Urban Vibrancy and Corporate Growth *

Casey Dougal
LeBow College of Business at Drexel University

Christopher A. Parsons
Rady School of Management at the University of California, San Diego

Sheridan Titman
McCombs Business School, University of Texas at Austin

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Abstract

We find that a firm's investment is highly sensitive to the investments of other firms headquartered nearby, even those in very different industries. It also responds to fluctuations in the cash flows and stock prices (q) of local firms outside its sector. These patterns do not appear to reflect exogenous area shocks such as local shocks to labor or real estate values, but rather suggest that local agglomeration economies are important determinants of firm investment and growth.

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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, it would be hard to find cities with more different trajectories. Austin's population has exploded, while Detroit has suffered population declines, the departure of key employers, and increased crime.[1] Meanwhile, Whole Foods has grown to become an industry leader in the grocery business, with Unisys reduced to a bit player, having twice flirted with bankruptcy in recent years.

Urban economists have long explored the connection between location and economic variables, for example, finding large differences in worker wages and productivity rates across geographic areas. We observe similar cross-sectional variation in the investment rates of public firms. In Figure 1, we plot contours of raw (Panel A) and industry-adjusted (Panel B) investment rates for firms headquartered in the twenty largest U.S. cities. Note two observations. First, the differences are large, with cities in the highest quartile such as Minneapolis and Denver (blue line in Panel A) investing at roughly twice the rate as cities in the lowest quartile such as Cleveland or Indianapolis (orange line). Second, these differences are persistent: the blue and orange lines never cross in either figure, and in most years, the ordering for all four contours is preserved. If we are willing to assume that investment rates are at least partially correlated with investment opportunities, then this evidence indicates large, persistent cross-city differences in investment opportunities.

Though interesting on its own, a perhaps more important question is what drives differences in investment rates across cities.. One possibility is that an area's exogenous attributes, like access to transportation or good weather, attract certain types of firms or workers, and this sorting generates differences in investment opportunities. A second is that the political environment, such as low taxes or business-friendly politicians, allows firms in some areas

[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.

to thrive more than others. Finally, it is possible for cities to generate their own internal momentum through *endogenous interactions*: one firm experiences a positive shock, and through spillover effects, propagate this shock to their neighbors. These spillovers arise from the endogenous interactions of the people living in the city – what we call vibrancy – that influence knowledge diffusion between a city's workers, technology spillovers between neighboring firms, or consumption externalities between its residents.[2]

The goal of this paper is to gauge the importance of these endogenous interactions on corporate investment choices. The general idea is that these interactions can potentially improve the overall quality of a firm's top management, thereby improving investment opportunities. Moreover, because these endogenous interactions are inherently dynamic, as we explain below, it is possible to separate these endogenous people-based explanations from the exogenous geographic and political explanations by examining the time series determinants of investment expenditures.

Our methodology is best illustrated with an example. Consider another Detroit-based firm, retailer K-Mart, and Minneapolis-based Target. These firms historically competed in essentially the same markets, but are headquartered, and hence managed, from different cities. In each year, we ask whether the investment rates of K-Mart and Target are related to the investment rates of other non-local retailers such as Arkansas-based Wal-Mart, as well as to the 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 Dow Chemical, and the investment rate of Target with investment rates of other Minneapolis companies like General Mills or paint manufacturer Valspar.

The results of this exercise reveal that time-varying locational factors play an important role in determining a firm's investment expenditures. 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

[2]For discussion of each type of spillover, respectively, see Moretti (2003), Jaffe, Trajtenberg, and Henderson (1993), and Glaeser, Kolko, and Saiz (2001).

as the industry effect (e.g., using Wal-mart to explain K-Mart's investment rate). To put this magnitude 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 General Mills have a banner year (20% investment increase). In this case, our parameter estimates suggest that Target would expect to realize an increase in its yearly investment rate of **over twice** that of K-Mart.

We extend these benchmark results by augmenting traditional investment-q regressions to account for the prospects of a firm's local peers. Even when controlling for a firm's own q and cash flows, a firm's investment remains strongly related to the average q and cash flows of its neighbors, even those in very different sectors. The latter result is noteworthy for two reasons. First, the magnitude alone: the impact of local cash flows on a firm's investment is nearly double that of its own cash flows! Second, it contributes to the longstanding debate of whether investment-cash flow sensitivities are more likely to reflect financial constraints or response to growth opportunities.[3] Because the cash flows of other firms (i.e., those of its neighbors) cannot reflect its own financing frictions, our results suggest that at least in some settings, cash flows are associated with investment expenditures because they provide information about a firm's investment opportunities (as discussed previously in Poterba (1988), Alti (2003)).

The fact that we are analyzing dynamic effects within cities means that the results cannot be explained by static geographical attributes such as access to waterways or good weather. On the other hand, the results could still be generated by local firms being subject to the same time-varying area shocks, like extreme weather events, local elections, and changes in municipal tax rates, rather than the local spillovers, which is the focus of our analysis.

The ideal laboratory for identifying local spillovers is to identify regions where only a

[3]See Fazzari, Hubbard, and Petersen (1988), Kaplan and Zingales (1997, 1999), Erickson and Whited (2000), Gomes (2001), Altı(2003), and Almeida, Campello, Weisbach (2004).

fraction of firms are initially influenced by an exogenous shock, and then look for a response by nearby firms. We carry out this identification strategy by focusing on cities dominated by a single industry, such as San Francisco and the technology sector or Houston and the energy industry. For these cities, we examine shocks to firms in the dominate industries, e.g., Houston oil firms, using the investment rates of firms *outside the city* as an instrument. We then look at the investment rates of other firms in the city, which we interpret as evidence of spillovers. For example, we ask whether a Houston-based furniture manufacturer is abnormally sensitive to the investment rate of non-Houston oil firms, or whether a biotech firm in the Bay Area is abnormally sensitive to the investment rates of tech companies outside of the Bay area. Because the initial shocks in these tests are measured outside of the city, the evidence cannot be generated from exogenous area shocks.

We also conduct additional analysis to rule out fluctuations in real estate prices driving our results. As a recent paper by Chaney, Sraer, and Thesmar's (2011) shows, real estate is often used as collateral for debt finance, mitigating financial frictions for constrained firms, and facilitating investment (see also Peek and Rosengren (2000), Gan (2007), and Tuzel (2010)). Consequently, increases in real estate prices could simultaneously ease financial frictions for many firms in an area leading to correlated investment behavior, but not necessarily because of spillovers.[4] While important for constrained firms, the 'collateral channel' does not appear to explain our results. First, we find that large firms rather than small firms tend to be most influenced by area effects. Second, the local co-movement in debt issuance – which higher collateral values facilitates – tends to be strongest among the *least* financially constrained firms.

Beside those mentioned already, our paper is related to previous work on the effects of location on stock returns, a literature beginning with Coval and Moskowitz's studies of the home bias among retail traders (1999) and the flow of private information in geographic networks (2001). Building upon this earlier work, Pirinsky and Wang (2006) find that stocks

[4]Of course, if land prices increase primarily because of the success of some local firms, which then allows other firms in the area to invest, this would qualify as a spillover.

of firms in the same city tend to move together, and 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. While these studies indicate that regional factors can impact firm valuation via local investment demands, our results suggest a complementary channel: the stocks of local firms move together due to fluctuations of investment opportunities.

The paper is organized as follows. Section 2 provides some additional background and a simple framework for organizing our empirical tests, followed by a description of our data in Section 3. We present our main empirical results in Section 4, namely that firms headquartered nearby exhibit similarity in their investment expenditures. Then, in Section 5, we design tests intended to better identify the specific mechanisms responsible for these regional correlations in investment. Section 6 considers some additional robustness checks and extensions to our main results. We then conclude and provide suggestions for future research.

2 Motivation and hypothesis development

In this paper we find that year to year changes in firm investments tend to have significant city affects. As we will show, there are strong regional effects in investment expenditures within the same industry (e.g., the investment expenditures of two Chicago-based paint manufacturers move together), as well as between dissimilar industries (e.g., the investment expenditures of a Chicago-based paint manufacturer and a Chicago-based pharmaceutical firm move together). The hope is that in addition to identifying these phenomena, our empirical tests will help us better understand *why* location is so important for corporate investment. In this section, we describe in more detail the various reasons why investment expenditures may be related to location, and discuss the extent to which our empirical tests can make these distinctions.

To be concrete, consider two nearby firms A and B, headquartered in the same city. Broadly, their investment expenditures may covary because: 1) of common exposure to some unobserved factor X, so that causation runs $X \to A$ and $X \to B$, and 2) through interactions between A and B, so that causation is either $X \to B \to A$ or $X \to A \to B$. As discussed as early as Marshall (1890), the difference between 1 and 2 is crucial for understanding the role local externalities play not only in city growth, but also for firms' investment policies.

As an illustration of common shocks that may simultaneously influence firms headquartered in a given region, consider the city of New Orleans. Strategically located at the mouth of the Mississippi, New Orleans' location was extremely advantageous for a number of industries in the 19th and early 20th century. However, over time, the city (and therefore, the firms operating in it) experienced two exogenous shifts, one over several decades and one at a discrete point in time. The long-lived effect, which stems from the decline in land-based transportation, has impacted a number of "waterway" cities including Buffalo, Rochester, and St. Louis. (Clearly, railroad and road construction had nothing specifically to do with the New Orleans economy, so we can think about these technological changes as being imposed on New Orleans from the outside.) The second effect is, of course, Hurricane Katrina, which devastated much of the city in 2005. In both cases, what is important is that there were exogenous shocks that simultaneously effected the prospects of most New Orleans firms ($X \to A$, $X \to B$).

This is different from the second family of effects, which Manski (1993) refers to as "endogenous" local effects. In this case local firms behave similarly, not because of a systematic exogenous factor, rather, it is because the endogenous choices of local firms influence each other. Such endogenous local effects give rise to agglomeration economies (and occasionally diseconomies), and provide the theoretical foundation for much of the modern urban economics literature. Part of our goal in this paper is to argue that these endogenous, local interactions that contribute to city growth also contribute to investment opportunities.

Below we describe a few specific types of local, endogenous interactions that are capable of generating common fluctuations in investment opportunities:

1. **Skill or knowledge spillovers.** An employee at firm A learns or develops new skills, and through social interactions, these skills diffuse to employees of firm B.

2. **Consumption externalities.** As discussed by Glaeser, Kolko, and Saiz (2001), the modern "consumer city" leads to consumption externalities that arise because of economies of scale in the production of some luxury and public goods (e.g., symphonies and fancy restaurants). As a result, if firm A becomes more prosperous, the consumption opportunities for the employees of firm B may improve, making it easier for firm B to attract employees. Here, the externality can be negative as well as positive, e.g., the prosperity of Firm A may drive up the cost of housing, increasing the cost of living for the employees of Firm B.

3. **Infrastructure.** Firm A invests more, leading to the development of infrastructure such as airports, roads, ports, power plants, etc. This may, in turn, lower firm B's cost of doing business, and change its investment decisions.

4. **Collateral values.** Firm A invests more, increasing its demand and the demands of its employees for real estate, driving up prices. If firm B also owns land, it can use its (now more valuable) land as collateral to finance its investment expenditures. See Chaney, Thesmar, and Sraer (2011).

5. **Herding.** Firms in a particular city may all choose to invest more because they are influenced by the same external factors that can affect their moods, e.g., the local team wins the Super Bowl or the weather is good. Alternatively, if there is prestige associated with a growing business they may increase investment together because of a "keeping up with the Jones" effect.

Although these explanations are neither mutually exclusive nor exhaustive, the crucial common element is that they all require firm-to-firm interactions. In some, the interaction is very direct (e.g., with knowledge spillovers), whereas in others (e.g., through collateral values), the interaction is more indirect. As we will discuss later, we have designed empirical tests that distinguish between the exogenous non-people based explanations and the endogenous people based explanations. However, for the most part, we cannot distinguish between the various people based explanations.

3 Data and variable construction

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).[5]

These industry groupings are intentionally broad. The reason is that we are interested in measuring the extent to which local effects operate *within* as well as *across* different industries. By segregating businesses based on these relatively coarse designations, we minimize the chance that our across-industry comparisons are picking up (at least meaningful) industry linkages, as they would with finer classifications. This caveat notwithstanding, in robustness checks, we repeat all of our analysis using alternative definitions for industry,

[5]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`.

including Fama-French 48, a recent text-based industry measure developed by Hoberg and Phillips (2012), and 2-digit SIC codes.

The second way we need to group firms is by location which, like the industry classifications described above, requires some subjectivity. We define a firm's location as the location of its headquarters. Although a firm's headquarters is often separated from its operations by hundreds or even thousands of miles, this separation may help rather than hurt our ability to identify the types of spillovers that are the focus of this study. For as we will show, local fluctuations around a firm's headquarters are especially important for: 1) large firms, and/or 2) companies with operations in several states. What this tells us is that regional effects are primarily transmitted to the firm through its *upper management*, who are mostly responsible for laying out the firm's investment plans. This certainly does not exclude the firm's rank-and-file workers from being influenced by local effects,[6] but at least in our context, the effect seems to be driven by how the firm's top executives perceive and incorporate information about local business conditions into firm strategy.

Accordingly, we use the zip code listed on COMPUSTAT (variable ADDZIP) to place each firm headquarters in one of the 20 largest "Economic Areas," hereafter EA, as defined by the United States Bureau of Economic Analysis.[7] 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."[8] The last sentence in this definition is important, because our concept of location is closely tied to labor markets. Specifically, we 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

[6]See Moretti (2009) for an excellent review about local labor markets.

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

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

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.

Panel B of Table 1 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.[9] 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

[9] 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.

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.[10] 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 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 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.[11] 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).[12] As seen, there is a bit more cross-sectional variation

[10] 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.

[11] 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.

[12] 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.

across industries – as would be expected given that area portfolios are diversified *across* industries – but nonetheless, we observe substantial dispersion 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.

4 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 looking at regressions of firm investment on the investment of their industry and area peers. Then, we consider the ability of standard investment determinants like q and $Cashflow$ to explain investment expenditures in subsection 4.2. 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.

4.1 Investment-investment regressions

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 we describe with city names like New York or Los Angeles, but keeping in mind that the unit of analysis is an "economic 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:

$$\begin{aligned} Investment_{j,t}^{i,a} = \delta + \sum_{k=0}^{2} \beta_{1,k} Investment_{p,t-k}^{i,-a} + \sum_{k=0}^{2} \beta_{2,k} Investment_{p,t-k}^{-i,a} + \\ \sum_{k=0}^{2} \beta_{3,k} Investment_{p,-j,t-k}^{i,a} + \beta_4 Controls_t^{i,a} + \epsilon_{j,t}^{i,a}. \end{aligned} \tag{1}$$

The dependent variable, $Investment_{j,t}^{i,a}$, 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, $Investment_{p,t-k}^{i,-a}$, 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.[13] Here, the goal is to capture year-

[13] 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.

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 the 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 measures 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 $t-2$). 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.[14] For example, Yahoo's investment expenditures enter as an explanatory variable when explaining Google's investment expenditures. Given that we have already accounted for aggregate industry effects through $Investment^{i,-a}_{p,t-k}$, and non-industry local effects through $Investment^{-i,a}_{p,t-k}$, 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 (2) 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.[15] Area fixed effects account for

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

[15] 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.

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.

Table 3, presents the results. 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 sample 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 (not reported).

The second column shows the estimates when we consider the influence of 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 changes to a firm's investment rate, 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 3 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.

4.2 Investment-q regressions

The second type of equation we 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:

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

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.

In the first column of Table 4, we include only the firm's own one-year lagged q 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.[16] 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 4 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

[16] 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, $t = 1.85$).

In addition to highlighting the importance of a firm's local environment for its investment plans, the predictive significance of the local $Cashflow$ variable is useful for another reason. In the investment-q literature, there is a longstanding debate about the reason why a firm's own cash flows so strongly predict investment. There are two mainstream explanations. The first, originally articulated by Fazzari, Hubbard, and Peterson (1988), is based on financial constraints: when firms face frictions to external finance, they tend to rely on internally generated cash flows to fund investments. The second is based on cash flows reflecting investment opportunities, over and above that reflected in the firm's stock price. For a variety of reasons, a firm's stock price may not be a sufficient statistic for its investment prospects, opening the door for other firm fundamentals (e.g., cash flows) to explain investment.[17]

Our results are relevant for this debate. For, although a firm's cash flows may impact investment for the two reasons described above, the cash flows of *other firms* does not suffer from this ambiguity. More specifically, the financial constraints faced by any one firm are unlikely to be related to the contemporaneous cash flows of neighboring firms without strong industry links (columns 2, 4 and 5). Likewise, columns 3 through 5 indicate that even controlling for the firm's own cash flows and q, profitability at the industry level is an important determinant of investment. Because sensitivity to cash flow *external* to the firm is difficult to square with financial frictions, our results provide support for the interpretation that cash flows provide information about investment opportunities.

5 Why do firms in the same city invest together?

Together, the results in Tables 3 and 4 indicate strong cross-industry comovement in the investment expenditures of neighboring firms. As we show below, we can rule out exogenous shocks such as weather events as the primary drivers of our results. We are, however, less able to distinguish between the various types of endogenous local interactions. In large part, this is the cost of conducting our analysis at a high level of spatial and industry aggregation. While large sample, aggregate estimates are useful for establishing an empirical foundation for future work, they are not ideal for identification. This caveat notwithstanding, in this section we present additional tests designed to be somewhat more specific about the channel at work.

[17]Reasons why stock prices may not capture all relevant information about investment opportunities includes stock prices reflecting average rather than marginal q (Erickson and Whited (2000)), technical reasons related to the firm's production technology or adjustment costs (e.g., Hayashi (1982)), and mispricing. See Alti (2003) for a discussion of the important issues in this literature.

5.1 Exogenous area shocks

Time-varying area shocks can generate correlations between local firms' investment expenditures without requiring local, endogenous interactions. Extreme weather like Hurricane Katrina or disruptions in local politics might be examples of events that can affect the investment opportunities of all firms in a local area. In this section, we present tests designed to distinguish between such exogenous events and endogenous interactions.

We start by identifying 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.

In addition to Houston, we identify three cities 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.) These cities and their respective dominant industries include: 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 2, except that now, only a single, dominant industry is included as a measure of local vibrancy.[18] 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

[18] 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.

Table 3, 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. To do this, we replace each of our local, dominant industry portfolios with industry portfolios that include firms from outside the region. For example, in column 3, the auto portfolio contains *no Detroit-based firms*. 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 firm's 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.

5.2 Differential area sensitivities to macro shocks

In the previous subsection, we present tests that explicitly rule out exogenous area shocks such as weather events or local politics as potential explanations for the observed regional correlations in investment expenditures. Another possible channel for generating regional correlation in investment expenditures, which we consider in this section, is through differential sensitivities to macro shocks.[19] Recall, that our benchmark regressions (the results shown in Table 3) control for macro shocks with year fixed effects, which implicitly assume that macro shocks affect all regions equally. However, in general, firm sensitivities to macro shocks vary across regions, and as a result, the investment rates of otherwise unrelated neighboring firms may be correlated.

To illustrate what we have in mind, suppose that there are only two kinds of firms in the economy: young and old. Young firms tend to be more flexible and have growth opportunities that are very sensitive to news about future economic growth. Old firms, on the other hand, have existing relationships with customers and suppliers, and other features that make it difficult for them to rapidly adjust investment expenditures when the macro environment changes. Suppose further that cities differ in the age distribution of their firms, e.g., firms on the West Coast tend to be younger.

Under these assumptions, the young firms exhibit stronger sensitivity to macro news than old firms, which means that the the predominately young firms in young-firm cities tend to invest more (less) when macro growth prospects are favorable (unfavorable). Likewise, the predominately old firms in old-firm cities will exhibit less sensitivity to macro effects. Because our benchmark regressions include year fixed effects, which implicitly assume that firms have the same investment sensitivity to macro news, a firm's deviation from the average sensitivity will wash into one or both of its area coefficients (i.e., those on the same area-different industry or same area-same industry portfolios).

To get a sense for how important cross-city differences in macro sensitivities are, we first estimate our benchmark regressions on samples from each of the individual economic regions. In other words, we run the following regression separately for San Francisco, Cleveland, Phoenix, etc.:

$$Investment^{i,a}_{j,t} = \delta + \beta_1 Investment^{i,-a}_{p,t} + \beta_2 Investment^{-i,a}_{p,t} + \beta_3 Investment^{i,a}_{p,-j,t} + \beta_4 Controls^{i,a}_{t} + \epsilon^{i,a}_{j,t},$$

[19] We thank the referee for raising this possibility.

and extract 20 estimates for β_2, one for each city. In addition, we run a second set of regressions that are akin to market model regressions for stock returns, except that we consider firm-specific and aggregate investment expenditures rather than stock returns:

$$Investment^{i,a}_{j,t} = \gamma + \alpha_1 Market\ Investment_{p,t} + \alpha_2 Controls^{i,a}_{t} + \nu^{i,a}_{j,t}.$$

In this exercise, we are estimating each city's average market sensitivity separately, rather than forcing the coefficients to be identical, as we did in our benchmark regression.

Figure 3 shows the results. The first observation to note is the heavy clustering around one on the x-axis, indicating that the investment rates in about half our cities move one-for-one with the overall market. Among this set are large, diversified cities such as Chicago, New York, Los Angeles, Philadelphia Washington D.C., Dallas, and Boston. About two-thirds of our sample firms reside in cities with macro betas between 0.8 and 1.2.

As mentioned above, we are interested in the extent to which cities with either very high, or very low, sensitivities to macro factors have the highest estimated area coefficients. Beginning with the former, Figure 3 indicates the cities with the highest macro-investment sensitivities are, by and large, the usual suspects: tech-heavy centers such as San Francisco, Denver, Phoenix, and Seattle, and the entertainment-hub Orlando. However, note also that the area coefficients for these cities are actually below the sample average, with only Orlando (home to only 28 firms in the typical year) being above.

The left part of the figure tells a similar story. Of the four cities with estimated macro sensitivities less than 0.8, St. Louis and Indianapolis have the second and third lowest, respectively, estimated coefficients in our sample. The average for these "low-beta" cities is also below the sample average. Together, the patterns in Figure 3 suggests that area effects are likely capturing more than cross-city differences in macro sensitivities.

Perhaps a more direct way to address cross-area differences in macro sensitivities is to allow the effect of the aggregate market on investment to vary across each of our 20 economic areas. Operationally, this amounts to removing the year fixed effects from our regressions, and replacing them with 20-1=19 *area* $\times$ *market* fixed effects, i.e., *Chicago* $\times$ *market investment*, *Atlanta* $\times$ *market investment*, etc. When we do this, the results in column 4 of Table 3 remain essentially the same: the coefficient on the *same area, different industry* portfolio changes from 0.211 to 0.209, and the coefficient on the *same area, same industry* portfolio changes from 0.183 to 0.182. Combined with the graphical results in Figure 3, it appears that different sensitivities to macro factors are not the primary driver of the correlations in local investment we observe.

Finally, while these tests suggest that different sensitivities to the aggregate U.S. economy probably do not generate the local investment correlations we observe, the observed correlation could be generated by different sensitivities to other systematic factors. As an example, suppose that a few large U.S. cities (e.g., New York, Chicago, or Los Angeles) are home to firms with a significant foreign presence, with more regional firms being located in smaller cities. Here, a shock to, say, the Chinese economy could disproportionately impact the prospects of firms in these large cities, leaving those in smaller cities comparatively unaffected. Likewise, one could imagine firms headquartered near an international border (e.g., San Diego or Seattle) being especially sensitive to foreign exchange rates.

While we acknowledge that neither our benchmark regressions nor Figure 3 rule out cross-area differences in global sensitivities, we also note that the results in Table 5 pose a particular challenge to this explanation. Recall that we found, for example, that Houston-based firms outside the energy industry are particularly sensitive to fluctuations in the energy industry, compared to their industry-match peers outside Houston. Although one might still claim that Houston's non-oil firms have different sensitivities to a global factor, it seems unlikely that: 1) this sensitivity would vary systematically with fluctuations in the energy industry (other than through interactions with Houston's oil-based firms), and that 2) this relationship would hold independently for the other three city-industry pairs considered in Table 5 (San Francisco-software, Detroit-automotive, and Atlanta-nondurables).

5.3 Real estate values and the collateral channel

Real estate price fluctuations are 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 (Chaney, Sraer, and Thesmar (2011)). Of course, this begs the question of what ultimately caused the common shock to land values: was it a natural disaster like Hurricane Katrina or simply one or more successful firms in any area buying up land? In the first case, there is no firm-to-firm interaction; however, in the second case, the demand for land by one local firm may ease financial constraints for neighboring firms. Although not a "people-based" social interaction such as information or knowledge diffusion, a result here would constitute a firm-to-firm interaction, and as such, is relevant for thinking about agglomeration economies.

Because the collateral story is implicitly about debt financing, Table 6 reports results of regressions that substitute *Debt issuance* (also scaled by lagged assets) for *investment* 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, $t = 2.07$).

At a broad level, the fact that we also find comovement in debt issuance suggests that at least part of the investment effect could be driven by common variation in collateral values. 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 investment, it is perhaps not surprising that we find virtually nothing here.

6 Further considerations and robustness

While the results in Tables 5 and 6 rule out two specific hypotheses, they do not identify what may *be* driving the local comovement we observe in investment expenditures. Here, we conduct a few additional cross-sectional tests that, although not definitive, provide more information about the most relevant types of local, endogenous interactions.

6.1 Large versus small firms

We start by splitting the sample into large and small firms in the first two columns of Table 7, a decomposition relevant for two reasons. First, we expect the collateral channel (see above) to be weaker for large firms, which are less likely to be financially constrained. Second, large firms are less likely to have regionally concentrated operations and sales forces. This therefore provides us the opportunity to test the importance of headquarters *per se* – more specifically, the local business environment of the firm's headquarters.

The first column shows the results for small firms, defined as those below the previous year's sample median across 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 roughly 30 percent higher for large firms (0.229, $t = 2.25$), versus that observed for small firms (0.175, $t = 2.87$). For local firms within the firm's industry, the effects are also more pronounced for large firms.

The fact that we observe the strongest results for large firms, combined with the quickness of the effect, poses a problem for many potential mechanisms. A plausible explanation, which is consistent with these observations, is that we are picking up communication between a city's top executives. Indeed, CEOs and CFOs of large firms are disproportionately represented on corporate boards, civic organizations, local charities, and other social organizations that facilitate interactions with other top managers (Engelberg, Gao, and Parsons (2013)). Moreover, executives of large firms simply have more opportunity to learn from and share ideas with other top managers and opinion leaders.

Second, while a CEO of a small company certainly has private information about his firm's own prospects, CEOs of large firms may have information (or valuable opinions about) events that extend beyond their own firms. The private meeting between Google chairman CEO Eric Schmidt and French President Francois Hollande in October 2012 comes to mind. In these and similar situations, CEOs of large, connected companies may have both the information and visibility to transmit these ideas to others in the area. What we cannot tell, of course, is the extent to which such effects represent actual information, or rather result from the *perception* of information. Regardless, that local effects are strongest for large firms – whose customer base and operations and the least localized – are strongly suggestive of communication between upper management of nearby firms.[20]

6.2 Do growing cities host growing firms?

Throughout our analysis, we have measured the vibrancy of a city's local economy using the investment rates of firms headquartered there. In the next five columns of Table 7, we consider two additional measures of a city's economy: population growth and per capita wage growth. In column 3, we simply add these control variables to our investment regressions. While the estimates and statistical significance of our area portfolios remain similar ($t = 2.18$), we also find that an area's population growth is an extremely strong determinant of investment expenditures ($t = 6.54$).

In the next two pairs of columns, we split the sample based on wage and population growth. Interestingly, only when a city is thriving does the effect of one's non-industry peer firms matter for investment decisions. When wage growth is below the sample median (column 4), the local, non-industry portfolio is not significantly different than zero ($t = 0.60$). Likewise, when a city's population stagnates (column 6), the estimated coefficient on the local portfolio is actually negative, although far from being statistically significant ($t = -0.20$). In contrast, columns 5 and 7 indicate, respectively, that high wage and population growth amplify the investment effect of a firm's local, non-industry peers.

Why should a firm's investment depend on city dynamics? And why should the performance of other firms be more important when a city is growing? These are different questions, although some of the same economic forces are at work. Thinking about the former question first, one possibility is that population and/or wage growth is a barometer for the quality of local human capital. Like a shock to any of the firm's inputs to production, access to a cheaper or better pool of workers is likely to make investment more profitable,

[20]We have also examined the impact of firm entry and exit on our findings. In unreported results, we find that excluding new firms and less successful firms from the sample increases the coefficient on the same-area/different-industry investment portfolio and decreases the different-area/same-industry investment coefficient, suggesting that for large, successful firms area dynamics matter as much as, and in some instances perhaps slightly more than, industry dynamics.

providing a potential explanation for why growing cities appear to host growing firms. However, causation could also go the other way, with thriving firms attracting new workers to the area. In either case, what is important is that the economic and statistical magnitude of our area portfolios is preserved in the presence of these controls, which column 5 indicates is the case.

A more subtle issue is why growing cities appear to magnify the effect of a firm's local peers. One possibility is akin to measurement error. If the performance of local firms is measured imperfectly (even though we are talking about relatively large portfolios), city-level information like population growth may nonetheless still contain information about the health of local companies. This is similar reasoning to what we saw in Table 4, where the stock prices of a firm's industry (non-local) peers still predicts its investment, even when its *own* stock price is included in the regression. In this case, the interaction between local firm and city performance may convey a cleaner signal about the prospects of local firms. Another alternative is that favorable demographic trends like growing population are complementary with investment prospects. Here, firms in growing areas ramp up investment in part *because* the area is growing, and may be expected to do so in the future.

6.3 Headquarter changes

To better establish that our investment comovement results are driven by the economic conditions surrounding firm headquarter locations, it is informative to examine what happens to these correlations when firms change headquarters. To this point, we have only used COMPUSTAT data to define firm location. Subsequently, we have ignored firm headquarter changes since COMPUSTAT backfills all location data, and therefore records only firms' current headquarters. To examine headquarter changes we use the historic headquarter information provided by the Compact Disclosure database[21]. This database covers the period from 1988 - 2006 and identifies 314 firm headquarter relocations corresponding to firms in

[21] We'd like to thank Joseph Engelberg for sharing this data.

our our current CRSP/COMPUSTAT sample. Overall, during this time period our sample has 8730 unique firms, implying that roughly 3.5% of firms moved headquarters at least once during this time-period.

To examine the effect of headquarter location changes we interact the same area-different industry and same area-same industry portfolios with a dummy variable that is zero before a firm relocates to their current headquarter location, and one forever after their relocation. We hypothesize that the when firms move to their current area the correlation between their own investment and the investment of the same area-different industry and same area-same industry portfolios will increase. Columns 8 and 9 of Table 7 report results for investment regressions including these interactions. Column 8 uses the full sample and column 9 reports results using only the sample of firms which changed headquarters. Consistent with our hypothesis we find that the interactions are positive in all cases, but statistically insignificant likely due to the small number location changes.

6.4 Clustering alternatives

We conclude our analysis with a number of robustness checks. In Table 8, 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 8, 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.

6.5 Varying industry definitions

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 9 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 9), 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.

7 Conclusion

For well over 100 years, urban economists have studied the connection between location and economic activity. The earliest studies emphasize physical attributes such as access to natural resources or transportation, but more recent work explores the influence of location on human capital. Here, the central idea is that a person's local environment has a first order effect on his choices – how much schooling he acquires, where he works and how hard, which friends he spends time with, how healthy he is, and even how long he lives. [22]

In this paper, the people under consideration are top executives at large, public companies. We consider whether, and to what extent, their local environments – specifically, the actions of other firm's headquartered nearby – influence the decisions they make for their own companies. Why they *would* might not be obvious. First, most of the firms in our sample (even the smallest ones) are relatively large, and thus, sell their products outside their headquarters' catchment areas. Second, the main comparisons we make are between firms located near one another, but operating in very different lines of business (e.g., oil refiners

[22] There is an extensive urban economics literature which examines the effects of city-living. For example, cities make workers more productive (Glaeser and Mare 2001); cities with high initial schooling levels have faster growth in their share of adults with college degrees than initially less educated cities (Berry and Glaesar 2005); and social interactions within cities play an important role in explaining the high cross-city variance of crime rates (Glaeser, Sacerdote, and Scheinkman 1996). See also Glaeser (2012).

and pharmaceuticals). Yet, our analysis suggests very strong "local effects" in corporate investment expenditures. Roughly speaking, when deciding how much to invest in a given year, what a firm's local neighbors are doing is about half as important as what other firms in its industry are doing. In other tests not reported here, when we measure the performance of a firm's local neighbors in other ways e.g., their profits or stock prices - similar results obtain.

Future research will hopefully dig deeper into how these human capital effects generate co-movements in local investment expenditures. Our analysis suggests that the answers to these questions may also provide useful insights into why cities grow. Indeed, cities with growing populations do host firms that invest more, which is consistent with the idea that an influx of new people, with new skills, facilitates the dissemination of new ideas. For example, when oil prices rise, Houston oil and gas firms tend to hire new managers, who may bring with them new ideas. If the knowledge imparted by these newcomers is easily transferrable across industries – 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 area's 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.

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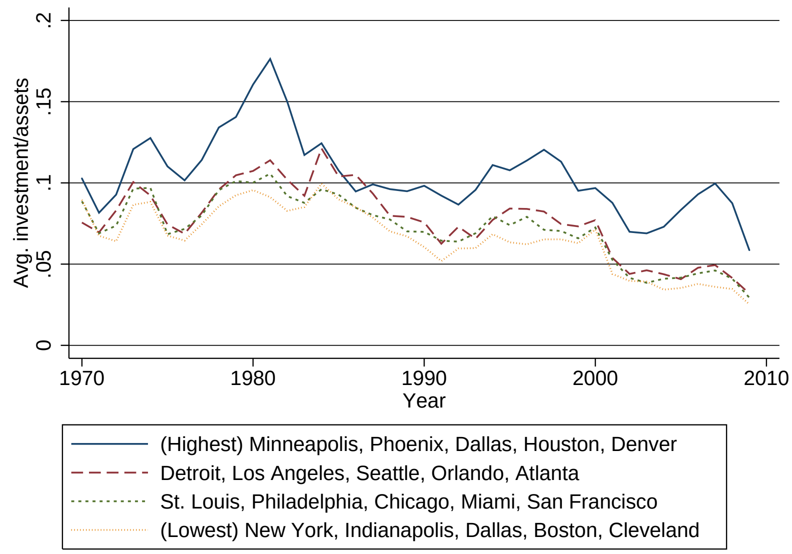
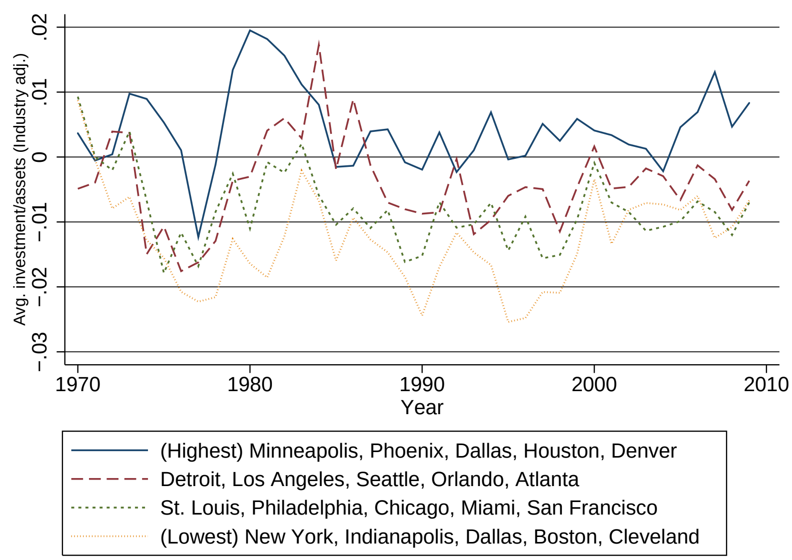
Figure 1: Average area investment rates across time

Panel A: Investment/assets



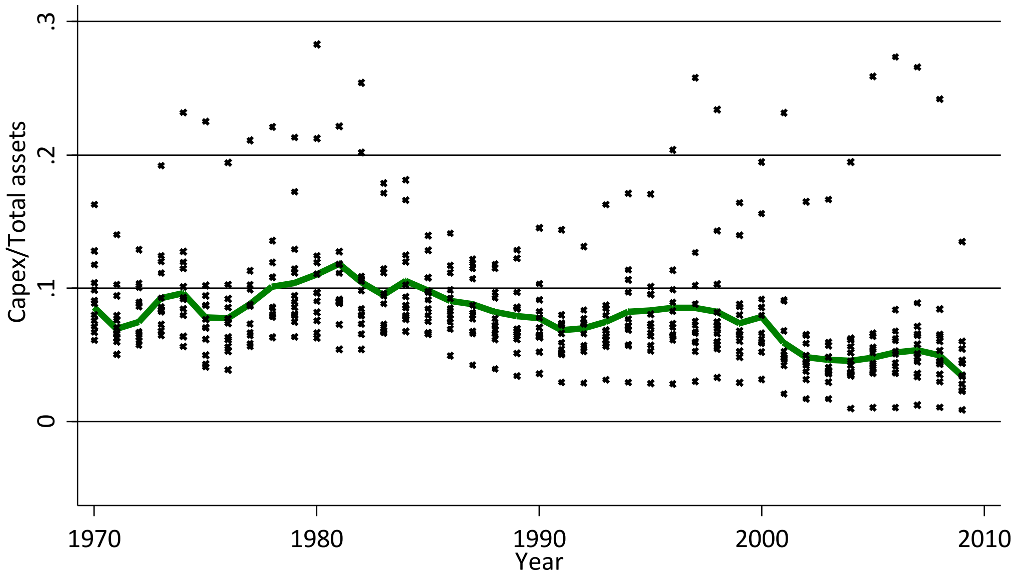
Panel B: Fama-French 12 Industry adjusted investment/assets



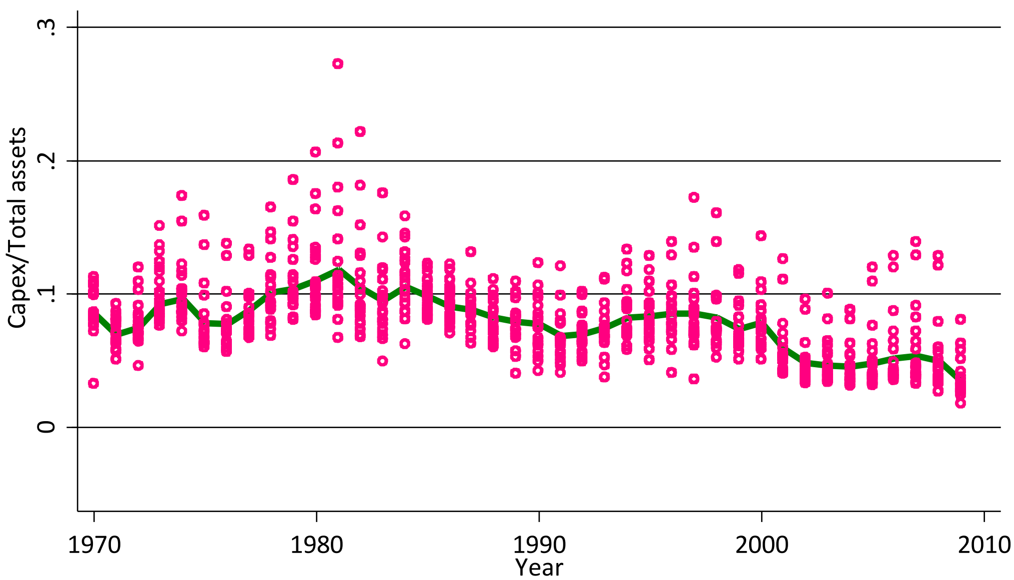
Panel A of this figure shows the average annual investment rate (capital expenditures divided by last year's assets) for 4 sets of areas grouped according to their investment levels over the entire sample period. The first group contains the five areas with the highest investment over the sample period (i.e., Minneapolis, Phoenix, Dallas, Houston, Denver), while the last group contains the five areas with the lowest investment rates (i.e., New York, Indianapolis, Dallas, Boston, Cleveland). Panel B shows the same figure using Fama-French 12 industry-adjusted investment rates.

Figure 2: Area and industry investment

Panel A: Industry investment

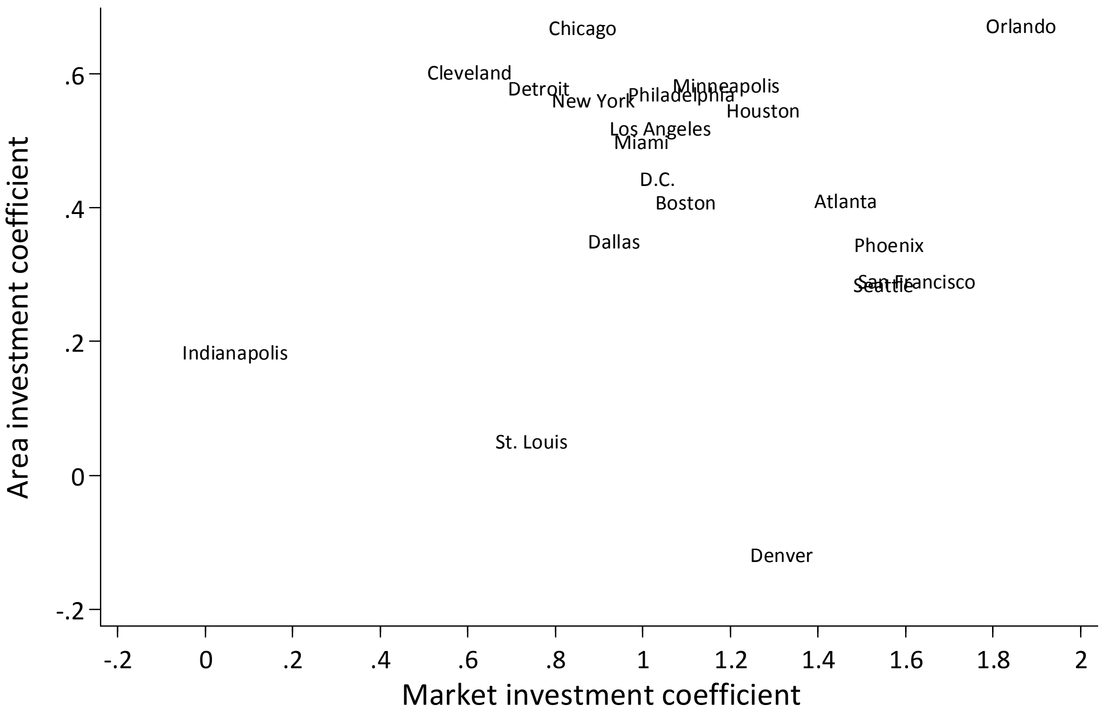


Panel B: Area investment



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.

Figure 3: Area versus market sensitivities



This figure plots coefficient estimates for $Market\ Investment_{p,t}$ (Market investment) and $Investment^{-i,a}_{p,t}$ (Area investment) from the following two regression estimated individually for each area:

$$Investment^{i,a}_{j,t} = \delta + \beta_1 Investment^{i,-a}_{p,t} + \beta_2 Investment^{-i,a}_{p,t} + \beta_3 Investment^{i,a}_{p,-j,t} + \beta_4 Controls^{i,a}_{t} + \epsilon^{i,a}_{j,t},$$

and

$$Investment^{i,a}_{j,t} = \gamma + \alpha_1 Market\ Investment_{p,t} + \alpha_2 Controls^{i,a}_{t} + \nu^{i,a}_{j,t}.$$

That is, we estimate the same regression as Table 4, column 4 by area excluding year fixed effects, and we estimate a regression of firm investment on the equal-weighted market investment average ($Market\ Investment_{p,t}$).

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 billions of 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	561	419	120	430	1,160
Los Angeles-Long Beach-Riverside, CA	19,055,411	271	106	133	292	399	133	107	15	96	285
Chicago-Naperville-Michigan City, IL-IN-WI	10,256,144	180	43	143	175	254	226	151	41	222	427
San Jose-San Francisco-Oakland, CA	9,338,048	235	140	58	231	427	310	324	18	131	793
Washington-Baltimore-Northern Virginia, DC-MD-VA-WV	8,830,103	133	60	51	158	205	119	120	7	53	310
Boston-Worcester-Manchester, MA-NH	8,193,115	219	96	96	232	341	143	135	12	74	340
Dallas-Fort Worth, TX	7,252,173	155	55	88	159	229	147	95	39	130	291
Detroit-Warren-Flint, MI	7,048,815	69	15	52	65	88	46	31	10	42	88
Philadelphia-Camden-Vineland, PA-NJ-DE-MD	6,874,604	139	46	83	147	195	84	70	14	55	194
Atlanta-Sandy Springs-Gainesville, GA-AL	6,818,366	98	48	44	104	164	116	95	15	92	248
Houston-Baytown-Huntsville, TX	6,088,680	137	49	69	149	202	152	146	22	78	419
Miami-Fort Lauderdale-Miami Beach, FL	6,013,949	105	46	48	108	167	32	31	3	14	78
Minneapolis-St. Paul-St. Cloud, MN-WI	5,068,485	123	54	55	128	199	94	91	7	44	231
Cleveland-Akron-Elyria, OH	4,662,474	77	16	60	73	102	56	47	8	34	126
Seattle-Tacoma-Olympia, WA	4,358,890	48	25	19	48	81	57	64	1	29	160
Phoenix-Mesa-Scottsdale, AZ	4,256,343	46	19	22	52	73	28	34	2	7	88
Orlando-The Villages, FL	4,047,955	28	12	15	27	43	6	6	0.3	2	15
Denver-Aurora-Boulder, CO	3,762,991	96	43	37	111	142	61	62	3	46	156
St. Louis-St. Charles-Farmington, MO-IL	3,317,985	45	13	31	46	64	54	42	8	44	104
Indianapolis-Anderson-Columbus, IN	3,254,963	28	11	16	28	44	14	16	1	5	37

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)), *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
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
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
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
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	Debt	q	Ret	Cash	Inv	Debt	q	Ret	Cash	Inv	Debt	q
Same ind./diff. area															
Return	1.0														
Cashflow	0.1	1.0													
Investment	-0.1	0.4	1.0												
Debt iss.	-0.2	0.1	0.5	1.0											
q	-0.2	-0.5	0.2	0.1	1.0										
Diff. ind./same area															
Return	0.7	0.0	-0.1	-0.2	-0.2	1.0									
Cashflow	0.0	0.4	0.2	0.1	-0.2	0.1	1.0								
Investment	-0.1	0.2	0.3	0.3	-0.1	-0.1	0.4	1.0							
Debt iss.	-0.2	0.1	0.3	0.4	0.1	-0.3	0.1	0.5	1.0						
q	-0.2	-0.3	-0.2	0.0	0.2	-0.3	-0.7	0.0	0.1	1.0					
Same ind./same area															
Return	0.8	0.1	-0.1	-0.2	-0.2	0.7	0.1	-0.1	-0.2	-0.2	1.0				
Cashflow	0.1	0.7	0.2	0.0	-0.4	0.1	0.4	0.1	0.0	-0.3	0.1	1.0			
Investment	-0.1	0.3	0.7	0.3	0.2	-0.1	0.2	0.3	0.2	-0.1	-0.1	0.2	1.0		
Debt iss.	-0.1	0.1	0.2	0.4	0.0	-0.1	0.0	0.2	0.3	0.0	-0.1	0.0	0.3	1.0	
q	-0.2	-0.4	0.1	0.1	0.8	-0.2	-0.3	0.0	0.1	0.3	-0.2	-0.5	0.1	0.0	1.0

Table 3: 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 ($Controls^{i,a}_{j,t}$). In every regression, standard errors are clustered by industry.

	(1) Investment	(2) Investment	(3) Investment	(4) Investment	(5) Investment	(6) Investment
Same industry/different area						
Investment (contemp.)	0.503***		0.508***	0.386***	0.353**	0.354**
	(3.43)		(3.57)	(3.48)	(3.09)	(3.09)
Investment (1 year lag)					-0.011	-0.036
					(-0.29)	(-0.79)
Investment (2 year lag)						-0.011
						(-1.16)
Different industry/same area						
Investment (contemp.)		0.186*	0.231**	0.211**	0.190***	0.188**
		(1.91)	(2.66)	(2.77)	(3.16)	(2.62)
Investment (1 year lag)					0.046	0.050**
					(1.45)	(2.57)
Investment (2 year lag)						-0.006
						(-0.14)
Same industry/same area						
Investment (contemp.)				0.183***	0.167***	0.158***
				(4.96)	(4.89)	(4.10)
Investment (1 year lag)					0.034*	0.058***
					(1.92)	(3.60)
Investment (2 year lag)						-0.007
						(-0.40)
Constant	-0.017	0.003	-0.022	-0.021	0.001	0.055***
	(-0.80)	(0.16)	(-1.05)	(-1.05)	(0.08)	(6.44)
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	88673	88673	88673	88656	77871	68511
R^2	0.525	0.515	0.526	0.527	0.531	0.535

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

Table 4: Investment-q regressions

This table shows estimates of the following regression:

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

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 4: Investment-q regressions

	(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	86676	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 5: Ruling out exogenous shocks

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: Ruling out exogenous shocks - 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: Debt issuance and the collateral channel

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 6: Debt issuance and the collateral channel

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 6: Debt issuance and the collateral channel - 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 7: Additional city controls and other robustness

This table shows estimates of the following regression

$$Investment_{j,t}^{i,a} = \delta + \beta_1 Investment_{p,t}^{i,-a} + \beta_2 Investment_{p,t}^{-i,a} + \beta_3 Investment_{p,-j,t}^{i,a} + \beta_4 Controls_t^{i,a} + \epsilon_{j,t}^{i,a}.$$

, i.e., the same regression as in column 4 of Table 4 with the following changes: Columns 1 and 2 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*). Column 3 results are reported for this regression with the addition of the area wage per employee growth rate and population growth rate as regressors. Columns 4 and 5 report regression results conditional on low area wage per employee growth (i.e., area wage per employee growth rates less than the U.S. median), and high growth (i.e., growth higher than the U.S. median value). Columns 6 and 7 report similar results sorting on high and low area population growth rates. Columns 8 and 9 examine the effect of headquarter relocations. Both columns add to our basic investment equation interactions of the same area-different industry and same area-same industry portfolios with a dummy variable that is zero before a firm relocates to their current headquarter location, and one forever after their relocation. Column 8 reports results using the full sample and column 9 reports results restricting the sample to only those firms which eventually change location. In every regression, standard errors are clustered by industry.

	(1) Small firms Investment	(2) Big firms Investment	(3) Investment	(4) Low wage growth Investment	(5) High wage growth Investment	(6) Low pop. growth Investment	(7) High pop. growth Investment	(8) Investment	(9) Investment
Investment - Same industry/different area	0.471**	0.320***	0.373***	0.270**	0.367***	0.135**	0.459***	0.385***	0.492***
	(2.76)	(4.07)	(3.51)	(2.32)	(3.49)	(2.23)	(4.61)	(3.52)	(6.06)
Investment - Different industry/same area	0.175**	0.229**	0.132*	0.046	0.200**	-0.020	0.169**	0.211**	0.268
	(2.87)	(2.25)	(2.18)	(0.60)	(2.31)	(-0.20)	(2.48)	(2.79)	(0.96)
Investment - Same industry/same area	0.130*	0.213***	0.170***	0.156***	0.149***	0.131*	0.143***	0.182***	0.142
	(2.10)	(4.71)	(4.75)	(3.12)	(4.29)	(2.16)	(4.20)	(5.05)	(1.21)
Wage per employee growth rate			0.078						
			(1.79)						
Population growth rate			0.392***						
			(6.54)						
Interaction - Different industry/same area								0.023	0.066
								(0.21)	(0.65)
Interaction - Same industry/same area								0.017	0.013
								(0.33)	(0.09)
Constant	0.015	-0.002	-0.022	0.025**	0.042**	0.058***	-0.003	-0.021	-0.006
	(0.28)	(-0.19)	(-1.14)	(2.28)	(2.56)	(5.34)	(-0.13)	(-1.05)	(-0.62)
Firm fixed effects	X	X	X	X	X	X	X	X	X
Area fixed effects	X	X	X	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X	X	X	X
Industry clustering	X	X	X	X	X	X	X	X	X
Observations	47384	41369	87986	34186	53730	40090	47729	88656	3947
R^2	0.511	0.635	0.526	0.609	0.568	0.559	0.550	0.527	0.521

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

Table 8: Clustering alternatives

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 Table 4A, column 8; Table 6, column 5; and Table 7A, column 6. Column 2 reports results using robust standard errors, but no clustering. Columns 3 to 7 cluster standard errors by industry-area, year, firm, area, and area-year respectively.

	(1) Clustering: Industry	(2) Clustering: None	(3) Clustering: Ind.-Area	(4) Clustering: Year	(5) Clustering: Firm	(6) Clustering: Area	(7) Clustering: Area-Year
Table 4A, column 6	Investment	Investment	Investment	Investment	Investment	Investment	Investment
Investment (contemp.)	0.188**	0.188***	0.188***	0.188***	0.188***	0.188**	0.188***
	(2.62)	(5.13)	(2.88)	(4.25)	(4.41)	(2.28)	(4.66)
1 year lag	0.050**	0.050	0.050*	0.050	0.050	0.050	0.050
	(2.57)	(1.22)	(1.78)	(1.08)	(1.27)	(1.47)	(1.19)
2 year lag	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(-0.14)	(-0.18)	(-0.18)	(-0.16)	(-0.16)	(-0.16)	(-0.15)
Table 6, column 5	Investment	Investment	Investment	Investment	Investment	Investment	Investment
q (1 year lag)	0.008*	0.008***	0.008**	0.008***	0.008***	0.008	0.008***
	(1.92)	(4.39)	(2.30)	(3.27)	(3.84)	(1.65)	(3.04)
2 year lag	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.97)	(0.65)	(0.50)	(0.49)	(0.58)	(0.53)	(0.57)
Cashflow (contemp.)	0.074**	0.074***	0.074**	0.074***	0.074***	0.074**	0.074***
	(2.32)	(4.00)	(2.49)	(3.22)	(3.49)	(2.41)	(3.25)
1 year lag	0.058**	0.058***	0.058**	0.058**	0.058***	0.058*	0.058**
	(2.21)	(3.28)	(2.12)	(2.02)	(2.99)	(1.94)	(2.41)
Table 7A, column 6	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.
Debt iss. (contemp.)	0.078**	0.078**	0.078**	0.078*	0.078*	0.078**	0.078*
	(2.20)	(2.00)	(2.03)	(1.79)	(1.85)	(2.19)	(1.80)
1 year lag	0.087**	0.087**	0.087**	0.087**	0.087**	0.087**	0.087**
	(2.31)	(2.18)	(2.09)	(2.36)	(2.04)	(2.24)	(2.36)
2 year lag	-0.032	-0.032	-0.032	-0.032	-0.032	-0.032	-0.032
	(-1.02)	(-0.84)	(-0.88)	(-0.74)	(-0.78)	(-0.95)	(-0.96)

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

Table 9: Varying industry definitions

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, column 4 uses the Hoberg-Phillips FIC 100 industry classification to construct portfolios – this is a much smaller sample running from 1996 to 2008., and column 5 uses 2-digit SIC codes to construct portfolios.

	(1) FF12	(2) FF17	(3) FF48	(4) HP	(5) SIC-2 digit
Table 4A, column 6	Investment	Investment	Investment	Investment	Investment
Investment (contemp.)	0.188**	0.171*	0.281***	0.605***	0.283**
	(2.62)	(1.93)	(2.85)	(2.68)	(2.44)
1 year lag	0.050**	0.037	0.108*	-0.081	0.031
	(2.57)	(0.62)	(1.88)	(-0.56)	(0.84)
2 year lag	-0.006	0.031	0.087	0.256	0.088*
	(-0.14)	(0.96)	(1.29)	(1.37)	(1.70)
Table 6, column 5	Investment	Investment	Investment	Investment	Investment
q (1 year lag)	0.008*	0.007*	0.008*	0.012**	0.008
	(1.92)	(1.77)	(1.83)	(2.00)	(1.53)
2 year lag	0.001	0.000	0.001	-0.003	-0.002
	(0.97)	(0.10)	(0.61)	(-0.80)	(-0.78)
Cashflow (contemp.)	0.074**	0.082**	0.152***	0.044	0.151***
	(2.32)	(2.22)	(3.75)	(0.64)	(3.02)
1 year lag	0.058**	0.014	0.020	-0.071	0.012
	(2.21)	(0.69)	(0.69)	(-0.79)	(0.42)
Table 7A, column 6	Debt iss.	Debt iss.	Debt iss.	Debt iss.	Debt iss.
Debt iss. (contemp.)	0.078**	0.047	0.112	0.236**	0.106
	(2.20)	(1.08)	(1.33)	(2.21)	(1.48)
1 year lag	0.087**	0.085	0.137**	0.242**	0.101**
	(2.31)	(1.51)	(2.11)	(2.45)	(2.14)
2 year lag	-0.032	0.035	0.086	0.047	0.062
	(-1.02)	(0.96)	(1.44)	(0.39)	(0.97)

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