Capital Market Relationships and Interfirm Information Spillovers*

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We investigate the role of capital market relationships in facilitating the flow of relevant competitive information between firms. Using patent citations as a proxy for interfirm knowledge spillovers, we find that firms are more likely to cite another firm's patent if this firm is covered by the same financial analyst. Difference-in-difference analyses exploiting exogenous shocks to analyst coverage overlaps over time suggest that the documented effects are not simply due to dynamic adjustments in firms' business models and corresponding changes in analyst coverage, but instead are consistent with a plausible causal relationship between analyst coverage overlaps and interfirm information spillovers. The effect is also stronger for analysts with relatively higher industry-specialization, a higher level of experience, a larger coverage portfolio, and higher activity, as well as firm pairs with larger geographic or organizational diversity. Overall, our findings suggest that capital market relationships do not only play an important role in facilitating information transfer and reducing information asymmetries between firms and capital markets, but also facilitate the production of relevant business intelligence through feedback and interfirm information transfers.

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Keywords: Capital market relationships; Analyst coverage; Information spillover; Knowledge flow; Feedback effect; Patent citations.

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Abstract

We investigate the role of capital market relationships in facilitating the flow of relevant competitive information between firms. Using patent citations as a proxy for interfirm knowledge spillovers, we find that firms are more likely to cite another firm's patent if this firm is covered by the same financial analyst. Difference-in-difference analyses exploiting exogenous shocks to analyst coverage overlaps over time suggest that the documented effects are not simply due to dynamic adjustments in firms' business models and corresponding changes in analyst coverage, but instead are consistent with a plausible causal relationship between analyst coverage overlaps and interfirm information spillovers. The effect is also stronger for analysts with relatively higher industry-specialization, a higher level of experience, a larger coverage portfolio, and higher activity, as well as firm pairs with larger geographic or organizational diversity. Overall, our findings suggest that capital market relationships do not only play an important role in facilitating information transfer and reducing information asymmetries between firms and capital markets, but also facilitate the production of relevant business intelligence through feedback and interfirm information transfers.

"*There are multiple ways to gain competitive intelligence through networking at industry and sell-side conferences and events, trade shows and interacting with analysts, institutional and retail investors, bankers, and key opinion leaders.*"

National Investor Relations Institute (NIRI), IR Update, October 2015

1. Introduction

Can firms gather relevant market and competitive intelligence from interactions and relationships with capital market participants, such as financial analysts and investors? In a competitive market place, characterized by rapid technological change and information overload, firms are continuously seeking to identify and adapt to new and relevant competitive information such as recent market developments, product trends, and activities of competitors. At the same time, it is difficult and costly for firms to constantly search and evaluate the activities of other firms and to evaluate corresponding implications for competition and market development, resulting in informational frictions (e.g., Geertz, 1978; Stuart, 1998; Vanhaverbeke et al., 2002). Understanding the role of the capital market relationships in facilitating such knowledge flows is an important research question, since long-term corporate and economic growth depends significantly on efficient allocation of corporate investment into activities that eventually result in product market innovations and shape the competitive landscape (Scotchmer and Green, 1990; Romer, 1990; Grossman and Helpman, 1991; Hagedoorn, 2002). Recent literature highlights that firms exposure to capital markets may impede corporate innovation due to short-term performance pressures while at the same time increased coverage by intermediaries may promote corporate innovation by decreasing information asymmetries between managers and the market and, hence, solving an undervaluation problem of investments in innovation (He and Tian, 2013; Guo et al., 2019; Clarke et al., 2015). In this paper, we extent this perspective and show that capital market relationships may affect corporate activities and innovation by facilitating knowledge flows between firms.

Firms may generate market and competitive intelligence from various sources, including commercial and publicly available databases and publications (e.g., reports by industry analysts, executive speeches, competitor websites, innovation reports, patent archives, etc.). However, anecdotal evidence suggests that one of the primary sources of relevant competitive or market intelligence are direct relationships and interactions with expert parties, such as industry experts, managers and board members, as well as customers and suppliers, due to the competitive advantage that such unique information may provide (see e.g., Miller, 2000; Walsh, 2015). Since capital market participants typically exhibit specific industry knowledge and systematically collect and analyze information for multiple firms at the same time, relationships and interactions with them may not only serve capital market-oriented objectives, such as disseminating new information or clarifying existing information (e.g., Rogers et al., 2009; Kirk and Markov, 2016; Tasker, 1998; Bushee et al., 2011). Instead capital market relationships may also promote the flow of market and competitive intelligence towards the firm and, hence, allow the firm to learn about recent market trends and competitor activities.

We test this conjecture and the existence of a potential feedback effect of capital market relationships by investigating the effect of financial analysts coverage overlaps on the likelihood that firms will include citations of other firms' innovations in forthcoming patents. The setting of analyst coverage overlaps and corporate patent citations allows us to overcome several potential limitations inherent when studying capital market relationships and interfirm knowledge flows. First, although firms frequently interact not only with financial analysts, but also with investors and other stock market participants, focusing on financial analysts allows for a cleaner and less biased identification of overlaps in capital market relationships between firms. While individual analyst coverage can easily be identified and tracked for a broad set of firms, identification of, e.g., investor overlaps between firms is difficult and inherently noisy, especially when measured over time and on an individual investor basis.

Financial analysts are also considered a key information intermediary in capital markets and their role and influence in gathering, processing, and disseminating relevant market- and firm-specific information has been well documented in prior literature (e.g., Gleason and Lee, 2003; Frankel et al., 2006; Markov et al., 2017; Chan and Hameed, 2006). Since analysts frequently interact with firms' senior management and investor relations managers (Soltes, 2014; Kirk and Markov, 2016; Green et al., 2014a,b) and even invest into on going relationships with corporate management (Brochet et al., 2014), they also represent a group of capital market participants that is relatively likely to facilitate interfirm knowledge flows; if they exist.

Second, while it is generally difficult to identify knowledge flows between firms, a substantial prior literature in economics and management has established patent citations as a useful proxy for the flow of (technological) knowledge between firms (Jaffe and Trajtenberg, 2002; Agrawal et al., 2017; Belenzon and Schankerman, 2013). When a firm applies for a patent, it will not only include information about the invention and the inventor, but also about the technological antecedents. This also includes citations of existing patents that, similar to bibliographic citations, reference prior work that forms the basis of the innovation. Although patent citations may be added by the filing firm as well as by the examiners during the entire patent application process, they have nevertheless been proven to be a useful proxy to determine potential knowledge and information spillover between clearly specified firms (Gomes-Casseres et al., 2006; Alcacer and Gittelman, 2006; Jaffe et al., 2000, 1993). The combination of coverage overlaps and patent citations thus allows us to identify and track links between firms over time, both in terms of joint capital market relationships and potential knowledge flows between them; a feature generally unavailable in other settings, such as corporate mergers and acquisitions. Given the importance of innovation for productivity and growth, capital market participants such as financial analysts are also likely to actively acquire and process patent-related information (e.g., Palmon and Yezegel, 2012; Tan et al., 2019).[1]

We find that firm pairs with a higher number of mutually shared financial analysts are more likely to cite existing patents in new patent applications than comparable firms pairs with few or no analyst coverage overlaps. An increase in common analysts is associated with an increase in citations by one percent, after controlling for citing firm and cited firm characteristics as well as firm pair and year fixed effects. The size of the effect is economically significant and also plausible compared to, e.g., interfirm alliances, which have been shown to result in an increase in cross-citations of about six percent (Gomes-Casseres et al., 2006). While this result is consistent with an information flow hypothesis under which financial analysts facilitate the flow of meaningful information towards or within the firms they cover, a more benign alternative explanation is that dynamic adjustments in firms' business models result in corresponding changes in analyst coverage. If analysts' decision to cover a firm is at least partly based on the similarity of the firm to other firms in the coverage portfolio, then changes in the similarity of paired firms' business models over time will be correlated with changes in analyst coverage overlap. However, when taking into account dynamic adjustments of technological similarity (Jaffe and Trajtenberg, 1996) and business similarity (Hoberg and Phillips, 2010, 2016) within firm pairs the coefficient estimate for analyst coverage overlaps remains similar in size and statistical significance. While measuring dynamic changes in firms' similarity is obviously not free from measurement error, the results nevertheless cast significant doubt that the documented effects are simply due to dynamic adjustments in firms' business models and corresponding changes in analyst coverage.

To better understand the direction of causation between analyst coverage overlaps and cross-firm patent citations, we conduct a variety of additional tests examining how patent citations change after exogenous shocks to analyst coverage overlaps and interact with vari-

[1] For example, a survey by the U.S. Patent and Trademark Office shows that financial analysts used the patent and trademark depository libraries to search for patent and trademark information (USPTO, 2003). Similarly, Tan et al. (2019) show that analysts can possess technological expertise and that this expertise is distinct from industry specialization.

ations in analyst characteristics. First, we explore the closure of brokerage houses as a quasi-natural experiment to study exogenous shocks to analyst coverage overlaps for different firm-pairs at different points in time (Hong and Kacperczyk, 2010; Kelly and Ljungqvist, 2012; He and Tian, 2013). The identification strategy exploits the fact that several brokerages had to close their research operations due to, e.g., decreases in revenue from trading, market-making, and investment banking, affecting different analysts at different points in time. Brokerage house closures directly affect existing overlaps in analyst coverage of firm pairs, while being exogenous to the paired firms' business development, productivity, and investment in innovation, and, hence, should be orthogonal to changes in the similarity of paired firms' underlying business models. Since brokerage house closures affect analyst coverage of different firms (and firm pairs) at different points in time, we also avoid problems from other potentially omitted variables correlated with a single brokerage shock and changes in business similarity (e.g., time trends). Using a difference-in-difference regression design, we find that an exogenous decrease in analyst coverage overlaps results in 7.4 percent fewer subsequent cross-patent citations for treated firm pairs compared to a control group of firm pairs for the same citing firm, but which are not affected by any brokerage house closure. This result supports the idea of a plausible causal relationship of analyst coverage overlaps and interfirm knowledge flows and is inconsistent with the explanation that analyst coverage overlaps and patent citations merely reflect firm pairs' business and technological similarity.

Second, we explore cross-sectional variation in characteristics of analysts with overlapping coverage. If analysts facilitate knowledge flows between firms the likelihood of a knowledge flow should be higher for those analysts that are more likely to possess relevant information. The cross-sectional results indeed suggest that this is the case. More specifically, we find that overlaps in analysts with relatively higher industry specialization, a higher level of experience, a larger coverage portfolio, and higher levels of forecasting activity are associated with higher levels of within-firm pair patent citations, consistent with the notion that analyst with more industry knowledge and firm-specific levels of activity are more likely to facilitate interfirm knowledge flows. Taken together, these additional tests are consistent with the conjecture that analyst coverage overlaps have a positive effect on interfirm knowledge flows.

While using patent citations as a proxy for interfirm knowledge flows offers several advantages for measurement and identification, the measure also entertains alternative explanations for the observed effect. According to the information flow hypothesis, patent citations represent information flows from one firm to another. However, patent citations may also represent differences in the level of patent-related disclosures by the citing firm, e.g., in response to variations in litigation risk or monitoring (i.e., patent citations may be strategic, see, e.g., Lampe, 2012). If firms engage in strategic citations (e.g., because they prefer to avoid citing other firms patents to increase the likelihood of success for their own patent applications), analyst coverage overlaps may affect the underlying incentives to cite patents by cross-covered firms, e.g., because analyst fulfill a monitoring role. This litigation risk hypothesis implies that cross-patent citations emerge primarily from changes in litigation risk of the citing firm towards the cited firm. We contrast the information flow and the litigation risk explanation with a number of additional tests.[2]

If capital market interactions serve an informational purpose for firms' seeking competitive intelligence, the role of these interactions should be more pronounced if there are larger information asymmetries between firms. We split the dependent variable into citations of patents from the same or from a different technological subclass and find that coverage overlaps are significantly more predictive for out-subclass patent citations. In addition, we

[2]It should be noted, though, that the consequences of an increased level of citations for the cited firm are not necessarily clear. In general, citations are viewed as an indication of the scientific contribution of the innovation. As such, patent citations are frequently used as a measure of the value of a particular innovation (e.g., Trajtenberg, 1990; Fischer and Leidinger, 2014; Hochberg et al., 2018). Similarly, Mann (2018) documents that patent portfolios with a high number of citations have many potential buyers and thus constitute a more valuable collateral. However, Lanjouw and Schankerman (2001) show that the number of citations is also associated with the patent's risk of becoming the target of litigation. Hence, it seems generally unclear whether received patent citations are beneficial or costly for the cited firm. As such, it is also unclear whether the litigation risk hypothesis is plausible given the ambiguous incentives of the cited firm to receive more citations.

also investigate variation in the cited firm's geographic location and organizational structure and document stronger effects of coverage overlaps for firm pairs for which the cited firm shows larger geographic or organizational diversity. Overall, the observed patterns are rather supportive of an information flow hypothesis supporting the the notion that analyst coverage overlaps help firms in identifying relevant peer information, especially if potential peer firms are more diverse and, hence, more difficult to monitor.

This study is among the first to highlight the role of capital market participants in facilitating interfirm information spillovers and as such documents a distinct benefit of analyst coverage and firms' interaction with capital market participants. This finding is important for several reasons. First. a recent literature in accounting and finance investigates the role of feedback from financial markets to firms, in particular with respect to firms' voluntary disclosure decisions (e.g., Langberg and Sivaramakrishnan, 2010; Zuo, 2016; Chapman and Green, 2017). However, the role of feedback effects from capital market interactions in terms of interfirm information spillovers remains largely unclear, despite knowledge flows and corporate partnership choices being important for innovative activity and economic growth (Scotchmer and Green, 1990; Romer, 1990; Grossman and Helpman, 1991; Hagedoorn, 2002). Since it is difficult and costly for firms to constantly search and evaluate the activities of other firms and the corresponding implications for competition and market development (Geertz, 1978; Stuart, 1998; Vanhaverbeke et al., 2002), firms may not only benefit from capital market interactions by optimizing their disclosure strategies, but also by obtaining relevant market and competitive intelligence for business development from informed capital market participants. The results documented in this study are consistent with this idea and suggest that feedback effects from capital markets may not only have implications for corporate disclosure and dissemination, but may also have 'real' effects on corporate strategy and investment.[3]

[3]In a related, but different study, Vorst (2018) investigates the role of common analysts in M&A transactions and finds that such transactions are more likely to occur and create more value if the potential acquirer and target have a common analysts. While this finding is consistent with the idea that the information produced by financial analysts can be valuable for corporate decision making, our study extents the scope of information flows beyond the notion of pure firm-specific or investment-related information. Instead, our

More specifically, this study also extents the perspective of how the exposure to capital markets affects corporate activities and investment in innovation. While recent literature documents that coverage by financial analysts can impair a firms willingness and ability to innovate due to increased visibility and short-term capital market pressures (He and Tian, 2013; Guo et al., 2019), the evidence in this paper suggests that increased overlaps in capital market participants closely following different firms can also have positive implications for innovation if coverage networks facilitate interfirm knowledge flows. This finding is also consistent with a social learning perspective of corporate actions and decision-making (e.g., Kaustia and Rantala, 2015).

Finally, the findings should also be relevant to the stream of literature in economics and management that examines the determinants of interfirm knowledge spillovers. The economic rationale for the disclosure function of the U.S. patent system is often set forth in the endogenous growth theory, which demonstrates that knowledge transfers among firms are important for long-run growth (Romer, 1990). This patent information transfer between inventors has been the center of various studies. For example, Jaffe et al. (1993) show that knowledge spillovers between inventors are strongly geographically localized. Gomes-Casseres et al. (2006) document that the sharing of technological knowledge may be promoted by interfirm alliances. Our findings extent this perspective by documenting that interactions with capital market participants can be an alternative, potentially important determinant of interfirm information spillovers.

2. Background and related literature

Public firms invest a considerable amount of resources and time to maintain ongoing relationships with capital market participants, e.g., by implementing structured investor

perspective is broader in the sense that we also aim to capture information flows relevant for, e.g., corporate strategy and innovation. That is also why we focus on cross-firm patent citations to capture information flows between firms.

relation programs, hosting analyst/investor days, organizing non-deal roadshows, or participating in broker-hosted or other investor-oriented conferences. The broader literature in accounting and finance typically views these interactions predominantely as disclosure mechanisms with information flowing from the firm to the capital market, e.g., by disseminating new information or by clarifying existing information (e.g., Rogers et al., 2009; Kirk and Markov, 2016; Tasker, 1998; Bushee et al., 2011). However, anecdotal evidence from corporate investor relations professionals also suggest that firms may actually generate relevant market and competitive intelligence from interactions with investors and other capital market participants (e.g., BNY Mellon, 2015; Walsh, 2015). Consistent with this notion, a recent survey with investor relation professionals by Brown et al. (2019) finds that more than 50 percent of participants view knowledge about industry trends and competitors as one of the most important services provided by financial analysts.

The idea that corporations can learn from capital markets is not new. Several, predominately analytical studies in finance and accounting have focused on the information role of public capital markets and generally establish that public prices should be informative for corporate investment and decision making (e.g., Dow and Gorton, 1997; Subrahmanyam and Titman, 1999; Dye and Sridhar, 2002; Bakke and Whited, 2010; Langberg and Sivaramakrishnan, 2010). Recent literature also documents that managers adapt corporate disclosure practice, such as voluntary management guidance, to signals observed in the market, such as stock prices or analysts' demand for specific information (e.g., Zuo, 2016; Chapman and Green, 2017). Little is known, however, about the mechanisms of these feedback affects and, more specifically, whether actual interactions with investors and other capital market participants may provide firms with an opportunity to gather relevant information about their external business environment, one of the key inputs to an organization's strategic decision making (e.g., Foucault and Fresard, 2014; Badertscher et al., 2013; Durnev and Mangen, 2009). Generating and understanding intelligence about, e.g., recent market developments or emerging competitive threads, directly affects an organizations ability to identify emerging risks and opportunities and, hence, ultimately affects its medium- and long-term competitiveness.

This is especially true for corporate investment in innovation. The innovation process is a long-term process that is characterized by a low level of predictability and a high level of idiosyncratic risks (e.g., Mata and Woerter, 2013; Bergemann and Hege, 2005; Hall et al., 2005; Holmstrom, 1989). The outcome of this process is sensitive to the communication and coordination among various actors (e.g., Forman and van Zeebroeck, 2018; Agrawal et al., 2017; Landry et al., 2002) and hence requires that individuals and business units in firms to frequently interact, collaborate and process mutually relevant information (e.g., Siegel and Hambrick, 2005). Consequently, firms are forced to create an interactive system of learning and information exchange to foster innovation (e.g., Jorde and Teece, 1990). In addition, if the knowledge base of an industry is complex and expanding and the source of expertise is widely dispersed learning in networks of firms gains importance in contrast to learning in individual firms (Powell et al., 1996). As such, it has been shown that interactions with other firms in the network can offer access to knowledge that is not readily available via market exchanges (Rothaermel and Hess, 2007; Gulati, 1999; Gulati et al., 2000).[4] More importantly for our study, this literture also shows that the learning process of corporate innovation is generally affected by the presence of specific (technology) information intermediaries that facilitate information transfers between firms and other actors (Lin et al., 2016; Knockaert et al., 2014; Yusuf, 2008; Howells, 2006). However, while information spillovers seem to be important for corporate innovation and growth, it remains an open question whether relationships and interactions with capital market participants also provide such informational feedback effects.

In examining the association between capital market relationships and interfirm knowledge spillovers, we focus on financial analysts, a key group of capital market participants. A

[4] Ahuja (2000) shows a positive relationship between the number of direct network connections of chemical firms and the innovative output. In addition, Schrader (1991) offers survey evidence that employees frequently give technical information or advice to colleagues in other firms, including direct competitors.

growing body of research suggests that highly developed capital markets generally promote innovation (e.g., Hsu et al., 2014) and that financial analysts seem to have a direct, though nuanced, effect on corporate investment in innovation. One the one hand, financial analysts may increase pressure on managers to meet short-term goals, thereby reducing the incentive to invest in long-term innovative projects (He and Tian, 2013). On the other hand, financial analysts may also promote innovation by providing investors with relevant information and analyses about firms' innovative activities and, hence, decreasing the possibility of market undervaluation (Guo et al., 2019).

Financial analysts are also relatively likely to facilitate interfirm knowledge flows; if they exist. There are a least three necessary conditions for capital market interactions to facilitate interfirm information spillovers. First, capital market participants need to actively search or process information that is related to potentially relevant knowledge for the firms they interact with. Financial analysts are not only often industry and even technology experts (e.g., Clement et al., 2007; Tan et al., 2019), but are typically also in close contact with managers, investors and other capital market participants (Bushee et al., 2011; Green et al., 2014a; Kadan et al., 2012). Their expertise and interaction activities allow them collect relevant information about new business developments or ongoing innovative activities (Park and Soltes, 2017; Klein et al., 2017). In addition, financial analysts typically work in an environment with a high degree of existing knowledge and a high frequency of new knowledge flows (Clement, 1999). Hence, the information environment of financial analysts generally adds to the available stock of information.

Second, there has to be an information channel that allows the firm to become aware of the knowledge a capital market participant possesses. Financial analysts frequently interact with firms' senior management and investor relations managers (Soltes, 2014; Kirk and Markov, 2016; Green et al., 2014a). These interactions are not limited to conference calls and telephone conversations around corporate news announcements. Analysts also play an important role in facilitating interaction between investors and corporate management and regularly participate in or even organize important interaction events such as analyst-investor days, roadshows, or corporate conference presentations (Green et al., 2014b). Hence, financial analysts will typically have several active interactions with the firm across various channels during the financial year, potentially allowing for reverse information flows to the firm.[5]

Finally, capital market participants need to be willing to share their competitive and market intelligence. It has been well documented that financial analysts invest into ongoing relationships with corporate management (Brochet et al., 2014). Besides additional sources of income (e.g., due to organizing road shows or broker-hosted conferences on behalf of a firm), access to management is an important source of information for analysts' research activities and affects forecasting performance (Green et al., 2014a; Brochet et al., 2014; Cohen et al., 2013; Mayew, 2008). If analysts generally wish to maintain good relationships with corporate management in order to keep access to timely corporate information, they should also have an incentive to share relevant market intelligence and competitive information. In addition, even without specific incentives to share information, also critical analyst questions, e.g., during private phone calls or conference call Q&As, are likely to reveal aspects of an analyst's (private) information set. At the same time, recent research also documents that firms are generally concerned about interfirm information spillovers (Asker and Ljungqvist, 2010; Chang et al., 2016; Rogan, 2013; Aobdia, 2015). Hence, whether an analyst actively or passively facilitates information flows might depend on the relative importance of the

[5]An implicit assumption maintained in our study is that the information gathered from interactions with capital market participants will actually be included in the information set of strategic and/or operational decision-makers. While the information flow between corporate departments is highly ideosyncratic and generally unobservable, anecdotal evidence from practitioner surveys suggest that an information flow is at least plausible. First, top managers frequently meet and interact with investors, financial analysts, and other capital market participants, which gives them direct access to their competitive and market intelligence (e.g., BNY Mellon, 2015; Bushee et al., 2011; Green et al., 2014a). Second, investor relations departments frequently provide information to the CEO and CFO, including market intelligence about peer information, industry trends as well as recent market trends and developments (BNY Mellon, 2015). Finally, a recent survey among investor relation professionals also suggests that investor relation departments do not only frequently interact with the accounting, finance, and corporate communication departments, but also with the strategy department (Steinbach et al., 2018).

analyst's relationships with the firms he covers. Ultimately, whether capital market relationships, or financial analysts specifically, facilitate interfirm information spillovers remains an empirical question.

3. Data and sample construction

3.1. Measuring interfirm knowledge flows

To identify interfirm knowledge flows, we follow a substantial prior literature in economics and finance and use patent citations as a proxy for the flow of relevant (technological) knowledge between firms (e.g., Agrawal et al., 2017; Belenzon and Schankerman, 2013; Gomes-Casseres et al., 2006; Jaffe et al., 1993).[6] Specifically, we use the number of citations to patents of firm Y (the cited firm) that are contained in patents applied for in each year by firm X (the citing firm) and look at the variation of citation flows across firm pairs and over time. Following prior literature, we interpret observed variation of citation flows as being associated with corresponding variations in the unobserved flow of (technological) knowledge from the cited firm to the citing firm.

Using the number of patent citations between two firms to measure interfirm knowledge flows has several key advantages for identification. Most importantly, patent citations capture potential knowledge and information flows between clearly specified firms, which allows for measurement of cross-sectional differences in knowledge flows between different firm pairs. In addition, since relevant citations emerge from any distinct patent application, we can further exploit time-series variation in citation flow. This allows us to take into account not only the characteristics of firms and their patenting activity, such as the total number of citations and the total stock of potentially citable patents in a given year, but also any

[6] See also Jaffe and Trajtenberg (2002) for a review of the literature that uses patent citations as a proxy for knowledge flows.

idiosyncratic characteristics of each distinct firm pair. Alternative measures of knowledge flows either lack specific ties between distinct firms (e.g., the introduction of product innovations) or relate to rather specific one time events (such as target selection in corporate mergers and acquisitions). Hence, patent citations are not only an established proxy for knowledge flows between distinct firms, but should also allow for a better identification of a potential effect of capital market relationships on interfirm knowledge flows.[7]

To identify cross-firm patent citations, we utilize patent information from the Kogan et al. (2017) patent database, which includes patent information for all patents issued in the U.S. between 1926 and 2010. An important choice when using cross-firm patent citations to measure interfirm knowledge flows is selecting the relevant patent pool and, hence, the sample of relevant (directional) firm pairs. The most extensive approach would be to use the set of directional firm pairs resulting from the Cartesian product of all unique firms that issued at least one patent during a given period of time.[8] This approach would, however, result in a sparse matrix of directional firm pairs due to the high-dimensional space and with many of the included pairs showing zero citations at any point in time. In addition, we expect information only to matter for decision-making within the undominated choice set of the patent pool. To address these issues, we apply several sample selection criteria to construct the relevant patent pool.

First, instead of including all directional pairs of firms that held a patent at any point in time, we only include a particular pair if the citing firm cites a patent of the cited firm at least once during in the period between 1926 and 2010 (i.e., the period with patent citation data

[7]A potential drawback of patent citations is that a citations are typically also added by the patent examiner during the application process and a such, not all citations represent actual knowledge flows from the cited to the citing firm (Jaffe and Trajtenberg, 2002). Similarly, patent citations may also fail to measure relevant knowledge flows, e.g., because not all inventions are patented or because firms may decide to strategically omit citations from a patent application (Lampe, 2012). However, it is unlikely that absent or extraneous patent citations are systematically related to the type of intercorporate relationships we study and, hence, we expect patent citations to be a meaningful, albeit noisy, signal of interfirm knowledge flows (see also Gomes-Casseres et al., 2006, for a related discussion).

[8]Firms without any patents are not included since such a firm can neither be a citing nor a cited firm and the resulting firm pair would, by definition, show zero cross-citations.

available in the Kogan et al. (2017) patent database). Using revealed preferences to select relevant firm-pairs ensures that our sample includes a broad set of eligible firm pairs and does not exclude any information of firm pair observations simply due to a lack of citations in a particular year, industry, etc..[9] Second, we exclude firm pair observations if the cited firm's total number of patents until and including year t is zero. This ensures that we only include firms with patents in year t that could constitute relevant competitive information. Third, we exclude firm pair observations if the citing firm's total number of citations in year t is zero. In other words, our sample excludes firm pair observations for which the citing firm does not show any innovative activity in year t, i.e., has not filed a patent application with the United States Patent and Trademark Office (USPTO). Finally, we exclude all firm pairs that represent self-citations (i.e., a firm citing its own existing patents). All three sample selection criteria assure that the cited firm possesses potentially relevant innovative capital and the citing firm shows innovative activity.[10]

For each eligible firm pair i-j, we then use the number of citations from citing firm i to cited firm j in year t as our measure for citation flow from the cited firm to the citing firm. For years without any cross-citation, we set the number of citations to zero. The measure accounts for all citations included in citing firm i's patents issued in year t for all patents issued by cited firm j up until year t. The resulting patent citation measure thus captures the extent to which past innovations of the cited firm up until year t are reflected in current innovations of the citing firm. We focus on directional firm pairs to exploit within firm pair

[9]An alternative approach would be to construct potential firm-pairs from the characteristics of cited patents. For each cited patent, one would identify a set of non-cited patents based on similar characteristics (e.g., technological similarity). While the matching approach avoids potential measurement error of the revealed preference approach due to timing mismatches (especially if it is based on small time windows), a key disadvantage is that it requires pre-specification of characteristics upon which patents are selected and, hence, is based on assumptions. The revealed preference approach avoids these assumptions regarding the relevant patent pool and since we use cross-citations over a time period of 84 years, potential measurement error is less of a concern.

[10]The resulting sample of directional firm pair observations is broader compared to, e.g., the sample used by Gomes-Casseres et al. (2006), since we do not want to exclude observations that potentially include information about the link between capital market relationships and interfirm knowledge spillovers. We replicate our analyses for various alternative sample specifications and find virtually the same results (see robustness checks).

variation in the direction of the information spillover (i.e., citations of IBM patents by Apple vs. citations of Apple patents by IBM). Hereafter, we use the terms *Citing* and *Cited* to indicate whether a variable refers to the citing firm i or to the cited firm j.

3.2. Analyst coverage overlaps and sample construction

We measure analyst coverage overlaps based on individual analyst forecasts obtained from the I/B/E/S Detail History database. We utilize all types of forecasts (e.g., earnings per share, revenue, etc.) for different time horizons to determine which analysts covered citing firm i and cited firm j of a given firm pair at any time during year t. We then aggregate individual analyst observations and measure the number of common analysts for citing firm i and cited firm j in year t for each distinct firm pair (e.g., the number of financial analysts in that cover IBM and Apple during the same year).

To construct the final sample of directional firm pair observations with citation and analyst data available, we match identified analyst coverage overlaps (the treatment variable) with the sample of cross-firm patent citations (the dependent variable) based on the year of the patent application. The time period between the initial patent application and the final patent grant can be considerable and often spans across several years. Citations of other patents can be added at any point of time during the application process.[11] Unfortunately, the Kogan et al. (2017) citation data is based on all citations as included in the granted patent and exact timing of when new citations are added during the patent application process is not available. Nevertheless, measuring information flow based on the application year of the patent instead of the grant year should be more accurate, since the application year is closer to when the invention actually occurred and since there may be significant delays caused by the application process (Griliches, 1990; Forman and van Zeebroeck, 2018).

[11] In fact, the applicant has a continuous duty to disclose to the USPTO any known prior work that is material to patentability. That implies that the applicant has to file an *Information Disclosure Statement (IDS)* to disclose relevant references to prior work to the examiner any time he becomes aware of new references.

Since the citation measure is based on the citations included in the final patent grant, the dependent variable does not only include the citations made during the application year, but will include all citations irrespective of when they were added during the application period. Figure 1 illustrates this relationship and the time structure of our measurement of analyst coverage overlaps and cross-firm patent citations. While the nature of the data makes it difficult to pinpoint the exact timing and effect size of an information flow between two firms, the matching based on application year in combination with our research design (see next section) should nevertheless facilitate identification of a potential relationship between analyst coverage overlaps and interfirm knowledge flows.

[INSERT FIGURE 1]

The resulting base sample ranges from 1980 to 2009 and contains 3,131,282 directional firm pair-year observations based on 296,833 directional pairs of citing and cited firms with 5,507 unique citing firms and 5,074 unique cited firms. Tables 1 and 2 present the distributions of observations across industries. By construction, a large proportion of observations originates from research intense industries; i.e., citing firms from in the field of electronics, industrial machinery, instruments, or chemical products account for more than 60 percent of the observations (see Table 1). At the same time, there is less concentration for firm pair combinations across industries. The five most frequent combinations account for only 20.54 percent of the observations in the sample (see Table 2).

Table 3 presents the distribution of observations over time. The sample period is one year shorter than the data available in the Kogan et al. (2017) database because the database contains only patents that have been granted until 2010. Hence, all patents contained in the database have application filing years before 2010. The final base sample is unbalanced since in some years a firm pair might not fulfill the sample construction criteria (e.g., the citing firm has no innovative activity).

[INSERT TABLES 1, 2, AND 3]

4. Baseline empirical results

As our baseline analysis we estimate the association between the number of common analysts and the number of citations of within firm pairs based on the following regression model:

$$\begin{aligned} Log(1 + Citations_{i,j,t}) = &\beta_0 + \beta_1 Common\ analysts_{i,j,t} \\ &+ \sum Firm\ pair_{i,j} + \sum Year_t + \sum Controls \end{aligned} \tag{1}$$

where $Citations$ is the number of citations from citing firm i to cited firm j in year t and $Common\ analysts$ is the number of common analysts of citing firm i and cited firm j in year t. The specification explicitly controls for time-invariant firm- and firm pair-characteristics that might affect interfirm information spillovers and analyst coverage overlaps (e.g., firms in the same industry might have stronger interfirm information spillovers and a higher likelihood of being covered by the same analyst) by including directional firm pair fixed effects. In addition, we include year fixed effects to controls for shocks over time that affect all firm pairs equally. This fixed effect structure assures that the analysis is not affected by general trends or the general similarity of the business model of the citing and cited firm.[12]

We control for the technological similarity of the citing firm i and the cited firm j in year t ($Technology\ similarity$). We follow Jaffe and Trajtenberg (1996), Gomes-Casseres et al. (2006), and Forman and van Zeebroeck (2018) and compute the share of patent portfolios

[12] We repeat the analysis with undirectional firm pair fixed effects and the coefficient size and significance is virtually identical to the baseline regression.

that fall in the same technological classes:

$$Technology\ similarity_{i,j,t} = \frac{\sum_{c=1}^{C} P_{ict}P_{jct}}{\sqrt{(\sum_{c=1}^{C} P_{ict}^2)(\sum_{c=1}^{C} P_{jct}^2)}} \tag{2}$$

where P_{ict} is the number of patents held by firm i in class c in year t, and P_{jct} is the number of patents held by firm j in class c in year t and C is the total number of technological classes.

Additional control variables include the total number of analysts that cover citing firm i and cited firm j, (*Citing total analysts* and *Cited total analysts*, respectively) and the logarithm of total assets of citing firm i and cited firm j (*Citing total assets* and *Cited total assets*, respectively) to control for the relative overall information environment of both firms. We also include the logarithm of the total number of citations made by citing firm i in year t (*Citing total citations*) to control for the overall citing activity of firm i. Similarly, we controls for the availability of citable patents of cited firm j by including the number of citable patents of firm j in year t (*Cited patent stock*). Jaffe and Trajtenberg (1996) show that firms cite patents that are between three and seven years old more often than younger or older patents. Therefore, we include the percentage of patents that are less than three years old and the percentage of patents that are between three and seven years old as additional controls for the likelihood of cross-citations (*Cited share* 0-2 *years* and *Cited share* 3-7 *years*). To control for potential correlations among the residuals, we calculate standard errors clustered by directional firm pairs (Petersen, 2009).[13]

Table 4 shows the descriptive statistics for the base sample. Citing firms in the sample cite on average 1,924 patents per year while cited firms possess on average 3,268 citable patents. 27.1 (23.7) percent of these patents are less than three years old (between three and seven years old). This indicates that sample firms possess sufficient recent innovative capital that is likely to constitute potentially relevant competitive knowledge. The average firm pair

[13] We repeat the analysis with standard errors clustered by undirectional firm pairs, citing firm, and citing SIC2 industry and the significance of the results is virtually identical to the baseline regression.

makes 1.5 directional cross-citations per year and has on average 0.58 common analysts in a given year. At the same time, there is considerable variation among firm pairs in the sample with a median (maximum) of zero (10,458) cross-citations and zero (56) common analysts. Hence, we are confident that while our sample selection criteria reduce noise in the sample, there is also no selection bias.

[INSERT TABLE 4]

Table 5 presents estimates of equation 1 for different fixed effects specifications. An increase in common analysts is associated with an increase in citations by 3.9 percent ($p \leq 0.01$), after controlling for citing firm and cited firm characteristics. Coefficient estimates for control variables are consistent with our expectations for all specifications. The inclusion of firm pair fixed effects increases the explanatory power from 28.1 to 61.2 percent (columns (2) and (3)) suggesting that time-invariant firm pair characteristics are an important determinant of interfirm information spillovers. At the same time, the coefficient estimate for *Common analysts* decreases to 1.0 percent if we include firm pair and year fixed effects. To rule out that the results are driven by changes at the firm level, we include Citing firm x Year fixed effects and Cited firm x Year fixed effects in column (4). We exclude all control variables that are measured at the firm level since they are subsumed by the fixed effects. The coefficient estimate for *Common analysts* increases to 1.1 percent and remains statistically significant. While the effect size is economically significant, it is also plausible in size when compared to, e.g., interfirm alliances, which have been shown to result in an increase in cross-citations of about 6 percent (Gomes-Casseres et al., 2006).

A potential concern of our baseline model is that the fixed effects structure in combination with our measure for technological similarity does not take into account changes in the similarity of firm pairs' business models over time. If analyst coverage portfolios are at least partly based on the similarity of business models (e.g., because analysts specialize in specific industries), changes in firm pairs' similarity will be correlated not only with the likelihood of patent citations, but also with changes on analyst coverage overlaps. To address this potentially correlated omitted variable, column (5) and (6) include a dynamic measure of *Business similarity* from Hoberg and Phillips (2010, 2016) to account for changes in the business similarity of citing and cited firm over time. We construct the variable based on the Hoberg and Phillips (2010, 2016) similarity measure at the two-digit SIC code level. Since the Hoberg and Phillips (2010, 2016) data starts in 1996 and contains only firm pairs that have a certain minimum level of similarity the sample reduces to 256,295 observations.

Our inferences remain unchanged when taking into account dynamic changes in firm pairs' business similarity. The coefficient estimates for *Business similarity* are positive and statistically significant ($p \leq 0.01$), suggesting that *Business similarity* is positively associated with interfirm information spillovers. At the same time, the coefficient estimates for *Common analysts* remain similar in statistical significance ($p \leq 0.01$). Due to the additional sample restrictions the coefficient estimate for *Common analysts* in column (5) and (6) represent the average treatment effect for firm pairs with, on average, higher levels of similarity compared to the full base sample. Hence, the coefficient estimates for *Common analysts* in columns (5) and (6) are larger than the coefficient estimates in columns (3) and (4). Since including *Business similarity* in the regression model does not change our inferences but imposes significant sample restrictions, we do not include the variable in the following analyses in order to maintain generalizability of our results.

[INSERT TABLE 5]

In Table 6 we present several additional analyses to ensure that our inference is not driven by the sample construction and model specifications. In column (1) we show the results for the analysis including only firm pair observations with citations (i.e., excluding firm pair observations without any cross-citation in a given year). This approach is similar to Gomes-Casseres et al. (2006) and it ensures that our results are not driven by the sample construction. The coefficient estimate for *Common analysts* remains statistical significant at the $p \leq 0.01$ level. In column (2) we present the results for the analysis using an citation indicator variable that takes the value of one if citing firm i cites the cited firm j in year t, and zero otherwise. This research design ensures that our results are not driven by the definition of the dependent variable (i.e., that the results are driven by outliers). While coefficient estimate is smaller compared to the baseline regression, it equally significant.

Furthermore, we repeat the analysis with a sample of firm pair observations with an analyst coverage overlap of zero or one (column (3)). The coefficient estimate in this setting is solely identified through firm pair observations that gain or lose one common analyst. The coefficient estimate suggests that the move from zero to one common analysts is associated with an increase in citations by 1.3 percent ($p \leq 0.01$).

In addition, to rule out that the results are driven by the definition of the treatment variable we include *Common analysts*^{2} as additional treatment variable (column (4)). The coefficient estimate for *Common analysts* is still positive and significant, however, *Common analysts*^{2} is negative and significant, suggesting a diminishing marginal effect of analyst coverage overlap. Finally, we use the natural logarithm of one plus the number of common analysts as alternative treatment variable in column (5) and find a statistically significant coefficient estimate for *Common analysts* at the $p \leq 0.01$ level. These results ensure that our findings are not driven by the sample construction and model specifications.[14]

[INSERT TABLE 6]

5. Approach to identification

To further address the concern that omitted variables are affecting our results, we follow two strategies to plausibly identify the effect of analyst coverage overlaps on interfirm infor-

[14]To further test whether the results are affected by the large size of the sample, we repeat the analysis with a random placebo treatment effect and compare the the resulting coefficient estimates with the coefficient estimates of the actual treatment. We repeat the analysis for 500 random treatments and find that none of the placebo coefficients exceed the actual coefficient.

mation spillovers. First, we explore brokerage house closures as a quasi-natural experiment to study exogenous shocks to analyst coverage overlaps. Second, we use the heterogeneity in analyst characteristics to identify plausible differences in the effect of analyst coverage overlaps on interfirm information spillovers.

5.1. Exogeneous variation in analyst coverage overlaps

We follow Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012), and He and Tian (2013) and use brokerage house closures to plausibly identify the causal effect of common analysts on interfirm information spillovers. This identification strategy uses the fact that various brokerage houses had to close their research operations due decreases in revenue from trading, market-making, and investment banking. The advantage of this setting is that brokerage house closures result in reductions of common analysts for different firm pairs at different points in time. In addition, Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012) show that brokerage house closures are exogenous to the characteristics of the affected firms which significantly reduces potentially remaining endogeneity concerns. If analyst coverage overlaps facilitate interfirm information spillovers, we should expect that the exogenous reduction in analyst coverage overlaps results in lower levels of interfirm information spillovers (i.e., because there are fewer common analysts to facilitate the information exchange between both firms after a brokerage house closure).

In order to ensure consistency and comparability with prior studies we use the brokerage house closures between 2000 and 2007 as documented in Kelly and Ljungqvist (2012). Also, we do not include brokerage house mergers to further reduce endogeneity concerns as the merged brokerage houses may selectively retain analysts with coverage portfolios that show larger interfirm information spillovers. Figure 2 illustrates the difference-in-difference design of the brokerage house closure setting. The treatment group are firm pairs with a common analyst in the pre-period that is affected by a brokerage house closure. The control group are firms pairs which common analysts are not affected by any brokerage house closure in the pre-period. The treatment group loses a common analyst in the post-period due to the brokerage house closure, while the control group does not lose a common analyst in the post-period. However, both treatment and control groups might have common analysts in the pre- and post-period that are not affiliated with a brokerages house closure.

[INSERT FIGURE 2]

Since many brokerage house closures occur over a period of several months, it is difficult to determine an exact closure or cut-off date. Hence, we consider all citing firms that have been covered by an analyst of a closing brokerage house between year t-1 to t+1 around the closure date as affected by a brokerage house closure. To ensure that citing firms are indeed affected by the closure, we exclude all citing firms which are for whatever reason still covered by the brokerage house in year t+2 according to I/B/E/S. Since we keep the citing firm constant and vary only the cited firm, we ensure the validity of the parallel trend assumption on the level of the citing firm. We further exclude citing firms that have been affected by more than one brokerage house closure to ensure a clean treatment effect (similar to Balakrishnan et al., 2014). Finally, the sample excludes all citing firms that lack a treatment observation. The analysis covers a five-year window around the treatment event (year t-2 to year t+2), which allows us to use all brokerage house closures until 2007.

Table 7 describes the distribution of observations across brokerage house closures. The final sample contains 16 brokerage house closures and 98.996 firm pair observations. The sample contains 25,056 directional firm pairs with 318 unique citing firms and 2,209 unique cited firms. The citing firm cites on average 1,623 patents per year while the cited firms has on average 4,912 citable patents. 30.9 (25.4) percent of these patents are on average less than three years old (between three and seven years old). The average firm pair makes 1.8 citations per year and has on average 0.5 common analysts that are not affiliated with the affected brokerage houses (untabulated). Overall, sample descriptives are comparable to the full base sample.

[INSERT TABLE 7]

We estimate the following regression model to determine the effect of an exogeneous loss of common analysts on interfirm information spillovers in the form of patwent citations:

$$\begin{aligned} Log(1 + Citations_{i,j,t}) =& \beta_0 + \beta_1 Common\ analyst\ loss_{i,j,t} + \beta_2 Common\ other\ analysts_{i,j,t} \\ & + \sum Firm\ pair_{i,j} + \sum Year_t + \sum Controls \end{aligned} \tag{3}$$

Common analyst loss is an indicator variable that takes the value of one in year t+1 and year t+2 after the closure date if the firm pair loses a common analyst due to the brokerage house closure, and zero otherwise. We omit the base terms since we include firm pair fixed effects and year fixed effects, which already take the base effects into account. In addition to the main treatment effect, we also include *Common other analysts* which is the number of common analysts of citing firm i and cited firm j in year t that are not affected by a brokerage house closure as an additional control variable. All other control variables are defined as in the main specification.

Table 8 presents the estimates of equation 3 with the natural logarithm of one plus the number of citations from citing firm i to cited firm j in year t as the dependent variable. Column (1) of Table 8 shows the regression results for the treatment variable *Common analyst loss*, taking into account citing firm and cited firm characteristics and directional firm pair clustering. Citing firms are, on average, less likely to cite patents of cited firms in new patent applications after the citing firm looses a common analyst with the cited firm. The loss of a common analyst decreases the level of cross-citations by 7.4 percent ($p \leq 0.01$), after controlling for citing firm and cited firm characteristics. The coefficient estimate for *Common other analysts* remains positive and statistically significant, which is consistent with the results of the main specification (see Table 5). Note that the size and significance of the coefficient estimate on *Common other analysts* also alleviates potential large sample size concerns of the main specification.

To test whether the parallel trend assumption is valid on the firm pair level, we examine the leads and lags of the treatment variable. Table 8 column (2) includes four separate indicator variables *Common analyst* $loss_{t-2}$, *Common analyst* $loss_{t-1}$, *Common analyst* $loss_{t+1}$, and *Common analyst* $loss_{t+2}$ that take the value of one in the indicated period if the firm pair loses a common analyst due to the brokerage house closure, and zero otherwise. We use year t of the brokerage house closure as the baseline. The coefficient estimates for *Common analyst* $loss_{t+1}$ and *Common analyst* $loss_{t+2}$ are statistically significant at the $p \leq 0.05$ and $p \leq 0.01$ level, respectively, while the coefficient estimates for *Common analyst* $loss_{t-2}$ and *Common analyst* $loss_{t-1}$ are not statistically significant at conventional levels. This pattern is consistent with the parallel trend assumption. The results are unchanged if we exclude the year of the brokerage house closure and use *Common analyst* $loss_{t-1}$ as our baseline. Overall, the difference-in-difference analysis suggests that an exogenous decrease in analyst coverage overlaps results in fewer interfirm information spillovers as measured by patent cross-citations, which is consistent interfirm information spillovers being causally related to analyst coverage overlaps.

[INSERT TABLE 8]

5.2. Variations in common analyst characteristics

As a second approach to plausible identify the relationship between analyst coverage overlaps and interfirm information spillovers, we exploit heterogeneity in the characteristics of common analysts. The analysis is based on the full base sample while we adjust the treatment variable *Common analysts* to reflect differences in four different analyst characteristics: (1) specialization, (2) portfolio size, (3) experience, and (4) level of coverage activity. If analyst coverage overlaps cause interfirm information spillovers, all four characteristics should be positively related to the level of patent citations since they should be related to an analyst's ability to effectively collect and process innovation-related information (see e.g., Clement (1999); Bradley et al. (2017)).

First, to determine financial analyst's specialization we use the Herfindahl Index (HI) and measure the industry concentration of analysts' coverage portfolios in year t on the two-digit SIC level (similar to Sonney (2007)). *Common industry analysts* is the number of common analysts with a Herfindahl Index exceeding 0.9 in year t. Similarly, *Common general analysts* is the number of common analysts that are general analysts (i.e., with a Herfindahl Index below 0.9) in year t.

Second, similar to Clement (1999) we determine the size of an analyst's coverage portfolio based on the number of firms an analyst covers in year t. More specifically, we classify analysts to cover a large portfolio of firms if the number of firms in the analyst's portfolio in year t exceeds the 90th percentile across all analyst portfolios in year t. *Common large portfolio analysts* (*Common regular portfolio analysts*) is then defined as the number of common analysts that are large (regular) portfolio analysts in year t.

The third analyst characteristic, experience, is based on the number of years since the first forecast activity of the analyst as recorded by I/B/E/S (similar to Clement (1999)). We classify an analyst as high experience analyst if the analyst's years of experience in year t exceed the 90th percentile across all analysts in year t. *Common high experience analysts* (*Common regular experience analysts*) is then defined as the number of common analysts that are high (regular) experience analysts in year t.

Finally, we measure an analyst's level of activity based on the number of days the analysts issues or updates a forecast. In contrast to the previous characteristics, we explicitly distinguish a common analyst's activity for the citing firm i and for the cited firm j in year t. Specifically, we classify an analyst as a high activity analyst for citing firm i (cited firm j) in year t if the number of days at which the analyst exhibits forecast activity for citing firm i (cited firm j) in year t exceeds the 50th percentile. We then label an analyst as a high activity analyst for both firms if the analyst exceeds the 50th percentile for both firms in year t. Similarly, we classify an analyst as low activity analyst for both firms if the analyst does not exceeds the 50th percentile for both firms in year t. The classification results in four activity-related treatment variables: *Common both high activity analysts*, (2) *Common only citing firm high activity analysts*, (3) *Common only cited firm high activity analysts*, and (4) *Common both low activity analysts*, where each variable captures the number of common analysts that are high (low) activity analysts for the citing, the cited, or both firms in year t.

As indicated in Table 4 Panel B, most common analysts are, on average, general analysts and have a regular level of experience (on average, 0.53 percentage points out of 0.58 total common analysts, respectively). The picture seems to be more diverse for analysts' portfolio size and level of activity. In particular, 0.24 percentage points out of the average of 0.58 total common analysts are large portfolio analysts. In terms of activity, 0.23 (0.18) percentage points out of the average of 0.58 total common analysts are associate with analysts that show high (low) activity for both the citing and the cited firm. The remainder 0.16 percentage points of common analysts exhibit high activity only for one firm in the average firm pair.

Table 9 presents the estimates of equation 1 with adjusted treatment variables for the full base sample. The results support our predictions. Column (1) shows that an increase in common industry analysts (common general analysts) is associated with an increase in cross-citations by 2.9 (0.8) percent, after controlling for citing and cited firm characteristics as well as fixed effects ($p \leq 0.01$). Furthermore, the Wald-test for differences of the coefficients is statistically significant at the $p \leq 0.01$ level, suggesting that overlaps in industry analysts lead to a higher level of interfirm information spillovers than overlaps in general analysts. Results are similar for analysts' portfolio size (column (2)) and experience (column (3)). An increase in common analysts with large coverage portfolios (high experience) is associated with an increase in citations by 1.5 (2.1) percent, which is significantly greater than the coefficient estimates for *Common regular portfolio analysts* (*Common regular experience analysts*). Again, these results are consistent with the notion that analysts with broader coverage portfolios and more experience should possess more potentially relevant information leading to a higher likelihood of interfirm information spillovers.

Finally, column (4) documents that overlaps in more active analysts are associated with more cross-citations. In particular, an increase in *Common both high activity analysts*, *Common only citing firm high activity analysts*, *Common only cited firm high activity analysts*, and *Common both low activity analysts* is associated with an increase in cross-citations of 1.4, 1.0, 0.8, and 0.4 percent, respectively. All coefficient estimates are positive, statistically significant ($p \leq 0.01$), and, with the exception of the medium levels of activity, significantly different from each other ($p \leq 0.1$). Again, the pattern is consistent with more active analysts interacting more frequently with the firm and processing more potentially relevant information which increases the likelihood of interfirm information spillovers. Overall, the analysis is consistent with the notion that the effect of analyst coverage overlaps on interfirm information spillovers varies systematically with analyst characteristics related to the level of relevant knowledge an analyst likely possesses. In particular, analyst coverage overlaps seem to be associated with higher levels of information spillovers if the analyst is likely to collect and processes more potentially relevant competitive information and/or to have more interactions with the citing or cited firm. This further supports our conjecture resulting from the previous analyses that capital market interactions plausibly facilitate the spillover of relevant competitive information between firms.

[INSERT TABLE 9]

6. Exploring alternative explanations

To broaden our understanding of interfirm information spillovers we also explore cross-sectional differences in firm pairs to understand which firms are more likely to benefit from analyst coverage overlaps. If capital market interactions serve an informational purpose for firms' seeking competitive intelligence, the role of these interactions should be more pronounced if firms exhibit higher levels of information asymmetry.

6.1. Variations in patent technology subclasses

The search costs of searches across different research domains are generally higher and the outcomes of the searches are more uncertain relative to searches within research domains (Fleming (2001), Schilling and Green (2011), Criscuolo and Verspagen (2008)). Searches in different technology areas imply higher information asymmetries and higher costs of monitoring for the citing firm due to a lack of relevant expertise within the citing firm. Therefore, an analyst should be a more relevant facilitator of interfirm information spillovers for technology areas that are not already in the focus of the citing firm. In contrast, analyst coverage overlaps should be less relevant for interfirm information spillovers in technology areas that are already in focus of the citing firm since these areas exhibit lower information asymmetries and lower costs of monitoring for the citing firm. Based on the USPTO classification system for technology classes and subclasses, we classify patents (and patent citations) into technology areas and determine whether citations are within the same or different subclasses.[15] In particular, we split the dependent variable *Citations* in *Out-subclass citations* and *In-subclass citations*. *Out-subclass citations* are citations of patents that have different technology subclasses. Similarly, *In-subclass citations* are citations of patents that have

[15]The USPTO uses the U.S. Patent Classification System (USPC) to organize all U.S. patent documents and other technical documents into collections based on common subject matter. The system comprises more than 450 classes, which generally delineate one technology from another, and about 150,000 subclasses, which are used to delineate processes, structural features, and functional features within each technology class.

identical technology subclasses.

Table 10 presents the coefficient estimates of equation 1 with the natural logarithm of one plus the number of in-subclass citations (column (1)) and out-subclass citations (column (2)) as the dependent variable. An increase in common analysts is associated with an increase in in-technology subclass citations by 0.4 percent, after controlling for citing firm and cited firm characteristics. In contrast, an increase in common analysts is associated with an increase in out-technology subclass citations by 0.9 percent. Both coefficient estimates are positive and statistically significant at the $p \leq 0.01$ level. More importantly, however, the coefficient estimate for the out-technology subclass citations is significantly larger than the coefficient estimate for in-technology subclass citations ($p \leq 0.01$), suggesting that common analysts are more relevant for interfirm information spillovers related to different (or new) technology areas. Overall, the evidence of this analysis suggests that capital market interactions help citing firms to identify relevant information of cited firms and hence reduce information asymmetries.

[INSERT TABLE 10]

6.2. Variations in firm characteristics

Next, we explore differences and similarities in firm characteristics, especially with respect to industry, geographical and organizational diversity. The influence of common analysts should be stronger in cases where the citing firm and the cited firm are located in the same industry since the behavior of firms in the same industry receives more attention than the behavior of firms in other industries (see Graham and Harvey, 2001; Leary and Roberts, 2014, for the related discussion). We use two-digit SIC codes to identify firm pairs that are located in the same industry. *Common industry* is an indicator variable that takes the value of one if the citing firm i and the cited firm j have the identical two-digit SIC code, and zero otherwise. We omit the base term since the inclusion of firm pair fixed effects already takes the base effect into account. In line with our expectation the coefficient estimate for the interaction of common industry with the number of common analysts is positive and statistically significant at the $p \leq 0.01$ level, suggesting that the effect of a common analyst is stronger for firms in the same industry (column (1)). The result is generally consistent with the larger coefficient observed for the reduced sample that requires a minimum level of similarity (column (5) in Table 5).

Finally, the influence of common analysts should be higher for cited firms that have a high level of diversity in geographic locations and organizational structures since it is more difficult for a citing firm to monitor innovation-related activities if cited firms are more diverse. Similar to Balakrishnan et al. (2014), Bushman et al. (2004) and Frankel et al. (2006), we use the cited firm's number of reported geographical segments (business segments) to measure geographical (organizational) diversity. More specifically, $Cited\ firm\ geographical\ diversity$ ($Cited\ firm\ organizational\ diversity$) is an indicator variables that takes the value of one if the number of reported geographical (business) segments of cited firm j in year t exceeds the 90th percentile, and zero otherwise. Columns (2) and (3) of Table 11 report the regression results. In line with expectation, the coefficient estimates for the interactions are positive and statistically significant at the $p \leq 0.01$ level, suggesting that the effect of a common analyst is stronger if cited firms are more difficult to monitor. Again, this result is consistent with the result of Table 10 that common analysts are more likely to facilitate information transfer towards citing firms if there are larger information asymmetries between citing and cited firm.

Overall, these cross-sectional patterns are consistent with the notion that overlaps in capital market relationships help firms in identifying relevant peer information, especially if potential peer firms are more diverse and, hence, more difficult to monitor.

[INSERT TABLE 11]

7. Conclusion

Anecdotal evidence suggests that many firms use investor relation activities not only to communicate value-relevant information to the capital market, but also seek to gain competitive intelligence through networking and interacting with analysts, investors, bankers, and other capital market participants (e.g., Walsh, 2015). We explore the role of capital market interactions in facilitating such interfirm information spillovers by investigating financial analyst coverage overlaps. Using patent citations as a proxy for interfirm information spillovers, we find that firm pairs with a higher number of mutually shared analysts are more likely to cite existing patents in new patent applications than comparable firm pairs with few or no analyst coverage overlaps. This finding is robust to controlling for changes in the similarity of firms' business models suggesting that the documented effect is not simply due to dynamic adjustments in firms business models and corresponding changes in analyst coverage. To further test for causality, we implement a difference-in-difference approach by investigating exogenous shocks to analyst coverage overlaps and find consistent evidence. The effect is also stronger for analysts with relatively higher industry-specialization, a higher level of experience, a larger coverage portfolio, and higher activity. These results are consistent with the notion that information-spillovers are more likely to occur if the analyst is relatively more likely to possess related knowledge. Finally, we discuss cross-sectional differences in firm pairs to understand which firms are more likely to benefit from analyst coverage overlaps. We find stronger effects for firm pairs with larger geographic or organizational diversity suggesting that analyst coverage overlaps are more relevant if firm are more diverse, i.e., are characterized by a relatively higher degree of asymmetric information.

Taken together, our findings highlight that capital market interactions do not only play an important role in facilitating information transfer and reducing information asymmetries between firms and the capital market, but also facilitate the generation of internal business intelligence through interfirm information transfers between firms that are covered by and interact with the same group of capital market participants.

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Appendix A

Table A1
Variable Definitions

Patent-related variables	
Citations	The number of citations from citing firm i to cited firm j in year t. Source: Kogan et al. (2017) Patent Data
Citation indicator	An indicator variable that takes the value of one if citing firm i cites the cited firm j in year t, and zero otherwise. Source: Kogan et al. (2017) Patent Data
Out-subclass citations	The number of citations from citing firm i to cited firm j in year t of patents that have different technology subclasses. Source: Kogan et al. (2017) Patent Data
In-subclass citations	The number of citations from citing firm i to cited firm j in year t of patents that have identical technology subclasses. Source: Kogan et al. (2017) Patent Data
Cited patent stock	The number of citable patents of firm j until and including year t. Source: Kogan et al. (2017) Patent Data
Cited share 0-2 years	The percentage of patents that are less than three years old of firm j in year t. Source: Kogan et al. (2017) Patent Data
Cited share 3-7 years	The percentage of patents that are between three and seven years old of firm j in year t. Source: Kogan et al. (2017) Patent Data
Citing total citations	The total number of citations made by citing firm i in year t. Source: Kogan et al. (2017) Patent Data

Table A1

Variable Definitions (continued)

Analyst-specific variables	
Common analysts	The number of common analysts of citing firm i and cited firm j in year t. Source: I/B/E/S Detail History
Citing total analysts	The total number of analysts that cover citing firm i in year t. Source: I/B/E/S Detail History
Cited total analysts	The total number of analysts that cover cited firm j in year t. Source: I/B/E/S Detail History
Common industry analysts	The number of common analysts that are industry analysts in year t. To determine financial analyst's specialization we use the Herfindahl Index (HI) and measure the industry concentration of analysts' coverage portfolios in year t on the two-digit SIC level (similar to Sonney (2007)). Industry analysts are analysts with a Herfindahl Index exceeding 0.9 in year t. Source: I/B/E/S Detail History
Common general analysts	The number of common analysts that are general analysts in year t. To determine financial analyst's specialization we use the Herfindahl Index (HI) and measure the industry concentration of analysts' coverage portfolios in year t on the two-digit SIC level (similar to Sonney (2007)). General analysts are analysts with a Herfindahl Index not exceeding 0.9 in year t. Source: I/B/E/S Detail History
Common large portfolio analysts	The number of common analysts that are large portfolio analysts in year t. We classify analysts to cover a large portfolio of firms if the number of firms in the analyst's portfolio in year t exceeds the 90th percentile across all analyst portfolios in year t. Source: I/B/E/S Detail History

Table A1

Variable Definitions (continued)

Common regular portfolio analysts	The number of common analysts that are regular portfolio analysts in year t. We classify analysts to cover a regular portfolio of firms if the number of firms in the analyst's portfolio in year t does not exceed the 90th percentile across all analyst portfolios in year t. Source: I/B/E/S Detail History
Common high experience analysts	The number of common analysts that are high experience analysts in year t. We classify an analyst as high experience analyst if the analyst's years of experience in year t exceed the 90th percentile across all analysts in year t. Source: I/B/E/S Detail History
Common regular experience analysts	The number of common analysts that are regular experience analysts in year t. We classify an analyst as high experience analyst if the analyst's years of experience in year t do not exceed the 90th percentile across all analysts in year t. Source: I/B/E/S Detail History
Common only citing firm high activity analysts	The number of common analysts that are high activity analysts for citing firm i in year t. We classify an analyst as a high activity analyst for citing firm i in year t if the number of days at which the analyst exhibits forecast activity for citing firm i in year t exceeds the 50th percentile. Source: I/B/E/S Detail History
Common only cited firm high activity analysts	The number of common analysts that are high activity analysts for cited firm j in year t. We classify an analyst as a high activity analyst for cited firm j in year t if the number of days at which the analyst exhibits forecast activity for cited firm j in year t exceeds the 50th percentile. Source: I/B/E/S Detail History

Table A1
Variable Definitions (continued)

Common both high activity analysts	The number of common analysts that are high activity analysts for both firms in year t. We classify an analyst as a high activity analyst for citing firm i (cited firm j) in year t if the number of days at which the analyst exhibits forecast activity for citing firm i (cited firm j) in year t exceeds the 50th percentile. We then label an analyst as a high activity analyst for both firms if the analyst exceeds the 50th percentile for both firms in year t. Source: I/B/E/S Detail History
Common both low activity analysts	The number of common analysts that are low activity analysts for both firms in year t. We classify an analyst as a low activity analyst for citing firm i (cited firm j) in year t if the number of days at which the analyst exhibits forecast activity for citing firm i (cited firm j) in year t does not exceed the 50th percentile. We then label an analyst as a low activity analyst for both firms if the analyst does not exceed the 50th percentile for both firms in year t. Source: I/B/E/S Detail History
Common loss	An indicator variable that takes the value of one in year t+1 and year t+2 after the brokerage house closure date if the firm pair loses a common analyst due to the brokerage house closure, and zero otherwise.
Common loss t±i	An indicator variable that takes the value of one in year t±i if the the firm loses a common analyst due to the brokerage house closure, and zero otherwise.
Common other analysts	The number of common analysts of citing firm i and cited firm j in year t that are not affected by a brokerage house closure.

Table A1

Variable Definitions (continued)

Other firm-specific variables	
Citing total assets	The total assets of citing firm i in year t. Source: CRSP Compustat Merged.
Cited total assets	The total assets of cited firm j in year t. Source: CRSP Compustat Merged.
Common industry	An indicator variable that takes the value of one if the citing firm i and the cited firm j have the identical two-digit SIC code, and zero otherwise. Source: CRSP Compustat Merged.
Business similarity	The Hoberg and Phillips (2010, 2016) similarity measure at the two-digit SIC level. Source: Hoberg and Phillips (2010, 2016) Industry Data
Technology similarity	The Jaffe and Trajtenberg (1996) similarity measure based on the share of patent portfolios that fall in the same technological classes. Technology similarity is calculated as follows: $$\frac{\sum_{c=1}^{C} P_{ict} P_{jct}}{\sqrt{(\sum_{c=1}^{C} P_{ict}^2)(\sum_{c=1}^{C} P_{jct}^2)}}$$ where P_{ict} is the number of patents held by firm i in class c in year t, and P_{jct} is the number of patents held by firm j in class c in year t and C is the total number of technological classes. Source: Kogan et al. (2017) Patent Data
Cited firm geographical diversity	An indicator variables that takes the value of one if the number of reported geographical segments of cited firm j in year t exceeds the 90th percentile, and zero otherwise. Source: Compustat Historical Segments data.

Table A1

Variable Definitions (continued)

Cited firm organizational diversity	An indicator variables that takes the value of one if the number of reported business segments of cited firm j in year t exceeds the 90th percentile, and zero otherwise. Source: Compustat Historical Segments data.

Figure 1

Illustration of the Main Specification

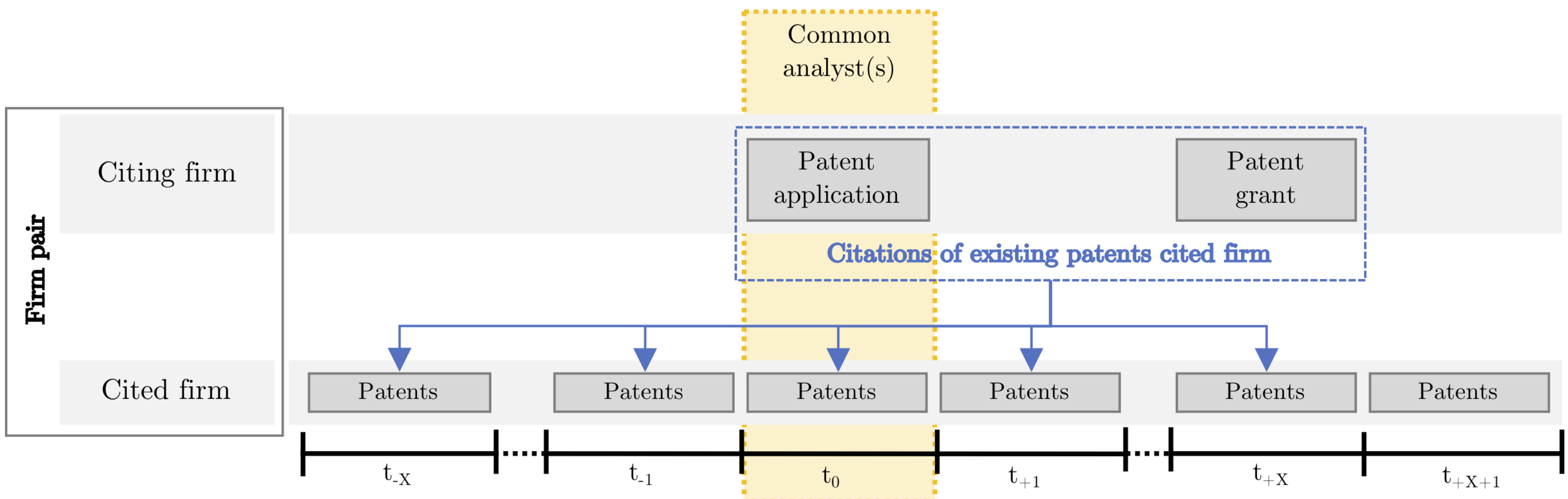

Figure 2

Illustration of the Difference-in-Difference Specification (Brokerage House Closure Setting)

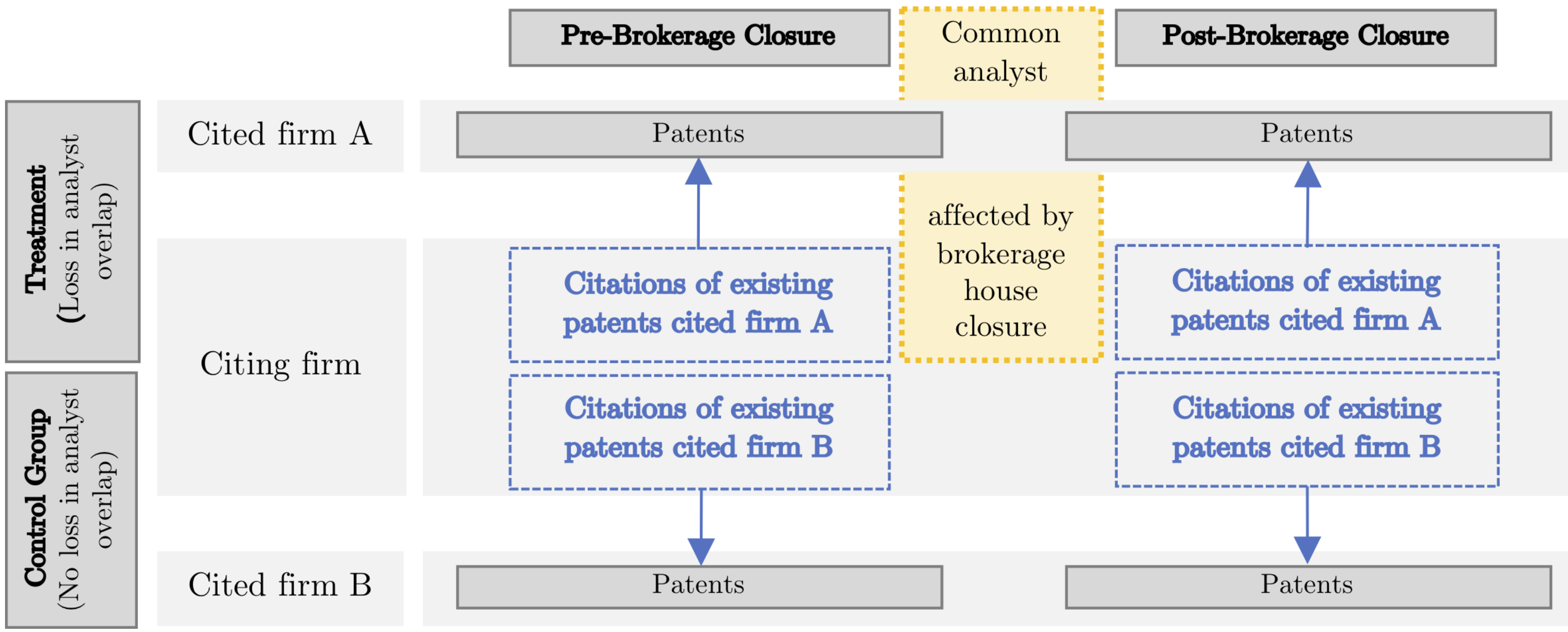

Table 1

Distribution of Observations by Citing industry (Top-30)

SIC	Description	N	Share
36	Electronic & Other Electric Equipment	642,464	20.52%
35	Industrial Machinery & Equipment	481,372	15.37%
38	Instruments & Related Products	412,549	13.18%
28	Chemical & Allied Products	402,502	12.85%
37	Transportation Equipment	235,200	7.51%
73	Business Services	190,077	6.07%
13	Oil & Gas Extraction	77,804	2.48%
48	Communications	74,731	2.39%
50	Wholesale Trade & Durable Goods	73,788	2.36%
33	Primary Metal Industries	58,923	1.88%
34	Fabricated Metal Products	57,222	1.83%
20	Food & Kindred Products	56,965	1.82%
30	Rubber & Miscellaneous Plastics Products	41,981	1.34%
26	Paper & Allied Products	38,813	1.24%
39	Miscellaneous Manufacturing Industries	37,714	1.20%
29	Petroleum & Coal Products	37,646	1.20%
51	Wholesale Trade & Nondurable Goods	24,327	0.78%
87	Engineering & Management Services	21,846	0.70%
32	Stone, Clay, & Glass Products	21,630	0.69%
22	Textile Mill Products	11,513	0.37%
25	Furniture & Fixtures	11,368	0.36%
10	Metal, Mining	11,176	0.36%
27	Printing & Publishing	11,132	0.36%
24	Lumber & Wood Products	8,664	0.28%
49	Electric, Gas, & Sanitary Services	8,231	0.26%
21	Tobacco Products	7,813	0.25%
67	Holding & Other Investment Offices	7,620	0.24%
89	Services, Not Elsewhere Classified	7,128	0.23%
16	Heavy Construction, Except Building	6,571	0.21%
63	Insurance Carriers	6,325	0.20%

Notes: Table 1 reports the distributions of observations by citing industry. These entries represent the 30 industries with the largest number of observations in our sample.

Table 2

Distribution of Observations by Citing Industry and Cited Industry (Top-30)

SIC	Description	SIC	Description	N	Share
36	Electronic & Other Electric Equipment	36	Electronic & Other Electric Equipment	213,671	6.82%
28	Chemical & Allied Products	28	Chemical & Allied Products	133,310	4.26%
36	Electronic & Other Electric Equipment	35	Industrial Machinery & Equipment	103,942	3.32%
35	Industrial Machinery & Equipment	36	Electronic & Other Electric Equipment	101,040	3.23%
35	Industrial Machinery & Equipment	35	Industrial Machinery & Equipment	91,210	2.91%
38	Instruments & Related Products	38	Instruments & Related Products	84,528	2.70%
36	Electronic & Other Electric Equipment	38	Instruments & Related Products	76,865	2.45%
38	Instruments & Related Products	36	Electronic & Other Electric Equipment	69,806	2.23%
35	Industrial Machinery & Equipment	38	Instruments & Related Products	60,303	1.93%
38	Instruments & Related Products	28	Chemical & Allied Products	59,946	1.91%
38	Instruments & Related Products	35	Industrial Machinery & Equipment	56,420	1.80%
36	Electronic & Other Electric Equipment	73	Business Services	51,290	1.64%
28	Chemical & Allied Products	38	Instruments & Related Products	50,203	1.60%
73	Business Services	36	Electronic & Other Electric Equipment	49,058	1.57%
35	Industrial Machinery & Equipment	28	Chemical & Allied Products	43,291	1.38%
36	Electronic & Other Electric Equipment	28	Chemical & Allied Products	40,496	1.29%
36	Electronic & Other Electric Equipment	37	Transportation Equipment	39,919	1.27%
37	Transportation Equipment	36	Electronic & Other Electric Equipment	39,674	1.27%
37	Transportation Equipment	35	Industrial Machinery & Equipment	38,165	1.22%
35	Industrial Machinery & Equipment	37	Transportation Equipment	38,050	1.22%
73	Business Services	73	Business Services	36,634	1.17%
28	Chemical & Allied Products	35	Industrial Machinery & Equipment	36,129	1.15%
35	Industrial Machinery & Equipment	73	Business Services	32,084	1.02%
73	Business Services	35	Industrial Machinery & Equipment	31,157	1.00%
28	Chemical & Allied Products	36	Electronic & Other Electric Equipment	29,092	0.93%
38	Instruments & Related Products	37	Transportation Equipment	28,146	0.90%
37	Transportation Equipment	38	Instruments & Related Products	27,544	0.88%
37	Transportation Equipment	37	Transportation Equipment	27,206	0.87%
37	Transportation Equipment	28	Chemical & Allied Products	24,697	0.79%
28	Chemical & Allied Products	37	Transportation Equipment	21,625	0.69%

Notes: Table 2 reports the distributions of observations by citing industry and cited industry. These entries represent the 30 industry pairs with the largest number of observations in our sample.

Table 3

Distribution of Observations by Year

Year	N	Share
1980	103,676	3.31%
1981	104,642	3.34%
1982	103,276	3.3%
1983	104,864	3.35%
1984	106,063	3.39%
1985	103,941	3.32%
1986	103,284	3.30%
1987	103,091	3.29%
1988	100,436	3.21%
1989	98,259	3.14%
1990	99,313	3.17%
1991	105,207	3.36%
1992	109,164	3.49%
1993	116,386	3.72%
1994	122,767	3.92%
1995	128,100	4.09%
1996	131,877	4.21%
1997	136,589	4.36%
1998	133,364	4.26%
1999	117,524	3.75%
2000	119,451	3.81%
2001	116,510	3.72%
2002	110,378	3.53%
2003	103,852	3.32%
2004	103,734	3.31%
2005	92,905	2.97%
2006	83,861	2.68%
2007	70,967	2.27%
2008	59,002	1.88%
2009	38,799	1.24%

Notes: Table 3 reports the distributions of observations by year.

Table 4

Descriptive Statistics

Panel A: Patent-related variables						
	N	Mean	St. Dev.	Min	Median	Max
Citations	3,131,282	1.502	18.744	0.000	0.000	10,458.000
Citation indicator	3,131,282	0.209	0.407	0.000	0.000	1.000
In-subclass citations	3,131,282	0.125	1.706	0.000	0.000	757.000
Out-subclass citations	3,131,282	1.377	17.322	0.000	0.000	9,701.000
Citing citations	3,131,282	1,923.566	4,889.785	1.000	341.000	70,875.000
Cited patent stock	3,131,282	3,267.693	7,174.769	1.000	504.000	66,902.000
Cited share 0-2 years	3,131,282	0.271	0.283	0.000	0.158	1.000
Cited share 3-7 years	3,131,282	0.237	0.182	0.000	0.203	1.000
Panel B: Analyst-specific variables						
	N	Mean	St. Dev.	Min	Median	Max
Common analysts	3,131,282	0.579	2.433	0.000	0.000	56.000
Common industry analysts	3,131,282	0.045	0.551	0.000	0.000	35.000
Common general analysts	3,131,282	0.534	2.202	0.000	0.000	56.000
Common large portfolio analysts	3,131,282	0.240	0.886	0.000	0.000	31.000
Common regular portfolio analysts	3,131,282	0.339	1.732	0.000	0.000	45.000
Common high experience analysts	3,131,282	0.047	0.283	0.000	0.000	8.000
Common regular experience analysts	3,131,282	0.532	2.260	0.000	0.000	54.000
Common both high activity analysts	3,131,282	0.233	1.278	0.000	0.000	37.000
Common only citing high activity analysts	3,131,282	0.084	0.429	0.000	0.000	27.000
Common only cited high activity analysts	3,131,282	0.084	0.429	0.000	0.000	27.000
Common both low activity analysts	3,131,282	0.178	0.796	0.000	0.000	29.000
Panel C: Other firm-specific variables						
	N	Mean	St. Dev.	Min	Median	Max
Technology similarity	3,131,282	0.139	0.182	0.000	0.070	1.000
Citing total analysts	3,131,282	16.958	14.862	0.000	14.000	76.000
Cited total analysts	3,131,282	16.511	14.811	3.000	13.000	76.000
Citing total assets	3,131,282	15,632.700	50,658.230	0.142	2,515.923	2,223,299.000
Cited total assets	3,131,282	14,121.120	45,252.870	0.089	2,390.900	1,119,796.000
Business similarity	256,295	0.050	0.046	0.000	0.038	0.939
Common industry	3,131,282	0.198	0.399	0.000	0.000	1.000
Cited firm geographical diversity	3,131,282	0.069	0.254	0.000	0.000	1.000
Cited firm organizational diversity	3,131,282	0.090	0.287	0.000	0.000	1.000

Notes: Table 4 reports the descriptive statistics for the patent-related variables (Panel A), the analyst-specific variables (Panel B), and the other firm-specific variables (Panel C) in our sample. Please refer to Appendix A for a full description of all variables.

Table 5

Main Specification: Common Analyst Coverage and Patent Citations

	log(Citations)					
	(1)	(2)	(3)	(4)	(5)	(6)
Common analysts	0.039***	0.010***	0.010***	0.011***	0.016***	0.022***
	(46.988)	(15.521)	(15.818)	(16.542)	(10.126)	(13.004)
Control variables						
Technology similarity	0.873***	0.352***	0.359***	0.518***	0.041**	0.130***
	(104.420)	(39.816)	(40.720)	(47.026)	(2.444)	(5.749)
Business similarity					0.258***	0.362***
					(3.249)	(3.762)
Citing total analysts	−0.000	0.000***	−0.000*		−0.002***	
	(−0.596)	(5.854)	(−1.741)		(−4.159)	
Cited total analysts	0.000***	0.000***	0.000		0.001***	
	(5.292)	(6.548)	(0.346)		(3.655)	
log(Citing total assets)	−0.044***	−0.035***	−0.009***		−0.005	
	(−85.916)	(−33.210)	(−7.526)		(−1.272)	
log(Cited total assets)	−0.009***	−0.009***	0.010***		0.014***	
	(−16.788)	(−8.975)	(9.057)		(3.188)	
log(Citing total citations)	−0.083***	−0.020***	−0.022***		−0.045***	
	(−43.145)	(−10.948)	(−11.777)		(−7.112)	
log(Citing total citations)^2	0.019***	0.016***	0.016***		0.027***	
	(88.035)	(73.810)	(71.748)		(38.683)	
log(Cited patent stock)	−0.063***	−0.025***	−0.032***		0.108***	
	(−42.579)	(−13.131)	(−17.057)		(17.149)	
log(Cited patent stock)^2	0.014***	0.012***	0.015***		−0.001	
	(86.400)	(49.174)	(56.264)		(−1.019)	
Cited share 0-2 years	0.179***	0.212***	0.123***		0.065***	
	(67.140)	(48.866)	(27.425)		(2.784)	
Cited share 3-7 years	0.211***	0.184***	0.093***		0.051**	
	(63.260)	(49.500)	(23.208)		(2.328)	
Firm pair fixed effects	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	No	Yes	No
Citing firm x Year fixed effects	No	No	No	Yes	No	Yes
Cited firm x Year fixed effects	No	No	No	Yes	No	Yes
N	3,131,282	3,131,282	3,131,282	3,131,282	256,295	256,295
Adjusted R^2	0.281	0.612	0.614	0.633	0.695	0.715

Notes: Table 5 reports the regression results for the relationship between analyst coverage and patent citations. Please refer to Appendix A for a full description of all variables. T-statistics clustered by directional firm pair are in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level (two-tailed), respectively.

Table 6

Alternative Sample, Citation Indicator, and Nonlinear Common Analyst Coverage

	log(Citations)| Citations>0	Citations indicator (1/0)	log(Citations)| Common analysts<2	log(Citations)	
	(1)	(2)	(3)	(4)	(5)
Common analysts	0.006***	0.003***	0.013***	0.016***	
	(6.375)	(15.028)	(9.236)	(17.063)	
Common analysts^2				−0.000***	
				(−7.365)	
log(Common analysts)					0.039***
					(20.856)
Control variables					
Technology similarity	0.299***	0.119***	0.264***	0.357***	0.360***
	(14.081)	(28.108)	(31.331)	(40.476)	(40.578)
Citing total analysts	−0.000**	0.000	0.000	−0.000**	−0.003***
	(−1.972)	(1.577)	(1.332)	(−2.270)	(−3.333)
Cited total analysts	0.000	0.000***	0.000***	−0.000	0.003***
	(0.497)	(3.356)	(4.729)	(−0.196)	(3.327)
log(Citing total assets)	0.001	−0.003***	−0.012***	−0.009***	−0.009***
	(0.224)	(−4.853)	(−10.886)	(−7.804)	(−7.189)
log(Cited total assets)	0.045***	0.006***	0.004***	0.009***	0.009***
	(10.320)	(10.374)	(3.628)	(8.665)	(7.678)
log(Citing total citations)	0.025***	0.052***	−0.008***	−0.022***	−0.022***
	(2.698)	(67.115)	(−4.632)	(−11.820)	(−11.833)
log(Citing total citations)^2	0.031***	0.004***	0.013***	0.016***	0.016***
	(39.449)	(45.182)	(64.936)	(71.793)	(71.881)
log(Cited patent stock)	0.025***	0.019***	−0.031***	−0.032***	−0.033***
	(2.952)	(21.486)	(−17.742)	(−17.107)	(−17.168)
log(Cited patent stock)^2	0.022***	0.004***	0.013***	0.015***	0.015***
	(26.303)	(41.916)	(52.021)	(56.339)	(56.424)
Cited share 0-2 years	0.402***	0.060***	0.091***	0.123***	0.123***
	(17.963)	(23.844)	(21.920)	(27.357)	(27.309)
Cited share 3-7 years	0.313***	0.047***	0.073***	0.093***	0.092***
	(14.378)	(19.782)	(19.480)	(23.124)	(23.071)
Firm pair fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
N	655,802	3,131,282	2,866,783	3,131,282	3,131,282
Adjusted R^2	0.682	0.350	0.570	0.614	0.614

Notes: Table 6 reports regression results for the relationship between analyst coverage and patent citations. Please refer to Appendix A for a full description of all variables. T-statistics clustered by directional firm pair are in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level (two-tailed), respectively.

Table 7

Brokerage House Closures and Affected Firm-Pairs

Broker	Closure date	Broker type	Observations
Brown Brothers Harriman & Co.	June 2000	Institutional	13,359
George K. Baum & Co.	October 2000	Retail or both	569
Emerald Research	July 2001	Retail or both	159
ABN AMRO	April 2002	Institutional	25,239
Robertson Stephens	July 2002	Retail or both	19,307
Frost Securities, Inc.	July 2002	Institutional	2,042
Vestigo-Fidelity Capital Markets	August 2002	Institutional	678
Commerce Capital Markets, Inc.	April 2003	Institutional	1,124
Schwab Soundview Capital Markets	October 2004	Institutional	9,004
J.B. Hanauer & Co.	February 2005	Institutional	834
Tradition Asiel Securities, Inc.	April 2005	Institutional	877
IRG Research	June 2005	Institutional	3,015
Wells Fargo Securities	August 2005	Retail or both	3,366
Moors & Cabot, Inc.	September 2006	Institutional	138
Prudential Equity Group, Inc.	June 2007	Institutional	17,624
Nollenberger Capital Partners	November 2007	Retail or both	1,661

Notes: Table 7 reports the distribution of observations by brokerage house closure event, the corresponding brokerage house closure date, and the broker type.

Table 8

Brokerage House Closures, Common Analyst Losses, and Patent Citations

	log(Citations)	
	(1)	(2)
Common loss	−0.074***	
	(−3.458)	
Common loss t-2		−0.009
		(−0.339)
Common loss t-1		−0.007
		(−0.284)
Common loss t+1		−0.057**
		(−2.252)
Common loss t+2		−0.106***
		(−3.687)
Control variables		
Common other analysts	0.016***	0.015***
	(3.715)	(3.673)
Technology similarity	0.033	0.033
	(0.773)	(0.764)
Citing total analysts	−0.001**	−0.001**
	(−2.090)	(−2.115)
Cited total analysts	0.002***	0.002***
	(2.831)	(2.829)
log(Citing total assets)	−0.003	−0.003
	(−0.404)	(−0.396)
log(Cited total assets)	0.006	0.006
	(0.763)	(0.770)
log(Citing total citations)	0.004	0.004
	(0.461)	(0.443)
log(Citing total citations)^2	0.018***	0.018***
	(20.580)	(20.598)
log(Cited patent stock)	0.097***	0.097***
	(7.151)	(7.144)
log(Cited patent stock)^2	−0.006***	−0.006***
	(−3.627)	(−3.626)
Cited share 0-2 years	0.023	0.023
	(0.528)	(0.523)
Cited share 3-7 years	0.034	0.034
	(0.818)	(0.817)
Firm pair fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	98,996	98,996
Adjusted R^2	0.670	0.670

Notes: Table 8 reports the regression results for the brokerage house closure setting. The dependent variable is the natural logarithm of one plus the number of citations from the citing firm to the cited firm in year t. Please refer to Appendix A for a full description of all variables. T-statistics clustered by directional firm pair are in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level (two-tailed), respectively.

Table 9

Analyst Characteristics, Common Analyst Coverage, and Patent Citations

	log(Citations)			
	(1)	(2)	(3)	(4)
Industry specialization				
Common industry analysts	0.029***			
	(10.857)			
Common general analysts	0.008***			
	(11.758)			
Portfolio size				
Common large portfolio analysts		0.015***		
		(10.871)		
Common regular portfolio analysts		0.007***		
		(8.630)		
Experience				
Common high experience analysts			0.021***	
			(6.362)	
Common regular experience analysts			0.009***	
			(13.006)	
Activity level				
Common both high activity analysts				0.014***
				(13.894)
Common only citing high activity analysts				0.010***
				(7.535)
Common only cited high activity analysts				0.008***
				(5.491)
Common both low activity analysts				0.005***
				(4.798)
Control variables				
Technology similarity	0.357***	0.359***	0.359***	0.359***
	(40.548)	(40.692)	(40.714)	(40.705)
Citing total analysts	−0.000*	−0.000**	−0.000*	−0.000
	(−1.670)	(−2.119)	(−1.687)	(−1.486)
Cited total analysts	0.000	−0.000	0.000	0.000
	(0.442)	(−0.043)	(0.393)	(0.679)
log(Citing total assets)	−0.009***	−0.009***	−0.009***	−0.009***
	(−7.666)	(−7.502)	(−7.537)	(−7.565)
log(Cited total assets)	0.010***	0.010***	0.010***	0.010***
	(8.915)	(9.124)	(9.035)	(8.988)
log(Citing total citations)	−0.022***	−0.022***	−0.022***	−0.022***
	(−11.740)	(−11.795)	(−11.754)	(−11.781)
log(Citing total citations)^2	0.016***	0.016***	0.016***	0.016***
	(71.822)	(71.771)	(71.771)	(71.757)
log(Cited patent stock)	−0.032***	−0.032***	−0.032***	−0.032***
	(−16.980)	(−17.113)	(−17.059)	(−17.045)
log(Cited patent stock)^2	0.015***	0.015***	0.015***	0.015***
	(56.293)	(56.276)	(56.270)	(56.264)
Cited share 0-2 years	0.123***	0.124***	0.123***	0.123***
	(27.470)	(27.488)	(27.399)	(27.415)
Cited share 3-7 years	0.093***	0.093***	0.093***	0.093***
	(23.256)	(23.261)	(23.185)	(23.218)
Firm pair fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
N	3,131,282	3,131,282	3,131,282	3,131,282
Adjusted R^2	0.614	0.614	0.614	0.614
Wald test p-value 1. coef. = 2. coef.	<0.001	<0.001	<0.001	0.034
Wald test p-value 1. coef. = 3. coef.				<0.001
Wald test p-value 1. coef. = 4. coef.				<0.001
Wald test p-value 2. coef. = 3. coef.				0.156
Wald test p-value 2. coef. = 4. coef.				0.001
Wald test p-value 3. coef. = 4. coef.				0.083

Notes: Table 9 reports the regression results for the relationship between various analyst characteristics, analyst coverage, and patent citations. Please refer to Appendix A for a full description of all variables. T-statistics clustered by directional firm pair are in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level (two-tailed), respectively.

Table 10

Common Analyst Coverage and In-subclass vs. Out-subclass Patent Citations

	log(In-subclass citations)	log(Out-subclass citations)
	(1)	(2)
Common analysts	0.004***	0.009***
	(10.593)	(15.104)
Control variables		
Technology similarity	0.114***	0.348***
	(25.574)	(40.463)
Citing total analysts	−0.000***	−0.000*
	(−3.948)	(−1.704)
Cited total analysts	0.000	−0.000
	(0.241)	(−0.345)
log(Citing total assets)	−0.000	−0.009***
	(−0.899)	(−7.839)
log(Cited total assets)	0.003***	0.009***
	(7.016)	(8.543)
log(Citing total citations)	−0.026***	−0.026***
	(−26.558)	(−13.926)
log(Citing total citations)^2	0.005***	0.016***
	(41.747)	(71.613)
log(Cited patent stock)	−0.013***	−0.036***
	(−14.744)	(−19.155)
log(Cited patent stock)^2	0.004***	0.015***
	(29.447)	(56.572)
Cited share 0-2 years	0.034***	0.116***
	(17.912)	(26.603)
Cited share 3-7 years	0.019***	0.090***
	(11.092)	(22.968)
Firm pair fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
N	3,131,282	3,131,282
Adjusted R^2	0.462	0.609
P-value col. (1) = col. (2)	<0.001	

Notes: Table 10 reports regression results for the relationship between analyst coverage and in-subclass versus out-subclass patent citations. Please refer to Appendix A for a full description of all variables. T-statistics clustered by directional firm pair are in parentheses. $*$, $**$, and $***$ represent significance at the 10 percent, 5 percent, and 1 percent level (two-tailed), respectively.

Table 11

Firm Characteristics, Common Analyst Coverage, and Patent Citations

	log(Citations)		
	(1)	(2)	(3)
Common analysts	0.007***	0.009***	0.009***
	(7.831)	(14.669)	(14.846)
Common industry			
Common analysts x Common industry	0.005***		
	(4.478)		
Geographical diversity			
Cited firm geographical diversity		−0.030***	
		(−10.211)	
Common analysts x Cited firm geographical diversity		0.018***	
		(8.469)	
Organizational diversity			
Cited firm organizational diversity			0.008***
			(2.972)
Common analysts x Cited firm organizational diversity			0.016***
			(7.778)
Control variables			
Technology similarity	0.358***	0.356***	0.356***
	(40.647)	(40.456)	(40.666)
Citing total analysts	−0.000	−0.000*	−0.000
	(−1.529)	(−1.665)	(−1.500)
Cited total analysts	0.000	0.000	0.000
	(0.568)	(0.730)	(0.841)
log(Citing total assets)	−0.009***	−0.009***	−0.009***
	(−7.585)	(−7.788)	(−7.657)
log(Cited total assets)	0.010***	0.010***	0.009***
	(8.996)	(8.930)	(8.499)
log(Citing total citations)	−0.022***	−0.022***	−0.022***
	(−11.769)	(−11.759)	(−11.762)
log(Citing total citations)^2	0.016***	0.016***	0.016***
	(71.766)	(71.843)	(71.844)
log(Cited patent stock)	−0.032***	−0.033***	−0.031***
	(−17.048)	(−17.248)	(−16.297)
log(Cited patent stock)^2	0.015***	0.015***	0.015***
	(56.265)	(56.562)	(55.789)
Cited share 0-2 years	0.123***	0.123***	0.120***
	(27.437)	(27.320)	(26.871)
Cited share 3-7 years	0.093***	0.092***	0.090***
	(23.240)	(23.048)	(22.743)
Firm pair fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
N	3,131,282	3,131,282	3,131,282
Adjusted R^2	0.614	0.614	0.614

Notes: Table 11 reports regression results for the relationship between analyst coverage and patent citations for different (cited) firm characteristics. Please refer to Appendix A for a full description of all variables. T-statistics clustered by directional firm pair are in parentheses. ∗, ∗∗, and ∗ ∗ ∗ represent significance at the 10 percent, 5 percent, and 1 percent level (two-tailed), respectively.