting intensity in high secrecy industries. Columns (3) and (4) present the results using the state-level tax credits as an instrument for R&D that are similar to the previous columns.

[Insert Table VI Here]

[30]The survey was performed with 1,478 R&D units or laboratories in 1994 and covers 34 manufacturing industries defined at the SIC 3-digit level. We measure the importance of secrecy using the average of two variables capturing the importance of secrecy for product and process innovation. We then assign firms into the low and high secrecy groups based on the sample median.

V Vertical Integration within Firms

Next, we take a different angle and use our text-based approach to develop a new firm-level measure of vertical integration. We then examine how firms' innovation activities are linked to their vertical organization both within industries, and within firms.

A Text-based Integration

Using the quantities developed in Section III, we define the extent to which a given firm is 'vertically integrated' by looking at a firm's vertical relatedness with itself ($UP_{i,i}$ or interchangeably $DOWN_{i,i}$ developed in Section III). Using our earlier notation, we have:

$$VI_i = [B \cdot V \cdot B']_{i,i}. \tag{2}$$

With this measure, a firm is more vertically integrated when its own 10-K business description contains words that are vertically related (upstream or downstream) to other words in its own business description. This occurs when a firm offers products or services at different stages of a supply chain.[31] In addition, we characterize whether a firm supplies products or services that are related to commodities that exit the U.S. supply chain. Using the exit correspondence matrix E defined in Section III, we can quantify the degree to which a firm is at the end of the supply chain as End Users$_i = [B \cdot E]_i$. We compute analogous measures of the extent to which the firm sells to retail, government, or export by replacing E with the fraction sold to each sub-group.

In the Internet Appendix, we provide evidence that further validates our measurement by showing that our text-based measure is highly correlated with explicit mentions by firms about their vertical organization, and to the intensity of transactions that take place within the firm boundaries (i.e., intra-firm trade) using industry level data on related-party trade from the Census (see for instance Nunn and Trefler

[31]Unfortunately, data limitations prevent us from determining the economic importance of each product from firms' product descriptions. Hence, while VI is a novel measure that uniquely captures firm-level vertical integration, it cannot account for each product-by-product importance.

(2013) or Antras and Chor (2013)).

Statistics for the text-based variables are reported in Appendix 2. The degree of vertical integration among firms is quite heterogeneous. The average and median value of vertical integration (VI) are 0.012 and 0.008 respectively, and the maximum is 0.116. Hence, there is a fair amount of right skewness as one would expect. In particular, most firms are not vertically integrated, but a smaller fraction do feature business descriptions that contain many words that are strongly vertically related. Hence, the firms situated toward the right tail of the distribution are likely to be the set of firms that are vertically integrated. Figure 4 displays the evolution of vertical integration over time, and we note a trend away from integration, especially in the late 1990s.

[Insert Figure 4 Here]

Table VII displays averages across quartiles of vertical integration. Consistent with the predictions of the model in Section II and the results on vertical acquisitions, integrated firms spend less on research and development than non-integrated firms. The average ratio of R&D over sales is roughly four times larger in low integration quartiles than in the high intergation quartiles (9.8% versus 2.7%). In contrast, vertically integrated firms appear to own larger portfolios of patents. The (log) number of patents is two times larger in the high integration quartile (0.835 versus 0.420). These univariate results summarize the key finding in this section, which we document more formally later.

[Insert Table VII Here]

The distinction between R&D and patents is well exemplified by the networking equipment industry, which includes Cisco, Broadcom, Citrix, Juniper, Novell, Sycamore, and Utstarcom. As highlighted by Figure 5, these firms became four to five fold more vertically integrated over our sample. They also experienced (A) levels of R&D that peaked in 2002 and then began to sharply decline, and (B) levels of patenting activity that increased four to five fold starting in 2001. These dynamics are broadly consistent with the idea that the conversion of unrealized innovation into realized patented innovation increased the incentives to vertically integrate as the importance of ownership and control rights shifts from the smaller innovative firms to the larger commercializing firms.

[Insert Figure 5 Here]

Table VII also reveals that vertically integrated firms are generally further from the end of the supply chain, and sell less output to retail and the government. Consistent with the fact that a large fraction of U.S. trade takes place intra-firm, vertically integrated firms are also more focused on exports (e.g. Zeile (1997) or Antras (2003)). In addition, vertically integrated firms operate in more concentrated markets (based on the TNIC HHI from Hoberg and Phillips (2015)). Consistent with Atalay, Hortascu, and Syverson (2014), they are larger, older, and are more capital-intensive firms, with lower growth opportunities (MB). Vertically integrated firms also have more business segments, as identified from the (NAICS-based) Compustat segment tapes. We also report an alternative measure of vertical integration based on NAICS industries and the Compustat segment tapes: $VI_{Segment}$, as used in Acemoglu, Johnson, and Mitton (2009). $VI_{Segment}$ is larger when the segments a given firm operates in share stronger vertical relations. Although this measure can only be obtained for multi-segment firms (less than 33% of observations in our sample), it is significantly positively correlated at 20% with our text-based measure.[32]

B R&D, Patents, and Vertical Integration

To further examine the effect of innovation activities on firm's degree of vertical integration, we estimate panel data regressions where the dependent variable is our measure of vertical integration (VI). We focus on within-industry and within-firm specifications and include year fixed effects in all specifications to isolate the apparent trend towards dis-integration in our sample.

[Insert Table VIII Here]

[32]In the Internet Appendix, we further illustrate our text-based measure of vertical integration by displaying the 30 most vertically integrated firms in 2008. A close look at these firms suggests a high degree of actual vertical relatedness among product offerings. Moreover, although they are highly integrated, these firms rank rather low on existing non-text measures of integration based on Compustat segments.

Table VIII presents results that largely confirm the univariate evidence: Firms operating in industries with high levels of R&D are less vertically integrated. This result obtains both within industries (when we include industry fixed effects in column (1)) and within firms (with firm fixed effects in column (2)). This latter result is important as it indicates that firms modify their degree of vertical integration over time as industry R&D varies. Economically, the negative link between R&D and integration is substantial: A one standard deviation increase in R&D intensity is associated with a 10% decrease in our text-based measure of integration in the within-industry specification, and with a 1.7% decrease in the within-firm specification where much variation is absorbed. Statistically, both findings are significant at the 1% level.

In sharp contrast, the coefficients on *#Patents/assets* are positive and significant. All else equal, firms operating in industries with higher patenting intensity are more likely to be vertically integrated. The economic magnitude of our estimates is large: Integration increases by 6.8% (1.9%) following a one standard deviation increase in patenting intensity in the within-industry (within-firm) specification. This result is again consistent with the ex post realization of successful innovation alleviating the ex ante need to incentivize relation-specific investment. Firms with successful innovation are more likely to increase integration to reduce the threat of ex post holdup.

Results in columns (3) and (4) indicate that the coefficient on the interaction between R&D and patenting is negative, while patenting remains positive and R&D remains negative. The results confirm that unrealized and realized innovation have opposite effects on firms' propensity to vertically integrate and suggest that the ongoing R&D effect dominates and innovation incentives remain important in these industries. The results with industry fixed effects are statistically and economically stronger but the results with firm fixed effects remain significant.[33]

Firms are also more likely to be integrated when they are more mature. In

[33]The Internet Appendix presents additional tests showing the robustness of our results (Tables IA.IV.1-IA.IV.9).

particular, integration is positively related to capital intensity and size in all specifications. It is also positively related to firm age and negatively related to market-to-book in within-industry specifications. The link to maturity is likely related to the irreversibility of integration, and firms will be more willing to commit to integration when product markets are more stable, and they are less likely to need to dis-integrate later due to changes in the product market. This issue of irreversibility also relates to the high fixed costs of integration, and integration is likely only profitable if gains are expected to remain stable over a suitably long horizon to amortize the fixed costs. Firms that are closer to the end of the supply chain ($End\ Users$) are also less likely to integrate, and firms with an observed conglomerate structure ($\#Segments$) are more likely to be vertically integrated.

C Instrumental Variables and Subsamples

As we did in Section IV, where we considered vertical acquisitions, we re-examine our multivariate tests using an instrumental variables framework based on State R&D tax credits. This test is important because the same omitted variables that might threaten our identification for acquisitions might also threaten our identification in the current setting. As discussed in Section IV, state R&D tax credits are a powerful instrument for R&D, and they also provide plausibly exogenous variation in R&D across firms in our sample.

We report the instrumental variables tests using state R&D tax credits as an instrument in last two columns of Table VIII. Column (6) displays the results from the second-stage estimation, which largely confirm our baseline results. Most notably, we continue to observe a negative and significant coefficient on instrumented industry R&D, which implies that an exogenous increase in industry R&D leads to lower levels of vertical integration at the firm level. The coefficient for patent intensity remains virtually identical in this instrumented estimation.

Finally, Table IX highlights that the effect of patenting intensity on firms' integration is only present in the low-secrecy subsample, where patents provide effective property rights on realized innovation. Firms' boundaries appear unrelated to patents in industries that rely on secrecy to protect innovation.

VI Conclusions

Our paper examines vertical acquisitions and changes to overall firm-specific vertical integration. We consider how the distinction between incentives to invest in R&D, and the potential for ex post holdup, influence vertical transactions and vertical integration. We also examine the role of maturity, as vertical integration is more likely when the supply chain is mature enough to support long-term gains from operational synergies.

We measure vertical relatedness using computational linguistics analysis of firm product descriptions and how these descriptions relate to product vocabularies from the BEA Input-Output tables. The result is a dynamic network of vertical relatedness between publicly-traded firms. We thus observe the extent to which acquisitions are vertical transactions and develop a new firm-level measure of vertical integration.

We show that unrealized innovation through R&D and realized innovation through patents affect the propensity to vertically integrate. Firms in high R&D industries are less likely to vertically integrate through own-production and vertical acquisitions. These results are robust to using state-level tax credits as an instrument for R&D. These findings are consistent with firms remaining separate to maintain ex ante incentives to invest in intangible capital and to maintain residual rights of control, as in the property rights theory of Grossman, Hart and Moore.

In contrast, firms in high patenting industries with high realized innovation are more likely to vertically integrate. In these industries, owners have more legally enforceable residual rights of control. They are more likely to integrate via acquisitions as control by firms investing in commercialization should prevent ex post holdup. These results reconcile some of the tension between the ex post hold-up literature of Klein, Crawford and Alchain (1979) and Williamson (1979), and the ex ante incentives of assigning residual rights of control as in Grossman and Hart (1986).

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Table I: BEA vocabulary example: Photographic and Photocopying Equipment

Description of Commodity Sub-Category	Value of Production ($Mil.)
Still cameras (hand-type cameras, process cameras for photoengraving and photolithography, and other still cameras)	266.1
Projectors	72.4
Still picture commercial-type processing equipment for film	40.5
All other still picture equipment, parts, attachments, and accessories	266.5
Photocopying equipment, including diffusion transfer, dye transfer, electrostatic, light and heat sensitive types, etc.	592.4
Microfilming, blueprinting, and white-printing equipment	20.7
Motion picture equipment (all sizes 8mm and greater)	149.0
Projection screens (for motion picture and/or still projection)	204.9
Motion picture processing equipment	23.0

Note: This table provides an example of the BEA commodity 'photographic and photocopying equipment' (IO Commodity Code #333315). The table displays its sub-commodities and their associated product text, along with the value of production for each sub-commodity.

Table II: Vertical Network Summary Statistics

Network:	Vert. Text-10%	Vert. Text-1%	NAICS-10%	NAICS-1%	TNIC-3
Granularity	10%	1%	9.48%	1.37%	2.33%
% of pairs in TNIC-3	1.33%	2.39%	2.67%	2.89%	100%
% of pairs in the same SIC	0.74%	1.03%	0.35%	0.20%	38.10%
% of pairs in the same NAICS	0.59%	0.66%	0.30%	0.18%	38.11%
% of pairs in the same SIC or NAICS	0.81%	1.09%	0.35%	0.20%	41.24%
% of pairs in Vert. Text-10%	100%	100%	10.48%	13.18%	6.15%
% of pairs in Vert. Text-1%	10%	100%	1.18%	1.21%	1.09%
% of pairs that include a financial firm	9.20%	1.80%	48.44%	34.31%	58.72%
% of (no fin.) pairs in Vert. Text-10%	100%	100%	19.90%	19.29%	11.63%
% of (no fin.) pairs in Vert. Text-1%	10%	100%	2.14%	1.71%	2.44%

Note: This table displays various characteristics for five networks: Vertical Text-10% and Vertical Text-1% vertical networks, NAICS-10% and NAICS-1% vertical networks, and the TNIC-3 horizontal network.

Table III: Mergers and Acquisitions - Sample Description

Measure:	**All**	**Text-Based**		**NAICS-based**	
Deal type:		Vertical	Non-Vertical	Vertical	Non-Vertical
		Panel A: Sample Description			
# Transactions	3,460	1,368	2,092	460	3,000
% Vertical (Non-Vertical)		39.54%	60.46%	13.29%	86.71%
# Upstream		687		199	
# Downstream		681		261	
		Panel B: Combined Acquirers and Targets Returns			
CAR(0)	0.49%	0.65%	0.38%[a]	0.46%	0.49%
CAR(-1,1)	0.86%	0.97%	0.79%	0.55%	0.91%
# Transactions	3,256	1,301	1,995	427	2,829

Note: Panel A displays statistics for vertical and non-vertical transactions (non-financial firms only). A transaction is vertical if the acquirer and target are pairs in the Vertical Text-10% network or the NAICS-10% network. Panel B displays the average cumulated abnormal announcement returns (CARs) of combined acquirers and targets. We include the superscript [a] when the difference in CARs between vertical and non-vertical transactions is significant at the 5% level.

Table IV: Vertical Transactions - Deal-level Analysis

Variable:	Ind.(R&D/ sales)	R&D/ sales	Ind.(#Patents/ Assets)	#Patents/ Assets
Panel A: Whole Sample				
(i) Vert. Targets	0.0555	0.0424	0.0076	0.0091
(ii) Non-Vert. Targets	0.1262	0.0813	0.0077	0.0069
(iii) Non-Merging Firms	0.0905	0.0622	0.0075	0.0082
t-statistic [(i)-(ii)]	(-16.67)^a	(-9.32)^a	(-0.30)	(3.36)^a
t-statistic [(i)-(iii)]	(-9.20)^a	(-5.34)^a	(0.27)	(1.45)
t-statistic [(ii)-(iii)]	(11.03)^a	(6.07)^a	(0.74)	(-2.42)^b
Panel B: Matched Targets I				
(i) Vert. Targets	0.0555	0.0424	0.0076	0.0091
(ii) Matched Vert. Targets	0.0953	0.0592	0.0072	0.0065
t-statistic [(i)-(ii)]	(-9.64)^a	(-4.01)^a	(0.94)	(3.44)^a
(i) Non-Vert. Targets	0.1262	0.0813	0.0077	0.0069
(ii) Matched Non-Vert. Targets	0.1073	0.0696	0.0079	0.0072
t-statistic [(i)-(ii)]	(4.15)^a	(2.66)^a	(-0.62)	(-0.52)
Panel C: Matched Targets II				
(i) Vert. Targets	0.0555	0.0424	0.0076	0.0091
(ii) Matched Vert. Targets	0.0802	0.0477	0.0061	0.0048
t-statistic [(i)-(ii)]	(-6.63)^a	(-1.36)	(3.81)^a	(6.39)^a
(i) Non-Vert. Targets	0.1262	0.0813	0.0077	0.0069
(ii) Matched Non-Vert. Targets	0.0931	0.0584	0.0072	0.0062
t-statistic [(i)-(ii)]	(7.67)^a	(5.62)^a	(1.62)	(1.21)

Note: Transactions are defined as vertical when the acquirer and target are in pairs in the Vertical Text-10% network. In Panel A, we compare targets of vertical and non-vertical deals, and non-merging firms. In Panel B, each target is compared to a "matched" non-merging target using a propensity score model based on industry , size, and year. In Panel C, the propensity score is based on industry, size, age, Market-to-Book, PPE/Assets, End Users, # of NAICS Segments, and year. We report t-statistics corresponding to tests of mean differences. Symbols ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5%, and 10% confidence levels.

Table V: The Determinants of Vertical Target Acquisitions

Dep. Variable:	**Prob(Target)**						
Specification:	Logit				IV Probit		
Deal type:	Vertical	Non-Vertical	Vertical	Non-Vertical	1st Stage	Vertical	Non-Vertical
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ind.(R&D/sales)	-0.312^{a}	0.340^{a}	-0.248^{a}	0.505^{a}		-0.205^{b}	-0.039
	(0.055)	(0.031)	(0.082)	(0.045)		(0.084)	(0.074)
Ind.(#Patents/asse)	0.338^{a}	-0.177^{a}	0.373^{a}	0.016	0.376^{a}	0.178^{a}	0.008
	(0.030)	(0.039)	(0.034)	(0.047)	(0.032)	(0.039)	(0.039)
Ind.(R&D/sales) $\times$ Ind.(#Patents/assets)			-0.043	-0.127^{a}			
			(0.034)	(0.026)			
Ind.(PPE/assets)	-0.023	-0.188^{a}	-0.016	-0.135^{b}	-0.181^{a}	-0.008	-0.112^{a}
	(0.034)	(0.052)	(0.034)	(0.053)	(0.012)	(0.026)	(0.026)
HHI	-0.100^{a}	-0.182^{a}	-0.100^{b}	-0.167^{a}	-0.114^{a}	-0.058^{a}	-0.118^{a}
	(0.039)	(0.033)	(0.039)	(0.033)	(0.009)	(0.022)	(0.019)
End User	-0.348^{a}	0.187^{a}	-0.346^{a}	0.208^{a}	0.038^{a}	-0.149^{a}	0.090^{a}
	(0.034)	(0.028)	(0.034)	(0.028)	(0.010)	(0.016)	(0.013)
#Segment (NAICS)	0.171^{a}	-0.013	0.171^{a}	-0.012	-0.009^{b}	0.092^{a}	-0.012
	(0.022)	(0.025)	(0.022)	(0.026)	(0.004)	(0.010)	(0.012)
log(Assets)	0.660^{a}	0.431^{a}	0.660^{a}	0.434^{a}	-0.009	0.247^{a}	0.164^{a}
	(0.037)	(0.029)	(0.037)	(0.029)	(0.009)	(0.016)	(0.013)
log(Age)	0.180^{a}	-0.031	0.181^{a}	-0.026	-0.104^{a}	0.071^{a}	-0.034^{b}
	(0.036)	(0.026)	(0.036)	(0.026)	(0.007)	(0.018)	(0.014)
MB	-0.269^{a}	-0.071^{b}	-0.271^{a}	-0.073^{b}	0.143^{a}	-0.078^{a}	0.009
	(0.052)	(0.029)	(0.052)	(0.029)	(0.012)	(0.024)	(0.018)
State R&D Tax Credit					8.052^{a}		
					(0.483)		
#obs.	45,198	45,198	45,198	45,198	45,198	45,198	45,198
Pseudo R^2	0.116	0.045	0.116	0.048			

Note: The dependent variable in the logistic models is a dummy indicating whether the given firm is a target in a vertical or non-vertical transaction in a given year. Vertical transactions are identified using the Vertical Text-10% network. The first four columns compare vertical and non-vertical transactions for the full sample. The last three columns report the results using state R&D tax credits as an instrument for R&D activity that is not related to organizational form. All independent variables are defined in Appendix 2. The independent variables are standardized for convenience. Standard errors are clustered by industry and year and are reported in parentheses. Symbols ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5%, and 10% confidence levels.

Table VI: Vertical Target Acquisitions: High Secrecy vs. Low Secrecy

Dep. Variable:	**Prob(Vertical Target)**			
Sub-Sample:	**Secrecy**			
Specification:	Logit		IV Probit	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Ind.(R&D/sales)	-0.755[a]	0.043	-0.326[b]	0.231
	(0.094)	(0.094)	(0.133)	(0.171)
Ind.(#Patents/assets)	0.295[a]	0.062	0.140[b]	-0.038
	(0.050)	(0.070)	(0.066)	(0.062)
Ind.(PPE/assets)	-0.061	-0.127	0.001	0.076
	(0.078)	(0.104)	(0.062)	(0.060)
HHI	-0.184[b]	-0.172[a]	-0.089[c]	-0.039
	(0.075)	(0.064)	(0.050)	(0.041)
End User	-0.188[a]	-0.218[a]	-0.083[b]	-0.095[a]
	(0.055)	(0.068)	(0.040)	(0.030)
#Segment (NAICS)	0.090[b]	0.138[a]	0.058[b]	0.080[a]
	(0.041)	(0.049)	(0.023)	(0.024)
log(Assets)	0.642[a]	0.664[a]	0.259[a]	0.255[a]
	(0.060)	(0.068)	(0.031)	(0.029)
log(Age)	0.146[b]	0.124[c]	-0.069[b]	0.075[a]
	(0.063)	(0.069)	(0.033)	(0.032)
MB	-0.251[b]	-0.408[a]	-0.085[c]	-0.169[a]
	(0.109)	(0.087)	(0.051)	(0.039)
#obs.	9,409	9,333	9,409	9,333
Pseudo R^2	0.137	0.095	NA	NA

Note: The dependent variable is a dummy indicating whether the given firm is a target in a vertical transaction in a given year. Vertical transactions are identified using the Vertical Text-10% network. All independent variables are defined in Appendix 2. The 'Low' and 'High' groups in the column headers correspond to industries where the importance of secrecy (as opposed to patents) for protecting innovation is below and respectively above the sample median as defined in the text. This sample is limited to 34 manufacturing industries. In all columns, the independent variables are standardized for convenience. Standard errors are clustered by industry and year and are reported in parentheses. Symbols ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5%, and 10% confidence levels.

Table VII: Averages by Quartiles of VI

Variable	Quartile 1 (Low VI)	Quartile 2	Quartile 3	Quartile 4 (High VI)
Panel A: Data from Text Analysis				
VI	0.002	0.006	0.011	0.028
Retail	0.396	0.366	0.346	0.301
Government	0.039	0.031	0.027	0.025
Export	0.079	0.084	0.087	0.095
End users	0.515	0.482	0.462	0.422
Panel B: Data from Existing Literature				
R&D/sales	0.098	0.062	0.047	0.027
#Patents/assets	0.006	0.008	0.008	0.007
log(1+#Patents)	0.420	0.504	0.640	0.835
PPE/assets	0.199	0.247	0.285	0.320
HHI	0.231	0.258	0.272	0.274
log(assets)	5.355	5.485	5.771	6.123
log(age)	2.736	2.788	2.970	3.318
#Segments	1.318	1.422	1.572	1.890
MB	2.355	2.080	1.880	1.606
$\text{VI}_{segment}$	0.006	0.009	0.013	0.024

Note: This table displays averages by (annually sorted) quartiles based on text-based vertical integration (VI). The sample includes 45,198 observations. All variables are defined in Appendix 2.

Table VIII: The Determinants of Vertical Integration

Dep. Variable:	(Text-based) VI					
Specification:	OLS-FE				Instrumental Variables	
	Baseline		Interaction		1st Stage	2nd Stage
	(1)	(2)	(3)	(4)	(5)	(6)
Ind.(R&D/sales)	-0.100^a	-0.017^a	-0.081^a	-0.012^c		-0.145^a
	(0.007)	(0.005)	(0.008)	(-0.006)		(0.034)
Ind.(#Patents/assets)	0.068^a	0.019^a	0.084^a	0.025^a	0.208^a	0.079^a
	(0.007)	(0.004)	(0.009)	(0.006)	(0.011)	(0.011)
Ind.(R&D/sales) × Ind.(#Patents/assets)			-0.014^a	-0.005^c		
			(0.004)	(0.002)		
Ind.(PPE/assets)	0.022^c	0.014	0.023^c	0.014	-0.171^a	0.014
	(0.012)	(0.009)	(0.012)	(0.009)	(0.008)	(0.012)
HHI	-0.107^a	-0.055^a	-0.106^a	-0.055^a	-0.064^a	-0.111^a
	(0.006)	(0.004)	(-0.006)	(0.004)^a	(0.004)	(0.007)
End User	-0.240^a	-0.142^a	-0.240^a	-0.142^a	-0.001	-0.240^a
	(0.007)	(0.006)	(0.007)	(0.006)	(0.003)	(0.007)
#Segment (NAICS)	0.131^a	0.041^a	0.131^a	0.041^a	-0.002	0.130^a
	(0.005)	(0.006)	(0.005)	(0.006)	(0.002)	(0.005)
log(Assets)	0.051^a	0.124^a	0.051^a	0.124^a	-0.008^a	0.050^a
	(0.004)	(0.010)	(0.004)	(0.011)	(0.003)	(0.004)
log(Age)	0.021^a	0.014	0.020^a	0.014	-0.038^a	0.018^a
	(0.004)	(0.010)	(0.004)	(0.010)	(0.002)	(0.004)
MB	-0.016^a	0.005^c	-0.016^a	0.005^b	0.034^a	-0.014^a
	(0.003)	(0.002)	(0.003)	(0.002)	(0.005)	(0.003)
State R&D Tax Credit					6.236^a	
					(0.238)	
Industry Fixed Effects	Yes	No	Yes	No	Yes	Yes
Firm Fixed Effects	No	Yes	No	Yes	No	No
#obs.	45,198	45,198	45,198	45,198	45,198	45,198
Adj. R^2	0.526	0.855	0.527	0.855	0.723	0.705

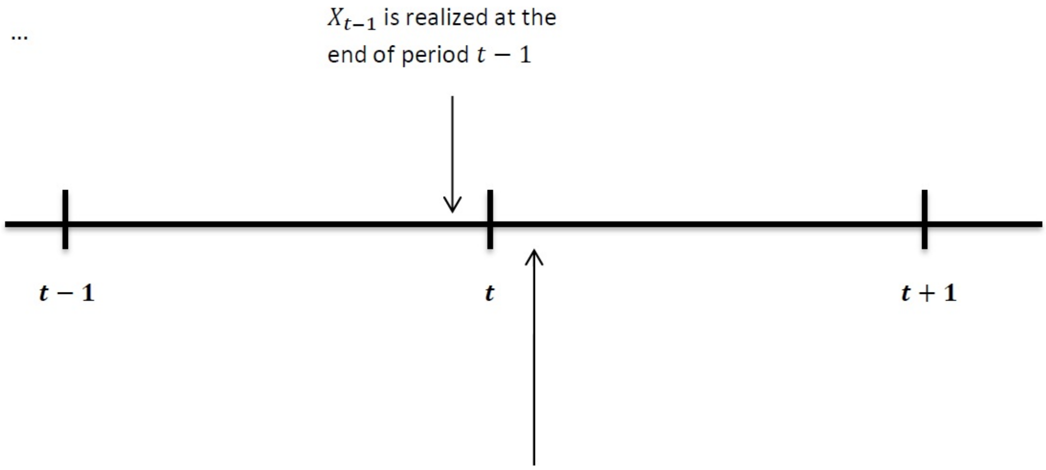
Note: The dependent variable is vertical integration VI. All independent variables are defined in Appendix 2. The independent variables are standardized for convenience. The first four columns are based on OLS regressions with industry or firm fixed effects as noted. The last two columns report the results using state R&D tax credits as an instrument for R&D activity that is not related to organizational form. Standard errors are clustered by industry and year and are reported in parentheses. Symbols ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5%, and 10% confidence levels.

Table IX: The Determinants of Vertical Integration: High vs. Low Secrecy Industries

Dep. Variable:	**(Text-based) VI**					
Sub-Sample:	**Secrecy**					
Specification:	OLS-FE				IV	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Ind.(R&D/sales)	-0.141^a	-0.104^a	-0.036^a	-0.004	-0.226^a	-0.309^a
	(0.015)	(0.016)	(0.013)	(0.013)	(0.076)	(0.081)
Ind.(#Patents/assets)	0.042^a	0.002	0.023^a	0.013	0.062^a	0.038^b
	(0.014)	(0.010)	(0.009)	(0.008)	(0.022)	(0.018)
Ind.(PPE/assets)	-0.027	0.077^a	0.017	-0.041^c	-0.049	0.046^b
	(0.029)	(0.023)	(0.024)	(0.023)	(0.034)	(0.024)
HHI	-0.173^a	-0.165^a	-0.069^a	-0.089^a	-0.184^a	-0.186^a
	(0.016)	(0.013)	(0.011)	(0.012)	(0.020)	(0.015)
End User	-0.25^a	-0.311^a	-0.227^a	-0.179^a	-0.250^a	-0.307^a
	(0.017)	(0.014)	(0.019)	(0.018)	(0.017)	(0.014)
#Segment (NAICS)	0.102^a	0.155^a	0.051^a	0.068^a	0.099^a	0.153^a
	(0.014)	(0.014)	(0.016)	(0.017)	(0.014)	(0.014)
log(Assets)	0.036^a	0.057^a	0.114^a	0.238^a	0.036^a	0.054^a
	(0.011)	(0.010)	(0.025)	(0.032)	(0.011)	(0.010)
log(Age)	0.002	-0.012	-0.008	0.012	-0.002	-0.024^b
	(0.014)	(0.012)	(0.032)	(0.030)	(0.015)	(0.012)
MB	-0.001	-0.046^a	0.001	0.004	0.001	-0.033^a
	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.009)
Industry Fixed Effects	Yes	Yes	No	No	Yes	Yes
Firm Fixed Effects	No	No	Yes	Yes	No	No
#obs.	9,409	9,333	9,409	9,333	9,409	9,333
Adj. R^2	0.570	0.509	0.857	0.815	0.748	0.777

Note: The dependent variable is vertical integration VI. All independent variables are defined in Appendix 2. The 'Low' and 'High' groups in the six columns correspond to industries where the importance of secrecy (as opposed to patents) for protecting innovation is below and respectively above the sample median as defined in the text. This sample is limited to 34 manufacturing industries. The independent variables are standardized for convenience. Standard errors are clustered by industry and year and are reported in parentheses. Symbols ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5%, and 10% confidence levels.

Figure 1:



At the beginning of period t

Actions:

(1) Producer decides I_t given X_{t-1}
(2) Choose x_t and y_t given I_t
(3) Renegotiation

Prices:

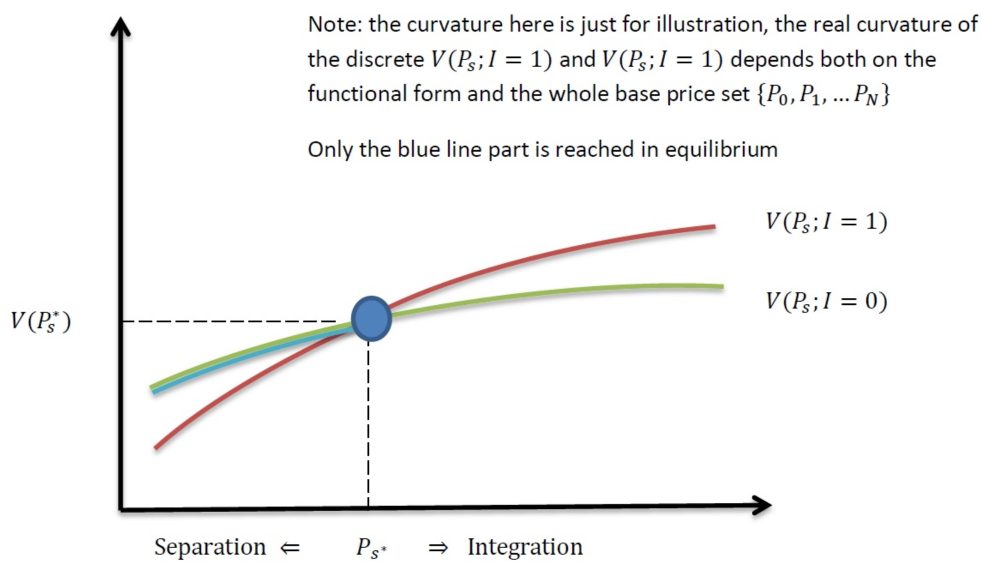
$$P_t = \begin{cases} P_t^b(1+y_t) & \text{if } I_t = 0 \\ P_t^b\big(1+\rho(y_t)\big) & \text{if } I_t = 1 \end{cases}$$

$$P_t^b = \begin{cases} P_s + (P_{s+1} - P_s)X_{t-1} & \text{if } P_{t-1}^b = P_s \text{ with } 0 \leq s < N \\ P_N & \text{if } P_{t-1}^b = P_N \end{cases}$$

Payoffs:

(1) $TS_t = P_t - Sx_t^g - Ry_t^h$
(2) The split of the sales depends on α
(3) Supplier's profit is αTS_t, and producer's profit is $(1-\alpha)TS_t$

Figure 2:



Note: the curvature here is just for illustration, the real curvature of the discrete $V(P_s; I = 1)$ and $V(P_s; I = 1)$ depends both on the functional form and the whole base price set $\{P_0, P_1, \dots P_N\}$
Only the blue line part is reached in equilibrium
$V(P_s; I = 1)$
$V(P_s; I = 0)$
$V(P_s^*)$
Separation $\Leftarrow$ P_{s^*} $\Rightarrow$ Integration

Figure 3: R&D and Patents prior to Acquisitions. The figure shows the average R&D (lower panel) and patenting activity (upper panel) of firms that are targets in vertical and non-vertical acquisitions prior to the acquisition. Solid lines represent vertical transactions identified using the Vertical Text-10% network. Dashed lines represent non-vertical transactions.

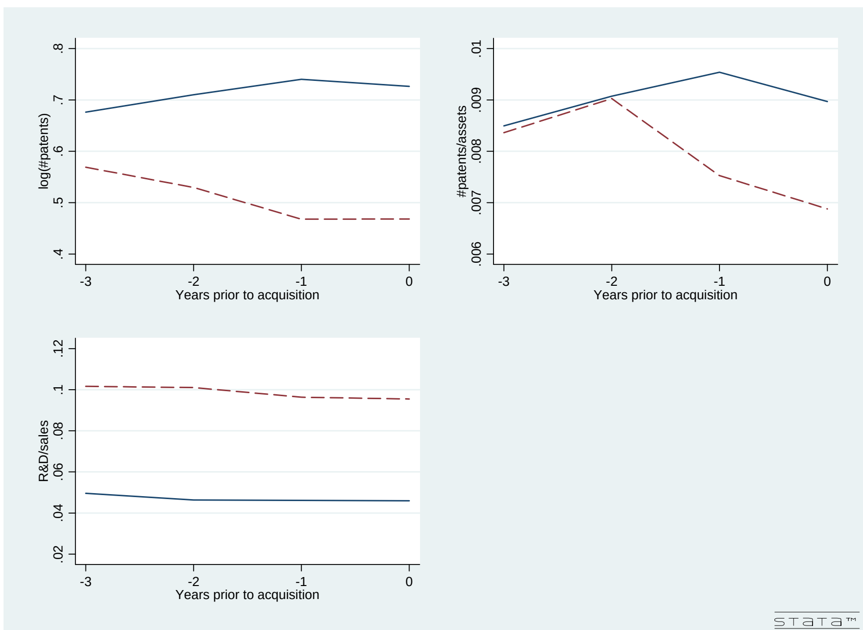


Figure 4: Evolution of sample-wide average (text-based) Vertical Integration over time. Vertical integration (VI) is defined in Section V.A. The solid blue line is the annual equal-weighted average VI. The dashed red line is the corresponding sales-weighted average.

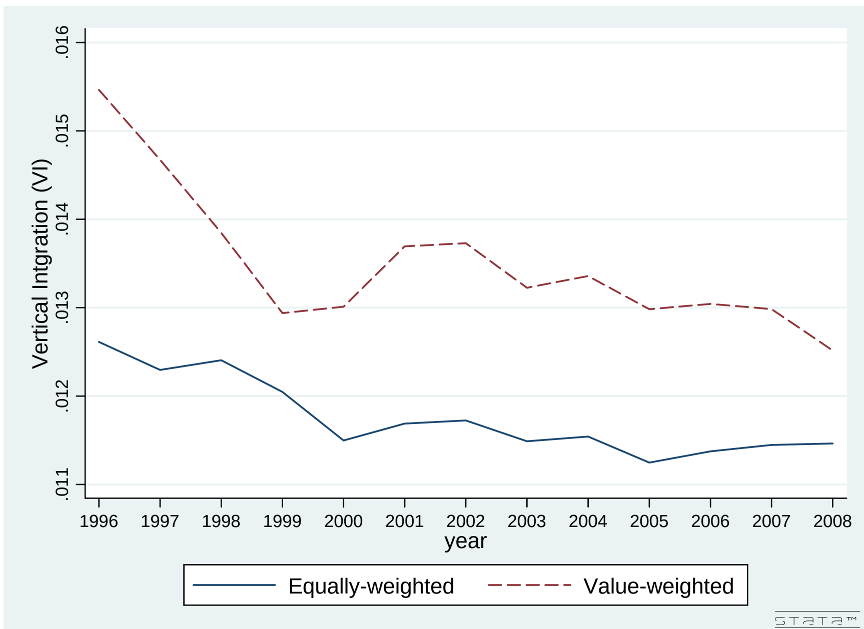


Figure 5: An Example: the Network Equipment Industry. The figure plots the evolution of text-based vertical integration (VI), patenting activity (log(#patents) and #patents/assets) and R&D activity (R&D/sales) for seven representative firms in the network equipment industry: Cisco, Broadcom, Citrix, Juniper, Novell, Sycamore, and Utstarcom.