Urban Vibrancy and Corporate Growth *

Casey Dougal

Kenan-Flagler School of Business, University of North Carolina at Chapel Hill

Christopher A. Parsons

Rady School of Management at the University of California, San Diego

Sheridan Titman

McCombs Business School, University of Texas at Austin

February 29, 2012

Abstract

We provide evidence that positive local spillovers strongly influence corporate investment decisions. A firm's investment is highly sensitive to the investments of other firms headquartered nearby, even those in very different industries. Moreover, a firm's investment is also related to the q and cash flows of nearby firms outside its industry, even when controlling for its *own* q and cash flows. Similar correlations are observed for capital raising, both debt and equity. These time-varying regional effects are large, averaging over half the size of the typical time-varying industry effect, and indicate that local agglomeration economies are important determinants of firm investment and growth.

Keywords: agglomeration economies, spillovers, investment, equity issuance, human capital

JEL: G30, R30

*We thank Andres Almazan, Aydoğan Altı, Cesare Fracassi and seminar participants at the University of North Carolina at Chapel Hill and University of Texas at Austin for helpful feedback. All errors are ours.

Send correspondence to Christopher Parsons, Rady School of Management, University of California, San Diego, Otterson Hall, Room 3S137 9500 Gilman Drive #0553 La Jolla, CA 92093-0553; telephone: 858-534-8782; fax: 858-534-0745. E-mail: caparsons@ucsd.edu.

1 Introduction

Twenty-five years ago, Detroit-based Unisys was the second largest computer company in the United States, and Whole Foods was still a fledging organic grocer, with scarcely a presence beyond its headquarters in Austin, Texas. Since that time, the diverging paths of their respective cities could hardly have been starker. While Austin has grown rapidly, Detroit has suffered population declines, the departure of key employers, and increased crime.[1] The question that we ask in this paper is whether the success of Whole Foods and the decline of Unisys can be linked, at least in part, to the diverging fortunes of Detroit and Austin.

The idea of "location" mattering for companies is certainly not new. It has, for example, long been recognized that geographical factors like proximity to transportation routes (St. Louis) or favorable weather (Los Angeles) influence the location choices of firms and the workers they employ. However, because these factors are static, they aren't particularly helpful when thinking about area *dynamics*, such as Austin's ascent and Detroit's demise. For this purpose, it is more appealing to think about locational factors that might ebb and flow over time. These factors depend on the people living in the city – what we call "vibrancy" – that influence knowledge diffusion between a city's workers (e.g., Moretti (2003)), technology spillovers between neighboring firms (e.g., Jaffe, Trajtenberg, and Henderson (1993)), or consumption externalities between its residents (e.g., Glaeser, Kolko, and Saiz (2001)).[2]

While there are occasional shocks to certain areas that are purely exogenous (e.g., Hurricane Katrina in New Orleans), it is more often the case that an area becomes vibrant when its resident firms are successful. Continuing the example above, the rise of Austin (home to Dell Computer) was heavily influenced by the development of the technology industry,

[1]According to the U.S. Census Bureau, Detroit's population declined from 1.51 million in 1970 to 713,000 in 2010. Austin's population more than tripled over the same period. Causation running from the fortunes of these companies and the growth of the cities is very unlikely.

[2]Marshall (1920) is generally credited with providing the first discussion of such local agglomeration economies. A necessarily incomplete list of other papers in this literature includes Henderson (1974, 2003), Lucas (1988), Glaeser et al. (1992), Rauch (1993), Audretsch and Feldman (1996), Ellison and Glaeser (1997,1999), Glaesar and Mare (2001), Rosenthal and Strange (2001), Simon and Nardinelli (2002), Wheaton and Lewis (2002), Shapiro (2006), Glaeser, and Kerr (2010) and Fisher, Davis and Whited (2011).

while Detroit's collapse was largely precipitated by the decline of U.S. auto manufacturing. Other prominent examples include Rochester, NY (home to struggling firms Xerox, Eastman Kodak, and Bausch and Lomb), the ascent of software clusters in Seattle and San Francisco, and the recent boom of energy hub Houston.

Our central thesis is that firm investment opportunities are positively linked to the vibrancy of its location. This might occur because firms in more vibrant locations find it easier to attract and retain high quality employees; or perhaps the diffusion of knowledge, ideas, or even enthusiasm can make existing workers more productive. In either case, the key empirical prediction is that the investment expenditures of neighboring firms move together in response to the ebbs and flows of local vibrancy. For example, the investment expenditures of Dow Chemical, headquartered in Detroit, might be correlated with the investment expenditures of Ford Motor Company (also in Detroit), even though they operate in completely different industries without strong links.

To establish intuition for our empirical tests, we begin with a reduced form model that links a firm's investment expenditures to the vibrancy of its location. The model contains two nearby firms, operating in different industries. For example, one might be an energy firm, and the other a developer of personal investing software, both located in Houston. Although the firms sell their respective products outside of the city, and thus are not connected on the demand side, they draw from a common pool of *local* inputs, such as land and labor. This competition for local resources creates an interdependence: when Firm 1 increases investment, it imposes a negative externality on Firm 2 by driving up local input prices. All else equal, this generates a negative correlation in the investment expenditures between the two neighboring firms.

However, this is only half of our story. If we allow for local vibrancy – like Firm 1's success increasing the motivation, knowledge, or skills of Firm 2's workers – the model predicts *positive* correlations in the investment expenditures of the two firms. Ultimately, whether such positive local externalities are large enough to overwhelm the negative effects of crowding out is an empirical question, and motivates the remainder of the paper.

Our first empirical tests simply characterize whether, in a given area, firms in different industries have similar investment rates. For example, we compare cross-region investment expenditures by Energy firms as follows: in any year, we rank different U.S. cities based on the average investment rates of firms *outside* Energy, e.g., those in general manufacturing, health care, software, and so on. Using only this non-Energy ranking, we find striking differences in the investment rates of Energy firms in different areas. In this specific example, the average investment expenditures-to-asset ratio of Energy firms in the top third most aggressively investing cities (in non-Energy industries) is 0.21, versus 0.14 in the bottom third ($t = 10.89$ for the difference). These cross-area differences are not exceptional, holding for every industry, and in the vast majority of years.

Although consistent with the model, the fact that we observe large regional effects in average investment rates is not particularly strong evidence of vibrancy. Indeed, these results are consistent with static effects (e.g., geographical advantages) that, while certainly relevant, are not our main focus. To hone in on the dynamic effects of location, we implement a regression framework that allows us to identify time-series variation in regional vibrancy, and link it to firm-level investment expenditures. Here, the experiment is to take an individual firm (our regressions all contain firm fixed effects), and regress its investment rate on the investment rates of firms: 1) within its industry, but located far away, and 2) outside its industry, but located nearby.[3]

To give a specific example, consider another Detroit-based firm, retailer K-Mart, and Minneapolis-based Target. In each year, we ask whether the investment rates of K-Mart and Target are related to the average investment rates of other non-local retailers such as Arkansas-based Wal-mart, as well as to the average investment rates of *non-retail* firms headquartered within their respective areas. For example, we explain the investment rate of K-Mart with the investment rates of other Detroit companies like Ford Motor Company and

[3]Additionally, some of our regressions also add a firm's local peers within the same industry, which can be thought of as the interaction between common industry and location.

Dow Chemical, and the investment rate of Target with investment rates other Minneapolis companies like U.S. Bancorp or Valspar (a paint manufacturer).

The results of this exercise reveal that time-varying locational factors play an important role in determining a firm's investment expenditures. Specifically, in the regressions described above, the city effect (e.g., using Dow to explain K-Mart's investment rate) is more than half as large as the industry effect (e.g., using Wal-mart to explain K-Mart's investment rate). To put this in perspective, and continuing with the example above, suppose that 1997 was a good year for retail, and that the typical U.S. retailer increased its investment rate by 10% year over year. Now, suppose that K-Mart's non-retailing neighbors like Ford have a flat year (0% investment change), and Target's non-retail peers like U.S. Bancorp have a banner year (20% investment increase). In this case, our parameter estimates suggest that Target would have investment growth *over twice* that of K-Mart.

Motivated by our model's predictions, our next tests link profitability shocks in one sector within a region to investment rates in another local sector. Specifically, on the right hand side of our investment regressions, we now include: 1) cash flows and Tobin's q for the firm itself, 2) aggregate cash flows and q for firms in the same industry but not in the same city (e.g., Target and K-Mart), 3) aggregate cash flows and q for firms in the same city but not in the same industry (e.g., K-Mart and Dow Chemical). Consistent with the model's predictions, we find that the average q of a firm's local, non-industry peers is a strong predictor of its investment, comparable in magnitude to both its own q and the industry q. Cash flows tell a similar story: when a firm's neighbors generate more cash, the firm increases its investment expenditures. The magnitude of the area cash flow effect is remarkable, being nearly double that of the firm's own cash flows, and about half of the industry effect.

Finally, we conclude by exploring whether the local effects that influence investment also influence the tendency of firms to raise external capital. While the investment regressions indicates local covariation in *current* investment opportunities, raising external finance suggests local covariation in the *expectation* of future opportunities. Using the same empirical framework described above, we look for local co-movement in secondary equity offerings (SEOs) and debt issuance. The results for SEOs are particularly strong, where we observe a contemporaneous local effect almost 70% of the contemporaneous industry effect. With debt, we observe the same cross-industry area effect, but it is weaker, in the neighborhood of 25-35% of the contemporaneous industry coefficient.

By examining the relation between investment and financing choices and location, we build on two distinct literatures. In particular, we draw heavily on the urban economics literature that studies the effect of agglomeration on worker productivity. Most of this work, such as Ciccone and Hall (1996), study cross-sectional relationships between urban characteristics, like city density and worker productivity. However, because there relationships are also consistent with selection effects – i.e., denser urban areas attracting more talented individuals – there is also an interest in considering time-series evidence. Glaeser and Mare (2001), for example, use worker fixed effects in their comparison of wages between urban and rural locations.[4] Although we study individual firms rather than workers, our focus is also on time-series variation, but in contrast with previous studies, we consider time series variation in the vibrancy of fixed geographical areas. Thus, at least insofar as they are reflecting investment opportunities, the concept of a good location is assumed to be about *when* as well as *where*.

We also contribute to the literature that examines the effect of stock prices and cash flows on investment expenditures. In addition to documenting the city-investment effect, our evidence of the importance of city-wide cash flows on firm level investment expenditures addresses a long standing debate in this literature. Fazzari, Hubbard, and Petersen (1988) first observed that high cash flows predicted high investment rates, which they interpreted as evidence that financial constraints were important.[5] That a firm's investment expenditures

[4]When workers move away from the cities, their wages do not decline, consistent with their urban work experience contributing to a stock of permanent human capital. In the reverse direction, wages improve, but the effect is gradual, occurring over several years.

[5]See also Kaplan and Zingales (1997, 1999), Erickson and Whited (2000), Gomes (2001), Altı(2003), and Almeida, Campello, Weisbach (2004).

are strongly related to the cash flows of neighboring firms in different industries – indeed, more strongly than to even its own cash flows – highlights the importance of cash flows as indicators of investment opportunities (e.g., Poterba (1988), Alti (2003)).

There is also a closely related literature that examines how a firm's land holdings, which can be used to collateralize debt issues, can influence the investment expenditures of financially constrained firms. Indeed, a recent paper by Chaney, Sraer, and Thesmar (2011) suggests that collateral values, which vary from city to city as their real estate values change, can generate location-specific investment effects.[6] Our analysis suggests that this collateral effect is not likely to be the main channel that generates the location-investment effect that we observe. Specifically, we find that large firms rather than the small firms tend to be most influenced by area effects, and the local co-movement in debt issuance – which higher collateral values facilitates – tends to be strongest among the *least* financially constrained firms.

Finally, our paper is also related to previous studies that examine the effect of location on stock returns. Pirinsky and Wang (2006) find that stocks of firms in the same city tend to move together. More recently, Korniotis and Kumar (2011) find that statewide economic factors (e.g., unemployment) forecast returns for stocks headquartered in those states roughly two quarters in advance. In contrast to our paper, which emphasizes how corporate fundamentals relate to locations, these papers argue that local return correlations are generated by temporary price pressure induced by trading of local investors.

The paper is organized as follows. Section 2 presents a simple model illustrating the tradeoffs associated with operating in healthy local economy (i.e., crowding out vs. positive locational externalities). We then discuss our empirical design in Section 3, and describe the data we use in Section 4. Our main empirical results regarding comovement in investment for local firms we present in Section 5, followed by a similar analysis of capital raising in Section 6. We conduct a number of robustness checks in Section 7, and then conclude.

[6] See also Peek and Rosengren (2000), Gan (2007), and Tuzel (2010).

2 Vibrancy and investment: a reduced form model

To fix ideas for the empirical analysis that follows, we begin with a reduced form theory that relates a firm's investment choices to those of its local peers. The goal of the model is to illustrate the following tension: when a firm's neighbors invest heavily, it receives both positive and negative externalities. Consequently, a firm's own investment may be either positively or negatively related to the investment rates of its neighbors, depending on the nature of the externalities.

It is easy to envision reasons why a firm's cost of doing business might increase when its neighbors expand. In the short run, competition for local resources like land and labor increases the prices for these inputs, putting downward pressure on investment.[7] Over longer horizons, increased traffic congestion, crime, or other urban disamenities may make it difficult for the firm to attract or retain high quality workers, and consequently, may reduce its longer term investment prospects.

Offsetting these effects however, are a number of positive local spillovers associated with increased investment. We refer to this general family of positive spillovers as *vibrancy.* As mentioned in the introduction, the literature has identified numerous sources of vibrancy, both in production and consumption. One example is local information flow, facilitating the diffusion of know-how between neighboring firms, enhancing the prospects of all. Another potential benefit accrues from the pooling of local labor markets, whereby access to a large group of common workers makes it easier for firms to grow (Dumais, Ellison and Glaeser (1997)).[8] Finally, there may be consumption externalities that make flourishing cities attractive places to live and work (e.g., Glaser, Kolko, and Saiz, 2001), so that one firm's growth has a positive effect on neighboring firms, perhaps with a delay.

[7]Bound and Holzer (2000) find, for example, that a 10% downward shift in local demand decreases wages by 4% and 7%, for college- and high school-educated workers, respectively. The disproportionate responses between these groups is generally attributed to higher skill workers having greater mobility (Topel (1986)).

[8]Note that there is also a flip side to this benefit. Almazan, de Motta, and Titman (2007) show that local labor market liquidity may poison firms' incentive to invest in worker training, if they anticipate rival local firms hiring workers away (post training).

Our simple model focuses on local production externalities. Specifically, we allow for one firm's investment rate (determined endogenously) to positively influence an exogenous technology parameter of a neighboring firm. Here, one could interpret investment as worker training, with some benefit accruing to neighboring firms as local workers mingle and share ideas. However, the particular way we model vibrancy is not particularly important, and one could just as easily interpret the empirics in the context of alternative channels, e.g., those based on local consumption rather than production externalities.

We begin in subsection 2.1 with a single firm to establish the benchmark results. To this we add another firm in subsection 2.2, but do not consider positive spillovers. Then, in subsection 2.3 we allow for positive spillovers, which is the main case of interest.

2.1 One firm

Consider a single firm with profit function:

$$\Pi = I[P\alpha - c(I)], \tag{1}$$

where I represents investment in a *local* production factor, such as land or labor. The firm converts each unit of I into output at rate $\alpha > 0$, which it sells *globally* at price $P > 0$, which we take as exogenous. The marginal cost of the local factor I is expressed $c(I) = \frac{\beta I}{2}$ with $\beta > 0$. Substituting and taking first order conditions, we have

$$P\alpha = \beta I^*, \tag{2}$$

where the left hand side is the (constant) marginal revenue from an additional unit of input I, and the right hand side is the (increasing) marginal cost. This implies the optimal choice of input

$$I^* = \frac{P\alpha}{\beta}, \tag{3}$$

its equilibrium cost

$$c^* = \frac{P\alpha}{2}, \tag{4}$$

and equilibrium profit

$$\Pi^* = \frac{P^2\alpha^2}{2\beta}. \tag{5}$$

2.2 Two firms, no vibrancy

We now add another *local* firm, and index the firms respectively as $i = 1, 2$. Since these firms operate in different industries, output prices and technology parameters are now firm-specific (i.e., P_i and α_i). However, because the firms are local, they draw from the same input pool, so that the common input price reflects both their demands, or $c_i = c_{-i} = \frac{\beta}{2}(I_i + I_{-i})$. In this case, each firm's problem becomes

$$\max_{I_i \in R^+} \quad P_i\alpha_i I_i - \frac{\beta}{2}(I_i + I_{-i})I_i, \tag{6}$$

which, after optimization and substitution gives the first order condition for each firm i:

$$P_i\alpha_i = \beta I_i^* + \frac{\beta}{2} I_{-i}. \tag{7}$$

At this point, it is useful to compare this optimality condition to that of the single firm case (Equation (2)). The left hand sides are identical, reflecting the fact that the introduction of a second firm – at least for now – does not change the marginal impact of input on revenue. For each additional unit of I, each firm still gains $P\alpha$ in revenue. However, the marginal costs, shown on the respective right hand sides, are not the same. Now, in addition to driving up the cost by demanding more I for itself as in the single-firm case (βI_i^*), the demand of the other firm also matters ($\frac{\beta}{2} I_{-i}$). Applying the same first order condition for the rival firm, $-i$, and substituting I_{-i}^* for I_{-i} in Equation (7), we have the optimal demand for firm i,

$$I_i^* = \frac{2}{3} \cdot \frac{2P_i\alpha_i - P_{-i}\alpha_{-i}}{\beta}. \tag{8}$$

the equilibrium cost,

$$c_i^* = c_{-i}^* = \frac{P_i\alpha_i + P_{-i}\alpha_{-i}}{3}, \tag{9}$$

and equilibrium profit for each firm i,

$$\Pi_i^* = \frac{2}{9\beta}(2P_i\alpha_i - P_{-i}\alpha_{-i})^2. \tag{10}$$

Of course, the two-firm case is interesting only when both firms produce positive quantities of output, which Equation (8) indicates occurs when

$$2P_i\alpha_i - P_{-i}\alpha_{-i} > 0, \quad i = 1, 2. \tag{11}$$

Intuitively, this condition simply requires that the marginal revenue benefits are not too dissimilar between firms 1 and 2. If they are, then one firm demands enough to completely crowd out the rival firm, and collapses the problem to the single firm case. Thus, for the remainder of this section, we assume that the pair of equations implied by (11) holds.

Proposition 1 *Provided Equation (11) holds, the investment of each firm i, I_i^* 1) increases with its own productivity, α_i, and output price, P_i, 2) decreases with its local rival's productivity, α_{-i}, and output price, P_{-i}, and 3) decreases as input supply becomes more elastic, i.e., as β decreases.*

We are mostly interested in the second part of this proposition, which formalizes the idea that when firms compete over a local resource, good news for one firm is bad news for the other. This follows directly from Equation (8). Note that a similar proposition would apply to the respective profits of both firms.[9]

[9] To see this, note that $\frac{\partial \Pi_i}{\partial P_2} = \frac{-4\alpha_2(2P_i\alpha_i - P_2\alpha_2)}{9\beta}$ which, given that conditions (11) hold, is strictly negative.

2.3 Two firms, with vibrancy

We now analyze the main case of interest, where shocks to one firm's prospects are transmitted to its neighbor. As mentioned previously, there are a number of ways one can model vibrancy that generate similar empirical implications. Here, we allow the investment level (I) of one firm to influence the productivity (α) of the other firm. To keep the expressions simple, positive spillovers are transmitted in only one direction. Specifically, firm 1 experiences a productivity shock in proportion to the investment of its neighbor, firm 2, and thus solves the problem

$$\max_{\hat{I}_1 \in R^+} \quad P_1(\alpha_1 + \Delta \hat{I}_2)\hat{I}_1 - \frac{\beta}{2}(\hat{I}_1 + \hat{I}_2)\hat{I}_1. \tag{12}$$

Relative to the previous case, the only difference is that firm $1's$ productivity is now enhanced by $\Delta \hat{I}_2$, to reflect spillovers from firm 2's investment level.[10] The corresponding optimality condition for firm 1 is

$$P_1(\alpha_1 + \Delta \hat{I}_2) = \beta \hat{I}_1^* + \frac{\beta}{2}\hat{I}_2, \tag{13}$$

where the left hand side now reflects a higher marginal benefit proportional to the vibrancy parameter Δ. Because vibrancy flows in only one direction ($2 \rightarrow 1$), firm 2 faces the same first order condition as in the previous section, i.e.,

$$P_2\alpha_2 = \beta \hat{I}_2^* + \frac{\beta}{2}\hat{I}_1. \tag{14}$$

Equating (14) and (13) allows us to solve for $\hat{I_1}^*$ and $\hat{I_2}^*$ in terms of the exogenous parameters,

$$\hat{I_1}^* = \frac{2\beta(2P_1\alpha_1 - P_2\alpha_2) + 4P_1P_2\alpha_2\Delta}{3\beta^2 + 2\beta P_1 \Delta}, \tag{15}$$

Also, the specific form of the profit function implies a nearly identical expression arises for α: $\frac{\partial \Pi_i}{\partial \alpha_2} = \frac{-4P_2(2P_i\alpha_i - P_2\alpha_2)}{9\beta} < 0$, implying both channels (prices and productivity) through which crowd out can occur.

[10] An alternative formulation of the problem allows vibrancy to be transmitted in both directions. We have solved this model, but it is considerably more complicated, and the tradeoffs are identical to the case presented here.

$$\hat{I_2}^* = \frac{2(2P_2\alpha_2 - P_1\alpha_1)}{3\beta + 2P_1\Delta}. \tag{16}$$

The first thing to note is that when $\Delta = 0$, so that vibrancy is turned off, Equations (15) and (16) collapse to the set of equations implied by (8). Compared to the no-vibrancy case, the investment of firm 2 - the transmitter of vibrancy – is unambiguously reduced. The reason is that although it experiences no return spillover from firm 1, its input costs are higher because of the increased investment of its rival.

On the other hand, the investment of the recipient (firm 1) will be strictly higher, assuming that $\Delta > 0$. More importantly for our empirical tests, however, there is a critical value of the vibrancy parameter, Δ, where firm 1 responds *positively* to an increase in its rival's price, P_2.[11] This is summarized in the following proposition.

Proposition 2 *There exists a critical value for vibrancy transmission, $\Delta^* = \frac{\beta}{2P_1}$, where for $\Delta \geq \Delta^*$, $\frac{\partial \hat{I_1}^*}{\partial P_2} \geq 0$ and $\frac{\partial \hat{\Pi_1}^*}{\partial P_2} \geq 0$. That is, when Δ is large enough, both firm 1's equilibrium investment ($\hat{I_1}^*$) and profits ($\hat{\Pi}_1^*$) are increasing in firm 2's input price, P_2, so that the investment rates of firms 1 and 2 are positively correlated.*

Proof.

For the first claim, $\frac{\partial \hat{I}_1}{\partial P_2} = \frac{4\alpha_2\Delta P_1 - 2\alpha_2\beta}{(3\beta^2+2\beta\Delta P_1)^2} = 0 \iff \Delta = \frac{\beta}{2P_1}$. For the second claim, $\hat{\Pi}_1 = \frac{P_1^2(8\alpha_2^2P_2^2\Delta^2+16\beta\alpha_2\alpha_1P_2\Delta+b\beta^2\alpha_1^2)-P_1(8\beta\alpha_2^2P_2^2+8\beta^2\alpha_2\alpha_1P_2)+2\beta^2\alpha_2^2P_2^2}{4\beta\Delta^2P_1^2+12\beta^2\Delta P_1+9\beta^3}$ follows from using Equation (12) and substituting Equations (13), and (14). The two roots are $\Delta = \frac{\beta(\alpha_2P_2-2\alpha_1P_1)}{2\alpha_2P2P_1}$, which is strictly negative given (11), and $\Delta = \frac{\beta}{2P_1}$. ∎

Proposition 2 describes the model's main empirical prediction: if vibrancy transmission, Δ, is high enough, then positive shocks to one firm's fundamentals will imply net positive shocks to surrounding firms. Note that the critical level depends on two parameters: the elasticity (β) of the input and the price of the recipient firm's output (P_1). Intuitively, when

[11] A nearly identical claim applies to changes in the rival's, productivity (α_2). Although the intuition is similar, we find it more intuitive to think about price fluctuations being a more important source of variation for the typical firm's annual performance.

the input costs are very elastic (i.e., when β is large), vibrancy must overcome a larger crowding out deficit. This is easier when the marginal benefit of production, the output price (P_1), is high.

3 Empirical design

The model described in the last section suggests that if vibrancy is sufficiently important, the investment rates of neighboring firms will tend to rise and fall together, even when operating in different industries. To measure the extent to which this is true, we run a series of regressions where the dependent variable is a firm's investment expenditures, which we explain with firm-level, industry-level, and area-level variables. Our specific interest is the importance of the area-level information, relative to that captured by industry- and firm-level attributes. In subsequent analysis, we will also examine capital raising, using the same set of explanatory variables as regressors.

Before describing the equations we estimate, it is necessary to define some notation. Each firm j operates in one of twelve Fama-French-12 industry classifications, indexed by $i \in \{1, 2, 3, ..., 12\}$. Headquarter locations are indexed by a, which for now we simply describe with city names like New York, Los Angeles, and so on. In the next section, we are more explicit about what constitutes an area. Time is indexed in years, denoted t.

A typical observation is defined with a quadruple $\{i, j, a, t\}$. For example, suppose that the unit of observation is Google (firm j) in 1997 (year t). In this case, the area, a, would refer to the San Francisco Bay Area (Google's headquarters), and i would correspond to Fama-French industry #6 (Business Equipment – Computers, software, and electronic equipment). This taxonomy permits us to partition every other firm (i.e., not firm j) into one of four mutually exclusive categories: same industry/same area (i, a), same industry/different area $(i, -a)$, different industry/same area $(-i, a)$, and different industry/different area $(-i, -a)$. Relative to Google, Yahoo (Bay Area-based Business Equipment) would be an example of a same industry/same area firm, Blackboard Inc. (Washington D.C.-based Business Equipment) an example of a same industry/different area firm, Genentech (Bay Area-based Healthcare) an example of a different industry/same area firm, and Apache Inc. (Houston-based Energy) an example of a different industry/different area firm.

The goal of this partitioning is to isolate *local* effects from *industry* effects on a firm's investment expenditures or tendency to raise external capital. Specifically, we estimate the following regression:

$$Investment^{i,a}_{j,t} = \delta + \sum_{k=0}^{2} \beta_{1,k} Investment^{i,-a}_{p,t-k} + \sum_{k=0}^{2} \beta_{2,k} Investment^{-i,a}_{p,t-k} + \sum_{k=0}^{2} \beta_{3,k} Investment^{i,a}_{p,-j,t-k} + \beta_4 Controls^{i,a}_{t} + \epsilon^{i,a}_{j,t}. \quad (17)$$

The dependent variable, $Investment^{i,a}_{j,t}$, is the investment of firm j, operating in industry i, in area a, during year t, and is defined as capital expenditures in year t divided by total assets in year $t-1$. Proceeding from left to right, the first explanatory variable, $Investment^{i,-a}_{p,t-k}$, is simply an industry control for investment in the current (t) and two previous years ($t-1$ and $t-2$). It is an equally weighted portfolio (p stands for portfolio) of firms *within* firm i's industry, but located *outside* its area.[12] Here, the goal is to capture year-to-year fluctuations in the investment expenditures of an entire industry, e.g., whether the investment rates of software firms increased from 1997 to 1998. The coefficients denoted by vector β_1 capture the sensitivity of firm i's year t investment to industry level variation, in both current ($\beta_{1,0}$) and previous ($\beta_{1,1}, \beta_{1,2}$) years.

We have a particular interest in the second vector of coefficients, β_2, which capture the investment sensitivity of firm i to the investment behavior of nearby firms, but in different industries. For example, β_2 would measure Google's investment sensitivity to that of local biotech firms like Genentech, both in the current year (t) and in previous years ($t-1$ and

[12] We construct industry portfolios using only firms located outside *any* of the 20 economic areas examined. This ensures that at any point in the time t, industry portfolios are identical for all firms in industry i. In other words, the composition of each industry portfolio does not change across areas.

$t-2$). Because there should be minimal overlap in the products of firms operating in different industries – note here that using broad industry classifications makes this less worrisome – the coefficient β_2 provides an estimate of the average "pure" local investment effect.

The final portfolio captures the investment behavior of firms in the same area (a), and also in the same industry (i) as firm j.[13] For example, Yahoo's investment behavior would enter as an explanatory variable when explaining Google's investment expenditures. Given that we have already accounted for aggregate industry effects through $Investment_{p,t-k}^{i,-a}$, and non-industry local effects through $Investment_{p,t-k}^{-i,a}$, β_3 can be interpreted as the interaction between the industry and local effects. Conceivably, the types of local spillovers (e.g., information diffusion) we envision for neighboring firms in different industries may be even stronger when they share industry linkages.

Finally, the *Control* variables in Equation (18) include firm, year, and area fixed effects. The inclusion of firm dummy variables essentially demeans both the left- and right-hand side variables by the average value(s) for each firm, so that the coefficients are identified from the time-series variation for each firm. Year dummies soak up average fluctuation in aggregate investment rates, and are akin to a market control.[14] Area fixed effects account for persistent differences in investment rates between areas – however, because all regressions include firm fixed effects, these area controls have very little incremental explanatory power, being relevant only in the few cases when firms change headquarter locations.

The second type of equation we will estimate is closely related, but instead of using investment on both the right and left hand side of the equation, we use standard determinants of investment as explanatory variables. In this case, we estimate the following equation:

[13] The $-j$ subscript indicates that the current observation is excluded from the same industry/same area portfolio.

[14] Note that this is virtually identical to including the investment rates of firms outside firm j's area, and outside its industry, $(-i,-a)$. Unsurprisingly, an alternative specification including the average investment rate of the $(-i,-a)$ portfolio leads to almost identical results.

$$
\begin{aligned}
Investment^{i,a}_{j,t} = \phi + \sum_{k=0}^{1} \alpha_{1,k}\, q^{i,-a}_{p,t-k-1} + \sum_{k=0}^{1} \alpha_{2,k}\, q^{-i,a}_{p,t-k-1} + \sum_{k=0}^{1} \alpha_{3,k}\, q^{i,a}_{p,-j,t-k-1} + \\
\sum_{k=0}^{1} \alpha_{4,k}\, Cashflow^{i,-a}_{p,t-k} + \sum_{k=0}^{1} \alpha_{5,k}\, Cashflow^{-i,a}_{p,t-k} + \sum_{k=0}^{1} \alpha_{6,k}\, Cashflow^{i,a}_{p,-j,t-k} + \\
\sum_{k=0}^{1} \alpha_{7,k}\, q^{i,a}_{j,t-k-1} + \sum_{k=0}^{1} \alpha_{8,k}\, Cashflow^{i,a}_{j,t-k} + \alpha_9\, Controls^{i,a}_{t} + \epsilon^{i,a}_{j,t}.
\end{aligned}
\tag{18}
$$

Although it looks considerably more complicated, we have made only two changes. First, the explanatory variables are now lagged q and contemporaneous $Cashflow$, instead of investment itself. As before, these variables are constructed at the portfolio level (note the subscript p), and therefore capture the same types of industry, local, or local-industry effects discussed above. The same industry/different area $(i, -a)$, different industry/same area $(-i, a)$, and same industry/same area (i, a) portfolio q are shown consecutively in the first row, and these same quantities for $Cashflow$ in the row beneath. As before, we include two lags of each variable.

The second change is that now, because the explanatory variables are determinants of investment rather than investment itself, we can include firm-specific information. In other words, in addition to including q and $Cashflow$ for a firm's industry or local neighbors, we also include these quantities for the firm itself. These variables are captured by the variables $q^{i,a}_{j,t-k-1}$ and $Cashflow^{i,a}_{j,t-k}$, respectively, and their coefficients as α_7 and α_8. The j subscript indicates that these regressors are formed at the firm-level, in contrast to variables formed at the portfolio (p) level.

Our final tests then re-estimate Regression (18), but instead of using investment expenditures as our dependent variable, we look at capital raising. Practically, this amounts simply to substituting either equity or debt issuance (both scaled by lagged assets) for investment in the first equation, on both the right and left hand side. In the second investment equation, the explanatory variables will stay the same, and only the dependent variable will change.

To save space, we do not repeat the estimating equations for equity and debt issuance here.

4 Data and variable construction

We now describe the data we employ to estimate the regressions described in Section 3. To construct our sample, we begin by first identifying all public companies listed on the NYSE, NASDAQ, or AMEX between January 1970 and December 2009. For each of these firms, we obtain monthly common stock returns from CRSP (which we then annualize), and yearly firm fundamental data and industry (SIC) codes from the CRSP/COMPUSTAT Merged Database. To minimize the influence of outliers, we winsorize all firm fundamental variables at the one percent level.

Each firm is classified by industry, i, and headquarter location, a. For industry classification, firms are assigned to their relevant Fama-French 12 category: Consumer Non-durables (1); Consumer Durables (2); Manufacturing (3); Energy – Oil, Gas, and Coal Extraction and Products (4); Chemicals (5); Business Equipment – Computers, Software, and Electronic Equipment (6); Telephone and Television Transmission (7); Utilities (8); Wholesale, Retail, and Some Services (9); Healthcare, Medical Equipment, and Drugs (10); Finance (11); and Other (12).[15] For location, we use the zip code listed on COMPUSTAT (variable ADDZIP) to place each firm headquarter in one of the 20 largest "Economic Areas," hereafter EA, as defined by the United States Bureau of Economic Analysis.[16]

An economic area (EA) is defined as "the relevant regional markets surrounding metropolitan or micropolitan statistical areas," and are "mainly determined by labor commuting patterns that delineate local labor markets and that also serve as proxies for local markets where businesses in the areas sell their products."[17] The last sentence in this definition is important, because our concept of location is closely tied to labor markets. Specifically, we

[15] For more details about how these industry designations are defined, see `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html`.

[16] Firms outside these 20 areas are used to construct the same industry/different area portfolios, but are otherwise ignored.

[17] See `http://www.bea.gov/regional/docs/econlist.cfm`.

want to identify firms that are sufficiently close that their respective workers interact, share information and ideas, and potentially even hire one another. Because the reach of such activities may span city boundaries – think about San Francisco and San Jose – we focus our analysis on somewhat larger economic areas, rather than on cities or even metropolitan statistical areas (MSAs).

Table 1 gives a sense of the distribution of firms and economic areas in our dataset. In Panel A, we rank each of the 20 EAs by population, in descending order. Next to this, we show the yearly distribution of the number of firms headquartered in each economic area. For example, the average number of firms headquartered in the New York-Newark-Bridgeport EA each year is 599. However, as indicated by the 10^{th} and 90^{th} percentiles, the number of firms changes fairly dramatically over the four decade sample period, differing by over a factor of two (398 vs. 814). Similar variation is observed for the other cities.

Moving down the table, we see generally that more populous areas host a larger number of firms. Detroit is a notable outlier, headquartering only 69 firms per year on average (dropping to 54 in 2009), which is similar to San Diego despite having more than twice the population. At the other end of the spectrum, Minneapolis and Houston both host somewhat more firms than their respective population rankings might indicate. The EA just above the median is Atlanta, home to 98 firms on average over our sample period.

In the next few columns, we rank EAs by aggregate market capitalizations, rather than by population. Generally, relative rankings are preserved, although there are some exceptions. Regions rich in technology (San Jose-San Francisco-Oakland) and energy (Houston-Baytown-Hunstville) have somewhat higher rankings based on size, and areas heavy in manufacturing (Philadelphia-Camden-Vineland) and durables (Detroit-Warren-Flint) are, perhaps predictably, a bit lower.

Figure 1 presents the same information graphically, in the form of a heat map, with reddish areas representing higher concentrations of companies. This figure makes clear that the Eastern seaboard and Midwest are home to a disproportionate number of firms, with nearly continuous bands of industrialization connecting Boston to Washington, D.C., and Pittsburgh to Detroit. Of the 20 largest EAs in the U.S., about two-thirds are located on or east of the Mississippi River. Moreover, these are among the most important, including 61% of the average population, and 59% of the firms in our sample.

Moving back to Table 1, Panel B breaks down each area into its industry constituents. For example, Consumer Non-durables (*NoDur*) represent, on average, about 10% of the total market capitalization of the New York EA.[18] Note that some cities are characterized by a consistently dominant industry – e.g., Houston (46% Energy) and Detroit (49% Consumer Durables)– being prime examples. Generally, heavy industry clustering reflects a common supply of natural resources (e.g., oil in the Gulf of Mexico) or transportation lanes (e.g., Great Lakes, Mississippi River).

In contrast, geographical features play a reduced role in the clustering of software, telecommunications, or other industries that make intensive use of human capital. Denver (42% Telephone and Television Transmission), the San Francisco Bay Area (37% Business Equipment), and Boston (32% Business Equipment) are well known cases. Here, information spillovers or other agglomeration effects are thought to give rise to industry clusters.[19] Of course, some areas are quite diversified, such as Chicago, where no one industry accounts for more than 17% of the total market capitalization. New York, Philadelphia, Miami, and Minnesota are all similarly balanced, with most other areas falling somewhere in between.

Table 2 presents summary statistics for the variables we will analyze, both as dependent and explanatory variables. In Panel A, we tabulate firm-level data. The first row shows that in the typical year, our regressions include almost 3,000 firms, with a minimum of 914 and

[18]For a given area, the market capitalization for each industry relative to the area's total market capitalization is averaged by year. This number is then normalized, so that rows sum to 100 percent for ease of interpretation.

[19]For instance, Saxenian (1994) describes how meeting places, such as the Wagon Wheel Bar located only a block from Intel, Raytheon, and Fairchild Semiconductor, "served as informal recruiting centers as well as listening posts; job information flowed freely along with shop talk." More formally, Jaffe, Trajtenberg, and Henderson (1993) find that new patents are five to 10 times more likely to cite patents from the same metropolitan area relative to a control group, even after eliminating patent citations from the same firm. They interpret their findings as evidence of knowledge spillovers in metropolitan areas.

a maximum of 4,522. The following rows characterize the means, standard deviations, and $10-50-90^{th}$ percentile cutoffs for *Stock Returns*, *Cashflow*, *Investment*, *Secondary Equity Issuance*, *Debt Issuance*, and q. The distribution of these variables is consistent with other studies of investment, e.g., Rauh (2006).

The remaining panels of Table 2 give a sense for the average size of the typical same industry-different area (137 firms), same area-different industry (174 firms), and same industry-same area (22 firms) portfolios.[20] To give a flavor for the year-to-year *variation* in the performances of these portfolios, Figure 2 plots the cross-sectional variation in aggregate investment for each of our Fama-French 12 industry portfolios (Panel A), and for each of our diversified area portfolios (Panel B).[21] As seen, there is a bit more cross-sectional variation across industries – as would be expected given that area portfolios are diversified *across* industries – but nonetheless, we observe substantial heterogeneity in the investment rates across our economic areas.

Finally, Panel B of Table 2 presents bivariate correlations between the different area and industry portfolios. In addition to the expected relationships among similar portfolio types (e.g., a large negative correlation between same industry-different area $Cashflow$ and same industry-different area *Equity issuance*), we also observe similar patterns between portfolio types (e.g., a large negative correlation between same industry-different area $Cashflow$ and different industry-same area *Equity issuance*), foreshadowing our multivariate regression results.

5 Local effects in corporate investment

Our main empirical tests address whether a firm's investment expenditures are related to the investment expenditures and investment prospects of firms located nearby. We begin by

[20]To ensure that portfolios are reasonably diversified, for the remainder of our analysis we require that all portfolios used in our analysis consist of more than five firms.

[21]For this figure, all industries in a given area are included. In the regressions, we typically break out a firm's local neighbors into those that share its industry, and those that do not.

showing some simple univariate comparisons in subsection 5.1, which provide evidence that the investment expenditures of firms in a given area tend to be correlated. Then, in subsection 5.2, we extend these univariate comparisons to a multivariate regression framework. Finally, we consider the ability of standard investment determinants like q and $Cashflow$ to explain investment expenditures in subsection 5.4. As we will see, even after controlling for the investment determinants at the firm and industry level, the cash flows and stock prices of its local peers still influences how much it invests.

5.1 Univariate evidence

For each of our Fama-French 12 industries, we rank our 20 areas by either their industry investment expenditures or the investment growth rate *outside* the industry of interest. Consider as an example industry classification 1, Consumer Non-durables. We calculate the average investment rate for Consumer Non-durables within each area, generating a cross-section of 20 city-level average investment rates among Consumer Non-durables for each year. Then, we calculate the average investment rate for every industry *except* Consumer Non-durables (i.e., industries 2 through 12) in Atlanta, Denver, San Diego, etc., which generates another 20 cross-sectional observations. We conduct this exercise for every industry in every year.

This procedure allows us to rank areas, from highest to lowest, in terms of their average investment rates outside the considered industry. Continuing the discussion of consumer non-durables, each year is associated with 20 city-average investment rates outside the consumer non-durables industry. With this ranking in place, we form three roughly equal groups: high investment cities, medium investment cities, and low investment cities.[22] This ranking can change year to year, and across industries.

The question of interest is whether a firm's local, but non-industry peer firms – recall that regions are ranked according to investment outside the industry of interest – appear to

[22]Conducting this same comparisons using above-below the median, or with quartiles makes virtually no difference.

influence its own investment choices in a given year. Table 3 shows the results. For each industry, we show two rows. In the first, all analysis is done in levels, i.e., the areas are ranked by average (scaled) investment levels, and the numbers shown in the first row are simply average investment-to-asset ratios. In the second row, everything is done using 1-year investment growth rates; here, areas are ranked by the average investment growth outside the industry being considered, and the numbers presented are changes in scaled investment.

Starting with the first row and continuing the specific example above, the table indicates that on average, the investment expenditures of consumer non-durable firms are considerably higher (0.05 vs. 0.07) for firms located in areas where investing firms outside consumer non-durables (e.g., Chemicals or Business Equipment) invest more. Proceeding down the table, this same pattern is observed for each industry. The average difference in scaled investment expenditures is about 0.02 (against a base rate of 0.07) in high vs. low investment areas, and is most pronounced in oil and gas (0.07), and less so in Healthcare (0.01), Utilities (0.01), Chemicals (0.01), and Manufacturing (0.01). In every case, simple means tests reject the hypothesis that these investment rates are equal.

The above results are basically cross-area comparisons: some areas are home to firms that heavily invest (in every industry), whereas others are home to firms that persistently invest lower amounts. While interesting, this is not particularly informative about the dynamics of investment – that is, whether a firm's neighbors ramping up or scaling back their investment alters its own investment choices. The second row within each industry heading addresses this question. Here, the procedure is the same, except conducted with investment changes rather than levels. We observe results that are a bit weaker, with only Consumer Durables, Manufacturing, Energy, and Chemicals showing statistically significant results. However, in ten of the twelve industries, the point estimates go the expected direction, the exceptions being Utilities and Consumer Non-durables.

5.2 Investment-investment regressions

In Table 4, we build on Table 3's analysis of investment changes by estimating multivariate regressions. The first column shows the results when we explain a firm's investment expenditures (scaled by lagged assets) with the average investment rates of firms in its industry. Recall that these industry portfolios are constructed from firms outside any of the 20 EAs, so that the same firm is never simultaneously on the right and left-hand side of the regression. The point estimate of 0.503 ($t = 3.43$) indicates that when the industry average investment-to-assets ratio increases by 1% relative to its long run average – say, from 7% to 8% – the typical firm increases its own investment rate by about 0.5%. Note that because all regressions include firm fixed effects, the coefficients should be interpreted as the change from each firm's panel average. Furthermore, because investment rates are close to being stationary over long horizons, estimates obtained from fixed effects or first differences regressions generate virtually identical results.

The second column shows the estimates when we replace same industry-different area with same area-different industry portfolios. The coefficient of 0.186 ($t = 1.91$) indicates that the investment sensitivity to the average investment of firms in the same area, but outside of its industry, is about one-third of the industry effect. When both are included simultaneously in the third column, the magnitude of the coefficient of the area investment portfolio increases to 0.231 ($t = 2.66$), almost half the magnitude of the coefficient of the industry portfolio (0.508, $t = 3.57$).

In the fourth column, we add the investment rate of the third and final portfolio, which includes firms both in the firm's industry, and headquartered nearby. Because the regression already includes the investment rates of a firm's industry and area (but different industry) counterparts, it is convenient to think about this portfolio as an interaction term between industry and area. Two observations are noteworthy. First, the magnitude on the same industry-same area portfolio is 0.183 ($t = 4.96$), slightly smaller economically than the different industry-same area portfolio (0.211, $t = 2.77$), but is statistically much stronger.

Second, the magnitude on the pure industry portfolio (row 1) drops somewhat to 0.386 ($t = 3.48$), virtually identical to the sum of the two local portfolios, $0.183 + 0.211 = 0.397$.

Together, these estimates imply that when predicting a firm's investment rate (specifically, relative to its long run average), the investment behavior of a firm's local peers is, on the margin, as important as the investment expenditures of the firm's non-local industry peers. About half of the local effect comes from firms within its own industry, with the other half coming from firms in very different industries.

Columns 5 and 6 of Table 4 add one- and two-year lags, respectively, for each investment portfolio. Focusing our attention on column 6, the first three rows indicate that for the non-local industry portfolio, only the contemporaneous value matters (0.354, $t = 3.09$); lagged values have negative, small, and insignificant coefficients. In other words, whatever information about investment opportunities is reflected by the behavior of a firm's same-industry, non-local peers is incorporated into its own investment plans very quickly.

In marked contrast, the effects of a firm's *local* peers, both inside and outside its industry, show up more gradually. The fifth row shows that even after controlling for contemporaneous investment (fourth row), the lagged investment rates of a firm's local, non-industry peers matter, with a point estimate of 0.050 and t-statistic of 2.57. Compared to the contemporaneous value (0.188, $t = 2.62$), this means that roughly 20% of the total local, non-industry effect shows up with a year lag. The delay is even more pronounced for local firms within the same industry, where the one year lag (0.058, $t = 3.60$) is about one-third as large as the contemporaneous coefficient (0.158, $t = 4.10$). Together, these findings suggest that although the majority of local effects are immediately reflected in investment plans, the full effect of regional vibrancy takes longer to emerge.

5.3 Discussion and further tests

Together, the results in Tables 3 and 4 indicate strong cross-industry comovement in the investment expenditures of neighboring firms. Before moving on to extensions of these main results, it is useful to describe potential mechanisms that may be generating these comovements, and then briefly discuss the extent to which they may explain the evidence.

1. **Vibrancy.** This refers to the general family of spillovers between local firms that we explore in the reduced form model presented in Section 2, but a number of similar models will produce similar results. While the specific channel that generates this vibrancy is less important, the crucial feature is that it depends on interactions between local firms and/or their workers.

2. **Exogenous area shocks.** Time-varying area shocks can generate correlations between local firms' investment expenditures without requiring local interactions. Extreme weather or disruptions in local politics might be examples of events that can effect the investment opportunities of all firms in a local area.

3. **Common variation in collateral values.** This is a special type of common area shock, but one that has particular importance when analyzing investment. The basic idea is that land is used as collateral for debt financing, so that firms owning land in the same general area may experience simultaneous fluctuations in their abilities to raise debt financing.[23] Of course, this begs the question of what ultimately caused the common shock to land values, but nonetheless, the lack of firm-to-firm interaction distinguishes this channel from vibrancy-related mechanisms.

4. **Residual industry linkages.** The concern here is that despite using very broad industry classifications (Fama-French 12), there may be supplier-customer relationships or other industry linkages between local firms in different industries. Under this scenario, investment correlations are due to explicit firm-to-firm interactions, not the implicit interactions we have in mind for our definition of vibrancy.

While it is likely that all of the above mechanisms contribute, at least somewhat, to the observed comovement of local investment, the goal of the rest of this subsection is to provide

[23]See, e.g., Chaney, Sraer, and Thesmar (2011).

additional evidence that suggests that a significant portion is due to the vibrancy channel.

We start by splitting the sample into large and small firms, a decomposition relevant for two reasons. First, we expect the collateral channel (the third alternative) to be weaker for large firms, which are less likely to be financially constrained. Second, note that local supplier-customer relationships (the fourth alternative) will disproportionately impact small firms with less diversified customer bases. To give a specific example, think about a Houston-based software firm that primarily sells its products to local oil and gas firms.[24] Here, the concern is that fluctuations in oil prices have a first order impact on the demands of Houston oil firms, and a second order impact on the software firm's demand. Therefore, by restricting attention to larger firms with less regional customer bases, we reduce the likelihood that these types of industry linkages are driving our results.

To test this idea, Column 7 shows the results for the same specification shown in column 6, but only for small firms, where small firms are defined as firms which have last year's total assets below last year's median total assets for all firms. The analysis for larger firms is shown immediately adjacent. This comparison reveals that the magnitude of the same area-different industry portfolio coefficient is over twice as large for large firms (0.237, $t = 2.29$), versus that observed for small firms (0.096, $t = 2.60$).[25] For local firms within the firm's industry, the effects are also more pronounced for large firms, particularly at one-year lags.

The next test is motivated directly by our model, which posits both positive and negative externalities when an area "heats up." Recall, a positive shock to a firm's local neighbors can have a positive or negative impact on its own investment expenditures depending on the tradeoff between increased vibrancy and the negative effects of crowding out. Although the *overall* pattern of positive investment comovement suggests a relatively minor role for crowding out, the final pair of columns in Table 4 examines *specific* situations where crowding

[24]In our setting, these firms would have different industry classifications. The software firm would go under the Business Equipment (Fama French 12 industry # 6), and the oil firm under Energy (Fama French 12 industry #4).

[25]We present separate regressions to ease exposition; however, if we were instead to aggregate all firms into a single regression and interact a dummy variable for "small firms" with the portfolio of investment for each firm's local, non-industry neighbors, the interaction is negative and significant at the 1% level.

out is likely to be more or less important.

The split we perform is between areas that have experienced a recent *positive* versus *negative* shock to average investment growth. In other words, we simply take the local, non-industry portfolios in our previous regressions, and divide them into two groups: 1) those that have increased year over year, and 2) those that have decreased.[26] Intuitively, this test exploits the downward rigidity of local input prices and the notion that prices respond more swiftly to demand increases than to decreases. Hence, we should expect an asymmetric response: the crowd-out effects of positive shocks should be muted because of the flexibility of local input prices. However, negative shocks should have a more pronounced effect, since vibrancy decreases, but because prices do not drop enough to soften the blow, investment is sharply decreased.

Indeed, this is exactly what columns 9 and 10 of Table 4 indicate. Following positive area shocks (column 9), we observe only weak evidence of positive comovement, (0.064, $t = 1.07$). This is consistent with local input prices such as wages or rent responding quickly to demand for local input, offsetting the effect of vibrancy. On the other hand, negative area investment shocks are much stronger, both economically (0.197) and statistically ($t = 2.59$). Note that while consistent with the model's predictions, this is additional evidence against a collateral story, which, because land prices also exhibit downward rigidity, should be stronger after positive area shocks.

While the final four columns of Table 4 help us rule out industry linkages and the collateral channel, what about time-varying area shocks like weather or local political shocks (the second alternative)? Recalling again our reduced form model, the defining feature of vibrancy is that it is transmitted *between* neighboring firms, not jointly *to* them for exogenous reasons. Thus, in this section, we identify subsets of the data where the direction of transmission is easier to infer.

[26] In the notation of Equation 18, we are simply comparing $Investment_{p,t}^{-i,a}$ to $Investment_{p,t-1}^{-i,a}$ for every firm i in year t.

The basic idea is to identify select areas where a single, local dominant industry exists. Then, we will use *industry-level* fluctuations in these dominant industries as our measures of local vibrancy. For example, we will use economy-wide fluctuations in the energy sector as a bellweather for Houston's vibrancy. The question of interest is whether non-energy firms in Houston respond disproportionately to fluctuations in the U.S. energy industry, compared to other non-energy firms located in areas where energy is less important for local business conditions.

To begin, we identify four areas where only one of the Fama-French 12 industries consistently accounts for 15% or more of the area's total market capitalization. Second, to make sure that one or two firms don't influence our results, we require at least ten firms in these "locally dominant" portfolios. Imposing these criteria result in the following four area (industry) pairings: Atlanta (Non-durables), Detroit (Durables), Houston (Energy), and the San Francisco Bay Area (Business Equipment).

Table 5 shows the results. In the first four columns of Panel A, we run area-level regressions similar to Equation 18, except that now, only a single, dominant industry is included as a measure of local vibrancy.[27] In each case, we see that even after controlling for the investment rates in each firm's industry, our single local, dominant portfolios appear very important for determining investment rates of local firms. In two of the areas – San Francisco Bay Area and Detroit – the local portfolio is comparable to the industry effect. As in Table 4, we also show these results for small (column 6) and large (column 7) firms. While significant for both groups, the local correlations are a bit stronger for large firms.

This evidence notwithstanding, it is still possible that time-varying location shocks could impact both an area's dominant industries, as well as other local firms. Panel B of Table 5 rules this out by construction, and thus provides direct evidence of a *causal* role for local vibrancy. Here, we replace each of our local, dominant industry portfolios with their

[27] Of course, this means that we must exclude each area's dominant industries from the left hand sides in the appropriate column. Moreover, year fixed effects are not permitted because they are perfectly collinear with each area's dominant industry portfolio.

corresponding industry portfolios. For example, in column 3, the regression contains *no Detroit-specific information.* Rather, it simply allows firms located in the Detroit area, but not in the durable (e.g., automotive) industry to exhibit correlation with a market-wide durables portfolio. The absence of any local variable on the right hand side of the regression means that time-varying local shocks cannot be driving the results.

When predicting a firms investment in Atlanta (column 1) or the San Francisco Bay Area (column 2), we see that the overall industry performance of the area's most important industry (e.g., a portfolio of computers and software for firms in the Bay Area) is an even more important determinant of investment than the firm's industry itself. For Detroit (column 3) and Houston (column 4) the ability of the locally dominant portfolio to predict investment is somewhat weaker, but in both cases is statistically significant. When all cities are aggregated in column 5, the magnitude is about one-third of the pure industry effect, similar to what we observed in Table 4. In the last pair of columns, we see that these effects are present to roughly equal degrees for small (column 6) and large (column 7) firms, the latter suggesting that industry linkages play a minor role at best.

5.4 Investment-q regressions

The results in the last subsection indicate strong, positive correlations in the investment rates of nearby firms. This is generally consistent with our model of local spillovers, whereby good news for one firm's investment prospects implies good news for the investment prospects of its neighbors. However, our model allows us to be even more specific about this linkage. Recall from Proposition 2 that the investment expenditures of the vibrancy recipient are positively related to the product prices (or profits) of neighboring firms – not just their investment expenditures. In this section, we test this implication by estimating standard investment regressions that include the firms's q and cash flows; the main innovation is that we also include these same quantities for the firm's industry and local peers.

In the first column, we include only the firm's own q (lagged one year) and contemporaneous cash flows, scaled by lagged assets. Consistent with many previous studies, both q and $Cashflow$ are significant determinants of a firm's investment rate.[28] The second column adds these same quantities, averaged over a firm's non-local, industry peers. Both industry coefficients have positive signs, but are statistically weaker than the firm's own values for q and $Cashflow$. For example, the coefficient on industry q is 0.015 ($t = 2.02$) versus 0.012 ($t = 8.33$) for the firm's own q. Although the coefficient on industry $Cashflow$ has a very large point estimate (0.205), it is imprecisely estimated (1.87), making it difficult to judge the size of the true effect.

In the third column, we add the average q and $Cashflow$ for the firm's local peer firms, but operating outside its industry. $Cashflow$ for the firm's local, non-industry neighbors is both economically (0.100) and statistically significant ($t = 2.68$), and surprisingly, is over twice as large as the firm's own cash flows (0.049, $t = 2.83$). By contrast, the average q for a firm's local, but different-industry neighbors has a positive point estimate, but is not statistically significant (0.006, $t = 1.22$).

The regression reported in the fourth column of Table 6 includes characteristics of the firm's industry peers, both inside and outside its local area. In this regression, both q variables are significant – the average q for firms in the same industry has a point estimate of 0.014, similar to the coefficient of the firm's own q. Likewise, both $Cashflow$ variables (same area-different industry and same industry-different area) are important determinants of the firm's investment rate. The industry variable is still marginally significant ($t = 1.88$), but with a large point estimate of 0.192. As for the average $Cashflow$ of a firm's non-industry local peers, except for the firm's own q, this is the most significant determinant of investment. The point estimate of 0.105 ($t = 3.90$) means that when the cash flow rates of neighboring firms increases by 1%, the typical firm increases its investment rate by about 0.1%.

The last two rows in the fourth column indicate that the average q and $Cashflow$ of a

[28]See for example, Fazzari, Hubbard, and Petersen (1988) and Kaplan and Zingales (1997).

firm's same industry, same area peers matter somewhat, but less so than the other variables. The coefficient on one-year lagged q has a positive point estimate, but is not significant. $Cashflow$ in the same industry is statistically significant ($t = 2.54$), but the point estimate is about $\frac{1}{5}$ the size of the area, non-industry analog, and about $\frac{1}{8}$ the size of the industry, non-area portfolio.

In the fifth column, we repeat the specification in the fourth column, but allow every explanatory variable to also enter at a one year lag. In these regressions, two-year lagged q is never significant, when one-year lagged q is included in the regression. On the other hand, $Cashflow$ fluctuations appear to influence not only current, but future investment. The third and fourth columns indicate that this pattern holds for the firm's own $Cashflow$, where the one-year lagged coefficient is about 60% as strong as the contemporaneous one (0.027 (vs. 0.040 ($t = 2.75$)). At least in terms of point estimates, this is also true for the non-local industry portfolio, where the coefficient on one-year lagged $Cashflow$ is 0.078, versus 0.137 for contemporaneous. However, neither are statistically significant at conventional levels.

The 11^{th} and 12^{th} rows indicate comparable magnitudes for $Cashflow$ among a firm's local, non-industry peers in the current year (0.074, $t = 2.32$) and one year ago (0.058, $t = 2.21$). Although the magnitudes are lower for a firm's same industry, local peers, the ratios are roughly the same. Contemporaneous average $Cashflow$ has a coefficient of 0.014 ($t = 1.91$), with a one-year lagged coefficient of (0.010, $t = 1.85$).

6 Local effects in *expected* investment: raising capital

The results in the last section indicate that a firm's near-term investment choices appear to be heavily influenced by the recent investment behavior and prospects of its neighbors, even those in very different industries. Here, we extend this line of reasoning to consider whether investment plans over longer horizons are similarly influenced by local factors. Because raising capital tends to be correlated with future increases in investment (e.g., Jung, Kim, Stulz

(1996)), we explore this possibility by examining the effect of location on equity (subsection 6.1) and debt (subsection 6.2) issues. The regressions we run have virtually identical structure to those just seen for investment; the only change is that either SEOs or debt issuance is substituted for investment.

6.1 Secondary equity issuance

We next characterize the extent to which secondary stock offerings tend to cluster in time, for a given geographic area. The regression structure in Panel A is identical to Equation (18), except that in both the right and left hand sides, *Equity issuance* replaces *Investment.* The definition of *Equity issuance* is the change in common equity, plus the change in deferred taxes, minus the change in retained earnings, all normalized by one-year lagged total assets.

The first column of Panel A, Table 7 indicates strong industry effects in the temporal clustering of SEOs. For the typical firm, a 1% increase in the amount of equity (scaled by last year's total assets) at the industry level is associated with a 0.5% increase in the firm's equity-issuance-to-lagged-assets ratio, with a t-statistic of almost 7. Similarly, we find that a similar 1% increase for the firm's local, non-industry peers increases its scaled equity issuance by about 0.3%. Statistically, they are almost identical, with a t-statistic of 6.98 for the non-local industry portfolio, and a t-statistic of 6.59 for the non-industry local portfolio. Subsequent columns that include the same industry-same area portfolio (column 4), reveal a fairly strong contemporaneous relationship (point estimate of 0.127, t = 5.05). The fifth column adds one-year lags for all three portfolios, but none are statistically significant. In the final column, all three point portfolios have negative point estimates – two of which are significant – indicating a roughly two-year boom and bust cycle in equity issuance.

Taking the final column as the most indicative of the underlying behavior, we see that variables that include local equity issuance have a combined effect (0.353) that is about as large as the non-local industry portfolio alone (0.396). As with the investment regressions, over half the local effect is from a firm's local, but different-industry neighbors (0.239), with the balance coming from its local, industry peers (0.114).

In Panel B, we replace *Equity issuance* on the right hand side with some of its determinants. We choose three: q, *Cashflow*, and *Stock returns.* The first row shows the results when only firm-specific information is used to explain secondary stock offerings. Consistent with previous results (e.g., Jung, Kim, Stulz (1996)), the firm's own lagged q is very important, with a t-statistic over 21, and its stock return over the past year (i.e., from $t-1$ to t) is positively related to equity issuance. Moreover, the coefficient on *Cashflow* is negative and significant, suggesting that firms with less need to raise capital issue less equity.

In column 2, we add these same quantities, averaged over the firm's non-local, but same-industry peer firms. Interestingly, non-local industry *Cashflow* is significant, but is *positively* related to equity issuance. This is consistent with a firm's own cash flows reflecting the need to raise cash, but the cash flows of its industry peers proxying for growth opportunities. The third column adds information about a firm's local, but non-industry peers. While all three variables have positive point estimates, only lagged average q is significant, with a magnitude of 0.021 ($t = 2.63$). In the fourth and final column, the same industry/same area portfolio is added, more or less mirroring the results for the area, non-industry portfolio. Lagged q is almost significant, and while cash flows have a positive point estimate, they are far from being significant at conventional levels.

6.2 Debt issuance

Table 8 reports results of regressions that substitute *Debt issuance* (also scaled by lagged assets) for *Equity issuance* as the dependent variable. The first column indicates that firms in the same industry tend to raise debt together, with a estimated coefficient of 0.321 ($t = 5.38$). In the second column, we show that the average *Debt issuance* rates of a firm's local non-industry neighbors influences its own tendency to raise debt, both by itself (column 2), and with the industry effect (column 3). With an estimated coefficient of 0.127 ($t = 3.14$), the ratio of the area-to-industry effect is about 40%.

Column 4 adds the average scaled debt issuance of the firm's local, industry peers. Although having a slightly smaller magnitude (0.087) compared to the portfolio of local, non-industry peers (0.112), the local, same industry portfolio is stronger from a statistical significance perspective ($t = 3.86$ versus 3.15). The next two columns add progressively longer lags of the explanatory variables to the regression. Including two years of lags (column 6) reveals that the debt issuance behavior of a firm's non-industry area peers is important both this year (0.078, $t = 2.20$) and next (0.087, $t = 2.31$). There is also some evidence that a firm's local, same-industry peers matter, but only contemporaneously (0.058, $t = 2.07$).

One potential explanation for local comovement in debt issuance is that nearby firms experience common shocks to collateral, for example to land holdings. This is an important alternative to consider, because as a recent paper by Chaney, Sraer, and Thesmar (2011) shows, such common fluctuations in collateral value may translate to common fluctuations in investment. To test for this possibility, the final four columns of Table 7 split the sample by two common used proxies for financial constraints: the Kaplan and Zingales Index (Kaplan and Zingales, 1997) in columns 7 and 8, and payout ratios (e.g., Chaney, Sraer, and Thesmar (2011)) in columns 9 and 10. The fourth row indicates that the contemporaneous area sensitivities are greatest among the *least* financially constrained firms; likewise, in the fifth row, the only statistically significant lagged effect is in the 9^{th} column, which considers only firms above the median payout rate. In summary, although exposure to increased land values may make it easier for firms to raise debt capital, our results are more consistent with common debt issuance reflecting common exposure to growth opportunities.

Finally, Panel B of Table 7 shows the results when we explain *Debt issuance* using portfolios of stock and operating characteristics, rather than *Debt issuance* itself. Because local comovement in debt was relatively weak compared to equity, it is perhaps not surprising that we find virtually nothing here.

7 Robustness

We conclude our analysis with a number of robustness checks. In Table 9, we present highlights of our results under various assumptions for the correlation structure of the residuals. For comparison, the first column shows the estimates under our baseline assumptions, where the residuals are clustered at the industry level. This is a conservative assumption given that our typical unit of observation is at the firm-year level; industry clustering accounts for autocorrelation within firms, as well as cross-sectional correlations within each Fama-French 12 grouping.

In the second column, we remove clustering altogether which, in nearly all cases, considerably reduces the estimated standard errors of the coefficient estimates. The results for industry-area clustering are shown in the third column. The t-statistics in this column are almost identical to those shown in the first column, suggesting that within an industry, allowing for correlations in residuals across areas is not particularly important. Our point estimates already account for time effects through year dummies, but in the fourth column, we allow for arbitrary cross-sectional correlation in residuals by clustering by year. This has an uneven, though modest, impact on inferences. The investment results (Tables 4A and 5) are a bit stronger, compared to only clustering on industry, whereas the capital raising regressions (Tables 6 and 7) are a bit weaker. The final column accounts only for within-firm clustering – possible only for Tables 4 through 6 – and indicates little change from the previous results.

In addition to the results shown in Table 9, we have conducted various other untabulated robustness exercises. These include clustering on multiple units simultaneously (e.g., clustering on industry, and clustering in time), running year-by-year cross sectional regressions and averaging the coefficients (Fama and McBeth (1973)), and pooling firms within an area-industry unit into a single observation. None of these alternatives has a meaningful impact on the main results.

The final table gives a sense for how our results change when we alter the construction of either our area or industry portfolios. As before, the first column of Table 10 presents our benchmark results, taken selectively from previous tables, where industries are defined using the Fama and French 12 classification shown in Tables 1 and 3. In the second column, we form industry portfolios at a slightly finer level, using 17 different industry classifications rather than 12, and in column 3, match firms to one of 48 different industries. Neither makes much of a difference, although the results strengthen slightly with the finer industry classifications.

Fama and French's industry classifications are based on SIC codes, and enjoy a rich tradition in the literature. However, recent work by Hoberg and Philipps (2011) form industry linkages by analyzing text written in annual 10-K reports. Intuitively, the idea is to measure the tendency of firms to describe their respective products using similar market vocabulary, and forming a "Hotelling-like product space" from which to form quasi-industry linkages.

In the fourth column, we present our results using these potentially superior industry designations, and find that in most cases, the results are substantially strengthened. Particularly in the investment regressions (row 1 of Table 10), the magnitude on the same area-different industry portfolio is higher, as is the coefficient on the same industry-different area portfolio (not shown in the table). The impact on area q on investment (row 4), *Equity issuance* (row 8), one-year lagged *Equity issuance* (row 9), and area q on *Equity issuance* (row 11) are all stronger with the Hoberg and Philipps (2011) classifications. The main takeaway from column 4 is that reducing measurement error generally strengthens our results.

8 Conclusion

A firm's location can potentially influence its opportunities in a number of ways. While initially, the urban economics literature emphasized the importance of proximity to resources and transportation, more recent work emphasizes the influence of location on human capital. This more recent literature motivates our analysis. Specifically, we conjecture that more vibrant urban areas both attract and create more talented managers, and that these managers, in turn, create better investment opportunities for the firms that employ them.

We find that not only do investment expenditures, controlling for industry effects, vary across urban areas, but that changes in investment expenditures exhibit strong area effects. Moreover, consistent with the characterization of vibrancy presented in our model, the profitability of firms in an area predicts the future investment expenditures of other firms in the area, even when they are in different industries. These results suggest that the opportunities offered by specific locations go beyond the static physical attributes of a city, like proximity to transportation, and are related to dynamic area effects like the quality of an area's human capital, which may change from year to year.

Future research will hopefully dig deeper into how these human capital effects generate co-movements in local investment expenditures. One mechanism, which is most consistent with our model, is that managers in one sector build human capital, and that these skills rub off on neighboring workers through social interactions. For example, when oil prices rise, Houston oil and gas firms tend to hire management consultants. If the knowledge imparted by these consultants is easily transferrable across industries – think about teaching managers how to better motivate employees - and if local social networks allow these ideas to spread, the investment opportunities of nearby firms may also improve. While it is hard to gauge the magnitude of such an effect, evidence such as Glaeser and Mare (2001) suggest that employment in dense urban areas where such ideas and skills are likely to spread impart long-lived human capital advantages.

It is also likely that ideas and views about economic prospects will be transmitted through these same local social networks. Indeed, investment expenditure co-movement within areas can arise if managers in the same area talk to the same people, and consequently, reach similar conclusions about area or macro *trends* that can influence their view of investment opportunities. Fracassi's (2011) findings of similar investment patterns between firms that share board members is consistent with this idea that communication networks can influence corporate investment expenditures.

While local sharing of information about trends is plausible, there are two observations worth mentioning. First, we expect trends about one's own industry to be the most relevant, and we have controlled for a firm's local, industry peers. Thus, the magnitudes we observe – about half the pure industry effect arise because of co-movements of the investment expenditures of local firms in different industries, where knowledge of trends should be much less relevant. Second, the strong positive relation between area cash flows (which are public information) and future investment expenditures would be hard to explain based solely on managers in an area sharing private information.

We, of course, cannot rule out the possibility that area co-movements arise because of irrational "herding," which would be the case if managers put too much weight on the beliefs of their neighbors. We also cannot rule out what we would characterize as a "keeping up with the Jones effect," where CEOs in the same cities tend to increase investment together as they compete to be important in their communities. In either case, at least some of the investment co-movement will be inefficient – however, the effect of this inefficiency can potentially be partly offset by the resulting positive spillovers. More detailed data on the ex post efficiency of investments – perhaps using plant level data – would help make this distinction.

Finally, it would be interesting to consider the possibility of better human capital being attracted by improvements in a city's consumption opportunities (a lá Glaeser and Gottlieb's (2006) "Consumer City"). While we expect these effects to operate over longer horizons, much like the migration to good-weather cities documented over the last four decades (Rappaport (2007)), it would be interesting to link changes in an areas investment expenditures to improvements in local amenities (see, e.g., Duranton and Turner's (2011) analysis of road development and local employment growth). Another possibility, worth exploring, is that the success in one sector influences the work ethic in other sectors, another "keeping up with the Jones" effect. Each of these potential aspects of vibrancy has been discussed in the urban economics literature, but we are unaware of any studies that directly link these effects to corporate performance and growth opportunities.

References

Almazan, A., A. D. Motta, and S. Titman. 2007. Firm Location and the Creation and Utilization of Human Capital. *Review of Economic Studies* 74: 1305–1327.

Almeida, H., M. Campello, and M. S. Weisbach. 2004. The Cash Flow Sensitivity of Cash. *Journal of Finance* 59: 17771804.

Alti, A. 2003. How Sensitive Is Investment To Cash Flow When Financing Is Frictionless? *Journal of Finance* 58: 707–722.

Audretsch, D. B., and M. P. Feldman. 2004. *Handbook of Regional and Urban Economics*, Volume 4, Chapter Chapter 61 - Knowledge spillovers and the geography of innovation, 2713–2739. Elsevier.

Bound, J., and H. Holzer. 2000. Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s. *Journal of Labor Economics* 18: 20–54.

Chaney, T., D. Sraer, and D. Thesmar. 2010. The Collateral Channel: How Real Estate Shocks affect Corporate Investment. *American Economic Review* Forthcoming.

Ciccone, A., and R. E. Hall. 1996. Productivity and the Density of Economic Activity. *American Economic Review* 86: 54–70.

Dumais, G., G. Ellison, and E. L. Glaeser. 2002. Geographic Concentration as a Dynamic Process. *The Review of Economics and Statistics* 84: 193–204.

Duranton, G., and M. A. Turner. 2011. The Fundamental Law of Road Congestion: Evidence from US Cities. *American Economic Review* 101: 2616–52.

Ellison, G., and E. L. Glaeser. 1997. Geographic Concentration in U.S. Manufacturing Industries: A Dartboard Approach. *Journal of Political Economy* 109: 889–927.

Ellison, G., and E. L. Glaeser. 1999. The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration? *American Economic Review* 89: 311–316.

Ellison, G., E. L. Glaeser, and W. R. Kerr. 2010. What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns. *American Economic Review* 100: 1195–1213.

Erickson, T., and T. M. Whited. 2000. Measurement Error and the Relationship between Investment and q. *Journal of Political Economy* 108: 1027–1057.

Fazzari, S., R. G. Hubbard, , and B. C. Petersen. 1988. Financing constraints and corporate investment. *Brookings Papers on Economic Activity* 1: 141–206.

Fisher, J. D., M. David, and T. M. Whited. 2009. Macroeconomic Implications of Agglomeration. Working paper.

Fracassi, C. 2011. Corporate Finance Policies and Social Networks. Working paper.

Gan, J. 2007. Collateral, Debt Capacity, and Corporate Investment: Evidence from a Natural Experiment. *Journal of Financial Economics* 85: 709–734.

Gao, P., J. Engelberg, and C. A. Parsons. The Price of a CEO's Rolodex. *Review of Financial Studies, forthcoming*.

Glaeser, E. L., and J. D. Gottlieb. 2006. Urban Resurgence and the Consumer City. *Harvard Institute of Economic Research, Discussion Paper Number 2109*.

Glaeser, E. L., H. D. Kallal, J. A. Scheinkman, and A. Shleifer. 1992. Growth in Cities. *Journal of Political Economy* 100: 1126–1152.

Glaeser, E. L., J. Kolko, and A. Saiz. 2001. Consumer City. *Journal of Economic Geography* 1: 27–50.

Glaeser, E. L., and D. Mare. 2001. Cities and Skills. *Journal of Labor Economics* 19: 316–342.

Glaeser, E. L., and M. G. Resseger. 2009. The Complementarity Between Cities and Skills. Working paper.

Gomes, J. F. 2001. Financing Investment. *American Economic Review* 91: 1263–1285.

Henderson, J. 1974. The Sizes and Types of Cities. *American Economic Review* 64: 640–56.

Henderson, J. 2003. Marshall's Scale Economies. *Journal of Urban Economics* 53: 1–28.

Hoberg, G., and G. Phillips. 2010a. Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis. *Review of Financial Studies* 23: 3773–3811.

Hoberg, G., and G. Phillips. 2010b. Text-Based Network Industries and Endogenous Product Differentiation. Working Paper.

Jaffe, A. B., M. Trajtenberg, and R. Henderson. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics* 108: 577–598.

Kaplan, S., and L. Zingales. 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *Quarterly Journal of Economics* 112: 169–215.

Kaplan, S., and L. Zingales. 2000. Investment-Cash Flow Sensitivities Are Not Valid Measures of Financing Constraints. *Quarterly Journal of Economics* 115: 707–12.

Korniotis, G., and A. Kumar. 2011. State-Level Business Cycles and Local Return Predictability. Working paper.

Lucas, R. 1988. On the Mechanics of Economic Development. *Journal of Monetary Economics* 22: 3–42.

Marshall, A. 1920. *Principles of Economics*. London, U.K.: MacMillan and Co.

Moretti, E. 2003. *Handbook of Urban and Regional Economics*, Chapter Chapter 8 - Human Capital Externalities in Cities. North Holland-Elsevier.

Peek, J., and E. S. Rosengren. 2000. Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States. *American Economic Review* 20: 30–45.

Pirinsky, C., and Q. Wang. 206. Does Corporate Headquarters Location Matter for Stock Returns? *Journal of Finance* 61: 1991–2015.

Poterba, J. 1988. Are Consumers Forward Looking? Evidence from Fiscal Experiments. *American Economic Review* 78: 413–18.

Rappaport, J. 2007. Moving to nice weather. *Regional Science and Urban Economics* 37: 375–398.

Rauch, J. 1993. Productivity Gains From Geographic Concentration of Human Capital: Evidence from Cities. *Journal of Urban Economics* 34: 380–400.

Rauh, J. 2006. Investment and Financing Constraints: Evidence from the Funding of Corporate Pension Plans. *Journal of Finance* 71: 34–72.

Rosenthal, S., and W. Strange. 2001. The Determinants of Agglomeration. *Journal of Urban Economics* 50: 191–229.

Saxenian, A. 1994. *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Cambridge, Massachusetts: Harvard University Press.

Shapiro, J. M. 2006. Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital. *Review of Economics and Statistics* 88: 324–335.

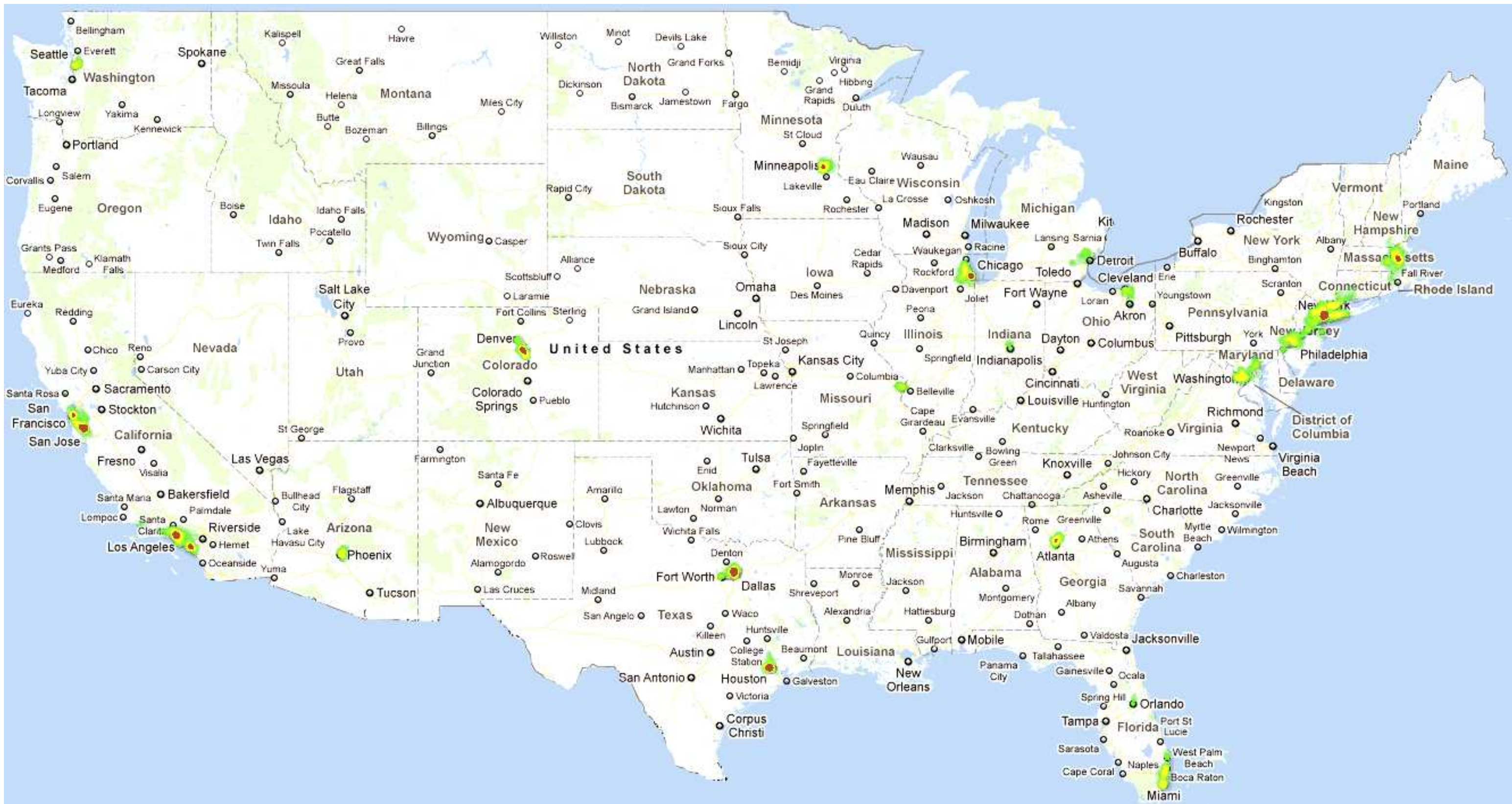
Simon, C., Clark, and Nardinelli. 2002. Human Capital and the Rise of American Cities: 1900-1990. *Regional Science and Urban Economics* 32: 59–96.

Topel, R. 1986. Local Labor Markets. *Journal of Political Economy* 94: S111–S143.

Tuzel, S. 2012. Corporate Real Estate Holdings and the Cross-Section of Stock Returns. *Review of Financial Studies* 25: 278–313.

Wheaton, W., and M. Lewis. 2002. Urban Wages and Labor Market Agglomeration. *Journal of Urban Economics* 51: 542–562.

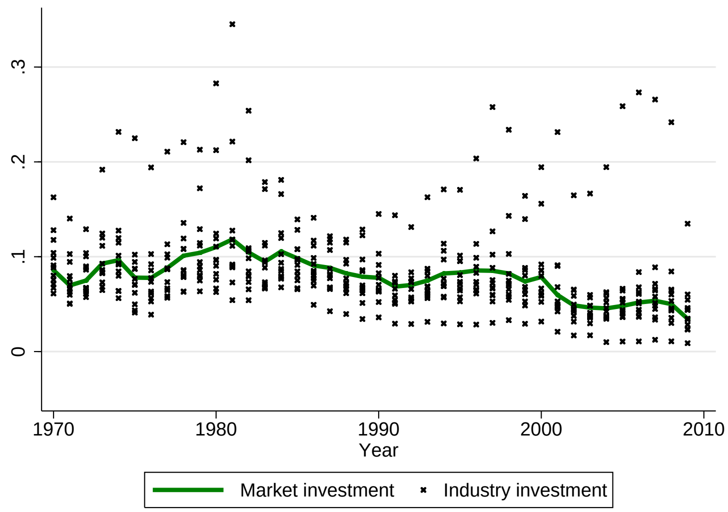
Figure 1: Heat map of firm location



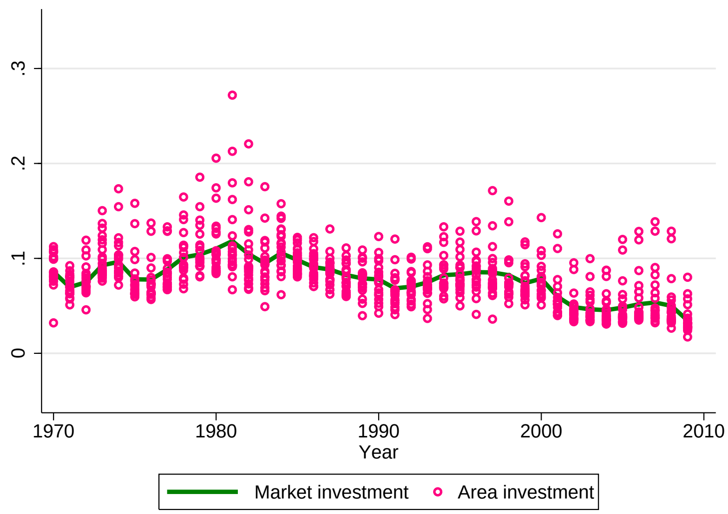
This figure illustrates the location of firms in our sample. Light green shading indicates relatively few firms per unit area, more firm density in yellow areas, and the most concentrated regions in red.

Figure 2: Area and industry investment

Panel A: Industry investment



Panel B: Area investment



Panel A of this figure illustrates the average yearly investment (capital expenditures divided by last year's assets) for the entire market over the sample time period (line) and the average yearly investment for each Fama-french 12 industry (x's). Panel B plots the average yearly investment (o's) for each of the twenty areas considered in our sample.

Table 1: Area statistics

This table shows summary statistics for each of the 20 economic areas (EA's) considered in our study. Listed in Panel A are each area's population in 2004; and annual summary statistics (mean, standard deviation, minimum, 10^{th}, 50^{th}, and 90^{th} percentiles, and maximum) for the number of firms per area and the market capitalization of all firms in each area. Market capitalization is in 100 million dollars. Panel B reports the average percentage of market capitalization for each industry relative to the total market capitalization in a given area. Industry title abbreviations used as column headers are as follows: Consumer Non-durables (*NoDur*); Consumer Durables (*Durbl*); Manufacturing (*Manuf*); Energy – Oil, Gas, and Coal Extraction and Products (*Enrgy*); Chemicals (*Chems*); Business Equipment – Computers, Software, and Electronic Equipment (*BusEq*); Telephone and Television Transmission (*Telcm*); Utilities (*Utils*); Wholesale, Retail, and Some Services (*Shops*); Healthcare, Medical Equipment, and Drugs (*Hlth*); Finance (*Fin*); and Other (*Other*).

Panel A: Area summary statistics

		Number of firms					Market capitalization				
BEA	Population	Mean	Sd	10^{th}	50^{th}	90^{th}	Mean	Sd	10^{th}	50^{th}	90^{th}
New York-Newark-Bridgeport, NY-NJ-CT-PA	22,874,458	599	170	398	584	814	5,607	4,191	1,204	4,297	11,600
Los Angeles-Long Beach-Riverside, CA	19,055,411	271	106	133	292	399	1,326	1,073	145	960	2,852
Chicago-Naperville-Michigan City, IL-IN-WI	10,256,144	180	43	143	175	254	2,261	1,509	413	2,215	4,266
San Jose-San Francisco-Oakland, CA	9,338,048	235	140	58	231	427	3,097	3,236	179	1,306	7,934
Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	8,830,103	133	60	51	158	205	1,188	1,203	71	528	3,101
Boston-Worcester-Manchester, MA-NH	8,193,115	219	96	96	232	341	1,429	1,347	124	744	3,397
Dallas-Fort Worth, TX	7,252,173	155	55	88	159	229	1,470	947	388	1,299	2,907
Detroit-Warren-Flint, MI	7,048,815	69	15	52	65	88	463	311	97	423	875
Philadelphia-Camden-Vineland, PA-NJ-DE-MD	6,874,604	139	46	83	147	195	837	696	143	548	1,943
Atlanta-Sandy Springs-Gainesville, GA-AL	6,818,366	98	48	44	104	164	1,156	954	147	924	2,483
Houston-Baytown-Huntsville, TX	6,088,680	137	49	69	149	202	1,523	1,456	215	778	4,192
Miami-Fort Lauderdale-Miami Beach, FL	6,013,949	105	46	48	108	167	319	306	32	144	781
Minneapolis-St. Paul-St. Cloud, MN-WI	5,068,485	123	54	55	128	199	942	908	74	441	2,311
Cleveland-Akron-Elyria, OH	4,662,474	77	16	60	73	102	559	470	80	338	1,258
Seattle-Tacoma-Olympia, WA	4,358,890	48	25	19	48	81	572	639	13	294	1,599
Phoenix-Mesa-Scottsdale, AZ	4,256,343	46	19	22	52	73	278	342	19	73	877
Orlando-The Villages, FL	4,047,955	28	12	15	27	43	55	63	3	20	145
Denver-Aurora-Boulder, CO	3,762,991	96	43	37	111	142	612	616	31	460	1,560
St. Louis-St. Charles-Farmington, MO-IL	3,317,985	45	13	31	46	64	537	415	79	443	1,044
Indianapolis-Anderson-Columbus, IN	3,254,963	28	11	16	28	44	144	157	13	50	371

Table 1: Area statistics - cont'd

Panel B: Percent market capitalization by industry

BEA\Industry	NoDur	Durbl	Manuf	Enrgy	Chems	BusEq	Telcm	Utils	Shops	Hlth	Fin	Other
New York-Newark-Bridgeport, NY-NJ-CT-PA	10	1	7	1	6	13	14	5	4	18	15	5
Los Angeles-Long Beach-Riverside, CA	3	5	6	28	<.5	11	2	6	6	9	16	9
Chicago-Naperville-Michigan City, IL-IN-WI	13	2	17	10	2	4	3	9	10	11	14	7
San Jose-San Francisco-Oakland, CA	3	<.5	4	14	2	37	5	6	8	4	14	4
Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	3	<.5	22	<.5	7	6	11	6	6	3	27	10
Boston-Worcester-Manchester, MA-NH	5	1	20	1	1	32	4	4	7	9	10	5
Dallas-Fort Worth, TX	2	3	4	27	2	8	13	7	11	3	7	14
Detroit-Warren-Flint, MI	<.5	49	13	<.5	<.5	3	<.5	17	3	<.5	5	9
Philadelphia-Camden-Vineland, PA-NJ-DE-MD	9	1	12	9	7	15	7	5	8	7	15	4
Atlanta-Sandy Springs-Gainesville, GA-AL	25	1	3	<.5	<.5	10	14	10	10	1	10	15
Houston-Baytown-Huntsville, TX	1	<.5	8	46	6	4	1	14	6	<.5	7	7
Miami-Fort Lauderdale-Miami Beach, FL	3	1	6	1	<.5	7	6	25	13	5	11	23
Minneapolis-St. Paul-St. Cloud, MN-WI	19	1	9	1	5	12	1	5	16	9	19	5
Cleveland-Akron-Elyria, OH	3	16	20	1	12	2	<.5	13	6	1	23	5
Seattle-Tacoma-Olympia, WA	<.5	9	4	<.5	<.5	22	10	9	15	6	21	4
Phoenix-Mesa-Scottsdale, AZ	1	<.5	25	<.5	2	15	<.5	15	5	2	4	32
Orlando-The Villages, FL	20	4	6	1	4	6	14	<.5	18	3	15	9
Denver-Aurora-Boulder, CO	5	<.5	8	17	1	3	42	6	2	2	3	12
St. Louis-St. Charles-Farmington, MO-IL	27	1	29	4	6	3	2	8	12	5	4	1
Indianapolis-Anderson-Columbus, IN	9	1	8	<.5	13	2	2	30	3	19	10	2

Table 2: Portfolio statistics

Panel A of this table reports annual summary statistics (mean, standard deviation, minimum, 10^{th}, 50^{th}, and 90^{th} percentiles, and maximum) for the following firm-level and portfolio-level variables: total number of firms in our sample per year (Obs. per year), number of firms per portfolio (*# of firms*), excess returns (*Returns*), *Cashflow* which is equal to income before extraordinary items plus depreciation and amortization normalized by last years assets (*Cashflow*(t)=[IB(t)+DP(t)]/AT(t-1)), *Investment* which is equal to capital expenditures normalized by last years assets (*Investment*(t)=CAPX(t)/AT(t-1)), *Equity issuance* which is equal to the change in common equity plus the change in deferred taxes minus the change in retained earnings all normalized by last years assets (*Equity issuance*(t)=[d.CEQ(t)+d.TXDB(t)-d.RE(t)]/AT(t-1)), *Debt issuance* which is equal to the change in total long-term debt plus the change in long-term debt due in one year plus notes payable divided by last years assets (*Debt issuance*(t)=[d.DLTT(t)+d.DD1(t)+NP(t)]/AT(t-1)), and Tobin's q which is equal to long-term debt plus debt in current liabilites plus market equity all divided by current assets (q(t)=[DLTT(t)+DLC(t)+CSHO(t)*PRCC_F(t)]/AT(t)). Results are shown for all firms; for same industry, different area portfolios – equal-weighted portfolios of firms in the same industry, but outside our set of 20 EAs; for different industry, same area portfolios – equal-weighted portfolios of firms that belong to the same industry and that are headquartered in the same area; and same area, same industry portfolios – equal-weighted portfolios of firms in the same area and industry. Panel B reports the correlation matrix for the different area, industry, and industry-area portfolios.

Panel A: Portfolio statistics

	Mean	Sd	Min	10^{th}	50^{th}	90^{th}	Max
Panel A: Firms							
Obs. per year	2885.34	986.05	914	1626	3065	4118	4522
Returns	0.07	0.59	-0.79	-0.60	-0.02	0.80	1.93
Cashflow	0.02	0.22	-0.99	-0.20	0.07	0.20	0.43
Investment	0.07	0.09	0.00	0.01	0.05	0.17	0.56
Equity iss.	0.10	0.32	-0.15	-0.02	0.01	0.27	2.01
Debt iss.	0.08	0.19	-0.27	-0.05	0.01	0.27	1.07
q	1.62	1.79	0.12	0.43	1.02	3.39	10.97
Panel B: Same industry, different area portfolios							
# of firms	137.33	89.95	6	35	130	241	416
Returns	0.08	0.26	-0.61	-0.25	0.07	0.43	1.02
Cashflow	0.05	0.05	-0.14	-0.01	0.06	0.11	0.23
Investment	0.08	0.04	0	0.04	0.08	0.14	0.35
Equity iss.	0.07	0.07	-0.01	0.01	0.04	0.18	0.46
Debt iss.	0.08	0.04	-0.05	0.03	0.07	0.13	0.30
q	1.41	0.65	0.34	0.6	1.34	2.29	3.99
Panel C: Different industry, same area portfolios							
# of firms	174.4	155.67	9	47	131	372	843
Returns	0.07	0.25	-0.53	-0.26	0.09	0.39	0.85
Cashflow	0.04	0.05	-0.17	-0.03	0.04	0.11	0.18
Investment	0.08	0.03	0.02	0.04	0.08	0.11	0.29
Equity iss.	0.09	0.07	-0.02	0.01	0.08	0.18	0.58
Debt iss.	0.08	0.04	-0.04	0.03	0.08	0.12	0.25
q	1.52	0.46	0.61	0.91	1.52	2.06	4.75
Panel D: Same industry, same area portfolios							
# of firms	21.97	23.14	6	7	15	47	266
Returns	0.07	0.3	-0.7	-0.31	0.06	0.46	1.42
Cashflow	0.04	0.09	-0.53	-0.07	0.06	0.12	0.27
Investment	0.08	0.05	0	0.03	0.07	0.13	0.56
Equity iss.	0.09	0.11	-0.12	0	0.04	0.24	1.12
Debt iss.	0.08	0.08	-0.11	0.01	0.07	0.16	1.07
q	1.51	0.82	0.15	0.65	1.35	2.62	6.25

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Portfolio statistics - cont'd

Panel B: Portfolio correlations

	Same industry/different area						Different industry/same area						Same industry/same area					
	Ret	Cash	Inv	Eq	Debt	q	Ret	Cash	Inv	Eq	Debt	q	Ret	Cash	Inv	Eq	Debt	q
Same ind./diff. area																		
Return	1.0																	
Cashflow	0.1	1.0																
Investment	-0.1	0.4	1.0															
Equity iss.	0.0	-0.6	0.1	1.0														
Debt iss.	-0.2	0.1	0.5	0.1	1.0													
q	-0.2	-0.5	0.2	0.8	0.1	1.0												
Diff. ind./same area																		
Return	0.7	0.0	-0.1	0.0	-0.2	-0.2	1.0											
Cashflow	0.0	0.4	0.2	-0.2	0.1	-0.2	0.1	1.0										
Investment	-0.1	0.2	0.3	-0.1	0.3	-0.1	-0.1	0.4	1.0									
Equity iss.	0.0	-0.2	-0.1	0.3	0.0	0.2	0.0	-0.7	0.0	1.0								
Debt iss.	-0.2	0.1	0.3	0.0	0.4	0.1	-0.3	0.1	0.5	0.0	1.0							
q	-0.2	-0.3	-0.2	0.2	0.0	0.2	-0.3	-0.7	0.0	0.8	0.1	1.0						
Same ind./same area																		
Return	0.8	0.1	-0.1	0.0	-0.2	-0.2	0.7	0.1	-0.1	0.0	-0.2	-0.2	1.0					
Cashflow	0.1	0.7	0.2	-0.5	0.0	-0.4	0.1	0.4	0.1	-0.3	0.0	-0.3	0.1	1.0				
Investment	-0.1	0.3	0.7	0.1	0.3	0.2	-0.1	0.2	0.3	-0.1	0.2	-0.1	-0.1	0.2	1.0			
Equity iss.	0.0	-0.4	0.0	0.6	0.1	0.5	0.0	-0.3	0.0	0.4	0.0	0.3	0.0	-0.6	0.1	1.0		
Debt iss.	-0.1	0.1	0.2	0.0	0.4	0.0	-0.1	0.0	0.2	0.0	0.3	0.0	-0.1	0.0	0.3	0.1	1.0	
q	-0.2	-0.4	0.1	0.6	0.1	0.8	-0.2	-0.3	0.0	0.3	0.1	0.3	-0.2	-0.5	0.1	0.7	0.0	1.0

Table 3: Univariate Differences

Every year for each firm an equal-weighted portfolio is formed of firms in the same area, but different industry. Areas are then ranked according to these portfolios. The average investment (both level and change) by industry is taken for firms in the areas in the bottom third and top third of this ranking and these averages are recorded in columns 1 and 2 respectively under the headings *Low area investment* and *High area investment.* The column titled *Difference* reports the differences between these two averages. The final column reports the t-statistic for this difference.

	Low area investment	High area investment	Difference	t-statistic
Ind. 1 - Consumer Non-Durables				
Level	0.05	0.07	-0.01***	-7.04
Change	-0.003	-0.004	0.001	0.35
Ind. 2 - Consumer Durables				
Level	0.05	0.07	-0.01***	-3.89
Change	-0.006	0.0001	-0.007**	-2.06
Ind. 3 - Manufacturing				
Level	0.06	0.08	-0.01***	-8.93
Change	-0.006	-0.002	-0.004**	-2.53
Ind. 4 - Energy				
Level	0.14	0.21	-0.07***	-10.89
Change	-0.019	0.004	-0.023***	-4.16
Ind. 5 - Chemicals				
Level	0.06	0.07	-0.01***	-3.76
Change	-0.007	-0.0002	-0.006**	-2.10
Ind. 6 - Business Equipment				
Level	0.07	0.07	-0.01***	-3.60
Change	-0.008	-0.006	-0.002	-1.26
Ind. 7 - Telephone and Television Transmission				
Level	0.09	0.12	-0.03***	-5.90
Change	-0.017	-0.009	-0.008	-1.44
Ind. 8 - Utilities				
Level	0.08	0.09	-0.01***	-3.05
Change	-0.002	-0.004	0.002	0.74
Ind. 9 - Wholesale, Retail, and Some Services				
Level	0.07	0.09	-0.02***	-10.63
Change	-0.008	-0.006	-0.001	-0.71
Ind. 10 - Healthcare, Medical Equipment, and Drugs				
Level	0.06	0.06	-0.01***	-3.30
Change	-0.007	-0.005	-0.002	-0.74
Ind. 11 - Finance				
Level	0.03	0.04	-0.02***	-9.46
Change	-0.003	-0.001	-0.002	-1.03
Ind. 12 - Other				
Level	0.08	0.10	-0.02***	-6.45
Change	-0.008	-0.005	-0.004	-1.57

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Investment on investment

This table shows estimates of the following regression:

$$Investment^{i,a}_{j,t} = \delta + \sum_{k=0}^{2} \beta_{1,k} Investment^{i,-a}_{p,t-k} + \sum_{k=0}^{2} \beta_{2,k} Investment^{-i,a}_{p,t-k} + \sum_{k=0}^{2} \beta_{3,k} Investment^{i,a}_{p,-j,t-k} + \beta_4 Controls^{i,a}_{t} + \epsilon^{i,a}_{j,t}.$$

where the dependent variable is investment (capital expenditures divided by last years assets) at year t for firm j which is headquartered in economic area (EA) a and belongs to industry i. The key independent variables are the equal-weighted average investment for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, $Investment^{i,-a}_{p,t}$; the equal-weighted investment for a portfolio of firms in the same area as the dependent variable, but outside of industry i, $Investment^{-i,a}_{p,t}$; and the equal-weighted investment for a portfolio of firms in the same area and industry as the dependent variable (excluding the independent variable itself), $Investment^{i,a}_{p,t}$. In addition to the contemporaneous values of these regressors, lagged values are also included as specified. Additional regressors include year and area fixed effects ($Controls^{i,a}_{j,t}$). Columns 7 and 8 rank firms each year by last years total assets and then report results for firms with lagged total assets less than last-year's median total assets (*Small firms*) and results for firms with lagged total assets greater than the median (*Big firms*). Columns 9 and 10 separate the sample of firms into those in areas with area investment higher than last year's area investment, $Investment^{-i,a}_{p,t} > Investment^{-i,a}_{p,t-1}$ (Positive shock), and those with area investment lower than last year's area investment $Investment^{-i,a}_{p,t} < Investment^{-i,a}_{p,t-1}$ (Negative shock). In every regression, standard errors are clustered by industry.

Table 4: Investment on investment - Cont'd

	(1)	(2)	(3)	(4)	(5)	(6)	(7) Small firms	(8) Big firms	(9) Pos. Shock	(10) Neg. Shock
	Investment	Investment	Investment	Investment	Investment	Investment	Investment	Investment	Investment	Investment
Same industry/different area										
Investment (contemp.)	0.503***		0.508***	0.386***	0.353**	0.354**	0.379*	0.331***	0.379***	0.329**
	(3.43)		(3.57)	(3.48)	(3.09)	(3.09)	(2.18)	(3.99)	(3.14)	(2.72)
Investment (1 year lag)					-0.011	-0.036	-0.023	-0.033**	-0.040	-0.019
					(-0.29)	(-0.79)	(-0.25)	(-2.22)	(-0.94)	(-0.36)
Investment (2 year lag)						-0.011	0.019	-0.020	0.036	-0.046***
						(-1.16)	(0.42)	(-1.19)	(1.02)	(-3.74)
Different industry/same area										
Investment (contemp.)		0.186*	0.231**	0.211**	0.190***	0.188**	0.096**	0.237**	0.064	0.197**
		(1.91)	(2.66)	(2.77)	(3.16)	(2.62)	(2.60)	(2.29)	(1.07)	(2.59)
Investment (1 year lag)					0.046	0.050**	0.087	0.024	0.141	0.051
					(1.45)	(2.57)	(1.49)	(0.92)	(1.56)	(1.34)
Investment (2 year lag)						-0.006	-0.020	0.021	0.059	-0.040
						(-0.14)	(-0.27)	(0.41)	(0.67)	(-0.82)
Same industry/same area										
Investment (contemp.)				0.183***	0.167***	0.158***	0.127**	0.167***	0.096**	0.181***
				(4.96)	(4.89)	(4.10)	(2.65)	(3.28)	(2.54)	(4.47)
Investment (1 year lag)					0.034*	0.058***	0.023	0.092***	0.068	0.068***
					(1.92)	(3.60)	(0.78)	(8.49)	(1.77)	(4.22)
Investment (2 year lag)						-0.007	0.025	-0.020*	-0.022	0.003
						(-0.40)	(0.91)	(-2.05)	(-1.19)	(0.14)
Constant	-0.017	0.003	-0.022	-0.021	0.001	0.055***	0.143***	0.003	0.018*	0.015
	(-0.80)	(0.16)	(-1.05)	(-1.05)	(0.08)	(6.44)	(15.85)	(0.29)	(1.93)	(1.59)
Firm fixed effects	X	X	X	X	X	X	X	X	X	X
Area fixed effects	X	X	X	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X	X	X	X	X
Industry clustering	X	X	X	X	X	X	X	X	X	X
Observations	88673	88673	88673	88656	77871	68511	34111	34400	30382	38129
R^2	0.525	0.515	0.526	0.527	0.531	0.535	0.496	0.632	0.599	0.567

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Dominant industry investment

Column 1 of panel A reports results where the dependent variable is the investment level for firms outside of the Consumer Non-durables industry (Fama-French 12 industry #1) in the Atlanta-Sandy Springs-Gainesville, GA-AL area and the independent variables are an industry control for the dependent variable, i.e., the equal-weighted average investment for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, and a control for the areas dominant industry, i.e., the equal-weighted average investment for a portfolio of firms in the Atlanta area non-durables industry. Similar regressions are reported in columns 2, 3, and 4 for the following area/industry pairings respectively: San Jose-San Francisco-Oakland, CA and Business Equipment (Fama-French 12 industry #6), Detroit-Warren-Flint, MI and Consumer Durables (Fama-French 12 industry #2), and Houston-Baytown-Huntsville, TX and Energy (Fama-French 12 industry #4). Column 5 includes pools the observations of columns 1 through 4 and estimates a local dominant industry average effect including year fixed effects. Columns 6 and 7 rank firms each year by last years assets and then report results for firms with lagged assets less than last-year's median assets (*Small firms*) and results for firms with lagged assets greater than the median (*Big firms*). All regressions exclude each area's dominant industries from the left hand sides in the appropriate column. Panel B reports regressions similar to panel A, except instead of using the areas dominant industry as the area portfolio, in its place is used the "marketwide" dominant industry. For example, in column 1 instead of using the average value of the Atlanta area non-durables industry as a regressor we replace that with the equal-weighted average investment for a portfolio of firms in the non-durables industry, but outside our set of 20 economic areas. **Panel A: Dominant industry investment by area**

	(1) Atlanta Investment	(2) San Jose Investment	(3) Detroit Investment	(4) Houston Investment	(5) All 4 areas Investment	(6) Small firms Investment	(7) Big firms Investment
Investment - Same industry/different area	0.687***	0.410***	0.429**	0.572***	0.387***	0.296**	0.382***
	(5.52)	(3.81)	(3.13)	(4.21)	(5.18)	(3.06)	(6.65)
Investment - ATL dom. industry (Non-durables)	0.420***						
	(4.16)						
Investment - SF dom. industry (Business Equipment)		0.327***					
		(3.55)					
Investment - DET dom. industry (Durables)			0.351***				
			(3.95)				
Investment - HOU dom. industry (Energy)				0.197***			
				(4.84)			
Investment - Local dom. industry, avg. effect					0.177***	0.153**	0.162***
					(3.92)	(2.57)	(3.21)
Constant	-0.003	0.016	0.006	-0.008	0.050***	0.009	0.045***
	(-0.29)	(1.76)	(0.61)	(-1.23)	(6.13)	(1.51)	(4.81)
Firm fixed effects	X	X	X	X	X	X	X
Year fixed effects					X	X	X
Industry clustering	X	X	X	X	X	X	X
Observations	3033	4023	1973	3247	11757	6223	5534
R^2	0.551	0.502	0.384	0.425	0.497	0.514	0.584

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Dominant industry investment - Cont'd

Panel B: Dominant industry investment

	(1) Atlanta Investment	(2) San Jose Investment	(3) Detroit Investment	(4) Houston Investment	(5) All 4 areas Investment	(6) Small firms Investment	(7) Big firms Investment
Investment - Same industry/different area	0.655***	0.408***	0.492***	0.661***	0.385***	0.311***	0.365***
	(5.96)	(3.71)	(3.49)	(5.64)	(5.29)	(3.14)	(6.53)
Investment - Non-durables (marketwide)	0.743***						
	(3.59)						
Investment - Business Equipment (marketwide)		0.497**					
		(2.75)					
Investment - Durables (marketwide)			0.296**				
			(2.31)				
Investment - Energy (marketwide)				0.139***			
				(4.75)			
Investment - Local dom. industry, avg. effect (marketwide)					0.120***	0.118*	0.118**
					(3.23)	(1.96)	(2.56)
Constant	-0.020	0.008	0.011	-0.003	0.006	0.008*	0.012
	(-1.65)	(0.65)	(1.40)	(-0.36)	(0.94)	(1.99)	(1.19)
Firm fixed effects	X	X	X	X	X	X	X
Year fixed effects					X	X	X
Industry clustering	X	X	X	X	X	X	X
Observations	3078	4023	2018	3247	12366	6543	5823
R^2	0.550	0.501	0.383	0.420	0.493	0.512	0.581

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Investment

This table shows estimates of the following regression:

$$Investment_{j,t}^{i,a} = \phi + \sum_{k=0}^{1} \alpha_{1,k}\, q_{p,t-k-1}^{i,-a} + \sum_{k=0}^{1} \alpha_{2,k}\, q_{p,t-k-1}^{-i,a} + \sum_{k=0}^{1} \alpha_{3,k}\, q_{p,-j,t-k-1}^{i,a} +$$
$$\sum_{k=0}^{1} \alpha_{4,k}\, Cashflow_{p,t-k}^{i,-a} + \sum_{k=0}^{1} \alpha_{5,k}\, Cashflow_{p,t-k}^{-i,a} + \sum_{k=0}^{1} \alpha_{6,k}\, Cashflow_{p,-j,t-k}^{i,a} +$$
$$\sum_{k=0}^{1} \alpha_{7,k}\, q_{j,t-k-1}^{i,a} + \sum_{k=0}^{1} \alpha_{8,k}\, Cashflow_{j,t-k}^{i,a} + \alpha_9\, Controls_t^{i,a} + \epsilon_{j,t}^{i,a}.$$

where the dependent variable is investment (capital expenditures divided by last years assets) at year t for firm j which is headquartered in economic area (EA) a and belongs to industry i. Regressors include firm i's own q, $q_{j,t-1}^{i,a}$, defined as long-term debt plus debt in current liabilities plus market equity all divided by current assets, and own cashflow, $Cashflow_{j,t}^{i,a}$, defined as income before extraordinary items plus depreciation and amortization normalized by last years assets. Other key independent variables are the equal-weighted average lagged q and cashflow for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, $q_{p,t-1}^{i,-a}$ and $Cashflow_{p,t}^{i,-a}$; the equal-weighted lagged q and cashflow for a portfolio of firms in the same area as the dependent variable, but outside of industry i, $q_{p,t-1}^{-i,a}$ and $Cashflow_{p,t}^{-i,a}$; and the equal-weighted lagged q and cashflow for a portfolio of firms in the same area and industry as the dependent variable (excluding the independent variable itself), $q_{p,-j,t-1}^{i,a}$ and $Cashflow_{p,-j,t}^{i,a}$. In addition to the contemporaneous values of these regressors, lagged values are also included as specified. Additional regressors include year and area fixed effects ($Controls_{j,t}^{i,a}$). All standard errors are clustered by industry.

Table 6: Investment

	(1) Investment	(2) Investment	(3) Investment	(4) Investment	(5) Investment
Own firm					
q (1 year lag)	0.013***	0.012***	0.013***	0.012***	0.011***
	(7.37)	(8.33)	(7.53)	(8.63)	(10.25)
2 year lag					0.001
					(1.17)
Cashflow	0.050**	0.048**	0.049**	0.047**	0.040**
	(2.83)	(3.00)	(2.83)	(3.00)	(2.75)
1 year lag					0.027***
					(3.65)
Same industry/different area					
q (1 year lag)		0.015*		0.014*	0.010**
		(2.02)		(2.11)	(2.23)
2 year lag					0.001
					(0.67)
Cashflow (contemp.)		0.205*		0.192*	0.137*
		(1.87)		(1.88)	(1.94)
1 year lag					0.078
					(1.64)
Different industry/same area					
q (1 year lag)			0.006	0.008*	0.008*
			(1.22)	(1.83)	(1.92)
2 year lag					0.001
					(0.97)
Cashflow (contemp.)			0.100**	0.105***	0.074**
			(2.68)	(3.90)	(2.32)
1 year lag					0.058**
					(2.21)
Same industry/same area					
q (1 year lag)				0.002	0.001
				(0.99)	(1.06)
2 year lag					0.002
					(1.55)
Cashflow				0.022**	0.014*
				(2.54)	(1.91)
1 year lag					0.010*
					(1.85)
Constant	-0.012	-0.035*	-0.017	-0.040*	0.027
	(-0.88)	(-1.98)	(-1.05)	(-1.84)	(1.35)
Firm fixed effects	X	X	X	X	X
Area fixed effects	X	X	X	X	X
Year fixed effects	X	X	X	X	X
Industry clustering	X	X	X	X	X
Observations	86676	86676	86676	86667	76360
R^2	0.547	0.551	0.548	0.552	0.555

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Equity Issuance

Panel A of this table shows estimates of the following regression:

$$Equity\ iss._{j,t}^{i,a} = \omega + \sum_{k=0}^{2} \eta_{1,k} Equity\ iss._{p,t-k}^{i,-a} + \sum_{k=0}^{2} \eta_{2,k} Equity\ iss._{p,t-k}^{-i,a} + \sum_{k=0}^{2} \eta_{3,k} Equity\ iss._{p,-j,t-k}^{i,a} + \eta_4 Controls_t^{i,a} + \epsilon_{j,t}^{i,a}.$$

where the dependent variable is secondary equity issuance (change in common equity plus the change in deferred taxes minus the change in retained earnings all normalized by last years assets) at year t for firm j which is headquartered in economic area (EA) a and belongs to industry i. The key independent variables are the equal-weighted average equity issuance for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, $Equity\ Iss._{p,t}^{i,-a}$; the equal-weighted equity issuance for a portfolio of firms in the same area as the dependent variable, but outside of industry i, $Equity\ Iss._{p,t}^{-i,a}$; and the equal-weighted equity issuance for a portfolio of firms in the same area and industry as the dependent variable (excluding the independent variable itself), $Equity\ Iss._{p,-j,t}^{i,a}$. In addition to the contemporaneous values of these regressors, lagged values are also included as specified. Additional regressors include year and area fixed effects ($Controls_{j,t}^{i,a}$). Panel B reports estimates for

$$\begin{aligned} Equity\ iss._{j,t}^{i,a} = \rho &+ \zeta_1 q_{p,t-1}^{i,-a} + \zeta_2 q_{p,t-1}^{-i,a} + \zeta_3 q_{p,-j,t-1}^{i,a} + \zeta_4 Cashflow_{p,t}^{i,-a} + \zeta_5 Cashflow_{p,t}^{-i,a} + \zeta_6 Cashflow_{p,-j,t}^{i,a} + \\ &\zeta_7 Return_{p,t}^{i,-a} + \zeta_8 Return_{p,t}^{-i,a} + \zeta_9 Return_{p,-j,t}^{i,a} + \zeta_{10} q_{j,t-1}^{i,a} + \zeta_{11} Cashflow_{j,t}^{i,a} + \zeta_{12} Return_{t,j}^{i,a} \zeta_{13} Controls_t^{i,a} + \epsilon_{j,t}^{i,a}. \end{aligned}$$

where the dependent variable is equity issuance at year t for firm j. Regressors include firm i's own q, $q_{j,t-1}^{i,a}$, defined as long-term debt plus debt in current liabilites plus market equity all divided by current assets, own cashflow, $Cashflow_{j,t}^{i,a}$, defined as income before extraordinary items plus depreciation and amortization normalized by last years assets, and own excess return, $Return_{j,t}^{i,a}$. Other key independent variables are the equal-weighted average lagged q, cashflow, and excess return for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, $q_{p,t-1}^{i,-a}$, $Cashflow_{p,t}^{i,-a}$, and $Return_{p,t}^{i,-a}$; the equal-weighted lagged q, cashflow, and excess return for a portfolio of firms in the same area as the dependent variable, but outside of industry i, $q_{p,t-1}^{-i,a}$, $Cashflow_{p,t}^{-i,a}$, and $Return_{p,t}^{-i,a}$; and the equal-weighted lagged q, cashflow, and excess return for a portfolio of firms in the same area and industry as the dependent variable (excluding the independent variable itself), $q_{p,-j,t-1}^{i,a}$, $Cashflow_{p,-j,t}^{i,a}$, and $Return_{p,-j,t}^{i,a}$. Additional regressors include year and area fixed effects ($Controls_{j,t}^{i,a}$). All standard errors are clustered by industry.

Table 7: Equity Issuance

Panel A: Equity issuance on equity issuance

	(1) Equity iss.	(2) Equity iss.	(3) Equity iss.	(4) Equity iss.	(5) Equity iss.	(6) Equity iss.
Same industry/different area						
Equity iss. (contemp.)	0.500***		0.505***	0.403***	0.396***	0.372***
	(6.92)		(6.98)	(7.83)	(6.84)	(6.18)
1 year lag					-0.095	-0.023
					(-1.51)	(-0.63)
2 year lag						-0.062
						(-1.30)
Different industry/same area						
Equity iss. (contemp.)		0.306***	0.316***	0.276***	0.246***	0.239***
		(7.73)	(6.59)	(7.15)	(6.10)	(4.63)
1 year lag					0.018	0.055
					(0.42)	(1.35)
2 year lag						-0.058**
						(-2.78)
Same industry/same area						
Equity iss. (contemp.)				0.127***	0.123***	0.114***
				(5.05)	(4.40)	(5.14)
1 year lag					-0.024*	-0.028
					(-1.95)	(-1.58)
2 year lag						-0.070***
						(-3.37)
Constant	-0.079	-0.081	-0.109	-0.121	-0.102***	0.071***
	(-0.40)	(-0.41)	(-0.57)	(-0.63)	(-3.27)	(5.76)
Firm fixed effects	X	X	X	X	X	X
Area fixed effects	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X
Industry clustering	X	X	X	X	X	X
Observations	85417	85417	85417	85403	74915	65862
R^2	0.375	0.373	0.376	0.377	0.394	0.394

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Equity Issuance - Cont'd

Panel B: Equity issuance on determinants

	(1) Equity iss.	(2) Equity iss.	(3) Equity iss.	(4) Equity iss.
Own firm				
q (1 year lag)	0.077***	0.077***	0.077***	0.077***
	(21.68)	(21.11)	(21.74)	(20.88)
Cashflow (contemp.)	-0.424***	-0.425***	-0.424***	-0.425***
	(-4.00)	(-4.02)	(-4.00)	(-4.03)
Stock return (contemp.)	0.088***	0.087***	0.088***	0.087***
	(4.96)	(4.93)	(4.94)	(4.94)
Same industry/different area				
q (1 year lag)		-0.001		-0.004
		(-0.12)		(-0.74)
Cashflow (contemp.)		0.127**		0.117
		(2.63)		(1.69)
Stock return (contemp.)		0.011		0.009
		(0.89)		(0.69)
Different industry/same area				
q (1 year lag)			0.021**	0.020**
			(2.63)	(2.43)
Cashflow (contemp.)			0.065	0.072
			(0.70)	(0.71)
Stock return (contemp.)			0.011	0.010
			(0.55)	(0.46)
Same industry/same area				
q (1 year lag)				0.005
				(1.64)
Cashflow (contemp.)				0.019
				(0.46)
Stock return (contemp.)				0.003
				(0.31)
Constant	-0.486***	-0.053	-0.087	-0.531***
	(-12.25)	(-0.49)	(-0.81)	(-14.01)
Firm fixed effects	X	X	X	X
Area fixed effects	X	X	X	X
Year fixed effects	X	X	X	X
Industry clustering	X	X	X	X
Observations	83292	83292	83292	83281
R^2	0.487	0.487	0.487	0.487

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Debt Issuance

Panel A of this table shows estimates of the following regression:

$$Debt\ iss._{j,t}^{i,a} = \iota + \sum_{k=0}^{2} \lambda_{1,k} Debt\ iss._{p,t-k}^{i,-a} + \sum_{k=0}^{2} \lambda_{2,k} Debt\ iss._{p,t-k}^{-i,a} + \sum_{k=0}^{2} \lambda_{3,k} Debt\ iss._{p,-j,t-k}^{i,a} + \lambda_4 Controls_t^{i,a} + \epsilon_{j,t}^{i,a}.$$

where the dependent variable is debt issuance (the change in total long-term debt plus the change in long-term debt due in one year plus notes payable divided by last years assets) at year t for firm j which is headquartered in economic area (EA) a and belongs to industry i. The key independent variables are the equal-weighted average debt issuance for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, $Debt\ Iss._{p,t}^{i,-a}$; the equal-weighted debt issuance for a portfolio of firms in the same area as the dependent variable, but outside of industry i, $Debt\ Iss._{p,t}^{-i,a}$; and the equal-weighted debt issuance for a portfolio of firms in the same area and industry as the dependent variable (excluding the independent variable itself), $Debt\ Iss._{p,-j,t}^{i,a}$. In addition to the contemporaneous values of these regressors, lagged values are also included as specified. Additional regressors include year and area fixed effects ($Controls_{j,t}^{i,a}$) In columns 7 through 10 firms are sorted by the degree to which they are financially constrained. In columns 7 and 8 firms are sorted on the Kaplan-Zingales (KZ) Index (Kaplan and Zingales, 1997). Firms with higher than median KZ rating, i.e. constrained firms, are included in the column 7 sample, while firms with lower than median KZ rating, i.e. unconstrained firms, are included in the sample used in column 8. In columns 9 and 10 firms are sorted by their payout ratio. Firms with lower than median payout ratios, i.e. constrained firms, are included in the column 9 sample, while firms with higher than median payout ratios, i.e. unconstrained firms, are included in the sample used in column 10.
Panel B reports estimates for

$$\begin{aligned} Debt\ iss._{j,t}^{i,a} = {} & \upsilon + \kappa_1 q_{p,t-1}^{i,-a} + \kappa_2 q_{p,t-1}^{-i,a} + \kappa_3 q_{p,-j,t-1}^{i,a} + \kappa_4 Cashflow_{p,t}^{i,-a} + \kappa_5 Cashflow_{p,t}^{-i,a} + \kappa_6 Cashflow_{p,-j,t}^{i,a} + \\ & \kappa_7 Return_{p,t}^{i,-a} + \kappa_8 Return_{p,t}^{-i,a} + \kappa_9 Return_{p,-j,t}^{i,a} + \kappa_{10} q_{j,t-1}^{i,a} + \kappa_{11} Cashflow_{j,t}^{i,a} + \kappa_{12} Return_{t,j}^{i,a} \kappa_{13} Controls_t^{i,a} + \epsilon_{j,t}^{i,a}. \end{aligned}$$

where the dependent variable is debt issuance at year t for firm j. Columns 1 through 4 use total debt issuance as the dependent variable and columns 5 and 6 use short-term and long-term debt issuance as the dependent variable, respectively. Regressors include firm i's own q, $q_{j,t-1}^{i,a}$, defined as the change in total long-term debt plus the change in long-term debt due in one year plus notes payable long-term debt plus debt in current liabilities plus market equity all divided by current assets, own cashflow, $Cashflow_{j,t}^{i,a}$, defined as income before extraordinary items plus depreciation and amortization normalized by last years assets, and own excess return, $Return_{j,t}^{i,a}$. Other key independent variables are the equal-weighted average lagged q, cashflow, and excess return for a portfolio of firms in the same industry as the dependent variable, but outside our set of 20 economic areas, $q_{p,t-1}^{i,-a}$, $Cashflow_{p,t}^{i,-a}$, and $Return_{p,t}^{i,-a}$; the equal-weighted lagged q, cashflow, and excess return for a portfolio of firms in the same area as the dependent variable, but outside of industry i, $q_{p,t-1}^{-i,a}$, $Cashflow_{p,t}^{-i,a}$, and $Return_{p,t}^{-i,a}$; and the equal-weighted lagged q, cashflow, and excess return for a portfolio of firms in the same area and industry as the dependent variable (excluding the independent variable itself), $q_{p,-j,t-1}^{i,a}$, $Cashflow_{p,-j,t}^{i,a}$, and $Return_{p,-j,t}^{i,a}$. Similar to Panel A, columns 5 through 8 report results for sub-samples of firms sorted by degree of financial constraint as indicated by the KZ Index (columns 5 and 6) and the payout ratio (columns 7 and 8). Additional regressors include year and area fixed effects ($Controls_{j,t}^{i,a}$). All standard errors are clustered by industry.

Table 8: Debt Issuance

Panel A: Debt issuance on debt issuance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
							Kaplan-Zingales		Payout ratio	
							Uncons.	Cons.	Uncons.	Cons.
	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.
Same industry/different area										
Debt iss. (contemp.)	0.321***		0.321***	0.285***	0.270***	0.284***	0.286***	0.205***	0.296***	0.185***
	(5.38)		(5.45)	(6.13)	(8.47)	(7.84)	(4.86)	(3.96)	(6.55)	(3.14)
1 year lag					0.032	0.045	0.064	0.063*	0.079	0.027
					(1.14)	(1.66)	(0.99)	(1.84)	(1.14)	(0.78)
2 year lag						-0.091*	-0.052	-0.084**	-0.112	-0.039
						(-1.98)	(-0.61)	(-2.25)	(-1.53)	(-0.91)
Different industry/same area										
Debt iss. (contemp.)		0.125**	0.127***	0.112***	0.063*	0.078**	0.095	0.048	0.119*	0.033
		(2.90)	(3.14)	(3.15)	(1.84)	(2.20)	(1.63)	(1.12)	(1.94)	(0.70)
1 year lag					0.060*	0.087**	0.083	0.091	0.134*	0.071
					(1.81)	(2.31)	(1.20)	(1.58)	(2.08)	(0.92)
2 year lag						-0.032	-0.004	-0.076	-0.058	-0.017
						(-1.02)	(-0.07)	(-1.16)	(-0.78)	(-0.33)
Same industry/same area										
Debt iss. (contemp.)				0.087***	0.062**	0.058*	0.028	0.070	0.039	0.038*
				(3.86)	(2.34)	(2.07)	(0.71)	(1.63)	(0.91)	(1.84)
1 year lag					0.022	0.020	-0.015	0.053*	-0.011	0.031*
					(1.04)	(0.94)	(-0.29)	(2.10)	(-0.22)	(2.01)
2 year lag						0.029*	0.026	0.028	0.047*	0.017
						(2.02)	(1.67)	(1.76)	(1.93)	(0.68)
Constant	-0.138**	-0.133**	-0.137**	-0.139**	0.430***	0.047***	-0.402***	0.036***	-0.040***	0.009
	(-2.55)	(-2.44)	(-2.55)	(-2.64)	(7.40)	(5.51)	(-39.96)	(5.67)	(-3.30)	(1.42)
Firm fixed effects	X	X	X	X	X	X	X	X	X	X
Area fixed effects	X	X	X	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X	X	X	X	X
Industry clustering	X	X	X	X	X	X	X	X	X	X
Observations	88107	88107	88107	88083	77000	67473	34681	31905	32134	29656
R^2	0.281	0.279	0.281	0.281	0.282	0.274	0.332	0.388	0.316	0.367

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Debt Issuance - Cont'd

Panel B: Debt issuance on determinants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					Kaplan-Zingales		Payout ratio	
					Uncons.	Cons.	Uncons.	Cons.
	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.
Own firm								
q (1 year lag)	0.016***	0.015***	0.016***	0.016***	0.014***	0.015***	0.017***	0.008**
	(6.83)	(7.14)	(6.86)	(7.31)	(7.06)	(6.52)	(5.96)	(2.76)
Cashflow (contemp.)	-0.054**	-0.054**	-0.054**	-0.055**	-0.088***	-0.018	-0.079***	0.115
	(-2.66)	(-2.75)	(-2.66)	(-2.76)	(-4.96)	(-0.56)	(-4.51)	(1.65)
Stock return (contemp.)	0.003*	0.004*	0.003*	0.004*	0.003	0.005	0.007**	-0.008**
	(1.85)	(1.89)	(1.87)	(1.89)	(1.21)	(1.45)	(2.53)	(-2.35)
Same industry/different area								
q (1 year lag)		0.001		0.001	0.001	0.001	0.003	0.005
		(0.12)		(0.16)	(0.15)	(0.22)	(0.54)	(0.81)
Cashflow (contemp.)		0.086		0.073	0.029	0.098	-0.013	0.082
		(1.04)		(0.86)	(0.38)	(1.31)	(-0.12)	(1.45)
Stock return (contemp.)		-0.005		-0.006	-0.019*	-0.003	0.005	-0.009
		(-0.55)		(-0.67)	(-2.18)	(-0.26)	(0.49)	(-0.93)
Different industry/same area								
q (1 year lag)			-0.002	-0.002	0.000	-0.004	-0.004	0.003
			(-0.32)	(-0.30)	(0.02)	(-0.42)	(-0.45)	(0.73)
Cashflow (contemp.)			0.006	0.008	-0.011	0.053	0.018	0.025
			(0.10)	(0.14)	(-0.11)	(0.76)	(0.19)	(0.53)
Stock return (contemp.)			-0.012*	-0.013**	-0.007	-0.026**	-0.007	-0.029**
			(-2.18)	(-2.32)	(-0.57)	(-2.61)	(-0.87)	(-2.88)
Same industry/same area								
q (1 year lag)				0.000	0.000	0.003	-0.005*	0.002
				(0.09)	(0.03)	(0.70)	(-1.89)	(0.48)
Cashflow (contemp.)				0.018	0.041**	-0.008	0.016	-0.014
				(1.27)	(2.45)	(-0.34)	(0.66)	(-0.44)
Stock return (contemp.)				0.000	0.005	-0.003	-0.005	0.004
				(0.09)	(0.79)	(-0.75)	(-1.13)	(0.49)
Constant	0.045	0.050	0.053	0.056	-0.248**	0.309***	0.107	0.028**
	(0.27)	(0.30)	(0.32)	(0.33)	(-2.63)	(8.95)	(1.60)	(2.91)
Firm fixed effects	X	X	X	X	X	X	X	X
Area fixed effects	X	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X	X	X
Industry clustering	X	X	X	X	X	X	X	X
Observations	86696	86696	86696	86686	46940	39412	43945	34420
R^2	0.288	0.288	0.288	0.288	0.348	0.430	0.336	0.401

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Main results under various alternatives for clustering

This table reports different industry/same area coefficient estimates for regression specifications used in previous tables varying the level at which standard errors are clustered. Column 1 reports results clustering standard errors by industry – i.e., it reports the same results as in Tables 4 – 8. Column 2 reports results using robust standard errors, but no clustering. Columns 3, 4, and 5 cluster standard errors by industry-area, year, and firm respectively.

	(1) Clustering: Industry	(2) Clustering: None	(3) Clustering: Ind.-Area	(4) Clustering: Year	(5) Clustering: Firm
Table 4A, column 6	Investment	Investment	Investment	Investment	Investment
Investment (contemp.)	0.188**	0.188***	0.188***	0.188***	0.188***
	(2.62)	(5.13)	(2.88)	(4.25)	(4.41)
1 year lag	0.050**	0.050	0.050*	0.050	0.050
	(2.57)	(1.22)	(1.78)	(1.08)	(1.27)
2 year lag	-0.006	-0.006	-0.006	-0.006	-0.006
	(-0.14)	(-0.18)	(-0.18)	(-0.16)	(-0.16)
Table 5, column 5	Investment	Investment	Investment	Investment	Investment
q (1 year lag)	0.008*	0.008***	0.008**	0.008***	0.008***
	(1.92)	(4.39)	(2.30)	(3.27)	(3.84)
2 year lag	0.001	0.001	0.001	0.001	0.001
	(0.97)	(0.65)	(0.50)	(0.49)	(0.58)
Cashflow (contemp.)	0.074**	0.074***	0.074**	0.074***	0.074***
	(2.32)	(4.00)	(2.49)	(3.22)	(3.49)
1 year lag	0.058**	0.058***	0.058**	0.058**	0.058***
	(2.21)	(3.28)	(2.12)	(2.02)	(2.99)
Table 6A, column 6	Eq. iss.	Eq. iss.	Eq. iss.	Eq. iss.	Eq. iss.
Equity iss. (contemp.)	0.239***	0.239***	0.239***	0.239***	0.239***
	(4.63)	(5.93)	(5.94)	(3.93)	(5.22)
1 year lag	0.055	0.055	0.055	0.055	0.055
	(1.35)	(1.49)	(1.44)	(1.62)	(1.41)
2 year lag	-0.058**	-0.058*	-0.058*	-0.058	-0.058
	(-2.78)	(-1.69)	(-1.86)	(-1.42)	(-1.54)
Table 7A, column 6	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.
Debt iss. (contemp.)	0.078**	0.078**	0.078**	0.078*	0.078*
	(2.20)	(2.00)	(2.03)	(1.79)	(1.85)
1 year lag	0.087**	0.087**	0.087**	0.087**	0.087**
	(2.31)	(2.18)	(2.09)	(2.36)	(2.04)
2 year lag	-0.032	-0.032	-0.032	-0.032	-0.032
	(-1.02)	(-0.84)	(-0.88)	(-0.74)	(-0.78)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Main results under various definitions for industry

This table reports reports different industry/same area coefficient estimates for regression specifications used in previous tables varying samples. Column 1 reports the same results as in Tables 4 – 8 for comparison. Column 2 reports results using the Fama-French 17 industry classification to construct portfolios rather than the Fama-French 12 industry classification used previously, column 3 uses the Fama-French 48 industry classification to construct portfolios, and column 4 uses the Hoberg-Phillips FIC 100 industry classification to construct portfolios – this is a much smaller sample running from 1996 to 2008.

	(1) FF12	(2) FF17	(3) FF48	(4) HP
Table 4A, column 6	Investment	Investment	Investment	Investment
Investment (contemp.)	0.188**	0.171*	0.281***	0.605***
	(2.62)	(1.93)	(2.85)	(2.68)
1 year lag	0.050**	0.037	0.108*	-0.081
	(2.57)	(0.62)	(1.88)	(-0.56)
2 year lag	-0.006	0.031	0.087	0.256
	(-0.14)	(0.96)	(1.29)	(1.37)
Table 5, column 5	Investment	Investment	Investment	Investment
q (1 year lag)	0.008*	0.007*	0.008*	0.012**
	(1.92)	(1.77)	(1.83)	(2.00)
2 year lag	0.001	0.000	0.001	-0.003
	(0.97)	(0.10)	(0.61)	(-0.80)
Cashflow (contemp.)	0.074**	0.082**	0.152***	0.044
	(2.32)	(2.22)	(3.75)	(0.64)
1 year lag	0.058**	0.014	0.020	-0.071
	(2.21)	(0.69)	(0.69)	(-0.79)
Table 6A, column 6	Eq. iss.	Eq. iss.	Eq. iss.	Eq. iss.
Equity iss. (contemp.)	0.239***	0.285***	0.367***	0.408***
	(4.63)	(4.95)	(5.67)	(3.94)
1 year lag	0.055	0.051**	0.083*	0.200**
	(1.35)	(2.18)	(1.89)	(2.37)
2 year lag	-0.058**	-0.109***	-0.069*	0.075
	(-2.78)	(-6.77)	(-1.76)	(0.99)
Table 7A, column 6	Debt iss.	Debt iss.	Debt iss.	Debt iss.
Debt iss. (contemp.)	0.078**	0.047	0.112	0.236**
	(2.20)	(1.08)	(1.33)	(2.21)
1 year lag	0.087**	0.085	0.137**	0.242**
	(2.31)	(1.51)	(2.11)	(2.45)
2 year lag	-0.032	0.035	0.086	0.047
	(-1.02)	(0.96)	(1.44)	(0.39)

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$