Corporate Investment and Innovation in the Presence of Competitor Constraints*

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Abstract

We study the relation between investment behavior and competitor financial constraints. Using inter-firm patent citations and text-based product market similarities to identify intransitive competitor networks, we find that firms increase investment spending, patenting activity, and employee poaching when competitor constraints become more binding. In addition, firms shift their investment composition (product market and patent portfolios) towards competitors who experience a relative tightening of constraints. These effects are robust to controlling for selection and correlated effects across competitors. To mitigate endogeneity concerns, we exploit the 2004 AJCA tax holiday and the 1989 junk bond crisis as exogenous shocks to competitor constraints and find similar effects.

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1 Introduction

A large literature in corporate finance considers the impact of financing frictions on a firm's choices. This literature provides compelling evidence that financial constraints can at times have a significant causal effect on a firm's investment decisions. If a firm is constrained in its ability to invest, theoretical considerations suggest that a firm's competitors may react to this limitation. Thus, financial constraints at the firm level may generate externalities for competitors' investment decisions. While related effects have been explored in the context of decisions related to capital structure, cash holdings, pricing, and firm location (Leary and Roberts (2014), Shleifer and Vishny (1992), Hoberg et al. (2014), and Chevalier (1995a)), this possible effect of financial constraints on competitor investment decisions has not been widely explored.

In this study, we consider how a firm changes both the level of its investment and the composition of its investment portfolio when one or more competitors experience a change in their level of financial constraints. From a theoretical perspective, the direction of these relationships is ambiguous, as less investment by competitors can impose both positive externalities (e.g., reduced competition) and negative externalities (e.g., reduced collateral values, less knowledge spillover). Our empirical findings indicate that firms generally increase their investment spending when competitor financial constraints become more binding. Moreover, firms appear to tilt their investment activities toward competitors who are relatively more constrained and away from competitors who are relatively less constrained.

A variety of theoretical models formalize the intuitive idea that financial health may open a firm up to aggressive investment behavior by its competitors. Important early models of this type include Fudenberg and Tirole (1986) and Bolton and Scharfstein (1990). However, testing hypotheses regarding competitor interactions is complicated by some challenging empirical obstacles. In particular, many measures of competition are quite coarse, and they impose that firms react identically to intra-group externalities. In addition, it is often difficult to separate time variation in competitor financial constraints from industry shocks that may directly affect the optimal level of investment.

We overcome these empirical obstacles by using two novel procedures to identify competitor networks. Our first measure, the *text-based* approach, borrows from Hoberg and Phillips (2015), who create a pairwise measure of competition based on similarities in the textual descriptions of firms' product market activities. We use these product market similarities to define competitors and to track the similarities in investment composition between competitors through time. Our second measure, the *citation-based* approach, exploits the cross-referencing of patent citations to identify firms that have closely related production technologies. We use this cross-referencing to compute a pairwise measure of patent portfolio similarity based on the degree of technological overlap between two competitors in any given year. These two approaches allow us to identify time-varying lists of a firms' competitors and track the overlap in their investment composition through time for different sample periods.

Importantly, both approaches allow each firm to have a unique set of competitors (i.e., the competitor networks are intransitive). This allows us to identify situations in which, for example, Nike competes with Callaway in golf apparel and competes with Reebok in athletic footwear, but Callaway and Reebok are not direct competitors with each other. This intransitive feature to the competitor identification better reflects economic reality, and it also allows us to exploit identification strategies that are not possible using standard transitive industry classifications such as SIC codes. In particular, our competitor identification procedures allow us, under fairly standard assumptions, to control for selection effects and for correlated effects across competitors by implementing firm-year or competitor-pair fixed effects transformations (Topa and Zenou (2015), Liu and Lee (2010), and Liu et al. (2012)).[1] Furthermore, we can examine how firms alter their investment composition in response to a tightening in a particular competitor's constraints, or in response to a shift in the relative constraints within their portfolio of competitors.

[1] Specifically, we assume additively separable heterogeneity. See Grieser and Hadlock (2016) for a recent analysis on common panel data estimation assumptions.

We start by providing suggestive evidence of a positive relation between a firm's investment level and common measures of competitor financial constraints in a standard panel data framework. In particular, using the Whited-Wu (WW) financial constraint index developed in Whited and Wu (2006), the Size-Age (SA) index developed by Hadlock and Pierce (2010), and the Delayed Investment (*Delay*) financial constraint index developed by Hoberg and Maksimovic (2015), we find that a one standard deviation tightening in lagged competitor constraints is associated with a 15-26% (6-16%) increase in patent applications (citations) and a 1.7-4.5% (4.1-6.6%) increase in capital expenditures (R&D).[2]

To augment our evidence on the level of investment activity, we consider shifts in the composition of a firm's investment. We exploit the information in our competitor networks to isolate competitor-specific responses and to rule out alternatives such as diversified firms shifting investments from failing segments to more stable ones. We find that a one standard deviation tightening in a given competitor's constraints leads a firm to increase its product market (patent portfolio) similarity with that competitor by 3.9-5.8% (2.2-11.1%), relative to the average similarity with that competitor. When we implement firm-year fixed effects transformations, we can interpret the results as firms shifting their composition toward competitors that have relatively more binding constraints and away from competitors that have relatively relaxed constraints. These results are consistent with firms gravitating toward reduced competition, and they suggest that the type of investment is also affected in substantive ways by competitor constraints.

While our initial evidence is suggestive, there is the usual vexing issue of endogeneity. In particular, one may be concerned with reverse causality. A firm that captures market share through increased investment may cause a competitor's profits to suffer. In turn, this may exacerbate agency conflicts for the competitor and increase the competitor's relative cost of external financing. If investment success is persistent, and most variation in competitor

[2] We find mixed evidence using the Kaplan and Zingales (1997) (KZ) index. This is consistent with a related study by Almeida et al. (2013) who also find mixed evidence using the KZ index because of a weak correlation with other measures of financing constraints.

constraints is cross-sectional in nature, then the problem of reverse causality cannot be sufficiently mitigated by lagging covariates in order to exploit the timing of investment decisions and changes in competitor constraints.

Furthermore, firms likely make equilibrium choices regarding investments and factors that could affect constraints in a way that may generate endogenous correlations in the data. For instance, more innovative investments may exhibit a higher degree of credit rationing, perhaps due to greater cash flow uncertainty or a greater reliance on inalienable human capital (i.e., Hart and Moore (1994)). If this is the case, then financing constraints might be positively associated with more innovative or fruitful markets, which firms may choose to gravitate towards for reasons other than the competitive channel we have posited. Since firms with similar characteristics are likely to select into similar environments, competitor constraints and firm investment opportunities might be positively correlated due to common omitted factors that we cannot perfectly control for in our empirical models. While our ability to control for unobserved heterogeneity at the competitor-pair and firm-year levels mitigates concerns of this nature, we cannot rule them out entirely.

To increase confidence that we have identified a meaningful causal relationship, we exploit two plausibly exogenous shocks that should affect competitor constraints while not affecting a firm's own investment opportunities, independent of the competitive feedback effects that we seek to identify. The first of these is the American Jobs Creation Act (AJCA) of 2004, which effectively relaxed constraints for firms that held foreign operations by lowering the effective tax rate on cash harvested from abroad.[3] The second shock is the 1989 junk bond market collapse, which tightened constraints sharply for firms that relied on this market as a major source of finance.[4]

We define the treatment group for the AJCA (junk bond crisis) to include firms without foreign operations (junk debt), but whose competitors earned income abroad from 2001-2003

[3] Dharmapala et al. (2011) and Faulkender and Petersen (2012) also use the AJCA as a shock to corporate cash flow. However, these studies focus on the firm that received the tax break, while we focus on the competitors of firms that benefited from the tax holiday.

[4] Lemmon et al. (2010) also use the junk bond crisis as an unanticipated tightening of financing constraints.

(relied on junk debt before 1989).[5] By construction, neither event should provide direct incentives to invest (disinvest) for the treatment groups. Thus, any changes in investment behavior should be driven primarily by changes to the financial strength of competitors. When using the variation in constraints driven by these plausibly exogenous events, our results are very similar to our initial evidence. In particular, we find that relaxed (tightened) competitor constraints are associated with less (more) investment activity, and we find that firms shift their investment composition away from less constrained competitors and toward more constrained competitors. Additionally, we show that these effects are concentrated among firms that have the most constrained competitors. These results are significant in both an economic and a statistical sense, and they increase our confidence that we have identified an underlying positive causal relation between competitor constraints and both the level and composition of investment spending.

As a final step toward showing that competitor constraints alter investment behavior, we turn our attention to a specific setting. We provide evidence that firms are more likely to hire inventors recently employed by a competitor when that competitor's constraints become more binding. Specifically, a one standard deviation tightening in competitor constraints corresponds to a 33.2-40.5% increased probability of inventor poaching, according to the *WW* and *SA* measures of constraints, and a 4.7-6.5% increase according to the *Delay* index. This effect holds when we implement firm fixed-effects transformations with the firm-year as the unit of observation and when we account for regional heterogeneity in the enforcement of noncompete agreements. We repeat this analysis with the inventor-year as the unit of observation and find similar effects. Analysis at the inventor level allows us to control for unobserved factors such as inventor mobility. These results further suggest that competitor constraints are not merely a proxy for latent unobservable common factors; rather, they directly influence a firm's investment opportunities.

In summary, our findings provide new insights regarding the implications of financial

[5]We estimate a version of the AJCA test with more inclusive treatment groups and conduct falsification tests in the spirit of Roberts and Whited (2013) for both the AJCA and junk debt crisis treatment events.

constraints. The aggressive investment that constraints appear to invite from competitors suggests that the consequences of being constrained may be even greater than commonly recognized. However, our results also suggest that the social loss of underinvestment due to constraints are potentially mitigated by competitors "filling in the gap" of constrained firms.[6] While estimating the net effect of these competing forces is beyond the scope of this paper, our findings suggest that this is an interesting avenue for future research. Finally, our results suggest that competitor constraints have a first-order effect on investment decisions and that studies on corporate investment should account for this effect in empirical specifications.

2 Literature Review

Our study is closely related to previous work that examines the effects of financing constraints on investment. This literature grew substantially following the influential work of Fazzari et al. (1988), who argued that insufficient access to external capital markets induces a positive correlation between investment spending and cash flows. Subsequent literature found similar results while also highlighting many difficulties in estimating constraints and investment interactions (e.g., Whited (1992), Alti (2003), Rauh (2006), Almeida and Campello (2007), Hadlock and Pierce (2010), and Hoberg and Maksimovic (2015)). While this literature has convincingly shown that financial constraints can sometimes have a large effect on investment choices, the focus thus far has been on frictions and subsequent investment distortions within the same firm, without regard for the potential impact on competitors.

One notable exception is the important work of Rauh (2006), who provides evidence that firms capture some of a competitor's unfunded projects. Specifically, he finds that firms increase investment when competitors with defined-benefit pensions have unexpected increases in required contributions. Our study broadens Rauh's results on the levels of investment spending to a larger, more general sample and multiple settings. In addition,

[6]Of course, the resulting industrial organization will largely determine the existence, and degree, of benefits for consumers.

we study changes in the composition of investment in response to tightening competitor constraints using product market and patent portfolio similarities. Furthermore, by using time-varying, intransitive competitor classifications for a large set of firms, we can exploit variation within competitor pairs and within a given firm-year to control for unobserved heterogeneity and selection effects. Finally, our evidence on inventor poaching speaks directly to firms capturing a competitor's unfunded projects.

The notion that competitor health can influence profits has been analyzed extensively in the context of predation, in which firms take costly actions to drive weakened competitors into bankruptcy in exchange for extracting higher rent in the future (e.g., Fudenberg and Tirole (1986) and Bolton and Scharfstein (1990)). Due to data limitations, empirical studies on predation typically focus on a particular industry. For example, Chevalier (1995a,b) provide evidence of predation in supermarkets during the LBO boom of the late 1980s, and Cookson (2010, 2014) studies predation in the casino and gaming industry. We contribute to this literature by broadening the analysis of investment decisions and competitor health to a general sample of firms, as well as studying the effect of competitor health on the composition of a firm's entire portfolio of projects. Furthermore, we focus on situations in which competitors may be financially constrained, but are not necessarily insolvent. Our evidence suggests that the financial health of competitors may influence investment opportunities on the margin, even when entry or exit (i.e., bankruptcy) is not imminent.[7]

Some studies offer evidence that firms take actions to avoid cash-poor states of the world by hedging (Adam et al. (2007)) or holding large cash reserves to capitalize on opportunities (Fresard (2010)), and these actions are consistent with product markets being chosen in equilibrium. Indeed, Haushalter et al. (2007) and Hoberg et al. (2014) document that firms tend to hold more cash and pay fewer dividends when their investment opportunities are more interdependent with those of competitors and when product markets are relatively more fluid. The findings of this literature are consistent with the evidence that we provide,

[7]Almeida and Philippon (2007) provide a detailed analysis on the infrequency of bankruptcies for public U.S. corporations.

since all three measures of constraints that we deploy are negatively related to a firms cash holdings after conditioning on standard control variables.

Within the literature on finance and innovation, our study is most closely related to the work of Almeida et al. (2011), who find that financial constraints can force managers to weed out less valuable intangible projects, and Brown et al. (2012), who find that R&D investment is exceptionally sensitive to financial constraints. Our results are consistent with the findings in these studies, since they suggest that financial constraints hinder a firm's intangible investment. However, while these studies focus on the impact of financing frictions on a firm's own investment, we show that financial constraints also impact the investment decisions of competitors.

3 Data and Summary Statistics

Patent data come from the National Bureau of Economic Research (NBER) patent data project, the Harvard Patent Database (Lai et al. (2014)), and Kogan et al. (2012) (KPSS). For each patent, we observe the patent's technological category, application date, grant date, the list of cited patents, and information about the patent's assignees. We use the patent application year as the year of record. Hall et al. (2001) point out that receiving grant status takes an average of two years after applying for a patent. The Harvard Patent Database includes information on patents granted through 2010, and the KPSS data include citation information through 2012. The combined data allow four years to receive grant status and six years to accumulate citations for the last patents in the NBER data (applied for in 2006).

It is well documented that patenting (*or patent citing*) propensities exhibit heterogeneity across patent technology classes and through time.[8] We follow related literature and employ a reduced-form approach to adjust for heterogeneity in patenting propensities (e.g., Seru (2014) and Lerner and Seru (2015)).[9] The procedure involves sorting patents into six major

[8]Lerner and Seru (2015) discuss the problems with truncation effects and patenting propensities in detail.
[9]This is a modified version of the approach first developed in Hall et al. (2001).

technological classes and 36 subcategories. Each patent is then scaled by the average number of patents filed by all firms within each technology subcategory and application year.[10] We also scale citations by the average number of citations received by patents in the same subcategory and application year. These adjusted patents (citations) are then aggregated to the firm-year level, creating a weighted sum of each firm's patents (citations).

Information on firm financials comes from the CRSP-COMPUSTAT merged database. We calculate the natural log of a firm's assets (*log(Assets)*) and sales (*log(Sales)*), *Market-to-book* ratio, research and development spending divided by Sales ($R\&D/Sales$), capital expenditures scaled by assets (*Capx/Assets*), cash plus cash equivalents scaled by assets (*cash + equiv/Assets*), earnings before interest, taxes and depreciation scaled by assets ($EBITDA/Assets$), and net property plant and equipment scaled by assets ($PP\&E/Assets$). We use market-to-book to control for changes in a firm's investment opportunities that are unrelated to peer-firms' financial constraints. The variables *cash + equiv/Assets*, $EBITDA/Assets$, and $PP\&E/Assets$ are additional controls related to a firm's investment opportunities, and they are commonly used as controls in regression specifications that include patent variables. Lerner and Seru (2015) document that these variables are important for mitigating any remaining truncation bias not accounted for by the adjustment procedure and the supplemental data detailed above.

4 Defining Firm Relationships

4.1 Text-Based Approach

Our first approach to classifying competitors, the *text-based* approach, uses the product market similarity measure developed in Hoberg and Phillips (2015). The authors first vectorize the product market vocabulary from 10-Ks according to a dictionary they develop.

[10] We estimate specifications with both the 6-category and the 36-category adjustments, and we find qualitatively similar results. Results presented in this manuscript are obtained with the 36-subcategory adjustment.

They then assign pairwise similarity scores based on the cosine similarity between two firms' vectorized product market descriptions. The cosine similarity between two firms is higher when the two firms' product market descriptions are more similar. The measure ranges from 0 (no similarity) to 1 (perfect similarity). Additionally, Hoberg and Phillips purge vertically related firms in industries classified as *upstream* or *downstream* industries according to the BEA input-output tables in order to ensure that their measure characterizes competitive relationships.[11]

Hoberg and Phillips (2015) provide evidence that their measure more accurately captures product market competition when compared to static and transitive industry classifications (e.g. SIC/NAIC codes). Specifically, they use the terrorist attacks of September 11, 2001, as an exogenous shock to spending on military goods, and they use the 2000 dot com bust as a shock to spending on software. They find that a plausibly exogenous increase (decrease) in demand leads to an increase (decrease) in product market similarity. This approach is similar to our analysis of the AJCA tax holiday and the junk bond crisis, except Hoberg and Phillips (2015) focus on industry-wide demand shocks, whereas we focus on events that affect a subset of a firm's competitors. Moreover, our analysis is based on shocks to a firm's financing constraints, rather than the demand for goods and services in the firm's primary industry.

A firm is classified as a competitor in our text-based network if they are listed as competitors according to the method in Hoberg and Phillips (2015). Our final text-based network of firms includes 4,211,311 competitor-pair-years and 63,429 firm-years. Each firm has an average of 66.39 related firms with an average cosine product similarity score of 0.051.

4.2 Citation-Based Approach

Our second approach uses information from the NBER patent data, which includes detailed information on patent-to-patent citations. A patent reviewer assigned by the USPTO

[11] Hoberg and Phillips (2015) find that vertical relationships account for only 4% of the initial relationships identified in their data.

is responsible for ensuring that a patent applicant has cited all relevant prior patents, which is required by law.[12] Thus, patent citations represent links between closely related patents, and they directly track the evolution of innovation within and between firms.

In our citation-based network, Firm A is defined as a competitor of Firm B at time t if Firm B cites Firm A from time t-5 to t-1. In determining the length of time that firms remain linked, we face a tradeoff between having more links in our sample and having the link represent a meaningful connection. For example, two firms that cited each other on patents developed 20 years prior, without any subsequent citations, might not represent a meaningful relationship because these firms might have changed their research and development focus drastically. On the other hand, shortening the window too much would unnecessarily rule out meaningful firm relationships and decrease the power of our tests. We believe using a 5-year window as our baseline provides a good, although admittedly subjective, balance between the relevance of citations and the number of firm links. We check the robustness of our results using 2-year and 7-year links, and we find similar results. These results are provided in the Internet Appendix in Table IA2.

Note that our definition of competitors is not necessarily reflexive. That is, Firm A can be considered a peer of Firm B without Firm B necessarily being a peer of Firm A. This would happen if Firm B cites Firm A, but Firm A does not cite Firm B during the previous five years. We define peers this way to avoid a mechanical relationship when we use citations received as our dependent variable.[13] Anjos and Fracassi (2015), Bena and Li (2014), and Ma (2015) are among other studies that use patents to categorize firm relationships. However, these studies use technological classes to classify competitors, while we use cross-firm patent citations.

Following Hoberg and Phillips (2015), we also purge our citation-based competitor network of up-stream and down-stream relationships. However, instead of omitting relationships based on BEA input-output tables, we omit firms identified as strategic alliances, joint ven-

[12] See Ozluturk et al. (2013) for a more in-depth discussion and description of this process.

[13] 38.6% of cited firms reciprocate citations to the citing firm in the same year.

tures, or supply chain partners.[14] This approach has the benefit that purged relationships are more likely to be firms in an existing vertical relationship; however, this approach also defines vertical relationships less broadly. The combination of results from the broader approach implemented by Hoberg and Phillips (2015) (used to construct our text-based network) and our more specific approach (used to construct our citation-based network) increases our confidence that we are indeed characterizing competitive relationships. As an additional step, we study investment and constraints for vertically related firms, and we do not find a strong relationship. The results are provided in Table IA8 of the Internet Appendix.

Our final citation-based network includes 594,149 competitor-pair-year observations and 21,458 firm-year observations for the period 1980-2006. Each firm has an average of 27.68 competitors in the citation-based network. Note that our patent sample, which uses the firm-year as the unit of observation, is slightly smaller than related studies, because we require firms to have patented during the previous five years in order to calculate our patent portfolio similarity measure, which we describe in the following section.

4.3 Patent Portfolio Similarity

In this section, we take advantage of the granularity of patent data to build a measure that allows us to study whether firms shift their patenting portfolio to have greater or lesser overlap with constrained competitors. We borrow from the approach in Bloom et al. (2013), who measure the technological proximity between competitors as the distance between patent portfolios. The USPTO classifies patents into one of 36 technology subcategories. It is rare for public corporations to patent entirely within a particular subcategory, which provides the potential for firms' patent portfolios to have varying degrees of overlap with each of their competitors.[15] To calculate the technological overlap between firms i and j at time t, we calculate the Mahlanobis Distance (MD) between their patent portfolios:

[14] Information on strategic alliances and joint ventures come from SDC, and information on customers and suppliers come from Computstat.

[15] Less than 27% of firms in our sample patent exclusively in one technology class.

$$MD_{i,j,t} = \sqrt{(\mathbf{P_{i,t,t+2}} - \mathbf{P_{j,t-5,t-1}})COV^{-1}(\mathbf{P_{i,t,t+2}} - \mathbf{P_{j,t-5,t-1}})}$$

where $\mathbf{P_{i,t,t+2}}$ is a 36×1 vector representing the number of firm i's patents in each ordered subcategory from year t to $t+2$, $\mathbf{P_{j,t-5,t-1}}$ is a 36×1 vector representing the number of firm j's patents in each ordered subcategory from year $t-5$ to $t-1$, and COV^{-1} is the variance-covariance matrix of year-level patent portfolios aggregated across all firms in the sample. Because of the overlap in our construction of $MD_{i,j,t}$, we cluster our standard errors at the firm level and the competitor-pair level.

Two given firms will have a smaller Mahalanobis distance if they patent in the same technology class more frequently (i.e., they will have more similar patent portfolios). Firms that have the same number of patents in each technology class will have a distance of zero. We scale our MD measure by the maximum observed MD in our sample (231.03) for expositional convenience, so that MD ranges from 0 to 1.

Note that if we calculated MD using the same time period for each firm's patent portfolio, the measure would be symmetric, which means that firm i is the same distance from firm j as firm j is from firm i at any given point in time. This is not the case in our definition, because firm i's patent portfolio is measured from time t to *t+2*, and it is compared with firm j's patent portfolio from *t-1* to *t-5*. We construct our measure this way in order to isolate movements of firms in response to changes in competitor constraints. For instance, suppose firm i has a competitor j that experiences a tightening in financing constraints. We would expect firm j to reduce investment or patenting activity. This would cause a change in MD between firms i and j, even if firm i does not change its patenting focus. Instead, we would like to study whether firm i's new patenting activity gravitates towards firm j's patenting activity in the recent past, in response to a tightening of firm j's constraints. This is the primary difference between our new measure of similarity and the product market similarity defined by Hoberg and Phillips (2015), which is an *ex post* measure between two firms' product markets measured at the same point in time.

Many potential measures can be used for estimating patent portfolio overlap. However, the Mahlanobis Distance has the added advantage that it does not treat technology classes as orthogonal. The variance-covariance matrix explicitly accounts for the fact that some technology classes are more related than others by inversely weighting observations according to cross-category patenting propensities.[16] For example, according to the MD measure, a firm that patents entirely in computer *hardware* is considered to have a greater overlap with a firm that patents entirely in computer *software* than it is with a firm that patents entirely in automobiles.

Under a metric that treats technology classes as orthogonal, a firm that patents solely in computer hardware would be completely unrelated to a firm that patents entirely in computer software. While this is possible, it is unlikely that there is no overlap between the two technology classes. Nonetheless, we repeat our analysis in the Internet Appendix with two alternative measures of patent portfolio overlap. First, we use Euclidean Distance, which is similar to MD, except it does not weight patenting portfolios by the covariance matrix, and therefore treats patent classes as orthogonal. Second, we calculate pairwise correlations between firms' patent portfolios. This measure is less related to MD, and it also treats technology classes as orthogonal. The results with these additional measures of similarity are presented in the Internet Appendix in Tables IA3.

4.4 Competitor Constraints

For measures of financial constraints, we use three standard empirical proxies from recent literature. First, we use the Whited-Wu (WW) financial constraint index developed in Whited and Wu (2006), who provide structural estimates of an investment Euler equation. Parameter estimates from the structural equation are used to calculate a constraint index

[16]Cross-category patenting propensities are estimated from the full sample of firms for each year.

from commonly used accounting variables:

$$WW_{it} = -0.091CF_{it} - 0.062DIVPOS_{it} + 0.021TLTD_{it} - 0.044LNTA_{it}$$
$$+0.102ISG_{it} - 0.035SG_{it},$$

where *CF* is a firm's cash flow, *DIVPOS* is a dummy variable indicating whether a firm pays cash dividends, *TLTD* is the ratio of long-term debt to total assets, *LNTA* is the log of total assets, *ISG* is the 3-digit SIC industry sales growth, and *SG* is firm-level sales growth.

Second, we use the the Size-Age (*SA*) index developed by Hadlock and Pierce (2010). Hadlock and Pierce read the MD&A section from a randomly selected sample of firm 10-Ks and find that size and age are the strongest predictors of financing constraints. Following Hadlock and Pierce (2010), we calculate the *SA* index as

$$SA_{it} = -0.737LNTA_{it} + 0.043LNTA_{it}^2 - 0.040AGE_{it},$$

where AGE is a firm's age and *LNTA* is the natural log of total assets.

As our final measure, we use the Delayed Investment (*Delay*) financial constraint index developed by Hoberg and Maksimovic (2015). Similar to Hadlock and Pierce, Hoberg and Maksimovic (2015) gather information on constraints from 10-Ks. Specifically, Hoberg and Maksimovic create a *Delay* index according to the extent to which firms mention curtailing, abandoning, or postponing investment. By automating the textual analysis of firm 10-Ks, Hoberg and Maksimovic (2015) are able to measure the *Delay* index directly from 10-Ks for a large set of firms, rather than extrapolating values from accounting information. Note however, that the *Delay* index is available from 1996-2013, whereas the other measures can be computed for any year in which data are available in COMPUSTAT. For this reason, our samples are generally smaller when using the *Delay* index as our measure of financial constraints.

Our financial constraints measures serve two purposes in our regression specifications.

First, we build financial constraint indices of a firm's competitors for our firm-level analyses. For analyses in which the competitor-pair is the unit of observation, we simply use the given competitor's *WW*, *SA*, or *Delay* index as measures of competitor constraints. Second, we use the *SA*, *WW*, and *Delay* indices as control variables for a firm's own financial constraints. These control variables are important because performance is likely correlated among firms investing in similar product markets or patenting in similar technologies, and we do not want our competitor constraint indices to simply proxy for a firm's own constraints.

We use our two competitor networks to construct our independent variables of interest for our firm-level analysis. We define a competitor's financial constraints as the average of the *WW* (*SA*, *Delay*) constraint index for a firm's competitors in year t:

$$CompConst_{i,t} = \frac{\sum\limits_{j \in C_t,} FC_{j,t}}{num(C_t)},$$

where C_t is the list of firms related to firm i, and $num(C_t)$ is the number of firms in C_t, defined for the text-based and citation-based networks, respectively.[17] We normalize these financial constraint variables to have mean 0 and a standard deviation of 1 to aid in the interpretation of the regression results across specifications. We construct analogous peer-firm variables to control for the natural log of average competitor *log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets.* The summary statistics are presented in Table 1. All variables are winsorized at the 1% level in each tail, which helps mitigate the influence of extreme observations.[18]

[17]Note that a firm is excluded from its average peer group constraint calculation. That is, a firm is not defined as a peer of itself.

[18]We obtain qualitatively similar results with more agressive winsorization and without winsorizing.

5 Empirical Results

5.1 Investment Levels and Competitor Constraints

We start by investigating changes in the level of corporate investment and innovation in response to a tightening in competitor constraints in a standard panel data framework. Specifically, we estimate the following equation:

$$Investment_{i,t} = \alpha_i + \gamma_1 Comp\,Const_{i,t-1} + \gamma_2 Own\,Const_{i,t-1} + \beta Controls_{i,t-1} + \theta_t + \epsilon_{i,t} \quad (1)$$

In this equation, our proxies for investment and innovation activity are (a) capital expenditures scaled by lagged assets, (b) research and development expenses scaled by sales, (c) adjusted patents, and (d) adjusted citations. The variable *Comp Const* is our measure of competitor financial constraints according to the *WW*, *SA*, and *Delay* constraint indices. The vector of controls includes *log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets*, and analogous competitor averages. All independent variables are lagged by one period. The firm-specific intercept allows for additive and time-invariant unobserved heterogeneity at the firm level.[19]

Competitor constraints may potentially generate positive or negative externalities for firms. For example, if competitors are forced to forgo projects because of financing constraints, then there is less potential for knowledge spillovers, which have been shown to increase investment productivity (see Powell and Giannella (2010), Bloom et al. (2013), and Grieser et al. (2016)). Similarly, if competitors are forced to cut projects that use inputs related to a firm's own production process, then this can lead to depressed collateral values, which may hinder a firm's own borrowing capacity (e.g., Hertzel and Officer (2012)). On the other hand, competitor constraints may reduce competition for a given firm and increase

[19] Patenting activity tends to be clustered in time due to technological breakthroughs and the compounding effects of knowledge spillovers. Although we adjust our patent measures to account for time- and industry-varying patent propensities, these adjustments are imperfect and do not account for time and industry varying shocks to financial constraints. For this reason, we include year dummies in the all regression specifications. Specifications with Industry×Year dummies can be found in Table IA2 of the Internet Appendix.

the profitability of some projects. If knowledge or collateral spillovers dominate competition effects, then we should expect competitor financial constraints to have a negative effect on investment activity ($\gamma_1 < 0$). On the other hand, if the competition channels outweigh the negative externalities, then investment and innovation should increase when peers experience a tightening in financial constraints ($\gamma_1 > 0$).

The results for OLS estimates of Equation 1 are presented in Table 2. Panel A presents results for our text-based network of competitors, with capital expenditures scaled by lagged assets as our dependent variable in Columns 1, 3, and 5; and research and development expenses scaled by sales are presented in Columns 2, 4, and 6. Panel B presents results for our citation-based network of competitors, with adjusted patents (*Adj Pat*) as our dependent variable in Columns 1, 3, and 5; and adjusted citations (*Adj Cite*) as our dependent variable in Columns 2, 4, and 6.

In both panels, we use the *WW* Index (Columns 1-2), the *SA* Index (Columns 3-4), and the *Delay* Index (Columns 5-6) to construct our constraint variables. All columns include firm fixed effects transformations and year dummies. The firm fixed effects transformation allows us to purge additive and time-invariant heterogeneity at the firm-level that may be arbitrarily correlated with the covariates. The year dummies help to control for aggregate shocks that simultaneously affect both financing constraints and investment or innovation.[20]

The results suggest that a one standard deviation tightening in competitor financing constraints leads to a 1.7-4.5% increase in capital expenditures as a percentage of assets and a 4.1-6.6% increase in R&D scaled by sales, relative to the respective unconditional sample averages. Similarly, a one standard deviation tightening of competitor constraints leads to a 15-26% (6-16%) increase in adjusted patents (adjusted citations). The positive and significant coefficient estimates suggest that firms increase investment activity and receive more citations after competitors experience a tightening in their financing constraints. The results for the patent variables are consistent with Almeida et al. (2013), who show that

[20]However, it is possible that aggregate shocks have a heterogeneous effect across industries. We present results with industry×year dummies in Table IA2 of the Internet Appendix.

debt overhang forces firms to sacrifice corporate innovation.[21] The results are also in line with Rauh (2006), who shows that unconstrained firms invest more when industry peers are constrained by pension funding requirements.

Note that competitor financial constraints and a firm's own financial constraints have the opposite effect on investment and patenting activity (i.e., $\gamma_1 > 0$ and $\gamma_2 < 0$), which mitigates the concern that our estimates are confounded by the reflection problem as identified by Manski (1993). We discuss the reflection problem in more detail in Section 6.

5.2 Investment Composition and Competitor Constraints

In this section, we take advantage of the detailed information contained in our competitor networks to study relationships at the competitor-pair level. We use our empirical measures of product market and patent portfolio similarity to study how firms alter their investment composition in response to a tightening in competitor constraints. To do so, we estimate the following equation:

$$\begin{aligned} Investment\,Similarity_{i,j,t} &= \alpha_{i,t} + \gamma_1 Comp\,Const_{j,t-1} + \gamma_2 Own\,Const_{i,t-1} \\ &\quad + \beta Controls_{i,j,t-1} + \epsilon_{i,t}, \end{aligned} \tag{2}$$

where we use product market similarity ($ProdSimilarity_{i,j,t}$) and the Mahlanobis Distance ($MD_{i,j,t}$) between firm i and competitor j at time t as measures of investment composition similarity. The variable $Comp\,Const$ is the financial constraint index (e.g., *WW, SA, Delay*) for competitor j, lagged by one period. Note that the competitor-pair is the unit of observation in this setting. The vector of controls includes *log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets* for both firms i and j, all lagged by one period.

The estimates of Equation 2 are presented in Table 3. In Panel A, our measure of

[21] Almeida et al. (2013) also argue that debt has a disciplining effect, as the forgone innovation appears to be less efficient projects.

investment similarity is the pairwise cosine similarity in product market descriptions (*Prod Similarity*) between two firms according to the text-based network of competitors developed by Hoberg and Phillips (2015) from 1996-2012. A higher *Prod Similarity* indicates a greater similarity between two firms' 10-K product descriptions. The dependent variable in Panel B is the Mahalanobis Distance (*MD*) between a firm's patent portfolio over the following three years and a that of its competitor over the previous 5-year period, according to our citation-based network of competitors from 1980-2006. A lower value represents patent portfolios that are closer in covariance-weighted distance or portfolios that are more similar.

In both panels, we use the *WW* Index (Columns 1-3), the *SA* Index (Columns 4-6), and the *Delay* Index (Columns 7-9) to construct our constraint variables. Specifications in Columns 2-3, 5-6, and 8-9 include $Firm \times Year$ fixed effects transformations. In these specifications, we can interpret the coefficient estimates for γ_1 as the shift in a firm's spending towards its more (increasingly) constrained competitors and away from its less (decreasingly) constrained competitors. Specifically, a one standard deviation tightening of competitor constraints results in a 3.9-5.8% increase in product market similarity and a 31.7-60.1% increase in patent portfolio similarity, relative to the respective sample averages.

In Columns 3, 6, and 9, we implement $Firm \times Competitor$ fixed effects transformations with $Firm \times Year$ dummies. These transformations control for time-invariant product market and patent portfolio similarities between firm i and competitor j. Thus, we can interpret the coefficient estimate for $CompConst$ in Columns 3, 6, and 9 as the effect that competitor financing constraints has on the investment composition overlap, relative to the average similarity for that competitor-pair. According to these specifications, a one standard deviation tightening of competitor constraints results in a 5.8% increase in product market similarity and a 2.1-11.7% increase in patent portfolio similarity. Notice the increase in the R^2 of these specifications relative to the specifications without competitor-pair fixed effects transformations. This increase suggests that much of the variation in patent portfolio similarity is driven by the cross-sectional variation in competitor-pair relationships. The influence of competitor financing constraints on the composition of a firm's patenting activity remains significant when isolating the variation to within competitor-pairs.

The increase in product market similarity represents a change in *ex post* similarity between competitor-pairs, which can be driven by movements from either competitor in a given pair. The $Firm \times Year$ transformations help to isolate how changes in firm j's constraints lead firm i to alter its investment composition in relation to firm j, relative to changes in investment composition similarity between firm i and its other competitors. The results with patent portfolio similarity (MD) as a measure of investment similarity are less prone to this issue, since they represent a shift in the patenting activity of firm i from time t to *t+2* towards the patenting activity of competitor j during time *t-5* to *t-1*.

6 Quasi-Experimental Evidence

Our baseline regressions are subject to potential endogeneity concerns. For example, increased investment may exacerbate rivals' financial constraints rather than rivals' financial constraints influencing investment activity. Additionally, our financial constraint measures could potentially exhibit significant measurement error (e.g., Erickson and Whited (2000)), which could create problems with inference if the measurement error is systematically related to any of the variables in our model specification. For example, if innovative firms tend to appear constrained, perhaps because they tend to be younger firms with less cash (e.g., Farre-Mensa and Ljungqvist (2016)), our results could be driven by a firm's movements toward innovative markets rather than by a gravitation toward financially constrained competitors.

A related concern is that, even if constraints are measured perfectly, they may be related to some unobserved characteristics that also affect our dependent variable. That is, our estimates may be subject to an omitted variable bias. For example, more innovative markets may exhibit a greater degree of credit rationing, and may also be prone to greater uncertainty or a greater reliance on intellectual property, rather than hard assets that can be pledged as collateral (e.g., Tirole (2006)). If this is indeed the case, financing constraints may be associated with more innovative or fruitful markets, which we cannot perfectly control for in our empirical models. This example highlights that firms may choose to gravitate towards these markets for reasons other than the competitive channel that we have posited.

Furthermore, since firms with similar characteristics are likely to select into similar environments, omitted variables may be related across competitors. This may cause competitor constraints to proxy for latent common unobservable factors that affect a firm's investment opportunities. This is a version of the reflection problem as identified by Manski (1993), in which peer firms select into similar environments and exhibit similar characteristics, which are likely to dictate similar actions. It is well established in the urban economics literature that detailed data on non-transitive peer interactions greatly mitigates concerns regarding the reflection problem (e.g., Topa and Zenou (2015)). Furthermore, as long as the relationships identified are meaningful, any missing relationships will only attenuate point estimates (see Helmers and Patnam (2014), Liu and Lee (2010), and Liu et al. (2012)). Our detailed competitor networks provide the ability to control for unobserved heterogeneity at the competitor-pair and firm-year level, which mitigates concerns regarding these selection effects. Nonetheless, we cannot entirely rule out the reflection concern without an exogenous source of variation in competitor constraints.

To address these concerns, we exploit two plausibly exogenous shocks that should only affect patenting activity through their effect on competitors' financial constraints.[22] First, we exploit the American Jobs Creation Act (AJCA) of 2004 as a positive shock to the cash holdings of a firm's financially constrained competitors that had significant international operations. We examine changes in the investment behavior of firms whose competitors were positively affected by the tax holiday relative to firms without competitors that were affected by the AJCA.

Second, we exploit the 1989 junk bond crisis as an adverse shock to the financial con-

[22] Our strategy of exploiting both a positive and negative shock is also implemented by Cohn and Wardlaw (2016), and Leary (2009).

straints of competitors that relied on external capital from the junk bond market before 1989. Lemmon et al. (2010), Almeida et al. (2011), and Almeida et al. (2013) also use the junk bond crisis as a negative shock to financing constraints. Similar to the AJCA event, we focus on changes in the investment behavior of firms that were not directly affected by the event but still compete with firms that were affected. Therefore, any effect should stem primarily from the impact of the crisis on competitors.

6.1 American Jobs Creation Act of 2004

The American Jobs Creation Act (AJCA) of 2004 was a federal tax act that enabled firms to repatriate foreign profits at a reduced tax rate for one year. Congress lowered the repatriation tax rate in order to encourage domestic investment, with the condition that repatriated foreign income must be used for investment and not paid out as dividends. This act potentially loosened financial constraints for firms that had significant foreign profits. While some firms ignored Congress and used these profits to payout dividends or repurchase shares (e.g., Dharmapala et al. (2011)), some constrained firms appear to have used these funds to increase investment (e.g., Faulkender and Petersen (2012)).

We use the AJCA tax holiday as a treatment event for firms with competitors that had significant foreign income before 2004 in a difference-in-differences framework. We use two years of data, both before and after the event, for the sample period 2002-2006. We define *Treated* firms as those with competitors that earned an average of at least 33% of pre-tax income from abroad during 2002-2003. We exclude firms with overseas revenue from the treatment group in Table 4, since the AJCA had the potential to directly affect such firms. We repeat our analysis with an extended sample that includes firms that had foreign operations in the treatment group, and we report the results in Table IA4 of the Internet Appendix.

In Table 4, Columns 1 and 2, the interaction term $Treated \times Post$ is statistically significant at the 1% level for Adjusted Patents (*Adj Pat*), Adjusted Citations (*Adj Cite*), and

R&D/Sales, but insignificant for *Capx/Assets*. These results suggest that firms decreased (or increased by less) investment spending and patenting activity when competitors received a temporary relaxation of cash constraints from the AJCA tax holiday. The lack of significance on capital expenditures is consistent with financial constraints mattering less for more tangible investments, which are arguably more easily pledged as collateral. Alternatively, our tests could simply lack the statistical power to detect a nonzero relationship for capital expenditures.

To sharpen our test, we study the effect of the AJCA for firms with competitors that were the most constrained before 2004. We should not expect firms to respond as strongly to changes in competitor cash flows if those competitors were already unconstrained before the AJCA tax holiday. We define *Comp Pre-const.* as an indicator variable equal to one if the competitor's average constraints rank above the median from 2002-2003 according to the *WW* Index (Columns 3-4), the *SA* Index (Columns 5-6), and the *Delayed Investment* Index (Columns 7-8). We measure constraints before 2004 to prevent the AJCA from directly influencing the constraint variables.[23] The triple interaction term in Table 4 ($Treated \times Post \times$ *Comp Pre-const.*) is negative and statistically significant when we use Adjusted Patents (*Adj Pat*), Adjusted Citations (*Adj Cite*), and *R&D/Sales* as dependent variables. These results suggest that the effect of firms reducing investment is concentrated on firms with competitors that were constrained before the AJCA.

We also exploit the 2004 AJCA tax holiday to study changes in investment composition at the competitor-pair-year level. Analysis at the competitor-pair level permits that a given firm can have both treated and untreated observations within the same year, since some competitors have foreign operations, while other competitors do not. For the dependent variable, we use the pairwise cosine similarity in product market descriptions (*Prod Similarity*) between two firms in the text-based network of competitors developed by Hoberg and

[23]Using breakpoints above and below the median also provides a natural interpretation for our interaction terms.

Phillips (2015).[24]

We report the results from our investment composition analysis at the competitor-pair level in Table 5. Specifications include firm fixed effects transformations and year dummies in Columns 1, 3, 5, and 7; competitor-pair fixed effects transformations in all Columns; and and $Firm \times Year$ dummies in Columns 2, 4, 6, and 8. The coefficient estimates suggest that firms decrease (increase by less) investment similarity with competitors that received a positive cash shock from the AJCA tax holiday (Columns 1-2). This effect also appears to be concentrated among firms whose competitors were constrained before the AJCA tax holiday according to the *WW* Index (Columns 3-4), the *SA* Index (Columns 5-6), and the *Delayed Investment* Index (Columns 7-8). These results suggest that firms most actively chose to shift their investment away from competitors that were constrained before the AJCA and received a positive cash flow shock.

6.2 Junk Bond Crisis of 1989

In 1989, Congress passed the Financial Institutions Reform, Recovery, and Enforcement Act, which severely limited the ability of savings and loan banks to hold junk debt. Soon after, junk-rated firms declared for bankruptcy at a significantly higher rate than historical trends. Together, these events led to the collapse of Drexel Burnham Lambert, which was, by a large margin, the largest issuer of junk bonds at the time. The collapse of Drexel resulted in a large, discrete jump in the cost of capital for firms that relied on junk debt as a source of financing, since such firms were soon unable to roll over their debt in 1989 and in early 1990. It is plausible that competitors could take advantage of junk-rated firms' inability to secure additional financing.

We exploit the junk bond crisis as a treatment event in a difference-in-differences framework. Specifically, we compare the difference in investment activity of firms with competitors

[24]Note that the latest patents in our sample were granted in 2006,thus we do not have a long enough time period to use MD as a dependent variable in the AJCA experimental design. This would require patents granted through 2009.

that relied on junk bonds as a source of financing to that of firms with competitors that did not issue junk bonds, before and after the junk bond market crash in 1989. This allows us to identify how a plausibly exogenous tightening of rival firms' financial constraints affects investment behavior. We define *Treated* firms as those with at least one competitor that used junk-rated debt rating before 1989, but did not rely on junk debt themselves. Our *Post-treatment* period includes 1990 and 1991.

In Table 6, Columns 1-4, we present results from our firm-year level analysis with *Capx/Assets* and *R&D/Sales* as our dependent variables. Specifications in Columns 1-4 include firm fixed effects transformations and year dummies. The coefficient estimates for the interaction term is positive and significant, which suggests that firms increased (decreased by less) investment spending when competitors were adversely affected by the junk bond market crash because of their reliance on junk debt as a source of funds.

In Columns 5-6, we present results from our competitor-pair analysis, using *MD* as our dependent variable.[25] In this setting, *Treatment* is defined for each of a firm's competitive relationships. Thus, a firm can have both *Treated* and *Control* competitor realtionships, depending on whether a given competitor held a junk debt rating from 1986-1989.

We restrict our pretreatment period in Columns 5-6 to 1986 and our post-treatment period to 1989. Coefficient estimates in Columns 5-6 are estimated with a first difference estimator with the competitor-pair as the unit of observation. Year dummies are also included to capture any aggregate changes in firm behavior between the two years. We leave a 3-year gap between our pre- and post-treatment periods to avoid contamination in the measurement of MD, since MD is computed as the distance between a firm's patent portfolio over the subsequent 3-year period and a competitor's patent portfolio from the previous five years. If we did not impose a 3-year gap for our pre-treatment sample, then there would be an overlap in the MD measure pre- and post-crisis.[26]

[25] We cannot include *Product Market Similarity* in this analysis, since the variable only becomes available after 1996.

[26] We perform the analysis without the 3-year gap, and we find similar results.

The estimate of the interaction term in Columns 5-6 is negative and statistically significant. On average, firms increased their patent portfolio overlap with competitors that were adversely affected by the junk bond crisis by 6.8-10.3%, relative to the sample average distance. These estimates suggest that an unexpected increase in a competitor's constraints causes a firm to tilt its investment towards that competitor's investments.

6.3 Falsification Tests

Roberts and Whited (2013) stress the usefulness of falsification tests in checking the validity of difference-in-differences experimental designs. One specific test they recommend is to repeat the difference-in-differences analysis on pre-event years as a placebo test. The estimated treatment effect should be statistically indistinguishable from zero. This helps to ensure that the observed change is not driven by some unobserved, alternative forces.

To enhance the validity of our difference-in-differences specification, we implement the falsification test outlined in Roberts and Whited (2013) by shifting the event window two years earlier. For the AJCA tax shock, we examine patenting outcomes from 2001-2004, using the same treatment group as before, but we use 2003 and 2004 as the post-treatment years. Similarly, for the junk bond crisis, we examine patenting outcomes from 1986-1989 using the same treatment group as before, but we use 1988 and 1989 as the post-treatment years.

We do not find a significant impact for the treatment on corporate investment levels or composition, as reported in Tables IA5, IA6, and IA7 of the Internet Appendix. The coefficients on all interaction terms are insignificant for all specifications. While this placebo test does not conclusively show that our experimental design is definitive, these results increases our confidence that we have identified a causal relationship.

7 Inventor Poaching

So far, we have focused our efforts on establishing a relation between corporate investment levels (investment composition) and competitor financing constraints. The evidence suggests that the positive externalities of competitor constraints outweigh the negative externalities. In this section, we exploit a specific setting to further show that competitor constraints are not merely a proxy for latent unobservable common factors; instead, they directly influence a firm's investment opportunities. To this end, we show that firms are more likely to hire inventors who work for competitors when those competitors experience a tightening in constraints.

The Harvard Patent Database includes detailed information on individual inventors (see Lai et al. (2014)). We observe the patent identification number for each patent on which an inventor is listed, the patent application and grant dates, and the firm that owns the patent at the time of application. We focus on serial inventors (i.e., inventors who file patents in at least two different years in the sample), and we exclude observations in which multiple firms are listed as owners of the same patent at the time of application.

We make the assumption that firms hiring inventors who were recently employed by competitors is indicative that the firm plans to pursue investment opportunities related to the investments of that competitor. To this end, we estimate the following specification :

$$\begin{aligned} Prob(Poach_{i,t+1,t+5}) &= \alpha_{i,t} + \gamma_1 CompConst_{j,t} + \gamma_2 OwnConst_{i,t} \\ &\quad + \beta Controls_{i,j,t} + NEI_{i,t} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

where *Poach* is a binary variable equal to 1 if an inventor listed on a competitor's patent application in year t is subsequently listed on a firm's own patent application from years *t+1* to *t+5* (and not listed on the patent applications of any other firms during the interim period). We exclude inventors who moved between more than two firms in a given 5-year period, and we only count inventors as poached in the earliest year that we observe them switching between a given competitor-pair.

Regional variation in the use and enforcement of noncompetition agreements may impact the incentives and abilities of employees to leave their current jobs for new employment (see Malsberger (2005)). We implement two approaches to mitigate the concern that our results are driven by differing compositions of inventors across regions with varying degrees of noncompete enforceability. First, we include dummy variables for each of the 12 categories of the Noncompetition Enforcement Index (NEI) developed in Garmaise (2009).[27] We implement this approach for the results presented in Tables 7 and 8. Second, we include the NEI measure in an interaction with the financial constraints measure to highlight that the effect is relatively concentrated in state-years with low noncompetition enforcement, and we report the results in Table IA13 of the Internet Appendix.

In Table 7, we present results from linear probability estimates of Equation 3. We calculate average competitor constraints (*Comp const*) and a firm's own constraints (*Own const*) according to the *WW* Index (Columns 1-2), the *SA* Index (Columns 3-4), and the *Delay* Index (Columns 5-6). The control variables *Log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets*, and analogous competitor averages are measured at time t. The specifications in all columns include firm fixed effects transformations and year dummies. The estimates for coefficient on *Comp Const* are statistically significant and economically large. In particular, a one standard deviation tightening in competitor constraints corresponds to a 33.2-40.5% increased probability of inventor poaching according to the *WW* and *SA* measures of constraints, and a 4.7-6.5% increase according to the *Delay* index.

Inventors differ in their mobility and propensity to change jobs, which may be related to selection into certain types of firms. For example, inventors that are more risk tolerant may also be more comfortable selecting into uncertain environments by seeking employment at a constrained firm. If risk-tolerant inventors are also more likely to change jobs frequently, then our estimates could be driven by the differing composition of inventor types across firms. To

[27]Garmaise (2009) generates a measure of the enforceability of noncompetition agreements across states based on a survey of jurisdiction enforcement along 12 dimensions.

mitigate concerns of this nature, we estimate a version of Equation 3 at the inventor level, which allows us to control for unobserved heterogeneity at the inventor level. Specifically, we estimate the following equation:

$$\begin{aligned} Prob(Departure_{k,t+1,t+5}) &= \alpha_{k,t} + \gamma Existing\,Employer\,Const_{j,t} \\ &\quad + \beta Controls_{j,t} + NEI_{i,t} + \epsilon_{k,t}, \end{aligned} \tag{4}$$

where *Departure* is a binary variable equal to 1 if inventor k listed on firm j's patent application in year t is subsequently listed on a competitor's patent application (and on no other firms' patent application) from years t to $t+5$. Inventors listed on multiple patents for the same firm with fewer than five years in between listings are assumed to be employed at the firm during the interim period, as long as they are not listed on patents issued by other firms during that time. We exclude inventors who moved between more than two firms in a given 5-year period, and we only count switches as departures in the last year that an inventor is observed patenting for the old firm.

In Table 8, we present linear probability model estimates for Equation 4. The coefficient estimates suggest that a one standard deviation tightening in the constraints of an inventor's current employer increases the chance that the inventor leaves for a competitor by .35-1.92 percentage points, which represents 15.6-60.5% of the unconditional sample average propensity to leave (3.17%). This evidence is consistent with our analysis at the firm-level. We report results from probit specifications of Equations 3 and 4 in the Internet Appendix in Tables IA9 and IA10, respectively.

8 Robustness

In this section, we outline supplemental analyses that test the robustness of our findings. We start by demonstrating that our method of using the cross-referencing of patents to define peers characterizes competitive relationships. We then show that our findings hold under a variety of settings and specifications.

8.1 Alternative Definitions of Peers

It is important that our approach to defining peers is indeed picking up relationships between competitors rather than between vertically related firms. For instance, it may be the case that firms "fill in the gap" for allies that are too constrained to develop the necessary innovation to compete in a technology market. This could partially explain the increase in patent applications that we observe in response to a tightening of peer firm constraints. For this reason, we purged our citation-based competitor network of firms identified as strategic alliances, joint ventures, or supply chain partners throughout our analysis. To further mitigate this concern, we examine the association between a firm's patenting activity and the financing constraints of a firm's supply chain partners. We create a new measure, $FC\_supplychain$, which is the average financial constraints across a firm's major customers (suppliers) listed in the Compustat historical segment file in a given year. This is analogous to our definition of $CompConst$.

Table IA8 of the Internet Appendix reports OLS regression estimates that test the relationship between patent applications (citations) and customer-supplier financing constraints. This analysis is similar to the specification of Table 2, but Table IA8 uses supply chain relationships instead of inter-firm patent citations to define peers. The customer-supplier specification is intended to serve as a placebo test for our main results. Columns 1-4 include include firm fixed effects transformations to account for investment heterogeneity across firms and year dummies to account for aggregate shocks to patenting activity. Columns 5-8 include $Industry \times Year$ fixed effects, which allows time-varying shocks to investment to have a heterogenous effect across industries.

The relationship between $FC\_supplychain$ and measures of corporate innovation is statistically insignificant in seven out of the eight specifications reported in Table IA8. This is despite a similar number of observations in our analysis in Table 2. These tests do not provide conclusive evidence that supplier or customer financial constraints are not important to firm innovation. However, these results suggest that our main findings in Table 2 are not driven by a mischaracterized classification of competitors (i.e., customers or suppliers).

8.2 Additional Analysis

In addition to checking that our networks properly characterize competitive relationships, we also perform extensive robustness analysis of our findings. In Table IA1, we estimate our specifications from Table 2 with $Industry \times Year$ dummy variables instead of $Year$ dummies, according to the Fama-French 48 industry classifications. In Table IA2, we estimate Equation 1 (Panel B of Table 2) with 2-year and 7-year competitor relationships instead of the 5-year assumption in our general analysis. In Table IA3, we estimate Equation 2 using different metrics to calculate patent portfolio similarity. Specifically, we use Euclidean distance and pairwise correlations to measure the pairwise overlap in competitor portfolios.

Finally, we allow for nonlinear specifications in our patent variable specifications in Table 2, as well as in our inventor poaching analysis in Tables 7 and 8. Specifically, in Table IA8, we estimate a Poisson specification of Panel B from Table 2; and in Tables IA9 and IA10, we estimate logit specifications of Equations 3 and 4 (Tables 7 and 8). Overall, the results from our robustness analysis are consistent with the analysis presented in the main text. While there are likely problems that we have not accounted for, the consistency of our results increases our confidence that we have documented a first-order relationship between competitor financing constraints and investment behavior.

9 Conclusion

A large and growing literature in corporate finance has aimed to understand the effects of financial constraints on corporate investment decisions. Most empirical work in this area implicitly assumes that firm decisions depend on their own constraints and are independent of the constraints of competitors or peers. This assumption is often driven by limited data on meaningful firm relationships and limited data about the composition of a firm's investments. Naturally, these limitations produce challenges for identifying a potential relation between investment decisions and competitor constraints.

In this paper, we attempt to overcome these obstacles by using two novel approaches to identify competitor networks and examine whether competitor financing constraints influence a firm's own investment opportunities. First, we classify competitors according to text-based product similarities developed by Hoberg and Phillips (2015), who assign pairwise similarity scores constructed from a comparison of firms' 10-K product market vocabularies. Second, we exploit the cross-referencing of patent citations to classify firms that compete in closely related production technologies. We then compute pairwise patent portfolio similarities to measure the degree of technological overlap between two competitors in a given year. This detailed information regarding product mix and patent portfolios allows us to study the nature of a firm's investment decisions regarding the type of investment made, and it allows us to study how investment decisions might depend on the actions or characteristics of competitors.

In a standard panel data framework, we find evidence that firms increase their level of investment spending in response to a tightening in competitor constraints, holding a firm's own constraints constant. To augment this evidence, we also consider shifts in the type of activity that firms pursue when competitor constraints become more binding. Firms appear to shift their investment composition towards that of relatively constrained competitors and away from that of unconstrained competitors.

Under fairly standard assumptions, the intransitive nature of our competitor networks allows us to control for selection and for correlated effects across competitors through firm-year and competitor-pair fixed effects transformations. To further mitigate endogeneity concerns, we exploit two plausibly exogenous shocks to competitor constraints that should not have a direct impact on a firm's own investment or patenting behavior. Specifically, we exploit the

American Jobs Creation Act of 2004 and the junk bond crisis of 1989 as a positive and a negative shock, respectively, to competitor financial constraints. Implementing these shocks in a difference-in-differences framework, we find evidence consistent with our initial results. Finally, we provide evidence that firms are more likely to hire inventors recently employed by a competitor when that competitor's constraints become more binding. These results further suggest that competitor constraints are not merely a proxy for latent unobservable common factors, but instead directly influence a firm's investment opportunities.

In summary, we provide evidence that financial constraints not only limit a firm's own spending, but also invite competition in the form of increased investment by competitors. This competitive feedback effect can potentially inflict damage in the long run, thus creating a permanent component to financing constraints. Our results also suggest that firms "fill in the gap" for the forgone investments of constrained competitors. This effect may potentially reduce the social loss from underinvestment due to financing frictions. Quantifying the long-run costs of financing constraints and evaluating the net welfare effect of competitors' reactions are potentially fruitful avenues for future research.

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Table 1: Summary Statistics

Summary statistics are reported for the citation-based network of competitors that we develop in this paper, and for the text-based network of competitors developed in Hoberg and Phillips (2015). Statistics are reported for firm-year observations in Panel A and pairwise competitor-year observations in Panel B. To compute *MD*, we calculate the Mahalanobis Distance between a firm's patent portfolio over the following three years and a that of its competitor over the previous 5-year period. A lower value represents patent portfolios that are closer in covariance-weighted distance, or are more similar. For *Prod Similarity*, we use pairwise cosine similarities between two firms' product description from their 10-Ks, as developed by Hoberg and Phillips (2015). A higher *Prod Similarity* indicates a greater similarity between two firms' product market descriptions. As measures of constraints, we use the Hadlock and Pierce (2010) Size-Age (*SA*) index, the Whited and Wu (2006) (*WW*) index, and the Hoberg and Maksimovic (2015) Delayed-Investment (*Delay*) index. All variables are winsorized at the 1% level (1% in each tail) and defined in the Internet Appendix. The financial constraint variables are standardized to have a mean of 0 and a standard deviation of 1 in the firm-level sample.

	Citation-Based Network (1980 - 2006)			Text-Based Network (1996 - 2012)		
	Mean	Median	SD	Mean	Median	SD
Panel A: Firm-Specific Variables						
Log(Assets)	4.690	2.166	4.558	3.955	3.867	2.004
Capx/Assets	0.064	0.060	0.049	0.070	0.037	0.105
R&D/Sales	0.234	0.740	0.046	0.276	0.002	1.032
Cash + equiv/Assets	0.198	0.214	0.112	0.214	0.118	0.234
PP&E/Assets	0.256	0.170	0.225	0.256	0.174	0.233
Market-to-book	2.144	1.647	1.573	2.140	1.472	2.092
Book Leverage	0.197	0.185	0.170	0.218	0.164	0.228
EBITDA/Assets	0.091	0.213	0.130	0.032	0.103	0.340
Adjusted Patents	0.533	0.795	0.191			
Adjusted Citations	1.640	1.681	1.256			
WW	0.000	0.012	1.000	0.000	-0.088	1.010
SA	0.000	0.018	1.000	0.000	0.001	1.003
Delay	0.000	0.005	0.973	0.000	0.003	0.998
Observations	21,458			63,429		
Panel B: Competitor-Pair Averages						
MD	0.276	0.225	0.218			
Prod Similarity				0.051	0.034	0.051
WW	-0.002	-0.019	1.001	-0.168	-0.214	0.891
SA	-0.001	-0.028	1.000	-0.171	-0.218	0.775
Delay	-0.003	-0.186	0.998	0.291	0.224	1.048
No. of Links per Firm	27.688	10.000	41.663	66.39	35.00	96.66
Observations	594,149			4,211,311		

Table 2: Corporate Investment and Competitor Constraints

OLS regression estimates are reported for the relationship between corporate investment and competitor financing constraints. The dependent variables include the natural log of truncation-adjusted patents (plus one) applied for in year t (*Adj Pat*), the natural log of adjusted citations (plus one) for patents applied for in t (*Adj Cite*), capital expenditures scaled by lagged assets (*Capx/Asset*), and R&D expenses scaled by sales (R&D/Sale). We calculate average competitor constraints (*Comp Const.*) and a firm's own constraints (*Own Const.*) according to the *WW* Index (Columns 1-2), the *SA* Index (Columns 3-4), and the *Delay* Index (Columns 5-6). We include *Log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets*, and analogous competitor averages (all lagged one period) as control variables. All specifications include firm fixed effects transformations and year dummies. Results for specifications with firm and industry×year (Fama-French 48) fixed effects transformations are reported in Table IA1 of the Internet Appendix. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail).

	WW		SA		Delay	
Panel A: Text-Based Network (1996-2012)						
	Capx/Asset	R&D/Sale	Capx/Asset	R&D/Sale	Capx/Asset	R&D/Sale
Comp Const.	0.0032***	0.0185***	0.0021***	0.0118**	0.0012**	0.0151***
	(0.0006)	(0.0031)	(0.0004)	(0.0050)	(0.0005)	(0.0036)
Own Const.	-0.0462***	-0.1814***	-0.0163***	-0.0059	-0.0009*	0.0032
	(0.0027)	(0.0203)	(0.0013)	(0.0104)	(0.0005)	(0.00)
R-squared	0.6631	0.8412	0.6594	0.8407	0.6598	0.8594
Observations	63,429	63,429	63,429	63,429	43,597	43,597
Panel B: Citation-Based Network (1980-2006)						
	Adj Pat	Adj Cite	Adj Pat	Adj Cite	Adj Pat	Adj Cite
Comp Const.	0.0876***	0.173***	0.140***	0.266***	0.0856***	0.1106***
	(0.012)	(0.0216)	(0.016)	(0.0297)	(0.0136)	(0.0387)
Own Const.	-0.118***	0.00135**	-0.330***	0.00112	-0.0002	0.0143
	(0.014)	(0.0006)	(0.033)	(0.0008)	(0.0051)	(0.0147)
R-squared	0.843	0.792	0.846	0.795	0.8232	0.7909
Observations	21,458	21,458	21,458	21,458	15,956	15,956
Firm FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Table 3: Investment Similarity and Competitor Constraints

OLS regression estimates are reported for the relationship between investment composition similarity and competitor financing constraints. Analysis in this table is conducted at the yearly competitor-pair level. The dependent variable in Panel B is the pairwise cosine similarity in product market descriptions (*Prod Similarity*) between two firms according to the text-based network of competitors developed by Hoberg and Phillips (2015) from 1996-2012. A higher *Prod Similarity* indicates a greater similarity between two firms' 10-K product descriptions. The dependent variable in Panel B is the Mahalanobis Distance (*MD*) between a firm's patent portfolio over the following three years and a that of its competitor over the previous 5-year period according to our citation-based network of competitors from 1980-2006. A lower value represents patent portfolios that are closer in covariance-weighted distance, or are more similar. We calculate competitor constraints (*Comp Const.*) and a firm's own constraints (*Own Const.*) according to the *WW* Index (Columns 1-3), the *SA* Index (Columns 4-6), and the *Delay* Index (Columns 7-9). We include *Log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets*, and those of its competitors (all lagged one period) as control variables. Specifications include firm fixed effects transformations and year dummies in Columns 1, 4, and 7; competitor-pair fixed effects transformations in Columns 3, 6, and 9; and firm×year dummies in Columns 2-3, 5-6, and 8-9. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail). Results from Tobit specifications are reported in Table IA7 of the Internet Appendix.

	WW			SA			Delay		
	Panel A: Text-Based Product Market Similarity								
Comp Const.	0.008***	0.003*	0.003***	0.008***	0.002**	0.003	0.0025***	0.0026***	0.003***
	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)
Own Const.	-0.0011***			-0.0021***			0.002		
	(0.0002)			(0.0006)			(0.001)		
R-squared	0.3461	0.3997	0.8665	0.3461	0.3997	0.8665	0.2318	0.2583	0.8514
Observations	4,211,311	4,211,311	4,211,311	4,211,311	4,211,311	4,211,311	1,927,573	1,927,573	1,927,573
	Panel B: Patent Portfolio Similarity (Mahalanobis Distance)								
Comp Const.	-0.1285***	-0.1302***	-0.0325***	-0.0852***	-0.0876***	-0.0058***	-0.166***	-0.1694***	-0.0092***
	(0.0043)	(0.0129)	(0.0008)	(0.0031)	(0.0028)	(0.0001)	(0.0086)	(0.0085)	(0.0032)
Own Const.	-0.0089			0.0156			-0.0056		
	(0.0109)			(0.0211)			(0.0139)		
R-squared	0.395	0.462	0.899	0.252	0.3067	0.9157	0.2836	0.3172	0.9431
Observations	594,149	594,149	594,149	594,149	594,149	594,149	89,251	89,251	89,251
Firm & Year	✓			✓			✓		
Firm × Year		✓	✓		✓	✓		✓	✓
Competitor Pair			✓			✓			✓
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4: AJCA Tax Holiday

Estimates are reported for difference-in-differences and triple-differences specifications using the 2004 AJCA tax holiday as a treatment event. We use two years of data both before and after the event for the sample period 2002-2006. The dependent variables include the natural log of truncation adjusted patents (plus one) applied for in year t (*Adj Pat*), the natural log of adjusted citations (plus one) for patents applied for in year t (*Adj Cite*), capital expenditures scaled by lagged assets (*Capx/Asset*), and R&D expenses scaled by sales (R&D/Sale). We define *Treated* firms as those with competitors that averaged at least 33% of pre-tax income from abroad during 2002-2003. For the specifications reported in this table, we exclude firms with any foreign profits themselves from the treatment and control groups. We define *Comp Pre-const.* as an indicator variable equal to one if a firm's pre-treatment average competitor constraints from 2002-2003 rank above the full sample median for the same period according to the *WW* Index (Columns 3-4), the *SA* Index (Columns 5-6), and the *Delayed Investment* Index (Columns 7-8). All specifications include firm fixed effects transformations and year dummies, which subsume the *Post, Treated, Comp Pre-const., and Treated×Comp Pre-const.* variables. For expositional convenience, we do not report the coefficient for *Post×Comp Pre-const.*. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail). Results from a specification in which we allow treated and control firms to have nonzero foreign income under 33%, and from falsification tests are reported in Tables IA4 and IA5, respectively, of the Internet Appendix.

			WW		SA		Delay	
Panel A: Text-Based Network								
	Capx/Asset	R&D/Sale	Capx/Asset	R&D/Sale	Capx/Asset	R&D/Sale	Capx/Asset	R&D/Sale
Treated×Post	-0.0056	-0.1072***	-0.0045	0.0297	-0.0039	-0.023	-0.0617**	-0.0425*
	(0.0035)	(0.0365)	(0.0045)	(0.0496)	(0.0046)	(0.0480)	(0.0293)	(0.0235)
Treated×Post× Comp Pre-const.			-0.0018	-0.3723***	-0.0013	-0.2576***	-0.1501*	-0.0650**
			(0.0070)	(0.0777)	(0.0069)	(0.0794)	(0.0771)	(0.0288)
R-squared	0.5256	0.8502	0.5345	0.8384	0.5342	0.8383	0.5347	0.7646
Observations	6,305	6,305	6,305	6,305	6,305	6,305	6,305	6,305
Panel B: Citation-Based Network								
	Adj Pat	Adj Cite	Adj Pat	Adj Cite	Adj Pat	Adj Cite	Adj Pat	Adj Cite
Treated×Post	-0.0679***	-0.278***	-0.0929***	-0.316***	-0.0673**	-0.230***	-0.0043	-0.1459
	(0.0187)	(0.0526)	(0.0268)	(0.0724)	(0.0307)	(0.0830)	(0.0542)	(0.1168)
Treated×Post× Comp Pre-const.			-0.0627**	-0.149**	-0.033	-0.108*	-0.118***	-0.425***
			(0.0265)	(0.0605)	(0.0227)	(0.0551)	(0.0241)	(0.0715)
R-squared	0.819	0.781	0.829	0.789	0.823	0.787	0.8207	0.7829
Observations	3,256	3,256	3,256	3,256	3,256	3,256	3,256	3,256
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 5: AJCA Tax Holiday and Product Market Similarity

Estimates are reported for difference-in-differences and triple-differences specifications using the 2004 AJCA tax holiday as a treatment event. Analysis in this table is conducted at the yearly competitor-pair level. The dependent variable is the pairwise cosine similarity in product market descriptions (*Prod Similarity*) between two firms in the text-based network of competitors developed by Hoberg and Phillips (2015). We use two years of data both before and after the event for the sample period 2002-2006. We define firm-competitor relationships as *Treated* if the given competitor earned an average of at least 33% of pre-tax income from abroad during 2002-2003. Note that a given firm can have both post-treated and untreated observations within the same year. For the specifications reported in this table, we exclude firms with any foreign profits themselves from the treatment and control groups. We define *Comp Pre-const.* as an indicator variable equal to one if competitor's average constraints rank above the median from 2002-2003 according to the *WW* Index (Columns 3-4), the *SA* Index (Columns 5-6), and the *Delayed Investment* Index (Columns 7-8). Specifications include firm fixed effects transformations and year dummies in Columns 1, 3, 5, and 7; competitor-pair fixed effects transformations in all Columns, and and firm×year dummies in Columns 2, 4, 6, and 8. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail). Results from a specification in which we allow treated and control firms to have foreign operations under 33%, and from falsification tests are reported in Tables IA4 and IA5, respectively, of the Internet Appendix.

			WW		SA		Delay	
	Text-Based Product Market Similarity							
Treated×*Post*	-0.0011***	0.0028	-0.0021***	-0.0020***	-0.0016	-0.0017*	-0.0004	-0.0002
	(0.0004)	(0.0019)	(0.0005)	(0.0005)	(0.0010)	(0.0009)	(0.0002)	(0.0002)
Treated×*Post*× Comp Pre-const.			-0.0063***	-0.0064***	-0.0003	-0.0006*	-0.0064***	-0.0082***
			(0.0016)	(0.0017)	(0.0003)	(0.0003)	(0.0025)	(0.0022)
Post× Comp Pre-const.			-0.0038***	-0.0019***	-0.0007***	-0.0003***	-0.0002	0.0006
			(0.0011)	(0.0006)	(0.0002)	(0.0001)	(0.0019)	(0.0010)
R-squared	0.8391	0.8656	0.8445	0.8695	0.8444	0.8695	0.8479	0.8704
nobs	187,901	187,901	187,901	187,901	187,901	187,901	187,901	187,901
Firm	✓		✓		✓		✓	
Year	✓		✓		✓		✓	
Firm × Year		✓		✓		✓		✓
Competitor Pair	✓	✓	✓	✓	✓	✓	✓	✓

Table 6: The Junk Bond Crisis, Competitor Constraints, and Corporate Investment

Estimates are reported for difference-in-differences specifications using the 1989 junk bond crisis as a treatment event. We use two years of data both pre- and *Post*- 1989 for the sample period 1987-1991 in Columns 1-4 (firm-level observations). In Columns 5-6, the dependent variable is the Mahalanobis Distance (*MD*) between a firm's patent portfolio over the following three years and a that of its competitor over the previous 5-year period according to our citation-based network of competitors. Because *MD* uses three years of forward data, we take the difference in MD between 1989 and 1986 to avoid using any post treatment period patents to construct the treatment group outcome variable during the pre-treatment period. Thus, there is effectively one observation per competitor pair in Columns 5-6. A lower value represents patent portfolios that are closer in covariance-weighted distance, or are more similar. We define *Treated* firms in Columns 1-4 as those with at least one competitor that held a junk debt rating 1989. In Columns 5-6, we define *Treated* firms as competitor pair observations in which the competitor held a junk debt rating in 1989. The variable of interest is the interaction effect (*Treated x Post*). Columns 1-4 include firm and year fixed effects transformations, which subsume the *Treated* and *Post* variables. Control variables are all lagged by one period. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail). Results from falsification tests of the analysis in this table are reported in Table IA8 of the Internet Appendix.

	Capx/Asset		R&D/Sale		Adj Patent		Adj Cite		ΔMD	
Treated×*Post*	0.0109**	0.0099**	0.0520**	0.0427**	0.0457	0.0575	5.0345***	5.1964***	-0.0277***	-0.0188***
	(0.0050)	(0.0045)	(0.0215)	(0.0213)	(0.1761)	(0.1784)	(2.0201)	(2.0397)	(0.0031)	(0.0031)
EBITDA/ASSETS		0.0280***		-0.036		-0.1643		-12.3674		0.0277*
		(0.0102)		(0.0598)		(0.5706)		(9.5615)		(0.0152)
LOG(sales)		0.0028		0.0315*		0.4027***		8.7857***		-0.0015**
		(0.0038)		(0.0174)		(0.1382)		(2.5324)		(0.0006)
Market-to-book		0.0049***		0.0012		-0.0251		0.3132		0.0035
		(0.0016)		(0.0087)		(0.0502)		(0.7651)		(0.0025)
Cash + equiv/Assets		0.0089		0.6016***		-1.2052***		-15.5490**		-0.0069
		(0.0132)		(0.0686)		(0.4485)		(7.5556)		(0.0129)
PP&E/Assets		0.2192***		0.4259***		-2.8280*		-16.3915		0.0056
		(0.0290)		(0.1024)		(1.5614)		(21.5531)		(0.0068)
Comp EBITDA/ASSETS		0.0169		0.1305		1.5183*		25.9416*		0.1754***
		(0.0447)		(0.2187)		(0.8770)		(13.6734)		(0.0215)
Comp LOG(sales)		0.0021		-0.0146		-0.2582***		-5.3227***		0
		(0.0030)		(0.0150)		(0.0860)		(1.3441)		(0.0006)
Comp Market-to-book		-0.0007		-0.0824***		-0.2734*		-7.5523***		-0.0087***
		(0.0057)		(0.0279)		(0.1485)		(2.5292)		(0.0030)
Comp Cash + equiv/Assets		0.0357		0.6289***		2.5284**		35.4299**		0.2097***
		(0.0473)		(0.2251)		(1.1745)		(15.6212)		(0.0168)
Comp PP&E/Assets		-0.0458		0.1284		0.3962		15.2002		-0.0506***
		(0.0376)		(0.2088)		(0.8763)		(13.3487)		(0.0065)
R-squared	0.6827	0.7203	0.767	0.7774	0.9745	0.9749	0.9712	0.9718	0.0184	0.1285
nobs	2,763	2,763	2,763	2,763	2,763	2,763	2,763	2,763	3,842	3,842
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: Inventor Poaching and Competitor Constraints

Linear probability model estimates are reported for the relationship between inventor poaching and competitor constraints. The analysis presented in this table is conducted at the firm level. The binary dependent variable *Poach* is equal to 1 if an inventor listed on a competitor's patent application in year t is subsequently listed on a firm's own patent application from years $t+1$ to $t+5$ (and listed on no other firms' patent applications during the interim period). We exclude inventors who moved between more than two firms in a given 5-year period, and we only count inventors as poached in the earliest year that we observe them switching between a given competitor-pair. Data on individual inventors come from the Harvard Patent Database inventor file (see (Lai et al., 2014)). We calculate average competitor constraints (*Comp Const.*) and a firm's own constraints (*Own Const.*) according to the *WW* Index (Columns 1-2), the *SA* Index (Columns 3-4), and the *Delay* Index (Columns 5-6). The control variables *Log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets*, and analogous competitor averages are measured at time *t*. The specifications in all columns include firm and year fixed effects transformations. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail). Results from probit specifications are reported in Table IA9 of the Internet Appendix.

	WW		SA		Delay	
	Poach Competitor Investor					
Comp Const.	0.0322***	0.0639***	0.0440***	0.0753***	0.0088***	0.0077*
	(0.0047)	(0.0108)	(0.0052)	(0.0109)	(0.0025)	(0.0044)
Own Const.	-0.0306***	-0.0190***	-0.0713***	-0.0531***	-0.0045	-0.0029
	(0.0050)	(0.0049)	(0.0087)	(0.0106)	(0.0041)	(0.0043)
EBITDA/Assets		0.0048		0.0049		0.0165
		(0.0165)		(0.0163)		(0.0203)
Log(Sales)		0.0241***		0.0149***		0.0152**
		(0.0047)		(0.0053)		(0.0061)
Market-to-book		0.0103***		0.0105***		0.0111***
		(0.0021)		(0.0021)		(0.0023)
Cash + equiv / Assets		-0.0187		-0.0305		-0.0144
		(0.0188)		(0.0189)		(0.0234)
PP&E/ Assets		0.0594		0.0501		0.1287**
		(0.0373)		(0.0373)		(0.0516)
Comp.		0.2474***		0.2791***		-0.0842
EBITDA/Assets		(0.0809)		(0.0818)		(0.0983)
Comp.		0.0266***		0.0183**		0.0398***
Log(Sales)		(0.0102)		(0.0090)		(0.0119)
Comp.		0.0075		0.0028		0.0049
Market-to-book		(0.0074)		(0.0073)		(0.0080)
Comp.		0.0738		-0.0110		-0.0351
Cash + equiv/Assets		(0.0813)		(0.0805)		(0.1006)
Comp.		-0.1401*		-0.0590		-0.1171
PP&E/ Assets		(0.0745)		(0.0752)		(0.1182)
R-squared	0.4007	0.4174	0.4037	0.4196	0.4258	0.4393
Observations	20,306	20,306	20,306	20,306	13,263	13,263
Firm	✓	✓	✓	✓	✓	✓
NEI	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓

Table 8: Inventor Departures and Financial Constraints

Linear probability model estimates are reported for the relationship between a firm's financial constraints and inventor departures for competitors. The analysis presented in this table is conducted at the inventor level. The binary dependent variable *Departure* is equal to 1 if an inventor listed on a firm's patent application in year t is subsequently listed on a competitor's patent application (and listed on no other firms' patent applications) from years t to $t+5$. Inventors listed on multiple patents for the same firm with fewer than five years in between are assumed to be employed at the firm during the interim period, as long as they are not listed on patents issued by other firms during that time. We exclude inventors who moved between more than two firms in a given 5-year period, and we only count switches as departures in the last year an inventor is observed patenting for the old firm. Data on individual inventors come from the Harvard Patent Database inventor file (see (Lai et al., 2014)). We calculate constraints (*Own Const.*) according to the *WW* Index (Columns 1-2), the *SA* Index (Columns 3-4), and the *Delay* Index (Columns 5-6). The control variables *Log(Sales), Market-to-book, EBITDA/Assets, PP&E/Assets, Cash + equiv/Assets* are measured at time t. The specifications in all columns include inventor and year fixed effects transformations. Standard errors clustered at the firm level are reported in parentheses below coefficient estimates. All variables are winsorized at the 1% level (1% in each tail). Results from probit specifications are presented in Table IA999 of the Internet Appendix.

	WW		SA		Delay	
	Inventor Departes for Competitor					
Own Const.	0.0192***	0.0045**	0.0189***	0.0037	0.0042***	0.0035***
	(0.0017)	(0.0019)	(0.0023)	(0.0035)	(0.0013)	(0.0013)
EBITDA/Assets		-0.0653***		-0.0663***		-0.0909***
		(0.0070)		(0.0070)		(0.0125)
Log(Sales)		-0.0071***		-0.0079***		-0.0073***
		(0.0011)		(0.0014)		(0.0028)
Market-to-book		-0.0038***		-0.0039***		-0.0058***
		(0.0004)		(0.0004)		(0.0008)
Cash + equiv / Assets		0.0347***		0.0353***		0.0697***
		(0.0060)		(0.0060)		(0.0101)
PP&E/ Assets		0.0166*		0.0178*		-0.0193
		(0.0094)		(0.0096)		(0.0214)
R-squared	0.3353	0.3363	0.3350	0.3363	0.4490	0.4505
Observations	435,618	435,618	435,618	435,618	145,975	145,975
Inventor	✓	✓	✓	✓	✓	✓
NEI	✓	✓	✓	✓	✓	✓
Application Year	✓	✓	✓	✓	✓	✓