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 interfirm patent citations and text-based product market similarities to identify intransitive competitor networks, we find that firms increase investment spending, patenting activity, and opportunistic hiring when competitor constraints become more binding. In addition, firms shift their investment composition (product market and patent portfolios) to compete more aggressively with relatively constrained 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 we find similar effects. (*JEL* G30, G32, O31, M54)

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A large body of literature in corporate finance 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. If externalities exist, they should be further understood to help gauge the welfare implications of financial constraints. While related effects have been studied in the context of decisions related to capital structure, cash holdings, product pricing, and firm location (Leary and Roberts (2014); Shleifer and Vishny (1992); Hoberg et al. (2014); Chevalier (1995a); Cookson (2010)), this possible effect of financial constraints on competitor investment decisions has not been widely explored.

In this paper, 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 competitor financial constraints can impose both positive externalities (e.g., reduced competition) and negative externalities (e.g., reduced collateral values, less knowledge spillover). Our empirical findings suggest that firms generally increase their investment spending when competitor financial constraints become more binding. Moreover, firms appear to tilt their investment composition to compete more aggressively with these relatively constrained competitors.

A variety of theoretical models formalize the idea that financial health may expose a firm to aggressive investment behavior by its competitors (e.g., Fudenberg and Tirole (1986); Bolton and Scharfstein (1990)). In addition, traditional theories of competition suggest that, all else equal, rivals choose to differentiate products to reduce competition (e.g., Hotelling (1929); Salop (1979)). By limiting a firm's ability to invest, financial constraints can reduce a firm's ability to compete with product market rivals. It follows from theory that the incentives for healthy rivals to differentiate from a constrained firm may be mitigated by the anticipation of reduced competition. Furthermore, healthy rivals may attempt to capture market share by encroaching on a constrained firm's product market, which would result in less product differentiation.

While theoretically appealing, testing hypotheses regarding competitor interactions and investment composition is challenging. In particular, that most empirical measures of corporate investment are restricted to aggregate spending at the firm level precludes their ability to measure shifts in the type of investment made. Furthermore, competitors are typically defined according to coarse industry classifications that assume static and transitive relationships. These features impose the assumption that firms react identically to intragroup externalities, which makes it difficult to separate variation in competitor financial constraints from industry shocks (Lang and Stulz, 1992). Overall, these limitations impede the ability to measure responses in investment to changes in competitor characteristics or actions.

We overcome these obstacles by using two novel procedures to identify competitor networks. Our first approach, the *text-based* approach, borrows from Hoberg and Phillips (2016), who create a pairwise measure of competition based on similarities in the textual descriptions of firms' product market activities. We use these product similarities to define our text-based network of competitors. Our second approach, the *citation-based* approach, exploits the cross-referencing of patent citations to identify firms with closely related production technologies. We use this cross-referencing to compute a pairwise measure of patent portfolio distance based on the degree of technological overlap between two competitors in any given year.

Importantly, both approaches allow each firm to have a unique set of competitors that vary through time.[1] This feature better reflects economic reality and facilitates identification strategies that are not possible with standard transitive industry classifications.[2] Furthermore, we can examine how firms alter their investment composition in response to a tight-

[1]For example, PepsiCo competes with Coca-Cola in beverages and also with Kellogg in breakfast food manufacturing; however, Coca-Cola and Kellogg are not direct competitors with each other.

[2]In particular, our intransitive competitor networks allow us to control for selection effects and for correlated effects across competitors by including firm-year or competitor-pair fixed effects (Topa and Zenou (2015); Liu and Lee (2010); Liu et al. (2012)).

ening in a particular competitor's constraints, or in response to a shift in relative constraints within their set of competitors.

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 1-standard-deviation tightening in lagged competitor constraints is associated with a 6.4%–22.9% (6.9%–17.7%) increase in patent applications (citations) and a 2.9%–4.7% (7.7%–16.8%) increase in capital expenditures (research and development, or R&D).[3]

To augment our evidence on the level of investment activity, we consider shifts in the composition of a firm's investment using product positioning and patent portfolios. Furthermore, we exploit the information in our competitor networks to isolate competitor-specific responses. We find that a 1-standard-deviation tightening in a given competitor's constraints leads a firm to increase its product market similarity (decrease patent portfolio distance) with its competitor by 3.5%–6.7% (1.0%–4.4%). These results are consistent with firms shifting investment spending to compete more aggressively with constrained competitors.

While our initial evidence is suggestive, one may be concerned about 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. Additionally, measurement error or omitted variables could lead to endogenous correlations between investments and financial constraints that we cannot perfectly control for in our empirical models. For instance, more innovative investments may exhibit a higher degree of credit rationing, perhaps because of

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

greater cash flow uncertainty or a greater reliance on inalienable human capital (i.e., Hart and Moore (1994)). If this is the case, financing constraints might be positively associated with more innovative or fruitful markets, which firms may choose to invest in more aggressively for reasons other than the competitive channel we have posited. While our ability to control for unobserved heterogeneity at the competitor-pair and firm-year levels mitigates these types of concerns, 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 only affect a firm's own investment opportunities through their effects on competitor constraints. First, the American Jobs Creation Act (AJCA) of 2004 effectively relaxed constraints for firms with foreign operations by lowering the tax rate on cash harvested from abroad. Second, the 1989 junk bond crisis tightened constraints sharply for firms that relied on this market as a major source of finance.

We define the treatment group for the AJCA (junk bond crisis) to include firms without foreign operations (junk debt), but only those firms whose competitors earned income abroad from 2001 to 2003 (relied on junk debt before 1989). By construction, neither event should provide direct incentives to invest/disinvest for the treatment groups. Thus, any changes in investment behavior should be primarily driven by changes in the financial strength of competitors. When using the variation in constraints-driven by these plausibly exogenous events, the 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 to compete more intensely (less intensely) with relatively constrained (unconstrained) competitors. Additionally, we show that these effects are concentrated on firms that have the most constrained competitors.

As a final step toward showing that competitor constraints alter investment behavior, we provide evidence that firms are more likely to opportunistically hire inventors recently employed by a competitor when that competitor's constraints become more binding. Specifically, a 1-standard-deviation tightening in competitor constraints corresponds to a 13.7%

to 20.1% standard deviation increase in the probability of opportunistic hiring, using either the *WW* or *SA* measures of constraints, and a 3.1% to 3.7% standard deviation increase is observed using the *Delay* index. This effect holds when we include firm fixed effects 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 control for unobserved heterogeneity, such as inventor mobility, by including inventor fixed effects. These results further suggest that competitor constraints are not merely a proxy for unobservable common factors; rather, they directly influence a firm's investment decisions.

Our analysis of investment composition relates to economic theories that cannot be tested by exclusively examining investment levels. Our findings are consistent with theories of product differentiation that formalize how competitors choose product characteristics in anticipation of future price competition (e.g., Hotelling (1929); Salop (1979)). These models conceive the principle of differentiation, which suggests that, all else equal, competitors maximize profits by differentiating as much as possible (Tirole, 1988). However, financial constraints may limit a competitor's ability to invest and therefore limit their ability to compete in the future. In anticipation of weaker competition, a relatively unconstrained firm may choose to decrease product differentiation from a constrained competitor to capture market share. Consistent with this notion, we observe that firms shift their investment spending to compete more aggressively with constrained competitors, suggesting they decrease differentiation when anticipated competition is reduced.

Our findings for R&D and patent activity suggest that, in conjunction with shifting resources to compete more intensely with constrained rivals, firms exploit this opportunity to establish barriers to competition. These barriers could come from reducing marginal costs (improving production efficiency), which is consistent with the classic result of the Cournot (1836) model in which a firm's market share increases as its marginal costs become relatively lower than that of rivals. Additionally, the increase in R&D (patent activity) that we observe could suggest that firms are establishing barriers to competition by improving the relative attributes of their products, consistent with the theory in Sutton (1991).

In summary, our findings provide new insights regarding the implications of financial 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 is potentially mitigated by competitors "filling in the gap" of constrained firms.[4] 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 their empirical specifications.

1 Literature Review

Our study closely relates 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 studies find 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); 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) that provides evidence that firms increase investment when competitors with defined-benefit pensions have unexpected

[4] Of course, the resultant industrial organization largely determines the existence, and degree, of benefits for consumers.

increases in required contributions. Our study broadens Rauh's results to a larger and more general sample. In addition, we can study changes in the composition of investment in response to tightening competitor constraints, which allows us to relate our results to a broader set of economic theories. Furthermore, by using time-varying and 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 the opportunistic hiring of inventors 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 higher future rents (e.g., Fudenberg and Tirole (1986); Bolton and Scharfstein (1990)). Because of data limitations, empirical studies on predation typically focus on a particular industry. For example, Chevalier (1995a,b) studies predation in supermarkets during the LBO boom of the late 1980s, and Cookson (2010, 2017) studies predation in the casino and gaming industry. We contribute to this literature by broadening the analysis to a general sample of firms, as well as studying the effect of competitor health on the composition of a firm's investment. Furthermore, we focus on cases 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.[5]

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 (Fresard, 2010), consistent with predicted equilibrium product market choices. 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 fluid. These findings are consistent with the evidence

[5] Almeida and Philippon (2007) provide a detailed description of the infrequency of bankruptcies for public corporations in the United States.

that we provide, which suggests that firms take advantage of constrained rivals.

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 force managers to weed out less valuable intangible projects, and with Brown et al. (2012), who find that R&D is exceptionally sensitive to financial constraints. Our results are consistent with these findings, because they suggest that financial constraints hinder a firm's intangible investment. Although these studies focus on the impact of financing frictions on a firm's own investment, we show that financial constraints also affect the investment decisions of competitors.

Our discussion has centered on the externalities that financial constraints may impose on competitor investment decisions. However, financial constraints may also influence aspects of complementary firm relationships. While much of the evidence on complementary relationships suggests an adverse shock to a firm's financial condition results in a contagion effect, it is plausible that, in some cases, a customer (supplier) can shift resources to "fill in the gap" for a constrained supplier (customer), which would be consistent with the results that we document.[6] To isolate the role that financial constraints play in competitor interactions, we attempt to purge complementary relationships from our citation-based network by following a procedure similar to Hoberg and Phillips (2016), who remove vertically related firms from their text-based network. Nonetheless, we cannot rule out that some remaining links in our network are complementary in nature.

Of course, complementary relationships may exist even for product market rivals. For instance, a large literature suggests that knowledge spillovers are a byproduct of competition (e.g., Bloom et al. (2013)). In our setting, competitors forced to forgo projects because of financing constraints reduce the potential for knowledge spillovers. In addition, contagion effects have been shown to manifest through reduced collateral values for competing firms (Shleifer and Vishny, 1992; Benmelech and Bergman, 2011). Our findings suggest that competitive effects outweigh these complimentary effects for product market rivals, on average.

[6] Hertzel et al. (2008) find that bankruptcy negatively affects related suppliers, and Boone and Ivanov (2012) find that bankruptcy has negative effects for strategic alliance partners.

2 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. (2017) (KPSS). For each patent, we observe the patent's technology 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. The Harvard Patent Database includes information on patents granted through 2010, and the KPSS data include citation information through 2012. These combined data allow 4 years to receive grant status and 6 years to accumulate citations for the last patents in the NBER data (applied for in 2006).[7]

It is well documented that patenting (or patent citing) propensities exhibit heterogeneity across patent technology classes and through time.[8] We follow the related literature and employ a reduced-form approach to adjust for heterogeneity in patenting propensities (e.g., Seru (2014); Lerner and Seru (2015)).[9] This procedure involves sorting patents into six major technology classes and 37 subcategories. Each patent (citation count) is then scaled by the average number of patents filed (citations received) by all firms within each technology 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*), 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 a firm's investment opportunities that are unrelated to competitors' financial constraints. The variables $EBITDA/assets$,

[7] Hall et al. (2001) report that receiving a grant takes 2 years, on average, after applying for a patent.
[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).

and $PP\&E/assets$ are additional variables commonly used as controls in regression specifications that include patent variables.[10]

To construct our final sample, we exclude firms in the utilities (SIC 4900–4999) and finance (SIC 6000–6999) sectors. All variables are inflation-adjusted to 1971 dollars, and all nondummy variables are winsorized at the 1% level in each tail, which helps mitigate the influence of extreme observations.[11] In addition, we drop firms headquartered outside of the United States, as well as firms with total CPI-adjusted assets or sales less than $1 million.

3 Defining Firm Relationships

3.1 Text-based approach

Our first approach to classifying competitors, the text-based approach, uses the product market similarity measure developed in Hoberg and Phillips (2016). They first vectorize the product market vocabulary from 10-Ks according to a constructed dictionary and then assign pairwise similarity scores based on the cosine similarity between two firms' vectorized product descriptions. The cosine similarity between two firms is higher when the two firms' product market descriptions are more similar. This similarity measure ranges from 0 (no similarity) to 1 (perfect similarity). Additionally, Hoberg and Phillips (2016) purge vertically related firms in industries classified as upstream or downstream according to the BEA input-output tables to ensure that their measure characterizes competitive relationships.[12]

A firm is classified as a competitor in our text-based network if it is defined as a competitor according to the Hoberg and Phillips (2016) procedure. Our final text-based network of firms includes 2,889,742 competitor-pair-years and 50,865 firm-years. Each firm has an average of 56.81 competitors, with an average cosine product similarity score of 0.037.

[10] 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.

[11] We obtain qualitatively similar results with more aggressive winsorization and without winsorizing.

[12] Hoberg and Phillips (2016) find that vertical relationships account for only 4% of the initial relationships identified in their data.

3.2 Citation-based approach

Our second approach uses information from the NBER patent data, which includes detailed information on patent-to-patent citations. Hall et al. (2001, p. 4) note, "Citations open up the possibility of tracing multiple linkages between inventions, inventors, scientists, firms, locations, etc." Indeed, a patent reviewer assigned by the USPTO is responsible for ensuring that a patent application has cited all relevant prior patents, which is required by law. Thus, citations indicate that firms are actively aware of each other's recent innovations, which makes them well suited for identifying potential firm interactions. In addition, the granularity of our citation-based network enables the use of firm, industry×year, and, in some cases, firm×year fixed effects in our empirical specifications to help control for unobserved heterogeneity.[13]

We define firm j as a competitor of firm i at time t if firm i cites firm j at any point between t-5 and t-1. As we select the window for defining competitors, we face a tradeoff between having more links in our sample and having the link represent a meaningful connection. We believe using a 5-year window as our baseline provides a reasonable balance between the relevance of citations and the number of firm links.[14] Note that our definition of competitors is not necessarily reflexive. That is, firm j can be considered a competitor of firm i without firm i necessarily being a competitor of firm j. This would be the case if firm i cites firm j, but firm j does not cite firm i in the t-5 to t-1 window. One advantage of this procedure is that we avoid detecting a mechanical relationship when we use citations received as our dependent variable.

While financial constraints may influence various aspects of firm relationships, our focus is on the role that financial constraints play in competitor interactions. Thus, a natural concern may be that our citation-based network includes firms with complementary rela-

[13] Citations are useful for our analysis, but more inclusive industry relationships (i.e., technology classes) may be more desirable to use in other settings.

[14] We check the robustness of our results using 2- and 7-year links, and we find similar results. The Internet Appendix provides these results in Table IA3.

tionships rather than competitive relationships. Following Hoberg and Phillips (2016), we attempt to purge our citation-based competitor network of upstream and downstream relationships using the BEA use tables from 1997 to 2016.[15] In addition, we omit firm pairs that are ever identified as strategic alliances, joint ventures, or supply chain partners, as well as firms that collaborate on a patent at any point during the sample period. Finally, we exclude all observations for up to 3 years preceding a merger between competitors.[16] While these steps have increased the likelihood that our citation-based network identifies competitive relationships, we cannot rule out that some complementary relationships remain, and therefore partially obfuscate our results.

To increase the power of our tests, we restrict our analysis to firms that have at least five competitors throughout the sample period. Our final citation-based network includes 354,871 competitor-pair-year observations and 17,230 firm-year observations for the period 1980 to 2006. Each firm has an average of 20.59 competitors in our citation-based network. Table 1 provides summary statistics for our sample.

3.3 Patent portfolio distance

In this section, we exploit the granularity of patent data to create a measure of technological distance between firms. We borrow from the approach in Bloom et al. (2013), who measure the technological proximity between competitors as the distance between patent portfolios. It is rare for public corporations to patent entirely within one of the 37 technology subcategories classified by the USPTO, which provides the potential for firms' patent portfolios to have varying degrees of overlap with each of their competitors.[17] Thus, a firm can alter the degree to which its products differ from those of competitors and therefore alter the intensity of competition with those competitors, by changing its patenting focus.

[15] The BEA use file contains summary-level supply table data from the Industry Economic Accounts (IEAs) for the years 1997 to 2016 and for industries defined according to the 2007 North American Industry Classification System (NAICS).

[16] Information on acquisitions, strategic alliances, and joint ventures come from Thomson Reuters SDC Platinum, and information on customers and suppliers come from Computstat.

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

To calculate the technological distance between firms i and j at time t, we calculate the Mahalanobis distance (MD) between their normalized patent portfolios:[18]

$$MD_{i,j,t} = \sqrt{(\mathbf{P_{i,t,t+2}} - \mathbf{P_{j,t-3,t-1}})\Omega(\mathbf{P_{i,t,t+2}} - \mathbf{P_{j,t-3,t-1}})},$$

where $\mathbf{P_{i,t,t+2}}$ is a vector representing the normalized portion of firm i's patents in each ordered subcategory from year t to $t+2$, $\mathbf{P_{j,t-3,t-1}}$ is a vector representing the normalized portion of firm j's patents in each ordered subcategory from year $t-3$ to $t-1$, and Ω is the weighting matrix with the diagonal elements equal to 1 and the off-diagonal elements equal to the uncentered correlations between technology classes.[19] We cluster standard errors at the firm level or the competitor-pair level to account for the overlap of $MD_{i,j,t}$ across time.

Note that firm i's patent portfolio is measured from time t to *t+2*, and it is compared to firm j's patent portfolio from *t-1* to *t-3*. We construct our measure this way to isolate the response of firm i to changes in competitor j's constraints. For instance, if competitor j of firm i experiences a tightening in financing constraints, we would expect firm j to reduce investment or patenting activity. This could cause a change in the 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 shifts its patenting activity to compete more aggressively with firm j, holding firm j's patenting activity constant.

Many potential measures can be used to estimate patent portfolio distance. However, the Mahalanobis distance has the advantage that it does not treat technology classes as orthogonal. The Ω matrix explicitly accounts for the fact that some technology classes are more closely related than others by weighting observations according to cross-category correlations. 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 has with a firm that patents entirely in automobiles.

[18] We normalize patent portfolios by dividing each patent vector by the square root of the dot product of the vector with itself so that their distance from the origin is 1.

[19] We calculate cross-category correlations in Ω after collapsing patents to the firm level so that each firm represents one observation in the full sample.

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. Although this is possible, it is more likely these two technology classes overlap. Nonetheless, we repeat our analysis for alternative measures of patent portfolio distance and present qualitatively similar results in the Internet Appendix.[20]

3.4 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. Second, we use the the size-age (SA) index developed by Hadlock and Pierce (2010). Hadlock and Pierce (2010) read the MD&A section from a randomly selected sample of firm 10-Ks, and they find that size and age are the strongest predictors of financing constraints. Third, we use the delayed investment (*Delay*) constraint index developed by Hoberg and Maksimovic (2015). Similar to Hadlock and Pierce (2010), Hoberg and Maksimovic (2015) gather information on constraints from 10-Ks. Specifically, Hoberg and Maksimovic (2015) 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) can directly measure the *Delay* index for a large set of firms, rather than extrapolating values from accounting information.[21] Section A.2 of the Internet Appendix provides additional details about the construction of these measures.

Our measures of financial constraints 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

[20]First, we use Mahalanobis distance calculated for unscaled patent portfolios (Table IA7). Then we use Euclidian distance and pairwise correlations, which treat technology classes as orthogonal (Table IA8)

[21]The *Delay* index is available from 1996 to 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.

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 that invest 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 define a competitor's financial constraints as the average of the *WW* (*SA*, *Delay*) constraint index for a firm's competitors in year t:

$$Comp\ const_{i,t} = \frac{\sum_{j \in C_{it}} FC_{j,t}}{num(C_{it})},$$

where C_{it} is the set of firms competing with firm i, and $num(C_{it})$ is the number of firms in C_{it}, defined for the text-based and citation-based networks, respectively. Firm i is excluded from C_{it}. We winsorize (1% each tail) and then normalize these financial constraint variables to have a mean of 0 and a standard deviation of 1. We construct analogous peer-firm variables to control for *log(sales)*, *Market-to-book*, *EBITDA/assets*, and *PP&E/assets*.

4 Empirical Results

4.1 Investment levels and competitor constraints

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

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

where our proxies for investment include (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*, and analogous competitor averages (all lagged by one period). The firm-specific intercept allows for additive and time-invariant unobserved heterogeneity at the firm level.

Competitor constraints may generate positive or negative externalities for firms. For example, if competitors are forced to forgo projects because of financing constraints, then knowledge spillovers, which have been shown to increase investment productivity (see Powell and Giannella (2010); Bloom et al. (2013)), are less likely. 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., Shleifer and Vishny (1992); Benmelech and Bergman (2011); Hertzel and Officer (2012)). On the other hand, competitor constraints may reduce competition for a given firm and increase the profitability of some projects. If complementary relationships (i.e., 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 of financial constraints ($\gamma_1 > 0$).

Table 2 presents the results for ordinary least square (OLS) estimates of Equation (1). Panel A presents results for our text-based network of competitors, using capital expenditures, scaled by lagged assets, as our dependent variable in Columns 1, 3, and 5. R&D, 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 and 2), the *SA* index (Columns 3 and 4), and the *Delay* index (Columns 5 and 6) to construct our constraint variables. All columns include firm and year fixed effects. The inclusion of firm fixed effects allows us to purge additive and time-invariant, firm-level heterogeneity that may be arbitrarily correlated with the covariates. The year dummies help control for aggregate shocks that simultaneously affect both financing constraints and investment or innovation.[22]

The results suggest that a 1-standard-deviation tightening of competitor constraints leads to a 2.9%–4.7% increase in capital expenditures as a percentage of assets and a 7.7%–16.8% increase in R&D scaled by sales, relative to the respective unconditional sample averages. Similarly, a 1-standard-deviation tightening of competitor constraints leads to a 6.4%–22.9% (6.9%–17.7%) increase in adjusted patents (adjusted citations).[23] The positive coefficient estimates suggest that firms increase investment activity and receive more citations after competitors experience a tightening of their financing constraints. The results for the patent variables are consistent with Almeida et al. (2013), who show that debt overhang compels firms to sacrifice innovation. The results are also in line with Rauh (2006), who shows that firms invest more when competitors are constrained by pension funding requirements.

4.2 Investment composition and competitor constraints

In this section, we exploit the information contained in our competitor networks to study relationships at the competitor-pair level. We use our measures of product market and patent portfolio distance to study how firms alter their investment composition in response to a tightening of competitor constraints. Moving beyond investment levels to study investment composition allows us to explore the validity of a wider range of economic theories, such as the principle of product differentiation (see Tirole, 1988). To do so, we estimate the following equation:

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

[22]We report specifications with Industry×Year fixed effects in Table IA2 of the Internet Appendix and find results qualitatively similar to those in Table 2.

[23]We explore these relationships separately for the debt- and equity-based measures of financial constraints developed by Hoberg and Maksimovic (2015) in Tables IA4 and IA5 of the Internet Appendix.

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

Table 3 presents estimates of Equation (2). In panel A, the dependent variable 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 (2016), from 1996 to 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 from years t to $t+2$ and that of its competitor from years $t-1$ to $t-3$, according to our citation-based network of competitors from 1980 to 2006. A lower MD indicates patent portfolios that are closer in correlation-weighted distance (i.e., 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, 8, and 9 include $Firm \times Year$ fixed effects. In these specifications, we can interpret the coefficient estimates for γ_1 as the shift in a firm's spending to compete more aggressively with more (increasingly) constrained competitors. The estimates in these models indicate that a 1-standard-deviation tightening of competitor constraints results in a 8.3%–18.1% increase in product market similarity and a 5.3-7.7% decrease in patent portfolio distance, relative to the respective sample averages.

In Columns 3, 6, and 9, we include $Firm \times Competitor$ and $Firm \times Year$ fixed effects to help control for time-invariant product market similarities and patent portfolio distances between firm i and competitor j.[24] Thus, we can interpret the coefficient estimate

[24]We implement the REGHDFE program in Stata, which is the updated and more general version of the REG2HDFE program highlighted by Gormley and Matsa (2013) to account for multiple high-dimensional

for *Comp const* in Columns 3, 6, and 9 as the effect that competitor financing constraints has on the investment composition overlap, relative to the average similarity (distance) for that competitor-pair. According to these specifications, a 1-standard-deviation tightening of competitor constraints results in a 3.5%–6.7% increase in product market similarity and a 1.0%–4.4% decrease in patent portfolio distance. The R^2s suggest that much of the variation in MD is driven by the cross-sectional variation in competitor-pair relationships. Nonetheless, 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 inclusion of $Firm \times Year$ fixed effects helps 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. However, the results for patent portfolio distance (*MD*) are less prone to this symmetry issue, because they represent a shift in the patenting activity of firm i from time t to *t+2* to have a lower technological distance from competitor j during time *t-3* to *t-1*.[25]

Overall, the results suggest that firms choose to compete more aggressively with relatively constrained competitors. In particular, firms choose to decrease their level of differentiation with competitors (i.e., increase product similarity or decrease technological distance) under the anticipation of reduced competition. The observed shift in patent activity in response to competitor constraints is also consistent with firms exploiting the opportunity to establish barriers to entry. These barriers could stem from an improvement in production efficiency, or from improving the relative attributes of their products.

fixed effects.

[25]We explore the potential influence of cross-sectional differences in patent portfolio size on our results. We find that smaller firms exhibit a stronger response to competitor constraints, and we discuss these results in Section A.3 of the Internet Appendix.

5 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 exhibit 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 firms increasing investment in innovative markets, rather than competing more aggressively with financially constrained competitors.

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 also may be prone to greater uncertainty or to a greater reliance on less pledgeable assets (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. In short, firms may choose to invest more heavily in these markets for reasons other than the competitive channel that we have posited.

Furthermore, because 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 unobservable common 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 is likely to dictate similar actions. It is well established in the urban economics literature that detailed data on nontransitive 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); 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 this 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 an effect on competitors' financial constraints.[26] First, we exploit the American Jobs Creation Act (AJCA) of 2004 as a shock to the cash holdings of a firm's financially constrained competitors with significant foreign operations. We examine changes in the investment behavior of firms whose competitors were positively affected by the tax holiday relative to firms without competitors directly affected by the AJCA.

Second, following the work of Lemmon et al. (2010), Almeida et al. (2011), and Almeida et al. (2013), we exploit the 1989 junk bond crisis as an adverse shock to the financial constraints of firms that relied on the junk bond market for external capital before 1989. However, we focus on changes in the investment behavior of firms that were not directly affected by the event, but rather competed with firms that were adversely affected. Therefore, any effect should stem primarily from the financial impact of the crisis on competitors.

5.1 American Jobs Creation Act of 2004

The American Jobs Creation Act (AJCA) of 2004 was a federal act that 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 pay out dividends or repurchase shares (e.g., Dharmapala et al. (2011)), some constrained firms appear to have used these

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

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 3 years of data, both before and after the event, for the sample period 2001 to 2006. We define treated firms as those with competitors that earned at least 33% of pretax income abroad from 2001 to 2003. We exclude firms with overseas revenue from the treatment group in Table 4, because the AJCA had the potential to directly affect such firms. Thus, control firms are those with no significant foreign income at all.

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*) and Adjusted Citations (*Adj cites*), and significant at the 5% level for *R&D/sales* and *Capx/assets*. These results suggest that firms decreased investment spending (or increased it less) and decreased patenting activity when competitors received a temporary relaxation of cash constraints from the AJCA tax holiday.

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 preconst.* as an indicator variable equal to 1 if the competitor's average constraints rank above the median from 2001 to 2003 according to the WW index (Columns 3 and 4), the SA index (Columns 5 and 6), and the *Delay* index (Columns 7 and 8). We measure constraints before 2004 to prevent the AJCA from directly influencing the constraint variables. The triple interaction term in Table 4 ($Treated \times Post \times$ *Comp preconst.*) is negative and statistically significant for all four dependent variables when we use the WW and SA indices as our measure of constraints. When *Delay* is used as the measure of constraints, the coefficient estimate for $R\&D/sales$ is significant at the 1% level, while the coefficient estimate for *Capx/assets* is insignificant at conventional levels. Overall, 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 allows a firm to have both treated and untreated observations within the same year, because some competitors have foreign operations, whereas other competitors do not. For the dependent variable, we use product market similarity (*Prod similarity*) between two firms in the text-based network of competitors developed by Hoberg and Phillips (2016). [27]

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

5.2 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 bankruptcy at a historic rate. 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, because such firms

[27]We acknowledge that truncation and publication bias could affect these tests because the shock occurs toward the end of our patent sample period. We apply the standard methods to address for this in patent counts and citations. However, there is no standard methodology MD, our measure of patent portfolio distance, and additional assumptions would be needed. Thus, as precaution, we exclude MD-related tests from these tax repatriation results.

were 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 that relied on junk bonds as a source of financing to the investment 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 issued junk-rated debt before 1989 but did not rely on junk debt themselves. Our *Post-treatment* period includes 1990 and 1991.

Table 6, Columns 1–8, presents results from our firm-year level analysis with *Capx/assets* *R&D/sales*, *Adj patent*, and *Adj cites* as our dependent variables. Specifications in Columns 1–8 include firm and year fixed effects. The coefficient estimates for the interaction term is positive and significant in all but one model (Column 6), which suggests that firms increased investment spending, in a relative sense, 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 9 and 10, we present results from our competitor-pair analysis, using *MD* as our dependent variable.[28] In this setting, treatment is defined for each of a firm's competitive relationships. Thus, a firm can have both treated and control competitor relationships, depending on whether a given competitor held a junk debt rating from 1986 to 1989.

We restrict our pretreatment period in Columns 9 and 10 to 1986, and we restrict our post-treatment period to 1989. The coefficient estimates in Columns 9 and 10 are estimated with a first difference estimator with the competitor-pair as the unit of observation. Year fixed effects are also included to capture any aggregate changes in firm behavior between the 2 years. We leave a 3-year gap between our pre- and post-treatment periods to avoid contamination in the measurement of MD, because MD is computed as the distance between

[28]This analysis precludes *Product Market Similarity*, because this variable becomes available only after 1996.

a firm's normalized patent portfolio from years t to $t+2$ and that of its competitor from years $t-3$ to $t-1$, according to our citation-based network of competitors. Thus, if we did not impose a 3-year gap for our pretreatment sample, then there would be an overlap in the MD measure pre- and post-crisis.

The estimate of the interaction term in Columns 9 and 10 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 1.81%–2.12%, 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 to compete more aggressively with that competitor.

5.3 Parallel trends and matching analysis

Establishing parallel trends helps mitigate concerns that differences between the treated and control groups are not constant before the treatment occurs. Additionally, it is important to ensure that only the treated group exhibits a response to the treatment event. In this section, we discuss our parallel trends analysis for both the AJCA repatriation tax shock and the junk bond crisis to address these concerns.

To help establish parallel trends, we implement a matching procedure to find treatment and control firms that are similar on observable characteristics. We use the pretreatment control variables (*log(sales)*, *Market-to-book*, *EBITDA/assets*, and *PP&E/assets*) to predict the probability of treatment. Then we match each treated firm with the nearest untreated firm that has the most similar ex ante predicted likelihood of receiving treatment. For the AJCA repatriation tax shock (junk bond crisis), treated firms are those whose competitors have significant foreign profits prior to the AJCA (issued junk bonds prior to the junk-bond crisis). Untreated nearest neighbors are firms that are the most similar to treated firms in the probability of treatment, but do not have competitors with foreign profits (junk bonds).[29]

[29] Our inclusion of firm-year fixed effects in the pairwise (competitor-pair level) regressions subsumes the interaction term for firms without both treated competitors and untreated competitors.

To establish the pretreatment trends and the post-treatment effects, we plot the coefficients for the following regression:

$$Y_{i,t} = \sum_{j=1,2,4,5,6} (\beta_j * \mathbb{1}[t=j]_{i,t} + \beta_{j,T} * \mathbb{1}[t=j] * Treated_{i,t}) + \gamma_i + \epsilon_{i,t},$$

where year 3 is the year immediately preceding treatment, and serves as the base year in our regression. We document the trends for *Capx/assets R&D/sales*, *Adj patent*, and *Adj cites* around the AJCA and junk bond crisis, respectively.

Figure IA1 in the Internet Appendix shows the trends, and Table IA9 in the Internet Appendix documents the coefficient estimates around the AJCA repatriation tax shock. For investment, the differences are not significant. For R&D, patents, and citations, we observe some small differences between the two groups before the treatment. However, the gap between the treatment and control groups widens substantially in the post-treatment period. Important for our analysis, this effect appears to be driven by the decrease in R&D, patents, and citations from the treatment group, which consists of firms whose competitors experience a cash windfall.

Figure IA2 in the Internet Appendix shows the trends, and Table IA10 in the Internet Appendix documents the coefficient estimates around the junk bond crisis. For R&D, the differences are not significant. For investment, patents, and citations, we see that the treated and control groups follow similar patterns before treatment. In the post-treatment period, we see that the gap widens between the treated and untreated firms. Again, most of the effect appears to be driven by changes in treated firm outcomes. Overall, this evidence is reassuring for our experimental design.

6 Opportunistic Hiring

In this section, we study a specific setting to further establish that competitor constraints are not merely a proxy for unobservable common factors; instead, they directly influence a firm's investment choices. To this end, we examine whether firms opportunistically hire inventors who work for competitors when those competitors experience a tightening of their financial constraints. We then examine whether the constraints of an inventor's current employer relates to the likelihood that they depart for a competing firm, which allows us to control for unobserved heterogeneity at the inventor level.

The Harvard Patent Database includes detailed information on patents and the locations of individual patent inventors (see Lai et al. (2014)). We observe the patent identification number for each of an inventor's patents, the patent application and grant dates, each inventor's location, and the firm that owns the patent at the time of application. By focusing on serial inventors (i.e., inventors who file patents in at least 2 different years in the sample), we can track the firms that inventors patent for through time.[30] Our sample includes 137,178 unique inventors that patent in multiple years from 1980 to 2006, spanning a total of 377,923 inventor-patent-years. Of these inventors, 21,957 move to a new firm for a total of 27,557 moves during the sample period. Of these moves, 12,291 inventors make 16,050 moves to a competing firm, according to our citation-based network.

6.1 Firm-level analysis

First, we examine the relationship between opportunistic hiring and competitor financial constraints at the firm level. Intuitively, hiring inventors who were recently employed by a competitor indicates that a firm plans to pursue investment opportunities related to the investments of that competitor. We use our citation-based network to classify competitors and estimate the following linear probability specification:

$$Hire_{i,t+1,t+5} = \alpha_i + \gamma_1 Comp\,const_{i,t} + \gamma_2 Own\,const_{i,t} + \beta Controls_{i,t} + \epsilon_{i,t}, \quad (3)$$

[30] We exclude observations in which multiple firms are listed as owners of the same patent at the time of application, because we are unable to resolve ambiguity regarding which firm should be assigned the patent. We also exclude observations in the 3 years leading to a merger/acquisition between two firms identified as competitors, according to our citation-based network. Acquisition data come from SDC Platinum.

where $Hire_{i,t+1,t+5}$ is a binary variable equal to 1 if firm i hires an inventor during the years *t+1* to *t+5* that appeared on a competitor's patent in year t, and 0 otherwise.[31] The variable $Comp\,const_{i,t}$ is the average financial constraints of firm i's competitors at time t, and $Own\,const_{i,t}$ is firm i's own constraints at time t. The control variables *log(sales), Market-to-book, EBITDA/assets, PP&E/assets*, and analogous competitor averages, are all measured at time t.

Table 7 presents 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 and 2), the *SA* index (Columns 3 and 4), and the *Delay* index (Columns 5 and 6). The specifications in all columns include firm and year fixed effects and standard errors clustered at the firm level. The estimates for the coefficient on *Comp const* are statistically significant and economically meaningful. In particular, a 1-standard-deviation tightening of competitor constraints corresponds to a 33.1%–40.4% increased probability of opportunistic hiring, according to the *WW* and *SA* measures of constraints, and a 4.5%–10.5% increase, according to the *Delay* index. Overall, these results suggest that firms opportunistically hire from competitors when those competitors are financially constrained.

Regional variation in the use and enforcement of noncompetition agreements may affect 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).[32] We implement this approach for each specification reported in Table 7. Second, we include the NEI

[31] We exclude inventors who move between more than three firms in a given 5-year period to mitigate concerns that our results are influenced by frequent movers. Dropping these observations has very little influence on our coefficient estimates.

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

measure in an interaction with the financial constraints measure, and we report the results in the Internet Appendix. These alternative results have no significant effect on our main finding, and they highlight that the effect is relatively concentrated in state-years with low noncompetition enforcement.

6.2 Inventor-level analysis

Opportunistic hiring requires inventors who are willing to change employers. However, inventors may differ in their mobility and willingness to change jobs, which can lead them to select into certain firms. For example, inventors who are more risk tolerant also may be more comfortable selecting into uncertain environments by choosing to work for a constrained firm. If risk-tolerant inventors are also more likely to change jobs frequently, then our estimates could be driven by differing compositions in the types of inventors across firms. To mitigate concerns of this nature, we turn our attention to analysis at the inventor level, which allows us to control for unobserved inventor-level heterogeneity.

In particular, we examine whether the constraints of an inventor's current employer relates to the likelihood that they depart for a competing firm, after controlling for their unobserved propensity to change jobs via the inclusion of inventor fixed effects. Using our citation-based network to classify competitors, we estimate the following linear probability specification:

$$Departure_{k,t+1,t+5} = \alpha_k + \gamma Current\,employer\,const_{j,t} + \beta Controls_{j,t} + \epsilon_{k,t}, \qquad (4)$$

where $Departure_{i,t+1,t+5}$ is a binary variable equal to 1 if inventor k moves to a competitor during years $t{+}1$ to $t{+}5$ and equal to 0 if inventor k patents for the same firm or for a noncompetitor during years $t{+}1$ to $t{+}5$.[33] The variable $Current\,employer\,const_{j,t}$ measures the financial constraints of the firm j that inventor k patents for in year t. The inventor-year is the unit of observation in Equation (4), in which an inventor enters the sample for each year

[33] We omit the observation if the inventor does not patent during the years $t{+}1$ to $t{+}5$.

in which she files for at least one new patent. As in our firm-level analysis, we include dummy variables for each of the 12 categories of the Noncompetition Enforcement index (NEI) developed in Garmaise (2009) in the vector of control variables for firm j ($Controls_{j,t}$).[34]

Table 8 presents linear probability model estimates for Equation (4). The coefficient estimates suggest that a 1-standard-deviation tightening of the constraints of an inventor's current employer increases the chance that the inventor leaves for a competitor by 0.19–1.70 percentage points, which represents 4.5%–40.4% of the unconditional sample average propensity of departing (4.2%). 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, and the results are similar.

7 Conclusion

We use information regarding a firm's product mix and patent portfolio in order to study how both the level and composition of investment spending depend on the financial constraints of competitors. We find evidence that firms increase their level of investment in response to a tightening of competitor constraints, while holding a firm's own constraints constant. We also find that firms shift the composition of their investment spending to compete more aggressively with relatively constrained competitors.

Most empirical studies on the effects of financial constraints implicitly assume that firm decisions depend on their own constraints and are independent of the constraints of competitors or peers. In contrast, our findings suggest that financial constraints not only limit a firm's own spending but they also invite competition in the form of increased investment by rivals. This competitive feedback effect can be detrimental to firms in the long run, thus creating a permanent effect stemming from financing constraints.

Our findings are also consistent with traditional theories of competition in which firms

[34] We estimate a specification with an interaction term between the NEI and financial constraints in Table IA12 of the Internet Appendix.

choose to differentiate products to the greatest extent possible in order to soften future competition (e.g., Hotelling (1929); Salop (1979); Tirole (1988)). In our setting, it appears that unconstrained firms decrease product differentiation with constrained competitors to steal market share in anticipation of weaker competition.

Finally, our results also suggest that, through competition, firms "fill in the gap" for the forgone investments of constrained competitors, which may 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 (2016). 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 normalized patent portfolio from years t to $t+2$ and that of its competitor from years $t-3$ to $t-1$, according to our citation-based network of competitors from 1980 to 2006. A lower value represents patent portfolios that are closer in correlation-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 (2016). 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.

	Citation-based network (1980–2006)			Text-based network (1996–2012)		
	Mean	Median	SD	Mean	Median	SD
A. Firm-specific variables						
log(sales)	4.858	4.966	1.964	4.022	4.024	2.004
Capx/assets	0.066	0.053	0.060	0.065	0.038	0.083
R&D/sales	0.208	0.052	0.668	0.147	0.003	0.585
PP&E/assets	0.252	0.223	0.167	0.261	0.189	0.225
Market-to-book	2.166	1.609	1.63	1.977	1.484	1.512
Book leverage	0.197	0.173	0.182	0.219	0.174	0.220
EBITDA/assets	0.106	0.135	0.193	0.087	0.118	0.204
WW	0.000	-0.015	1.000	0.000	0.022	1.000
SA	0.000	0.047	1.000	0.000	0.001	1.000
Delay	0.000	0.065	1.000	0.000	-0.090	1.000
Adjusted patents	0.682	0.328	0.868			
Adjusted citations	2.036	1.804	1.726			
Observations	17,230			50,865		
B. Competitor-pair averages						
MD	0.597	0.637	0.184			
Prod similarity				0.037	0.025	0.038
WW	0.003	-0.132	1.000	0.000	0.055	1.000
SA	0.000	-0.185	1.000	0.000	0.022	1.000
Delay	0.000	0.049	1.000	0.000	-0.070	1.000
No. of links per firm	20.596	13.000	36.407	56.812	28.000	64.37
Observations	354,871			2,889,742		

Table 2: Corporate investment and competitor constraints

OLS regression estimates are reported for the relationship between corporate investment and competitor financing constraints. The firm-year is the unit of observation in this analysis. The dependent variables include the natural log of truncation-adjusted patents (plus 1) applied for in year t (*Adj pat*), the natural log of adjusted citations (plus 1) 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/aale). We calculate average competitor constraints (*Comp const.*) and a firm's own constraints (*Own const.*) according to the *WW* index (Columns 1 and 2), the *SA* index (Columns 3 and 4), and the *Delay* index (Columns 5 and 6). We include *log(sales), Market-to-book, EBITDA/assets, PP&E/assets*, and analogous competitor averages (all lagged one period), as control variables. All specifications include firm and year fixed effects. Table IA2 of the Internet Appendix reports the results for specifications with firm and industry×year (Fama-French 48) fixed effects. 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	
	A. Text-based network, 1996–2012					
	Capx/asset	R&D/sale	Capx/asset	R&D/sale	Capx/asset	R&D/sale
Comp const.	0.0031**	0.0248***	0.0026*	0.0188***	0.0019***	0.0114***
	(0.0015)	(0.0086)	(0.0014)	(0.0043)	(0.0005)	(0.0031)
Own const.	-0.0045***	-0.0332***	-0.0291***	-0.0219***	-0.0001	0.0117***
	(0.0011)	(0.0095)	(0.0057)	(0.0257)	(0.0005)	(0.0044)
R-squared	.6623	.8025	.6621	.7419	.6846	.7610
Observations	50,865	50,865	50,865	50,865	36,615	36,615
	B. Citation-based network, 1980–2006					
	Adj pat	Adj cite	Adj pat	Adj cite	Adj pat	Adj cite
Comp const.	0.1526***	0.3271***	0.1561***	0.3598***	0.0436***	0.1396***
	(0.0528)	(0.0951)	(0.0239)	(0.0264)	(0.0056)	(0.0145)
Own const.	-0.1517***	-0.0174***	-0.3421***	-0.0586***	-0.0415	-0.0717
	(0.0491)	(0.0026)	(0.0549)	(0.0196)	(0.1095)	(0.2283)
R-squared	.8558	.8055	.8572	.8066	.8498	.8164
Observations	17,230	17,230	17,230	17,230	12,016	12,016
Firm FEs	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓

Table 3: Investment similarity and competitor constraints

OLS regression estimates are reported for the relationship between investment composition similarity and competitor financing constraints. The competitor-pair-year is the unit of observation in this analysis. The dependent variable in panel A 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 (2016) from 1996 to 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 normalized patent portfolio from years t to $t+2$ and that of its competitor from years $t-3$ to $t-1$, according to our citation-based network of competitors from 1980 to 2006. A lower value represents patent portfolios that are closer in correlation-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, and PP&E/assets* for a firm and its competitors (all lagged one period) as control variables. Specifications include firm and year fixed effects in Columns 1, 4, and 7; competitor-pair fixed effects in Columns 3, 6, and 9; and firm×year fixed effects in Columns 2, 3, 5, 6, 8, and 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).

	WW			SA			Delay		
A. Text-based product market similarity: text-based network									
Comp const.	0.0052***	0.0032***	0.0025***	0.0067***	0.0048***	0.0013***	0.0031***	0.0033***	0.0017***
	(0.0012)	(0.0007)	(0.0003)	(0.0016)	(0.0013)	(0.0003)	(0.0008)	(0.0009)	(0.0005)
Own const.	-0.0009			-0.0023***			0.0010		
	(0.0013)			(0.0006)			(0.0015)		
R-squared	.3228	.3530	.8096	.3226	.3527	.8096	.2409	.2721	.8176
Observations	2,889,742	2,889,742	2,889,742	2,889,742	2,889,742	2,889,742	1,850,473	1,850,473	1,850,473
B. Patent portfolio distance (Mahalanobis distance) - citation-based network									
Comp const.	-0.0317***	-0.0318***	-0.0251***	-0.0320***	-0.0321***	-0.0261***	-0.0429***	-0.0461***	-0.0061***
	(0.0022)	(0.0021)	(0.0019)	(0.0022)	(0.0022)	(0.0022)	(0.0008)	(0.0082)	(0.0093)
Own const.	0.0042			-0.0117*			-0.0006		
	(0.0028)			(0.0066)			(0.001)		
R-squared	.1957	.2442	.6604	.1964	.2446	.6616	.2014	.2426	.6661
Observations	354,871	354,871	354,871	354,871	354,871	354,871	161,073	161,073	161,073
Firm & year FEs	✓			✓			✓		
Firm × year FEs		✓	✓		✓	✓		✓	✓
Competitor pair FEs			✓			✓			✓
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. The firm-year is the unit of observation in this analysis. We use 2 years of data both before and after the event for the sample period 2001 to 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 pretax income from abroad during 2001 to 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 preconst.* as an indicator variable equal to 1 if a firm's pretreatment average competitor constraints from 2001 to 2003 rank above the full sample median for the same period according to the *WW* index (Columns 3 and 4), the *SA* index (Columns 5 and 6), and the *Delay* index (Columns 7 and 8). All specifications include firm and year fixed effects, which subsume the *Post*, *Treated*, *Comp preconst.*, and *Treated*× *Comp preconst.* variables. For expositional convenience, we do not report the coefficient for *Post*× *Comp preconst.* 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). Table IA9 of the Internet Appendix reports the results from a matched sample analysis.

			WW		SA		Delay	
	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*	-0.0042**	-0.0749***	0.0004	0.0022	0.0003	0.0004	-0.0076*	0.0044
	(0.0017)	(0.0169)	(0.0024)	(0.0100)	(0.0021)	(0.0064)	(0.0042)	(0.0112)
Treated× *Post*×			-0.0078**	-0.1230***	-0.0073**	-0.1208***	0.0038	-0.0986***
Comp preconst.			(0.0035)	(0.0293)	(0.0034)	(0.0282)	(0.0046)	(0.0249)
R-squared	.7083	.9245	.7148	.9286	.7154	.9284	.7144	.9281
Observations	3,358	3,358	3,358	3,358	3,358	3,358	3,358	3,358
	B. Citation-based network							
	Adj pat	Adj cite	Adj pat	Adj cite	Adj pat	Adj cite	Adj pat	Adj cite
Treated× *Post*	-0.1415***	-0.5354***	-0.0607***	-0.3682***	-0.0517***	-0.3519***	-0.0407	-0.3566***
	(0.0261)	(0.0781)	(0.0160)	(0.0806)	(0.0187)	(0.0861)	(0.0248)	(0.1183)
Treated× *Post*×			-0.1282***	-0.2620**	-0.1376***	-0.2864**	-0.1249***	-0.2430*
Comp preconst.			(0.0348)	(0.1311)	(0.0335)	(0.1313)	(0.0333)	(0.1423)
R-squared	.8225	.7659	.8290	.7771	.8273	.7735	.8261	.7729
Observations	2,716	2,716	2,716	2,716	2,716	2,716	2,716	2,716
Firm FEs	✓	✓	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓

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. The competitor-pair-year is the unit of observation in this analysis. The dependent variable 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 (2016). We use 2 years of data both before and after the event for the sample period 2001 to 2006. We define firm-competitor relationships as treated if the given competitor earned an average of at least 33% of pretax income from abroad from 2001 to 2003. Note that a given firm can have both treated and control 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 preconst.* as an indicator variable equal to 1 if competitor's average constraints rank above the median from 2001 to 2003 according to the *WW* index (Columns 3 and 4), the *SA* index (Columns 5 and 6), and the *Delay* index (Columns 7 and 8). Specifications include firm and year fixed effects in Columns 1, 3, 5, and 7; competitor-pair fixed effects in all columns, and firm×year fixed effects 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).

			WW		SA		Delay	
	Text-based product market similarity (text-based network)							
Treated×*Post*	-0.0023***	0.0031*	-0.0034**	-0.0027*	-0.0020	-0.0012	-0.0009*	-0.0003
	(0.0006)	(0.0017)	(0.0015)	(0.0015)	(0.0020)	(0.0021)	(0.0005)	(0.0002)
Post×			-0.0033***	-0.0021***	-0.0012***	-0.0009***	-0.0005*	-0.0016
Comp preconst.			(0.0013)	(0.0007)	(0.0003)	(0.0002)	(0.0003)	(0.0055)
Treated×*Post*×			-0.0051***	-0.0044**	-0.0015*	-0.0014	-0.0042**	-0.0077***
Comp preconst.			(0.0017)	(0.0021)	(0.0008)	(0.0033)	(0.0019)	(0.0025)
R-squared	.8421	.8688	.8393	.8592	.8399	.8718	.8164	.8729
Observations	139,059	139,059	139,059	139,059	139,059	139,059	132,872	132,872
Firm	✓		✓		✓		✓	
Year	✓		✓		✓		✓	
Firm × year		✓		✓		✓		✓
Competitor pair	✓	✓	✓	✓	✓	✓	✓	✓

Table 6: 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 2 years of data both before and after 1989 for the sample period 1987 to 1991 in Columns 1–8 (firm-level observations). In Columns 1–4, competitors are defined according to our text-based network, and in Columns 5–10 competitors are defined according to our citation-based network. In Columns 9 and 10 (competitor-pair-level observations), the dependent variable is the Mahalanobis distance (*MD*) between a firm's normalized patent portfolio from years t to $t+2$ and that of its competitor from years $t-3$ to $t-1$. Because *MD* uses 3 years of forward-looking data, we take the difference in MD between 1989 (which covers patent portfolios from 1989 to 1991) and 1986 (which covers patent portfolios from 1986 to 1988) to avoid using any patents during post treatment period to construct the treatment group outcome variable during the pretreatment period. Thus, Columns 9 and 10 effectively have one observation per competitor-pair. A lower *MD* represents patent portfolios that are closer in correlation-weighted distance, or are more similar. We define treated firms in Columns 1–8 as those with at least one competitor that held a junk debt rating 1989. In Columns 9 and 10, 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 ($Treated \times Post$). Columns 1–8 include firm and year fixed effects, 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).

	Capx/asset		R&D/sale		Adj patent		Adj cite		ΔMD	
$Treated \times Post$	0.0106**	0.0089*	0.0291***	0.0192***	0.0242**	0.0256*	0.0668**	0.0748**	-0.0127***	-0.0108**
	(0.0047)	(0.0045)	(0.0068)	(0.0071)	(0.0123)	(0.0135)	(0.0297)	(0.0353)	(0.0042)	(0.0051)
EBITDA/assets		0.0170		0.0107		0.1421		0.3910*		0.0355**
		(0.0161)		(0.0415)		(0.0921)		(0.2072)		(0.0168)
log(sales)		0.0030*		0.0028		-0.0092		0.0018		-0.0024**
		(0.0018)		(0.0031)		(0.0079)		(0.0156)		(0.0011)
Market-to-book		-0.0047		-0.0039		0.0026		0.0432		0.0008
		(0.0036)		(0.0075)		(0.0159)		(0.0376)		(0.0017)
PP&E/assets		-0.0291		-0.0189		-0.0445		-0.2589		0.0016
		(0.0206)		(0.0380)		(0.0981)		(0.1899)		(0.0095)
Comp EBITDA/assets		0.0360***		0.1416***		0.0279		0.0496		0.0952***
		(0.0125)		(0.0226)		(0.0575)		(0.1130)		(0.0199)
Comp log(sales)		0.0042		-0.0195***		0.0560**		0.0475		0.0023
		(0.0034)		(0.0070)		(0.0228)		(0.0349)		(0.0048)
Comp market-to-book		0.0071***		-0.0147***		0.0018		0.0066		-0.0137**
		(0.0025)		(0.0035)		(0.0095)		(0.0174)		(0.0058)
Comp PP&E/assets		0.2165***		-0.0444		0.0743		0.2860		-0.0397***
		(0.0255)		(0.0351)		(0.0856)		(0.1751)		(0.0088)
R-squared	.6621	.7477	.8958	.9036	.9568	.9586	.8428	.8465	.0191	.1066
Observations	2,035	1,831	2,035	1,831	2,035	1,831	2,035	1,831	2,420	2,420
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: Opportunistic hiring and competitor constraints

Linear probability model estimates are reported for the relationship between the opportunistic hiring of inventors and competitor constraints. The firm-year is the unit of observation in this analysis. The dependent variable $Hire_{i,t+1,t+5}$ is a binary variable equal to 1 if firm i hires an inventor during the years $t+1$ to $t+5$ that appeared on a competitor's patent in year t, and 0 otherwise. Competitors are defined according to our citation-based network of competitors from 1980 to 2006. 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 and 2), the *SA* index (Columns 3 and 4), and the *Delay* index (Columns 5 and 6). The control variables *log(sales)*, *Market-to-book*, *EBITDA/assets*, *PP&E/assets*, and analogous competitor averages, are measured at time *t*. The specifications in all columns include firm, year, and NEI fixed effects. NEI refers to the Noncompetition Enforcement index developed in Garmaise (2009). 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). Table IA15 of the Internet Appendix reports results from probit specifications.

	WW		SA		Delay	
	Opportunistic hiring of competitor inventors (citation-based network)					
Comp const.	0.0387***	0.0531***	0.0514***	0.0593***	0.0089***	0.0105***
	(0.0048)	(0.0070)	(0.0052)	(0.0069)	(0.0025)	(0.0024)
Own const.	-0.0348***	-0.0233***	-0.0558***	-0.0291***	-0.0036	-0.0022
	(0.0053)	(0.0047)	(0.0089)	(0.0098)	(0.0041)	(0.0042)
EBITDA/assets		-0.0086		-0.0084		0.0159
		(0.0159)		(0.0157)		(0.0200)
log(sales)		0.0252***		0.0217***		0.0146**
		(0.0045)		(0.0051)		(0.0060)
Market-to-book		0.0102***		0.0146***		0.0129***
		(0.0020)		(0.0029)		(0.0025)
PP&E/ assets		0.0505		0.0390		0.1121**
		(0.0361)		(0.0360)		(0.0498)
Comp.		0.3023***		0.3186***		-0.0826
EBITDA/assets		(0.0749)		(0.0749)		(0.0949)
Comp.		0.0200**		0.0143**		0.0384***
log(sales)		(0.0095)		(0.0072)		(0.0114)
Comp.		-0.0019		-0.0062		0.0027
Market-to-book		(0.0069)		(0.0068)		(0.0079)
Comp.		-0.0834		-0.0010		-0.1490
PP&E/ assets		(0.0686)		(0.0701)		(0.1150)
R-squared	.4207	.4248	.4225	.4259	.4331	.4386
Observations	17,117	17,117	17,117	17,117	11,211	11,211
Firm FEs	✓	✓	✓	✓	✓	✓
NEI	✓	✓	✓	✓	✓	✓
Year FEs	✓	✓	✓	✓	✓	✓

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 inventor-patent-year is the unit of observation in this analysis. The dependent variable $Departure_{i,t+1,t+5}$ is a binary variable equal to 1 if inventor k moves to a competitor during years *t+1* to *t+5* and equal to 0 if inventor k patents for the same firm or for a noncompetitor during years *t+1* to *t+5*. We omit the observation if the inventor does not patent during the years *t+1* to *t+5*. Competitors are defined according to our citation-based network of competitors from 1980 to 2006. Data on individual inventors come from the Harvard Patent Database inventor file (see (Lai et al., 2014)). The variable $Current\,employer\,const_{j,t}$ measures the financial constraints of the firm j that inventor k patents for in year t, according to the *WW* index (Columns 1 and 2), the *SA* index (Columns 3 and 4), and the *Delay* index (Columns 5 and 6). The control variables *log(sales)*, *Market-to-book*, *EBITDA/assets*, and *PP&E/assets* are measured at time t. The specifications in all columns include inventor, year, and NEI fixed effects. NEI refers to the Noncompetition Enforcement index developed in Garmaise (2009). 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). Table IA16 of the Internet Appendix presents results from probit specifications.

	WW		SA		Delay	
	Inventor departs for competitor (citation-based network)					
Current employer const.	0.0170***	0.0139***	0.0149***	0.0050	0.0044***	0.0019*
	(0.0020)	(0.0022)	(0.0027)	(0.0033)	(0.0013)	(0.0011)
EBITDA/assets		-0.0019**		-0.0097***		-0.0116***
		(0.0011)		(0.0018)		(0.0026)
log(sales)		-0.0046***		-0.0046***		-0.0019***
		(0.0005)		(0.0004)		(0.0006)
Market-to-book		-0.0536***		-0.0539***		-0.0386***
		(0.0063)		(0.0060)		(0.0076)
PP&E/ assets		0.0380***		0.0389***		-0.0167
		(0.0107)		(0.0106)		(0.0186)
R-squared	.3408	.3437	.3405	.3436	.4490	.4267
Observations	377,923	377,923	377,923	377,923	134,722	134,722
Inventor FEs	✓	✓	✓	✓	✓	✓
NEI	✓	✓	✓	✓	✓	✓
Application year FEs	✓	✓	✓	✓	✓	✓