Urban Vibrancy and Firm Value Creation

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City level differences in industry-adjusted Tobin's q, an estimate of the value created for shareholders, are large, and have widened sharply over the last twenty years. Proxies for a city's appeal to high-skill workers, such as existing education rates and favorable weather, are strongly associated with Tobin's q, both in levels and changes. These results indicate that shareholders have recently captured a bigger part of the benefits associated with superior locations. The higher stock prices of firms in these locations appear to be driven by *future* growth opportunities, rather than improvements in *current* operating efficiency.

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1 Introduction

Several decades of recent research in urban economics demonstrate that there exist large and persistent differences not only between urban and rural areas, but also between cities. Dramatic disparities in wages, real estate prices, rents, and various measures of productivity have been documented, and rather than narrowing over time, such cross-city heterogeneity has expanded.[1] Although the specific reasons why some areas prosper so much more than others are debatable – in particular the role played by agglomeration – there is little debate that physical location, now more than ever, is systematically related to a host of outcomes of interest to economists.

This paper extends the urban economics literature by considering geographic differences in the *value created for the shareholders of public companies*. Using the ratio of a firm's market value to that of its invested capital (Tobin's q) to approximate value creation, we ask whether there are meaningful differences across headquarter cities, after controlling for industry effects. The results indicate that: 1) Industry-adjusted q ratios differ widely across cities, 2) these differences have widened sharply over the last 20 years, and 3) cities associated value creation have distinct characteristics that promote growth opportunities for resident firms.

Given that many measures of output and performance vary geographically, it is fair to first ask what, if anything, we learn that is special by examining geographic patterns in the value created for public shareholders. In our view, there are three reasons.

The first concerns how the benefits of a superior location are divided between various stakeholders.[2] Most standard models (e.g., Rosen-Roback) assume mobile and perfectly competitive firms that compete away any rents from location-based productivity differences, leaving any surplus (or deficit) to be captured by the less mobile resources – specifically land owners, and if there are migration costs, workers. However, if firms have market power, or if for other reasons capital is not perfectly mobile (e.g., there are adjustment costs), some of the surplus will accrue to shareholders.

[1] For example, Van Nieuwerburgh and Weill (2010) and Gyourko, Mayer, and Sinai (2013) both document increased dispersion in real estate prices over the last several decades. As for wages, Baum-Snow and Pavan (2012) show that the gap between large and small cities has grown considerably since 1980. With respect to innovation, Sonn and Storper (2008) and Kwon, Lee, Lee, Oh (2017) both show that patent citations are increasingly geographically concentrated, complementing earlier work that documents significant spatial clustering in R&D (Jaffe, Trajtenberg and Henderson (1993), Audretsch and Feldman 1994, Feldman (1994), and Thompson and Fox-Kean (2005)).

[2] Recent examples include Hornbeck and Moretti (2015) and Hseih and Moretti (2017), both of which provide empirical estimates of the extent to which land owners and workers share in the surplus associated with local shocks to total factor productivity.

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Although casual empiricism suggests that some metro areas seem disproportinately associated with shareholder value creation,[3] the extent to which firm values systematically differ in the cross-section of cities has not been systematically studied in the extant literature.

A second contribution relates to measurement. Before considering how the effects of local productivity differences are divided between the relevant stakeholders, productivity itself must be quantified. As described in Rosenthal and Strange (2004), researchers have taken two broad approaches. The first attempts to estimate productivity functions directly using data on output (e.g., units sold, revenues) and inputs (e.g., amount and/or cost of materials), using either plant-level or accounting data (e.g., Henderson (2003)). The second is indirect, and uses variables presumably related to productivity, such as a city's growth in population and/or new establishments,[4] wages,[5] or rents.[6] [7]

Such approaches are particularly well suited to measure the productivity of *existing* plants and factories, but their ability to capture value creation linked to *future* productivity is less obvious. In particular, design, innovation, engineering and similar 'creative' activities are likely to influence a firm's profitability and/or other value-added measure years, or even decades into the future. In such cases, a forward-looking measure of long-run value creation – a natural feature of securities prices – adds a complementary perspective to studies that characterize city-level productivity differences mostly with flow, rather than stock, variables. As we will see, this ends up being an important distinction, not only conceptually, but for identifying which cities constitute superior locations for value creation.

The third and final motivation for looking at firm values is that their first differences, i.e., stock

[3]For example, consider that as of year-end 2015, over two thirds of the market capitalization of the 50 largest new firms having gone public since 1980 are headquartered in just two major metropolitan areas: the Bay Area and Seattle. This phenomenon spans various sectors, and features household names such as Apple, Google, Gilead, PayPal, Ross Stores, Amazon, Microsoft, Zillow, Costco, and Starbucks. See Appendix Table A1 for a complete list.

[4]Examples include Henderson, Kuncoro, and Turner (1995) and Glaeser, Kallal, Scheinkman and Shleifer (1992), both of which relate urban agglomeration to city-level employment growth. Likewise, Rosenthal and Strange (2003) explores the link between local productivity shocks and the creation of new establishments.

[5] Studies that use wages to infer differences in regional productivity include Glaeser and Mare (2001), Wheaton and Lewis (2002), Glaeser (2011), Combes, Duranton, and Gobillon (2008, 2012), and de la Roca and Puga (2017).

[6]See, for example, Dekle and Eaton (1999).

[7]Because of the link between wages, rents and preferences for amenities, cross-city changes in these variables capture more than just changes in productivity. Indeed, Gyourko, Mayer, and Sinai (2013) describe a setting where real estate prices in high amenity cities (what they refer superstar cities) respond to macro shifts in the income distribution, rather than local productivity differences. They argue, for example, that the Bay area would have become more expensive relative to other regions, even in the absence of a positive location specific shock, if a macro shock to income increased the demand for Bay Area specific amenities.

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returns, capture unexpected changes. Consequently, movements in financial securities provide a precise measure of when the benefits (or costs) related to a particular location became recognized by the market. As we will also see, the data suggest a rapid divergence between the cities least, and most, associated with value creation during the 1990s, corresponding to the introduction of the internet.

We start with a descriptive exercise in Section 3, comparing average Tobin's q between cities, and time-series variation within them. The sample consists of the 38 U.S. cities that contain at least five public firms for every year 1975-2014, and the firms headquartered in them. This results in about 80,000 firm-year observations, which in the average year, collectively account for 90% of the total market capitalization of domestic equities.

In panel regressions of firm-year level q on city fixed effects, year fixed effects, and industry fixed effects, we find that Tobin's q is strongly associated with headquarter location, with the effect growing over time. From 1975-1994, the F-statistic on city fixed effects is 4.20, corresponding to a p-value less than 0.1%. However, in the period after 1995, the F-stat increases sharply to 9.62, which bootstrap analysis indicates is significantly greater than that in the pre-1995 period.[8]

These city-specific differences in value creation are not distributed equally across firms. Rather, the firms most responsible for the widening geographical value gap are ones for which human capital is particularly important. For example, headquarter fixed effects have significantly more explanatory power for industries with high R&D compared to those in less innovative sectors. Likewise, young firms (public less than 10 years) are about twice as sensitive to city fixed effects as are older ones. One intriguing finding is that the importance of city effects does not meaningfully differ between – and if anything is stronger among – large firms versus small ones. Because large companies have less localized operations and customer bases, this is perhaps the most direct evidence that the observed city-specific patterns in value creation are attributable to upper management, who tend to be housed at corporate headquarters.[9]

[8]We select the year 1995 to correspond roughly with the inflection point of the IT wave, with year-over-year growth in websites of over 1000% from 1993 through 1997. Shifting the breakpoint a few years in either direction, or considering the entire decade of the 1990s as a single breakpoint, gives similar results (see Section 3.3). These patterns are robust to alternative definitions of industrial sectors, such as 3-digit SIC, 4-digit SIC, or Fama-French 48. See Table 4.

[9]Bloom, Sadun, and Van Reenen (2012) reach a similar conclusion in an international setting, comparing IT-related productivity in European establishments owned by: 1) US-based multinational corporations, and 2) domestic (European) firms. The authors attribute the higher productivity of the former establishments to superior management practices originating in the US.

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Importantly, the growing importance of headquarter location for value creation represents more than just one or two "superstar" cities. Indeed, firms headquartered in Silicon Valley have experienced some of the sharpest valuation increases over the last twenty years; but other areas with large gains include Boston, Minneapolis, Seattle, and Washington D.C. At the other end, declines in average q are observed in manufacturing centers, such as Cleveland and St. Louis, as well as in energy hubs Oklahoma City and Houston. As above, such comparisons account for differences in industrial composition.

As with the cross-section of firms, the attraction and/or creation of human capital plays a central role in the varying fortunes of headquarter cities. For this analysis, we link the levels and changes in Tobin's q to higher education rates and good weather, which prior studies indicate are correlated with a city's ability to attract and/or develop human capital. Both have been shown to predict wage and population growth, and serve as our proxies for the immigration and/or development of high value-added workers that may influence firm values.[10] When we relate these to Tobin's q, we are thus testing the joint hypothesis that productivity has grown faster in cities with high stocks of human capital, and that shareholders of public companies share in the resulting surplus.

Confirming prior work, we find that cities with the highest levels of education (measured in 1970, which predates the start of our sample) and most pleasant weather experience sharp spikes in land values and wages. Moreover, we find strong increases in Tobin's q. On an industry-adjusted basis, Tobin's q for the five most educated cities (in 1970) have increased 0.38 more than those for the five least educated cities. A similar comparison, using either maximum July temperature, or an index of pleasant weather that also penalizes cities for cold Januaries and/or precipitation, gives a difference in Tobin's q of 0.29.[11]

While these results indicate that the importance of headquarter cities has increased over time, and that these differences appear to be related to human capital, decomposing Tobin's q allows us to be even more explicit about the specific channel(s) that allow firms in some cities to flourish more

[10] Rauch (1993), Moretti (2004a), and Shapiro (2006) document that controlling for observable worker attributes, wages are higher in more educated cities, suggesting that productivity is also higher. Likewise, city-level consumption amenities have dramatically grown in importance, due in large part to growing incomes (Glaeser, Kolko, and Saiz (2001)). For example, pleasant weather – cooler summers, warmer winters, and less rain – has become strongly related to migration patterns over the last several decades (Rappaport (2007)).

[11] Although the motivation for the human capital proxies come from the literature on urban growth, weather and/or education are important for Tobin's q beyond their effects on population growth. Indeed, while both a city's size and population growth are positively related to industry-adjusted Tobin's q ratios, neither has a meaningful impact on the explanatory power of the education or weather variables.

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than others. The decomposition indicates three possibilities. First, local productivity differences may show up in a firm's current operating profits, perhaps through process improvements, knowledge sharing within or across local companies, or other efficiency gains. The second component is through future profits, via growth opportunities, i.e., stock prices may rise in expectation of future productivity innovations, irrespective of a firm's current performance. Third, holding current and expected cash flows constant, differences in the expected rate of return required by investors, perhaps because of perceived risk differences – may influence firm values.

As it turns out, our results appear to be driven almost exclusively by differences in expected future growth; in fact, current operating profits for high-q cities are lower rather than higher, and their expected rates of return are, if anything, higher than low-q cities. For example, cities with the highest values of industry-adjusted Tobin's q also tend to have high values of investment rates and R&D, both of which measure managerial expectations of growth opportunities. These correlations are robust not only in the cross-section of cities, but also in the time series, i.e., cities with the largest increases in Tobin's q also have the largest increases in investment and R&D.

On the other hand, operating performance is uniformly worse in cities with the highest values of Tobin's q, and like above, cities with positive changes in q have shrinking, not growing, profit margins. We view this disconnect between current and expected future performance as significant because, as mentioned above, it underscores the importance of how local productivity is measured. Whereas most value-added measures capture existing productivity,[12] capitalized measures like Tobin's q reflect benefits perhaps into the far distant future. This is more than a theoretical point, as it potentially changes the set of cities identified as being the most productive. For example, in 2015, of the top-10 cities ranked in terms of industry-adjusted return on assets, none have significantly positive industry-adjusted Tobin's q, and all but two are negative.

One of the reasons why high-q cities have lower-than-average profit margins is likely due to the higher cost of locally supplied factors, such as land and labor. Indeed, we find evidence consistent with this possibility: profits tend to be highest in cities with low wages and cheap real estate, but of course, these are precisely the cities where Tobin's q ratios are lowest.[13] In this way, our stock-based

[12] For an excellent contemporary review on value-added measures and their use in the rent-sharing literature, see Card, Carduso, Heining, and Kline (2016). See also Syverson (2011) for further discussion regarding approaches to measuring productivity differentials.

[13] See Moretti (2013) which, in studying the wage gap between college and high school graduates, finds that a substantial portion reflects cost-of-living adjustments, as college graduates are more likely to settle in high-cost cities.

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findings provide support for city-level measures of productivity that rely on factor prices, with the idea that firms willing to pay higher costs must derive an offsetting benefit. Here, our contribution is to show that although such benefits may take years or even decades to materialize into profits, securities prices provide a reliable window into the future.

We conclude by considering the third component of Tobin's q, the expected rate of return, which must be measured indirectly using *realized* returns. For example, an extensive finance literature concludes that stocks with high Tobin's q have low expected returns based on their low historical returns.[14] Applying this to the cross-section of cities, if low required rates of return are the main driver of high average q in areas such as Boston and Seattle, we would eventually expect to see firms headquartered in such "glamour" cities to have lower rates of return. Instead, we find the opposite – a return *premium* in glamour (high-q) cities, and mild underperformance in value (low-q) cities. This suggests that differences in city-level average q are difficult to reconcile with differences in expected returns.[15]

A closer look at the time-series patterns of the glamour/value-city return effect suggests that these differences in realized returns may not reflect differences in expected rates of return. As we show, most of the return difference is generated from 1990-2000, during which the value created by the emerging internet technology became largely recognized by the stock market. Whether we identify glamour cities using average q at the start of the 1990s, or using long-lived determinants such as good weather or education rates, a stock portfolio comprised of the top five cities grew to about twice the value of a portfolio involving all other cities. (Returns are adjusted for differences across industries). It is also noteworthy that even though technology stocks fell sharply during the "bust" in 2000 and afterward, the value premium associated with being headquartered in high human capital cities appears to be permanent, i.e., there was no industry-adjusted reversal for high-q cities post-2000, suggesting that the city-specific value creation observed in the 1990s appears to be permanent.

See also Eeckhout, Pinheiro, and Schmidheiny (2014).

[14]Firms with high market-to-book ratios (so-called glamour stocks) have lower risk-adjusted returns than low market-to-book firms (value stocks). Prominent explanations for this finding include differences in risk (e.g., Fama and French (1992)) and mispricing (e.g., Lakonishok, Shleifer, and Vishny (1994)).

[15]Eisfeldt and Papanikolaou (2013) documents higher returns among firms with high levels of *organizational capital*, which are productivity enhancements linked to a firm's key employees. In their model, the possibility of losing key employees generates a risk premium. Whereas we do not explore whether such mobility of high-skill workers differs between cities, to the extent that a city's industry-adjusted q captures organizational capital, the results here are consistent with their theoretical predictions, except applied to the cross-section of cities rather than firms.

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Our first set of findings – increased dispersion in valuation ratios across cities – is, to our knowledge, new to the literature, and contributes to a growing number of studies exploring the link between *where* a firm operates and *how* it performs. Whereas the earliest finance and geography studies approached the issue from the perspective of investors, emphasizing regional differences in information (Coval and Moskowitz (1999, 2001)) or discount rates (Pirinsky and Wang (2006), Hong, Kubik, and Stein (2008)), recent studies attempt to understand how geographic factors impact a firm's real business decisions.[16] And, although we focus on the role human capital plays in the regional distribution of growth opportunities, other geographic factors such as a healthy venture capital sector or local tax rates (Moretti and Wilson (forthcoming)) may play complementary roles, and deserve future study.

The results relating a city's education levels and weather to firm values contribute to urban economics studies exploring contemporary determinants of city growth. Importantly however, while the link between city size and productivity is well established, we find that weather and education are related to Tobin's q beyond their effects on population.[17] Thus, a city's ability to create value appears less about adding rank-and-file workers, and more about attracting the "right" people – highly skilled, educated workers in industries where productivity spillovers play a crucial role. In this way, our results directly complement Bacoloda, Blumb, and Strange (2009) and Glaeser and Resseger (2010), both of which document that agglomeration effects are stronger in cities with high concentrations of highly skill workers.

2 Data

To construct our sample, we start with all public companies in COMPUSTAT traded on the NYSE, NASDAQ, or AMEX over the years 1975 – 2015. Then, using the COMPUSTAT variable *ADDZIP*, we infer the headquarter city for each firm. To define cities, we aggregate the "Large Central Metro" and "Large Fringe Metro" counties, as designated by the 2006 National Center for Health Statistics (NCHS) Urban Rural Classification Scheme for Counties, in each core-based statistical

[16] For example, studies have shown the impact of firm location on public firm investment (Dougal, Parsons, and Titman, 2015); fraud (Parsons, Sulaeman, Titman, 2018a and 2018b); innovation (Matray, 2014); CEO compensation (Francis et al., 2016); payout policy (Becker, Ivkovic, and Weisbenner, 2011; John, Knyazeva, and Knyazeva, 2011); equity issuance (Loughran, 2008); and merger activity (Almazan, De Motta, Titman, and Uysal, 2010).

[17] See, for example, Glaeser and Mare (2001), Glaeser (2011), Combes, Duranton, Gobillon, Puga, and Roux (2012), Behrens, Duranton, and Robert-Nicoud (2014), and de la Roca and Puga (2017).

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area (CBSA). We then trim the list of headquarter cities to those which, for every year in the 4-decade sample, had at least five public firms headquartered therein. Our sample consists of all firms headquartered in one of these 38 cities. In the average year, these firms represent about 87% of the total market capitalization of the NYSE/NASDAQ/AMEX universe.

Table 1 summarizes various demographic and firm-level variables for each city. Population, shown in millions in the first column, ranges from 17.6 million (New York City) to slightly under one million (Richmond, VA), with an interquartile range of 2.4 million to 8.05 million. Shown adjacent are average population growth rates. Generally, population growth has flagged in the Northeast, averaging less than 1% for Boston (0.51%), Hartford (0.39%), New York City (0.35%), and Philadelphia (0.35%). Ex-manufacturing hubs in the Midwest have fared even worse, with Pittsburgh (-0.32%), Cleveland (-0.23%), and Detroit (-0.05%) all having suffered population declines. Offsetting these are cities in the Southeast, Sun Belt, and West, with the largest percentage wise gains seen in Phoenix (3.28%), Atlanta (2.60%), and Dallas (2.43%).

The third and fourth columns present, respectively, the average number of publicly traded firms and market capitalization. Unsurprisingly, larger cities are home to more firms, with a cross-city correlation of 84%. Likewise, as with population, column four shows that the total market capitalization of the sample is disproportionately concentrated in a few cities, with New York, Chicago, Dallas, San Francisco, and San Jose contributing as much as all other cities combined.

Table 1 also reports city-level averages for the variables used in our study: Tobin's q, investment rates, research and development, operating income scaled by sales, return on assets, and monthly stock returns. Details regarding variable construction are provided in Appendix A1. All firm-level variables are winsorized at the one percent level to minimize the influence of outliers. Population figures are constructed using data from the Bureau of Economic Analysis (BEA) Regional Economic Accounts. Industry classifications are defined as 2-digit Standard Industrial Classification (SIC) code groupings.

3 Geography and Tobin's q

We begin by estimating differences in valuation ratios (Tobin's q) across major U.S. cities, with an eye on how regional heterogeneity may have evolved over time. Section 3.1 starts with univariate

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differences, followed by Section 3.2, which formalizes these patterns in a regression framework. We then conclude with some robustness and extensions to our main results in section 3.3.

3.1 Univariate comparisons

For each city's 40-year history, Table 1 shows the average of several firm-level variables. Our specific interest is Tobin's q, the average of which clearly differs between cities. On the high end, firms headquartered in the Bay Area tend to have very high valuation ratios – 2.8 on average for both San Francisco and San Jose-based firms – with other West Coast technology hubs Seattle and San Diego not far behind. Relatively high valuations are also observed in Minneapolis, Washington D.C., and Boston, all of which have Tobin's q averages that exceed 2.2, versus an overall average of 1.9.

A large cluster of cities in the middle of the distribution includes large, fairly well-diversified cities such as Altanta (1.9), Chicago (1.8), Dallas (1.8), New York (2.0), and Philadelphia (2.0), and Phoenix (1.8). At the lower end are many former manufacturing hubs, many in the Midwest and Northeast. The lowest average valuation ratios are observed in Cleveland (1.4), Buffalo (1.5), Charlotte (1.5), Hartford (1.5), Houston (1.6), Milwaukee (1.5), and Richmond (1.6). In a unified regression including all firm-year observations (roughly 90,000), the null hypothesis that Tobin's q is the same across cities is strongly rejected ($p < 0.001$).

For our purposes, of greater interest is how this city-level heterogeneity has changed over time, particularly around the IT revolution beginning in the early 1990s. Figure 1 plots the average, value-weighted Tobin's q for each city in two sub-periods: 1975-1994 (left) and 1995-2015 (right). Lines connect a city's average q in the early period to that in the later period. For example, Kansas City had the highest ranked average q in the early period, but slipped to 16^{th} when measured after 1995.

Two things stand out about Figure 1. First, just eyeballing the differences between time periods, it is clear that the average differences between cities has expanded considerably in the latter two decades. The standard deviation in q across cities is 0.30 in the first twenty years, but 0.67 in the last two decades. Second, although there are dramatic exceptions such as San Francisco (going from 29^{th} to 5^{th}), Portland (26^{th} to 10^{th}), Denver (9^{th} to 31^{st}), and Providence (13^{th} to 33^{rd}), there is considerable persistence in the ordinal rankings. For example, the three cities with the lowest

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value-weighted average q prior to 1995 – Oklahoma City, Buffalo, and Detroit – are also the lowest after 1995. Among the cities ranked in the bottom ten in the first half of the sample, only San Francisco ranks above the median afterward. At the other end, Las Vegas (6^{th} to 21^{st}) and Denver are the only ones originally in the top ten to dip below the median.

3.2 Fixed effects regressions

Table 2 formalizes these differences in a regression framework. We estimate regressions of Tobin's q, separately for the twenty year period from 1975-1994, and the following two decades (1995-2014). Of interest are the estimated coefficients on headquarter fixed effects and in particular, whether their significance changes over time.

Columns 1 and 2 show the results when only year and headquarter city fixed effects are included. In the early half of the sample, the F-statistic on the city fixed effects takes a value of 5.74 ($p < 0.01$), indicating significant geographic differences in average valuation ratios. However, headquarter location appears to be much more important in the latter two decades, as evidenced by an F-statistic of almost 17. After 1995, relative to Chicago (the omitted city), about half the cities have significant point estimates, with nine positive and nine negative.

While the dramatic ascent of the San Francisco Bay Area is clear, the estimated city effects suggest that there is more to the story. Relative to Chicago, firms in Boston, Seattle, and Washington D.C. have experienced gains on par with those observed in Silicon Valley. On the other hand, manufacturing hubs such as Cleveland and St. Louis have fared much poorer, with marginally weaker declines observed in Hartford, Houston, Oklahoma City, and Nashville.

When interpreting these findings, an important observation is that cities differ in terms of industrial composition. Although a number of cities are well diversified across sectors – examples include Chicago, Philadelphia, and New York – many others are relatively concentrated in one or a few sectors. For example, in each of the following cities, at least 30% of resident firms are from the same industrial sector: Detroit (transportation equipment), Houston (oil/gas), Louisville (eating and drinking places), Nashville (health services), Oklahoma City (oil/gas), San Jose (electronic and other electrical equipment and components), and Seattle (business services).

To account for potential heterogeneity in the distribution of sectors across regions, columns 3

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and 4 add industry fixed effects constructed using 2-digit SIC codes.[18] As seen, controlling for industry also reduces the significance of the headquarter fixed effects, most so in the latter two decades. Nevertheless, the importance of location remains much more important in the second half of the sample ($F = 9.62$) compared to the first ($F = 4.20$). As before, bootstraps indicate that the difference in estimated city fixed effects pre- and post-1995 is highly significant ($p < 0.01$).

The growing importance of location can also be appreciated by comparing the incremental explanatory power in the early and post-1995 periods. In the first two decades, relative to a model that includes industry and year controls, city fixed effects add 1.3% to the R^2 (17.5% versus 16.2%). However, in the most recent two decades, the fraction of Tobin's q attributable to headquarter location almost doubles to 2.3% (15.2% versus 12.9%).

Another possible explanation is that average firm age tends to differ between cities. For example, San Francisco has a disproportionate concentration of young companies, many in technology. If initial public offerings tend to cluster disproportionately in some cities rather than others, and if such young firms have high average q (they do), perhaps this explains some of the cross-city variation we observe. To address this possibility, we include in the regression a series of non-parametric dummies for firm age (years being publicly listed): < 5 years, 5-10, 10-15, 15-20, 20-25, and > 25 years. The fraction of firm-years in each bin are, respectively, 28%, 20%, 16%, 11%, 7% and 18%.

As indicated in columns 5 and 6, these controls slightly reduce the significance of the city fixed effects for both halves of the sample, but the F-statistic is still over twice as large in the last two decade compared to the first ($F = 3.07$ versus $F = 7.55$). Bootstrap analysis indicates that this difference is significant at the 1% level.

Before proceeding, we note two features of these empirical patterns. First, similar persistence to what we observed in Figure 1 carries through in regressions that control for temporal, industry, and life cycle effects. In column 2 of Table 2 for example (only year fixed effects), of the eighteen cities with estimates significant at the 5% level in the latter half of the sample, all have point estimates of the same sign in the earlier half (column 1). Or, making the comparison in reverse, every statistically significant city in the first 20 years (column 1) remains significant, and with the

[18]To minimize the influence of outliers, industry effects are only estimated for years in which at least five firms sharing the same 2-digit SIC code. Otherwise, firms are re-classified as SIC 2-Digit 99, or "Nonclassifiable Establishments." This procedure yields 27 industries.

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same sign, in the latter half (column 2). Similar persistence is observed in the adjacent columns which control, respectively, for industry and firm age. These observations, combined with the general strengthening of the city dummies, suggest that the technology revolution that began in the mid-1990s primarily served to reinforce whatever cross-city differences existed beforehand.

Second, the magnitudes reported in Table 2 are substantial. Examining the last two columns of Table 2, the estimates suggest that even after controlling for industry, time, and firm age, average valuations across cities can easily differ by 25% or more. Even ignoring the five lowest and five highest city-level coefficients, the average firm in Minneapolis ($6th$ highest) has a Tobin's q 0.25 higher than those in Chicago, whereas Nashville-headquartered firms ($6th$ lowest) have deficits of almost the same magnitude (-0.27). Using Chicago' post-1995 average q (2.36) as a benchmark, these estimates imply that the average q (net of controls) in Minneapolis is almost 25% higher ($2.36 + 0.25 = 2.61$) compared to Nashville ($2.36 - 0.27 = 2.09$). At the more extreme ends of the distribution, the percentage differences are larger still.

3.3 Robustness and alternative specifications

In addition to year, industry, and firm age controls, we conducted a number of robustness checks and extensions to our benchmark specifications. Below we describe the highlights of this exercise.

Industrial clustering. Although Table 2 already includes industry fixed effects in columns 3-6, the estimated coefficients capture the *average* cross-city industry effect, and do not account for the fact that even within similar sectors, firms located in clusters (e.g., Palo Alto's Hewlett-Packard) may systematically differ from firms outside them (e.g., IBM, located in Armonk, New York). Consequently, if either agglomerative or selection forces related to clustering have strengthened over time, then perhaps industrial hubs such as Houston (energy), Detroit (automobiles), Seattle (software), and the San Francisco Bay Area (software and technology) are the primary drivers of the observed patterns.

In Table 3, we attempt to drill deeper into this issue. Under three different definitions for industrial clusters (Panels A-C), we re-estimate city fixed effects, both in the early (before 1995) and late period (1995 and afterward), using the final specification from Table 2. Of interest is whether the increased significance of city fixed effects in the latter two decades (as seen in the full sample) differs between clusters and non-clusters.

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In panel A, we designate city c a cluster for industry i if it contains at least 10% of industry i's public firms in a given year. Using this definition, we observe remarkably similar F-statistics between clusters and non-clusters, both before (F=2.65; F=2.76) and after 1995 (F=5.50; F=5.71). When clusters are defined by market capitalization in Panel B (using the same 10% threshold), the results are, if anything, stronger for firms *outside* clusters. The last panel (C) is the coarsest split – companies headquartered in California versus elsewhere – with the idea that the entire state might, to some extent, function as a single technology cluster.[19] Excluding California-headquartered firms appears to have a measurable, but relatively small, impact.[20] Overall, the evidence in Table 3 appears to reject the idea that the growing importance of location is more than simply relabeling of a (growing) cluster effect.

Alternative industry controls. Panel A of Table 4 presents our key result when sectors are defined differently. Using three-digit SIC codes (columns 1 and 2) rather than two (Table 2), the F-statistic on city dummies still increases markedly after 1995 ($F = 5.83$) versus before ($F = 2.13$), a statistically significant difference. Results using a more refined industry definition (4-digit SIC) are shown in columns 3 and 4, giving an even stronger result than our benchmark specification. Finally, the last two columns indicate that city fixed effects are collectively and significantly more important after 1995, when industries are defined using Fama and French's (48) classification. In addition, we have also experimented with dynamic industry controls via *industry* $\times$ *year* fixed effects, which has little effect on the results.[21]

Alternative area classifications. In the next panel (B) of Table 4, we vary the region that constitutes a "city." The geographical unit in the first two columns is smaller than in our main specification, including only firms headquartered in the core counties surrounding a CBSA's principle city. Despite decreasing the sample size by about 40% and the number of estimable cities from 38 to 31, the pre- and post-1995 change in city fixed effects is similar, if not slightly stronger, compared to Table 2. When the geographic unit is expanded relative to our benchmark definition (as

[19]As of 2015, approximately 35% of California-based firms are in high technology industries, where high-tech firms are defined as 3-digit SIC 283, 357, 366, 367, 382, 384, 481, 482, 489, 737, 873 (see Kile and Phillips (2009)), versus 18% elsewhere. Furthermore, California contained 25% of the country's public technology firms, and 28% of the total market value.

[20]Outside of California, the F-statistic on city fixed effects is 2.69 in the first two decades of the sample (versus 3.07 with California included), and 6.31 when estimated over the last twenty years (versus 7.55). When bootstrapped, this difference is significant at the 1% level, as it is for the entire sample.

[21]For example, interacting 2-digit-SIC codes with each year gives an F-statistic on headquarter fixed effects of 3.07 in the first two decades, versus 7.70 in the latter two. This difference is statistically significant at the 1% level.

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in columns 3 and 4), resulting in a slightly (4%) larger sample and four additional cities estimated, the results remain quantitatively and qualitatively similar.

Alternative breakpoints for the IT revolution. Table 2 identifies a single year (1995) as ushering in the information age, whereas in reality, the transition took several years, and continues to expand even today. However, when thinking about the impact on stock valuation, the question is when the market became aware that the impact of IT was likely to be significant. It seems clear that 1990 is too early (the first website wasn't online until a year later)[22] and likewise, that the dot-com bust (2000) is too late. We choose 1995 because it coincides with the midpoint of the steepest percentage wise growth in the number of websites, from about 100 in 1993 to over 1,000,000 in 1997.

However, the estimates in the final panel (C) of Table 4 indicates that there is little special about this particular year. If we back up three years to 1992 (columns 1 and 2), or advance three years to 1998 (columns 3 and 4), the change in the F-statistic for city fixed effects is very similar to our baseline model. In the last pair of columns, we are completely agnostic about the specific transition year, considering the entire 1990s decade as the 'breakpoint.' Here too, the F-statistic for headquarter is over twice as large after 2000 ($F = 5.41$) compared to 1989 and before ($F = 2.34$).

4 Which firms are most sensitive to locational factors?

The prior results suggest that headquarter location is increasingly informative about firm values, but because only average effects are reported, do not identity which types of firms benefit more, or less, from regional factors. This section attempts to make some progress on this issue.

Research and Development. Our first test splits the sample using the intensity of R&D expenditures at the industry level. Here, the idea is that the types of creative workers we have discussed so far – i.e., highly educated scientists, engineers, and top managers – are especially important for firms investing heavily in innovation. During each year, and for each 2-digit SIC industry, we sum research and development expenses across all firms, and divide by the sum of lagged assets. We then rank industries by this aggregate measure, and split the sample by below/above median, creating two samples of roughly the same size each year. Then, for each group, we re-estimate the

[22] The first website (http://info.cern.ch/hypertext/WWW/TheProject.html.), created by Tim Berners-Lee, went live on August 6, 1991. Incidentally, the content of the site was dedicated mostly to how to create a website, and explained the use of hypertext.

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model from the last two columns in Table 2.

Panel A of Table 5 shows the results. We start the comparison with columns 1 and 3, which correspond, respectively, to the high- and low-R&D industries for the early period (1975-1994). The F-values for headquarter fixed effects are very similar (2.72 versus 2.53), suggesting that while location seems to matter for both samples ($p < 0.01$), the difference between high and low-R&D industries is not meaningful. Moving to the next twenty years in columns 2 and 4, the conclusion changes. While the F-stat for the low-R&D group increases slightly to 3.93, the difference relative to the early period is small and not significant. However, for the high R&D group, headquarter location becomes much more important ($F = 8.57$), a significant increase compared to the prior two decades.

Firm age. The next panel (B) shows the results sorted by the number of years since a firm's IPO. Here too, we hypothesize that young firms are likely to invest heavily in innovation, and accordingly, are particular sensitive to the quality of their human capital stock. In the leftmost pair of columns, the sample consists of firms having been public for ten or fewer years, and in columns 3 and 4, all other firm-year observations.[23]

Comparing columns 1 and 2, we see that among young firms, the effect of headquarter location is much more significant over the last twenty years ($F = 9.36$), compared to the prior two decade ($F = 4.58$), a significant increase. On the other hand, for firms having been public a decade or more (columns 3 and 4), city fixed effects appear less important, both in a static and dynamic sense. Indeed, in the first twenty years, headquarters are not significant ($F = 1.22$; $p = 0.17$), only becoming so after 1995 ($F = 3.27$; $p < 0.01$). Together with Panel A, these findings suggest that the location of a firm's headquarters is substantially more important for companies with values most sensitive to human capital.

Firm size. We conclude this section with a cross-sectional cut on firm size in Table 6. We do this for several reasons. First, for both large and small firms alike, headquarters contains a heavy concentration of top managers and employees involved in soft activities such as strategy, idea generation, and design. However, because large firms have more geographically diversified

[23] This ranking is inherently dynamic, implying that some firms will be classified as old firms for our entire sample (e.g., General Electric, Coca-Cola), and others will switch categories ten years after their initial public offering. For example, Cisco went public in February 1990, and accordingly, is classified as young until February 2000, and old afterward.

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customer bases and manufacturing facilities (often overseas), a cross-sectional size cut provides some information about whether locational attributes are most relevant for a firm's creative talent versus its rank-and-file employees.

As both panels of Table 6 indicate, the increased importance of headquarter location is, if anything, *more* pronounced for large firms. Using the NYSE breakpoint (Panel A), both large and small firms show a similar increase in statistical significance for city fixed effects after 1995, but the diff-in-diff is not statistically significant. If instead we cut the sample using the median market capitalization (Panel B), only the half comprised of larger firms shows a significant increase (F=3.23 before 1995, and F=7.15 after 1995).

That large firms appear to be influenced as much, and perhaps even more than, small firms is useful in helping interpret the results. For example, on the real side, local financial constraints may loosen (via private equity or banks becoming healthier), tax rates may change (Moretti and Wilson (forthcoming)), or property values may increase (Chaney, Sraer, and Thesmar (2012)), any of which could act as a tailwind to local firms.[24] Further, to the extent that stocks are held by local investors (e.g., Coval and Moskowitz (1999)), wealth effects may influence discount rates, which in turn may influence values. However, in each of these cases, it seems clear that such factors should matter less, on the margin, to large firms with less reliance on local financial institutions and customers, and who are less likely to be financially constrained (Fazzari, Hubbard, and Peterson (1988), Kaplan and Zingales (1997), Whited and Wu (2006)). What both small and large firms have in common, of course, is that their key employees tend to be housed at corporate headquarters; consequently, when an area becomes more productive or intellectually vibrant (e.g., through idea spillovers), firms of all sizes should benefit.

5 Glamour cities

Summarizing the results to this point, headquarter location is increasingly informative about firm values (Section 3), with the effect concentrated among firms for which high human capital is most important (Section 4). A natural next question would seem to be exploring the cross-section from

[24] Moretti and Wilson's recent work on personal tax rates should be interpreted here less as an alternative to human capital flows influencing firm values, and more as a microfoundation for why some cities might be increasingly attractive to high value-added workers.

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the perspective of cities themselves, asking for example, which cities have experienced the sharpest gains in shareholder wealth.

While there are likely to be a number of regional attributes that may influence locally headquartered companies, our analysis here focuses on an area's stock of human capital. We examine two variables shown to be related to regional productivity and wages in the urban economics literature – college education and good weather – and use them to explain the regional dispersion in firm valuations. The basic idea is that cities either rich in, or able to attract, skilled workers were a kind of 'dry powder' for the technological revolution in the 1990s, and that the subsequent gains were ultimately reflected in market values.

5.1 College education

Our first measure of a city's human capital is the percent of its residents with a college degree. Several studies in the urban economics literature rely upon a similar measure of the quality of a city's workforce, including recent work by Moretti (2004a), Glaeser and Berry (2005), and Shapiro (2006). To minimize concerns about reverse causality, we calculate the percentage in 1970, which predates the beginning of our sample by five years.

In the first column of Table 7, we ask whether the percentage of a city's residents with a college degree in 1970 is related to the stock valuations of local firms. Importantly, we include an interaction with the post-1995 dummy variable, which allows the slopes to differ before and after the year 1995. In the first two decades, we estimate a coefficient of 2.42 ($p < 0.01$), indicating that before 1995, more educated cities tended to have higher valuation ratios. This magnitude suggests that a 2% change in college education rates (roughly the interquartile range between cities) is associated with a increase in q of about 0.05. However, as indicated by the interaction term, the spread in q between cities with initially high and low college education rates has dramatically expanded over the last two decades. After 1995, the same 2% would predict an increase in Tobin's q of $(2.42 + 4.03) * .02 = 0.13$, more than doubling the effect prior to 1995.

A complementary way of exploring the relation between education and Tobin's q is to conduct the analysis at the city-level, rather than at the firm-level. Using the estimates in the last two columns of Table 2, we take the difference in each city's industry-adjusted q between the early (pre-1995) and later (post-1995) periods, and plot these differences against education. Figure 2

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shows this graphically. To gauge the magnitude of the slope of this line, compare a city with a college education rate of 14% (the average of all cities above the median) to a city with a rate of 10% (the average for all cities below the median). The regression estimate indicates that Tobin's q, on average, would be $3.77 \times (0.14 - 0.10) = 0.15$ units higher in the more educated city. Despite both the x and y variables between generated regressors, which introduces measurement error that biases the regression slope to zero, the estimated coefficient on college education is significant at the 1% level.

5.2 Good weather

Our second proxy for the strength of an area's human capital relates to weather. As documented by Rappaport (2007), throughout the twentieth century, U.S. residents have consistently moved to areas with good weather, in particular warmer winters and cooler, less humid summers. Rappaport interprets this increased appetite for good weather as resulting from growing incomes, i.e., the value of pleasant weather as a consumption amenity has increased. Regardless of the mechanism, our hypothesis is that cities with good weather are primed not only to experience population growth generally, but because prices in the best weather cities tend to be higher (e.g., San Francisco), these locations may be disproportionately attractive to workers of especially high skill or talent. It is these workers, we hypothesize, that have the largest impact on firm values.

Returning to Table 7, the second column shows the results that explain firm-year variation in Tobin's q using each city's average July temperature. As with college education, we allow for a structural break in the slope around the year 1995. The negative slope in the first two decades suggests that in the 1970s and 1980s, cities with hot summers tend to have lower than average valuation ratios. However, as with education rates, the importance of July temperature is about three times as strong over the last twenty years, as indicated by the significant ($p < 0.01$) interaction term.

To give a sense of the size of these regression estimates, a shift the size of the interquartile range in July temperature (9 degrees) is associated with a change in Tobin's q of $0.03 \times 9 = 0.27$, or about two-thirds of the standard deviation of Tobin's q across cities (0.38). A similar result obtains using each city's average July *heat index*, which takes into account relative humidity in addition to temperature (column 3). Here too, higher values, which indicate hotter and/or muggier weather,

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are associated with lower Tobin's q, with a more negative slope after 1995.

A perhaps more complete measure of good weather is the average annual number of "pleasant days," which require: 1) a maximum temperature no higher than 85 degrees F, 2) a minimum temperature no lower than 45 degrees F, 3) a mean temperature between 55 and 75 degrees F and 3) no measurable precipitation.[25] Cities on the West Coast rank highly in this dimension, with California cities owning the top four spots, followed by (perhaps more surprisingly) Seattle in fifth place. The other extreme includes cities that regularly dip below 45 degrees F (e.g., Salt Lake City), and those with both hot summer and cold winters, such as St. Louis, Cincinnati, and Louisville.

As with July temperature and heat index, the logarithm of pleasant days is cross-sectionally related to Tobin's q, but much more strongly in recent decades. Prior to 1995, an increase in the percentage of pleasant days of 64%, which spans the interquartile range – Nashville is at the 25^{th} percentile (50 days) with Tampa is 75^{th} percentile (82 days) – is associated with an approximate increase in Tobin's q of $[log(82) - log(50)] \times 0.10 = 0.05$. However, in the last twenty years, the effect is over three times as large, with the same shift in pleasant weather predicting a change in q of 0.18.

Similar to what Figure 2 shows with education, Figure 3 shows that cities with the best weather have experienced the largest *increases* in industry-adjusted Tobin's q. Panel A presents the graph for all cities, whereas Panel B excludes cities in California (note the different range for the x axis). Although the significance of the best-fit line is stronger with California included ($t = 2.55$ versus 1.82), interestingly, the slopes are almost identical (0.24 versus 0.25).

5.3 A city size premium in Tobin's q?

Note that in addition to the weather and education variables already discussed, all the estimates in Table 7 feature controls for city size and growth, and allow both sets of estimates to differ between the early and late halves of the sample. By including these controls, we attempt to distinguish between the agglomeration benefits associated with locating in large and/or growing cities, which is the subject of a substantial urban labor literature, versus the benefits of being located in cities

[25] An interactive map with these data for most U.S. cities is available here: http://kellegous.com/j/2014/02/03/pleasant-places/.

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with a highly skilled workforce (which may also be large and/or growing).[26]

The coefficients reported in the bottom several rows of Table 7 captures the city-size and growth effects. To capture city size, for each year, we classify large cities as those in the top third in terms of population, and small cities as those in the bottom third. Medium-sized cities are in between, and are the omitted category in the regression. As can be seen, in the pre-1995 period, our estimates fail to find a reliable relation between city size and Tobin's q. However, in the later period, there is a significant negative effect among small cities, with average magnitudes in the -0.15 to -0.25 range, depending on the specification. Interestingly, we fail to find evidence of a difference in q's in big and medium sized cities in the last twenty years after we control for weather and education. Figure 4 shows industry-adjusted Tobin's q against average population sizes, confirming the positive relation implied by the regression coefficients.

To control for growth, we also include each city's year-over-year change in raw population as an explanatory variable in our Tobin's q regressions. And, as with city size, we interact this with an indicator for the post-1994 period. Across most specifications (the exception being the last column), Tobin's q tends to be higher in growing cities during the first twenty years of our sample. However, in about half the cases, this effect is wiped out by a negative coefficient in the later period, suggesting that raw population growth has perhaps become less important for value creation. One illustration of the ambiguous effect of population growth is that none of the ten fastest growing U.S. cities from 1975-2015 experienced a positive increase in industry-adjusted average q, between the first and second halves of our sample.

Together, the results here seem to indicate that, consistent with the urban literature on worker wages, city size is positively related to shareholder value, particularly among smaller cities in recent years, with the effects of growth being more ambiguous. It also suggests that education and weather are not simply capturing dynamics in raw population. Here, one possibility is that although places with educated workers and pleasant weather may be positive predictors of overall population growth, their appeal may be especially strong for high value-added workers, who potentially have the largest impact on Tobin's q.

[26] The *urban wage premium* refers to the finding that urban workers earn about 30-60% more than their more rural counterparts. For example, Glaeser (2011) documents a 30% urban premium within the United States; Combes, Duranton, and Gobillon (2008) find roughly double this magnitude in France; De la Roca and Puga (2015) study wages in Spain, estimating a 55% premium between the largest Spanish cities and rural areas. This evidence indicates that workers tend to be more productive in larger cities.

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6 Margins, growth, or risk?

The prior analysis indicates that headquarter cities are (increasingly) informative about Tobin's q, and that these changes are positively related to a city's human capital stock. In this section, we decompose Tobin's q, in an attempt to better understand how/why high value-added workers lead to higher firm values. To organize the discussion, we start with a definition and simple decomposition:

$$q = \frac{MVA}{BVA} \tag{1}$$

$$log(q) = log\left(\sum_{t=1}^{\infty} \frac{FCF_t}{r_t}\right) - log(BVA) \tag{2}$$

where FCF_t is the firm's free cash flow at time t, r_t is the gross discount rate from now until time t, MVA is the market value of the firm's assets, and BVA is the corresponding book value. Assuming that for all t, $FCF_t = FCF_{t-1} * (1+g)$, and $r_t = r$, this expression simplifies to

$$log(q) = log\left(\frac{FCF}{BVA}\right) + log(1+g) - log(r-g). \tag{3}$$

This decomposition indicates that variation in q can be attributed to differences in how much cash a firm generates relative to its assets in place ($\frac{FCF}{BVA}$), the growth rate of cash flow (g), and the discount rate investors apply to the cash flow stream (r). In the following sections, we consider each of these components separately, in an attempt to clarify what appears to be most responsible for the cross-sectional dispersion of Tobin's q, as well as its dynamics over time.

6.1 Profit margins

The first element of the above decomposition measures the rate at which cash flows are currently being generated. All else equal, more efficient firms will have higher valuation ratios. Accordingly, we explore whether: 1) In the cross-section, do cities with high average industry-adjusted q have higher industry-adjusted profit margins? 2) In the time-series, do increases (decreases) in city-level average industry-adjusted q pre/post-1995 correlate with similar increases (decreases) in industry-adjusted profits?

For the first question, we regress profitability measured at the firm-year level on city-of-headquarter

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fixed effects, controlling for industry and year fixed effects (as we did for Tobin's q in Table 2). Although stock prices ultimately reflect capitalized cash flows, one operational complication is that cash flows exhibit substantial year-to-year variation, for example, being influenced by a firm's investment policy.[27] Thus, in hopes of obtaining more stable measures of performance, we measure profitability using return-on-assets (net income divided by the book value of assets), as well as the ratio of operating income to sales ($\frac{OI}{Sales}$). With city-of-headquarter fixed effects for both measures, we ask whether firms in high-q cities tend to also be more profitable.

Panel A of Figure 5 shows the results. The x-axis represents the regression estimate of each city's industry-adjusted fixed effect for each measure of firm profitability. For example, Cleveland's abnormal $\frac{OI}{Sales}$ is 0.16, shown at the bottom right hand portion of the figure with a blue diamond; likewise, Cleveland's estimated fixed effect for ROA (0.24) is depicted with a green triangle. Each of these is mapped to Cleveland's industry-adjusted Tobin's q (-0.46), plotted on the y-axis. The cross-sectional relationships imply a negative relation between a city's industry-adjusted profitability, and its industry-adjusted Tobin's q. Thus, Panel A of Figure 5 provides no support for the hypothesis that regional dispersion in q is driven by current profitability – in fact, the result goes in the unexpected direction.

We also examine whether *changes* in q are positively correlated with changes in firm profitability at the city level. To see if this is the case, we estimate city-of-headquarter fixed effects from 1974-1994, and then again from 1995-2015, for both profitability measures (as we did with Tobin's q in Table 2). For each city, we then plot in Panel B of Figure 5 the difference in the estimated fixed effects for each profitability measure (x-axis), against the difference between a city's industry-adjusted Tobin's q in the first and second halves of the sample (y axis).

For both the triangles (ROA) and diamonds ($\frac{OI}{Sales}$), we observe negative cross-sectional relationships, indicating that on average, profit margins and Tobin's q tend to move in opposite directions over time within cities. In both cases, the estimated slopes are significant at conventional levels (see columns 4 and 5 of Appendix Table A2), with the caveat that both x and y variables are estimated, which biases OLS coefficients toward zero. Together, the results here suggest that both in the cross-section, as well as in the time-series, city-level variation is not well accounted for by

[27] For a discussion of the empirical challenges associated with measuring growth rates in earnings and cash flows, see Chan, Karceski, and Lakonishok (2003).

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differences in the profitability of resident firms.

6.2 Growth

We next consider variables intended to capture a firm's growth prospects. Rather than calculate growth rates of either of the profit margins explored above, which are extremely volatile, we rely on proxies that capture *managerial perceptions* of the firm's future opportunities.[28] These are investment expenditures and research and development scaled by lagged assets.[29]

As with the analysis of firm profitability above, Panel A of Figure 6 shows the cross-sectional relation between a city's average industry-adjusted q, and measures of its industry-adjusted growth. In both cases, we observe a strong positive relation. That both proxies behave the same way (i.e., being positively related to city-level q), combined with the results in the preceding section, suggests that regional variation in q reflects, at least partly, differences in expected growth prospects.

However, there are some important caveats to this interpretation, owing to measurement issues related to our proxies for growth. Returning to Equation 3, note that we are taking R&D and investment as indicators for managerial beliefs about growth rates (g) in cash flows. However, because R&D is treated as an accounting expense, it lowers book values (BVA), which Equation 3 indicates will increase Tobin's q. As it turns out, this effect is quantitatively modest. If we capitalize R&D expenditures and depreciate them over time (5 or 10 years), rather than expense them, the relation between industry-adjusted q and industry-adjusted R&D is nearly identical.[30]

Moving to the time series, Panel B of Figure 6 show the results of a similar exercise as described in the preceding section, except the x variables are R&D and investment. In both cases, changes in a city's industry-adjusted q are positively correlated with changes in industry-adjusted measures of growth expectations. (See also Appendix Table A2 for the OLS output for each regression shown in the figure.)

[28] Ideally, we would measure growth rates in earnings or free cash flows, and link city-of-headquarter fixed effects for these measures to the those for Tobin's q. However, because a large percentage of firm-year observations have negative earnings, and thus cannot serve as a benchmark for calculating growth in later years, missing observations result for about one-third of the observations. Further, beyond such cases, earnings are very close to zero for another substantial fraction of companies, leading to highly volatile estimates. See Lakonishok, Shleifer, and Vishny (1994) and Chan, Karceski, and Lakonishok (2003).

[29] Investment is defined as capital expenditures divided by lagged net property, plant, and equipment (CAPX/L.PPENT). For examples of papers that have adopted a similar definition, see Kaplan and Zingales (1997), Bertrand and Schoar (2004), and Chaney, Sraer, and Thesmar (2012).

[30] We have also estimated this relation using the modified q measure of Peters of Taylor (2017), and find similar results.

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The findings in this and the prior section highlight that being headquartered in thriving metro areas such as Seattle, Boston, Silicon Valley, and Washington D.C. is a double edged sword. On the one hand, high q ratios in such cities are sustained by a virtuous cycle of highly skilled workers, and the incentives for local companies to help them develop through training, and thus attracting the next generation of skilled workers. On the other hand, such growth is not free, and may come at the expense of short-run profits. For example, Figure 7 reveals that property prices and wages are higher in cities with high Tobin's q, in part explaining the lower profitability of firms located there. The figure's y-axis shows each city's change in abnormal q (between the first and second 20-year period), and on the x-axis, the log change in housing prices (squares) and average wages (triangles).[31] As seen, rising valuation ratios tend to correspond to increases in both real estate prices and wages. Because all else equal, lower margins should equate to lower stock prices, increases in growth opportunities must be strong enough to overcome the but-for effects of higher costs.

6.3 Expected returns

Finally, Equation 3 indicates that Tobin's q can vary cross-sectionally because discount rates investors apply to firms' future cash flows may differ. For example, the cash flows generated in high q cities may be less risky, and consequently, may be discounted at lower rates than the cash flows generated in low q cities. If these discount rate spreads widened over our sample period, it would have caused the regional gap in observed q ratios to also widen.

Unfortunately, exploring this explanation for the increase in the Tobin's q dispersion is challenging because discount rates are not directly observable. We will instead follow the asset pricing literature (with the caveats discussed below) and explore the relationship between expected rates of return and city characteristics, by examining the realized returns over our 40-year sample period.

As a first step, we estimate the Tobin's q associated with each city by estimating cross-sectional regressions of Tobin's q on industry and city fixed effects for each individual year. The five cities with the smallest (most negative) estimated city fixed effects in these regressions are designated as "value" over the subsequent year, and the top five (most positive) are classified as "glamour."

[31] Note that housing prices are measured starting in 1980 (the earliest that reliable housing data are available), whereas wages begin in 1970. To avoid look-ahead bias, changes in a city's Tobin's q are measured starting in 1980 for the comparison with house prices.

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In our second step, we estimate Fama-MacBeth regressions of monthly stock returns, on variables representing the previous year's Tobin q of the firm's headquarter city, the contemporaneous returns of the firm's industry portfolio, and standard firm specific controls, like the firm's own lagged market-to-book ratio, size, profitability, and trailing six-month returns. The key explanatory variables are either the lagged value of the industry-adjusted Tobin q for each city, or dummy variables indicating whether the cities are classified as glamour or value cities.

Table 8 reports the results of these regressions. The results reported in the first column indicates that a unit change in industry-adjusted Tobin's q is associated with a monthly return premium of about 30 basis points ($p < 0.01$). The next several columns break out the results for glamour and value cities separately. The estimates in column 2 indicates that over the four-decade sample period, stocks in glamour cities realized higher returns of about 2.5% per year ($p < 0.01$). As for stocks headquartered in value cities, the point estimate is negative, but is not statistically significant. The last three columns break up the sample into the pre-1990 period (column 3), the 1990s (column 4) and post-2000 (column 5). This sub-period analysis indicates that the city glamour/value return difference is observed in each sub-period, but it is almost three times as strong in the 1990s.

The findings in Table 8 provide two important takeaways. First, over the entire sample, cities with high industry-adjusted average q have high industry-adjusted returns, which is inconsistent with the hypothesis that firms in high Tobin's q cities have low required rates of return. Of course, the strength of this argument depends on how accurately realized returns measures expected returns. For example, it is unlikely that the very high glamour/value city return spread in the 1990s represented differences in expected rates of return. Given the size of the observed effect – the glamour/value-city spread is about 7% per year – these returns were likely to have been unanticipated, and reflect either expected future cash flow shocks from the IT revolution, or alternatively, an increase in values due to an unexpected decline in required rates of return in glamour cities. The fact that glamour cities continue to outperform value cities in the post-2000 period (and for more than a decade) supports the latter argument, which is our second takeaway.

As we have already seen in Section 5, cities with the highest industry-adjusted q are associated with rates of higher education and good weather, both proxies for human capital. A natural question, then, is whether using these *determinants* for a city's q, rather than q itself, generates similar stock return spreads. Table 9 shows that it does. In Panel A, we estimate Fama-McBeth

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regressions using both continuous and discrete measures of city-level higher education, and of pleasant weather.

The first two columns include twin indicator variables, one identifying the top five cities in terms of college education, and another identifying the bottom five. The reference group is thus captured by all other cities. In both columns, we estimate a significant coefficient on the top-five education dummy, indicating that on average, firms headquartered in Denver, Salt Lake City, Washington, San Francisco, San Jose outperformed reference cities (neither how nor low education rates) by about fifty basis points per month, or six percent annually. Although the point estimate for the least educated cities is negative, it is not statistically significant.

Moving to Panel B, we present the results of a trading strategy that takes long positions in the five most highly educated cities (listed above), and short positions in the five least educated. We regress the time series of the returns from this hedge strategy against standard risk factors, focusing on the residual (unexplained) monthly return. Without the industry adjustment (column 1 of Panel B), we estimate significant monthly alphas of about one percent per month, with magnitudes about 30% lower with the industry adjustment. In both cases, the trading strategy confirms the Fama-MacBeth regressions, and suggests that firms headquartered in highly educated cities benefited disproportionately from the IT revolution in the 1990s.

Returning to Panel A, the next pair of columns conduct a similar analysis involving pleasant weather. Firms headquartered in the five cities with the largest number of pleasant days (four of which are in California) appear to experience better returns, on the order of five percent per year. The trading strategy (Panel B) gives similar results, with an almost identical magnitude for the model that include industry returns as a control (column 4).

The last pair of columns in each panel estimate the impact of combining education and weather into a composite measure. We create a composite variable by adding the city-level ranks using college education and pleasant weather, and then re-rank cities based on the sum. In the right tail, this composite ranking resembles the weather ranking, since cities in California score very high in weather, and above average in education. Consequently, the abnormal returns for the top five cities are similar (about forty basis points per month), with slightly stronger returns in the long-short portfolio analysis.

For a visual representation of these patterns, Figure 8 shows how the value of a hypothetical

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dollar invested in the: 1) top five cities, 2) the bottom five cities, and 3) all others, would have evolved through the 1990s. All returns are net of 2-digit SIC industry effects. As seen, the blue line (representing firms in the top five cities) experienced nearly a doubling of value, even on an industry adjusted basis. Firms outside these five cities underperformed their industry benchmarks, with those in the bottom five cities performing (slightly) worse still.

To give a sense of the differential value creation across cities, in January 1990, public firms in the top five cities (ranked in terms of these human capital measures) were collectively worth \$203 billion, which constituted 7.1% of the aggregate U.S. market capitalization of all firms. Ten years later, the total market value of these incumbent firms (e.g. Microsoft, Intel) had swelled to \$1.9 trillion, or 12.4% of the stock market. Of this 20.7%, 8.3% is due to firms having gone public during the 1990s (e.g., Amazon, Google), with the balance to firms already public by 1990 (e.g. Microsoft, Intel).

7 Conclusion

The evidence in this paper indicates that a favorable location can be a source of comparative advantage for firms, and the magnitude of the benefits of a favorable location has increased over time. As we show, firms in what we call *glamour cities* have higher industry-adjusted Tobin's q than firms in other cities, and these differences are substantially larger in the post-1990 period compared to years prior. We also document that in the 1990s, existing firms in the most vibrant locations essentially doubled in value relative to their industry counterparts in other cities.

In some respects, what we do not find is as interesting as what we do find. First, although high-q cities tend to be growing cities, growth per se is not an important determinant of value creation. Indeed, none of the ten fastest growing cities in the 1975-2015 period experienced a positive increase in industry-adjusted average q in the latter half of our sample period. Thus, although education levels and weather do predict population growth, value creation for public companies seems to be less about adding people, and more about attracting the "right" kind of worker.

Our second important 'non-result' is that we do not find evidence that firms in the more favorable locations experience higher profitability. The fact that winning cities are associated with high stock prices, but not with high realized profits, indicates that these favorable locations

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facilitate the creation of new opportunities, but do not bear fruit immediately. In this way, we view our results as analogous to the observation that younger workers in major cities do not realize higher immediate real compensation, but because they tend to build human capital in more vibrant locations, their long-term compensation is higher.[32]

Finally, note that although new firms do tend to disproportionately choose to locate in glamour cities, the entry of new firms does not appear to entirely compete away the benefits that the incumbent firms experience from a good location.[33] This evidence suggests that understanding the nature of the competitive dynamics between workers and firms in these locations may be key to understanding other aspects of these urban economies. For example, Silicon Valley hosts firms like Facebook, Apple and Google, which benefit from being in a location that allows them to attract and retain the best talent. These firms pay their employees extremely well, but apparently, because of these firms' market power, their shareholders capture some of the benefits of the firms' access to this superior talent. Theoretical models that provide more precise empirical guidance on such dynamics, and subsequent empirical work, are fruitful opportunities for future work.

[32] See Glaeser and Mare (2001) and de la Roca and Puga (2015).

[33] Recall Appendix Table A1, which shows the heavy concentration of initial public offerings in a small number of cities.

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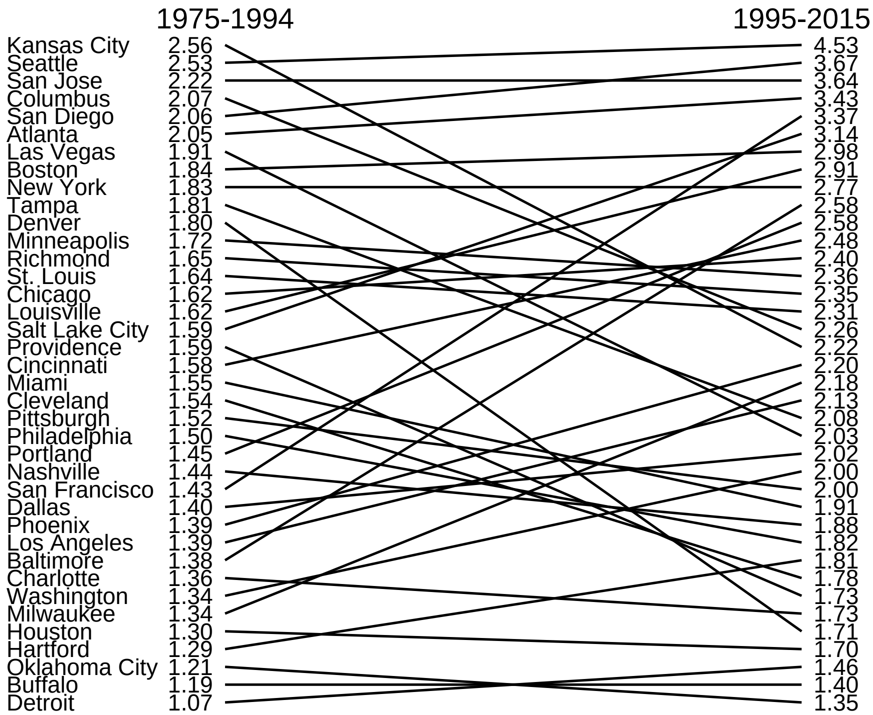

Figure 1: Average Area Q Pre- and Post-1995 This plot lists the value-weighted average Q for firms by area for the years 1975 – 1994 and the years 1995 – 2015.

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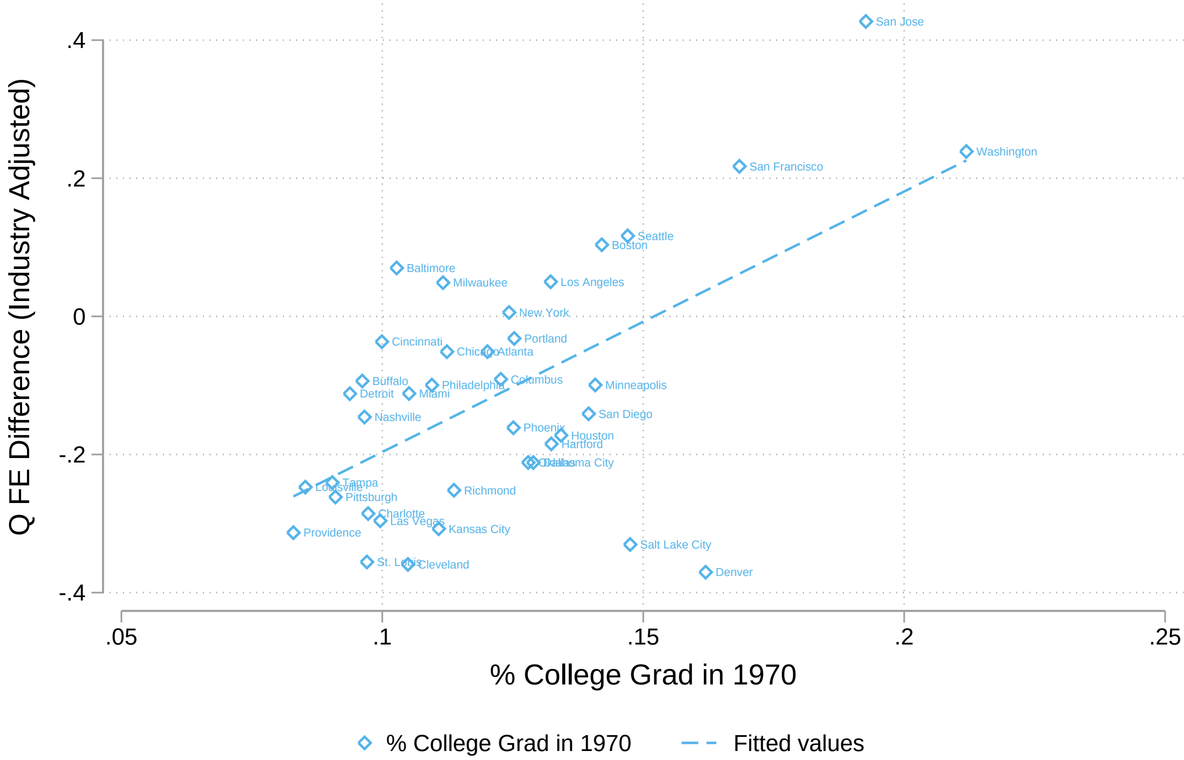

Figure 2: Changes in Area Q Versus Pre-Existing Human Capital Stock This plot shows the change in an area's Q fixed effect estimate as reported columns 5 and 6 of Table 2 versus the area's percentage of college graduates in 1970.

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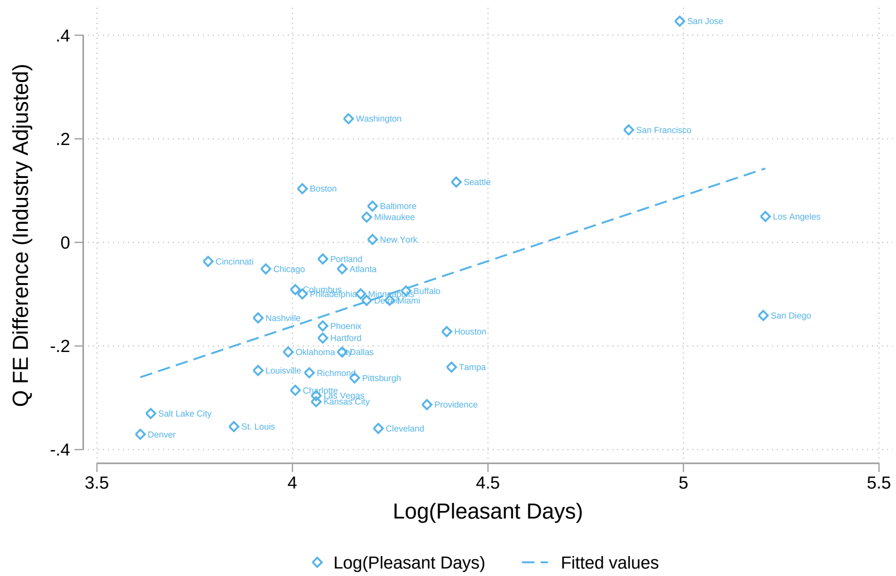
Panel A: All Areas



Panel B: Excluding California Areas

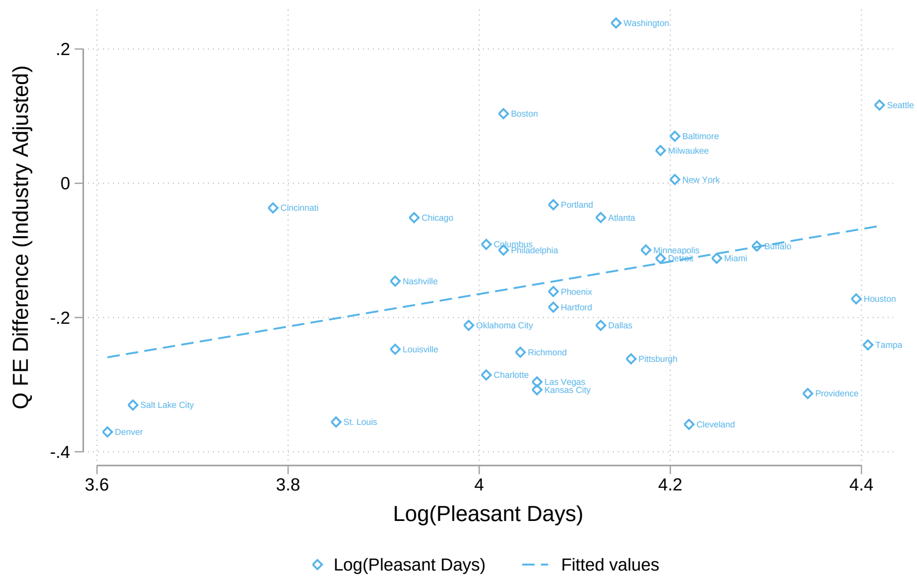


Figure 3: Change in Area Q Versus Log(Pleasant Days) This plot shows the change in an area's Q fixed effect estimate as reported columns 5 and 6 of Table 2 versus the log of an area's number of pleasant days per year, where a pleasant day is defined as a day with the average temperature over 1992 - 2014 between 55 and 75 degrees Fahrenheit, a minimum temperature above 45 degrees Fahrenheit, a maximum temperature below 85 degrees Fahrenheit and no significant precipitation or snow depth. Panel A includes all areas while Panel B excludes areas located in California.

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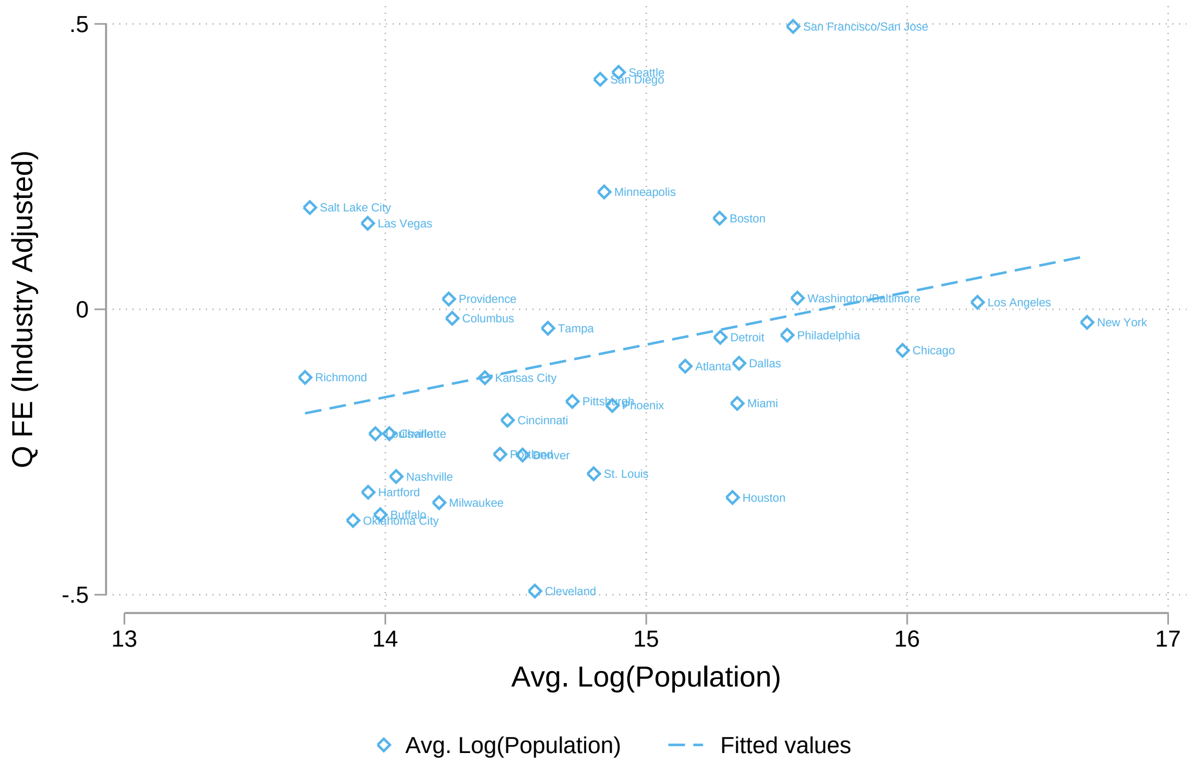

Figure 4: Area Q Versus Area Population This plot shows each city's average industry-adjusted Tobin's q (i.e., the area fixed effects from a regression of firm q on area, industry, age, and year fixed effects) versus each city's average log population.

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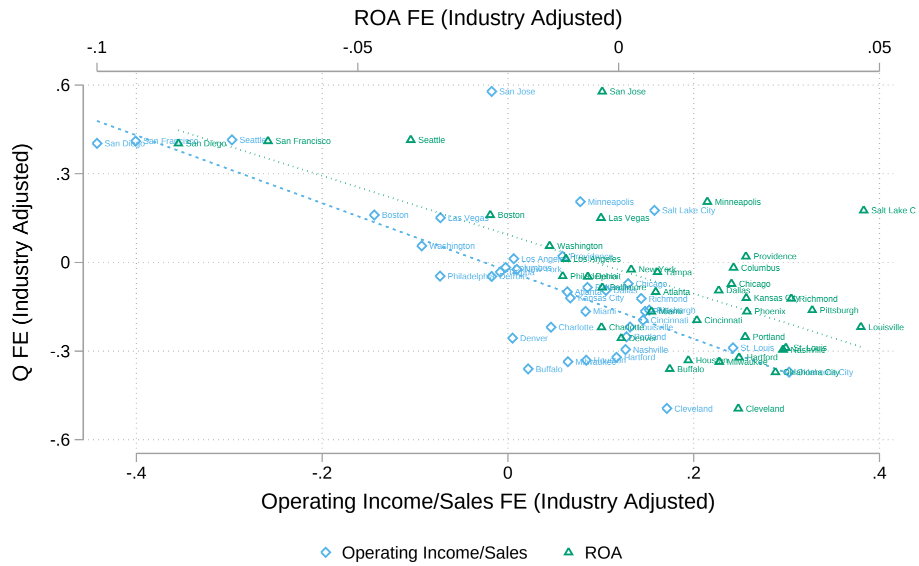
Panel A: Levels



Panel B: Changes

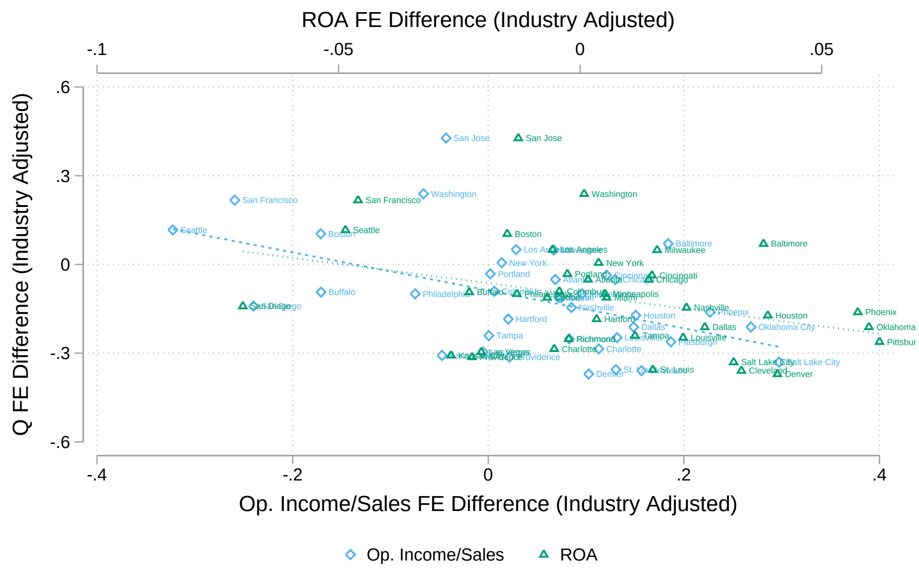


Figure 5: Area Q Versus Area Profit Margins Panel A of this plot shows each city's industry- and year-adjusted Tobin's q versus each city's industry- and year-adjusted operating income-to-sales (blue diamonds) and return on assets (green triangles). Panel B plots each city's change in industry- and year-adjusted Tobin's q (as reported columns 5 and 6 of Table 2) versus each city's change in industry- and year-adjusted operating income-to-sales (blue diamonds) and return on assets (green triangles). In both panels, the top y-axis applies to operating income and the bottom to ROA.

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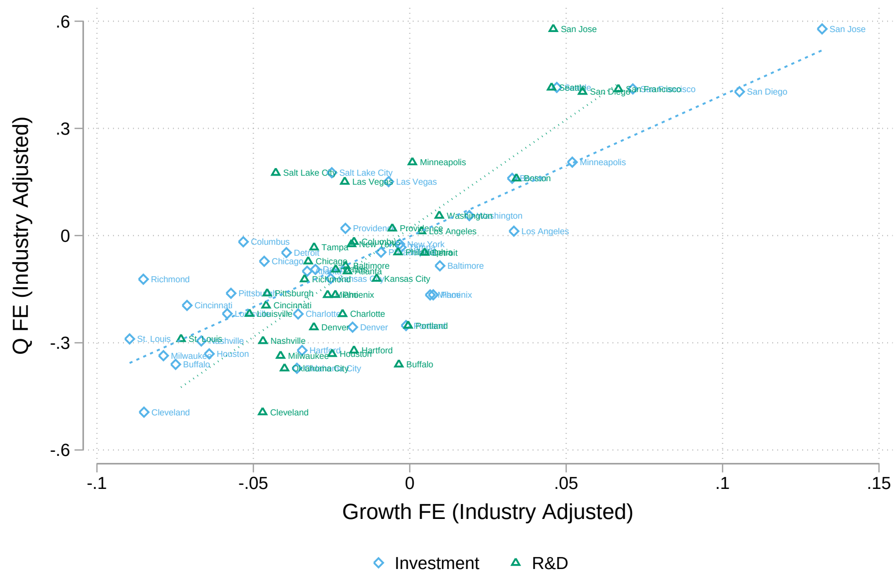
Panel A: Levels



Panel B: Changes

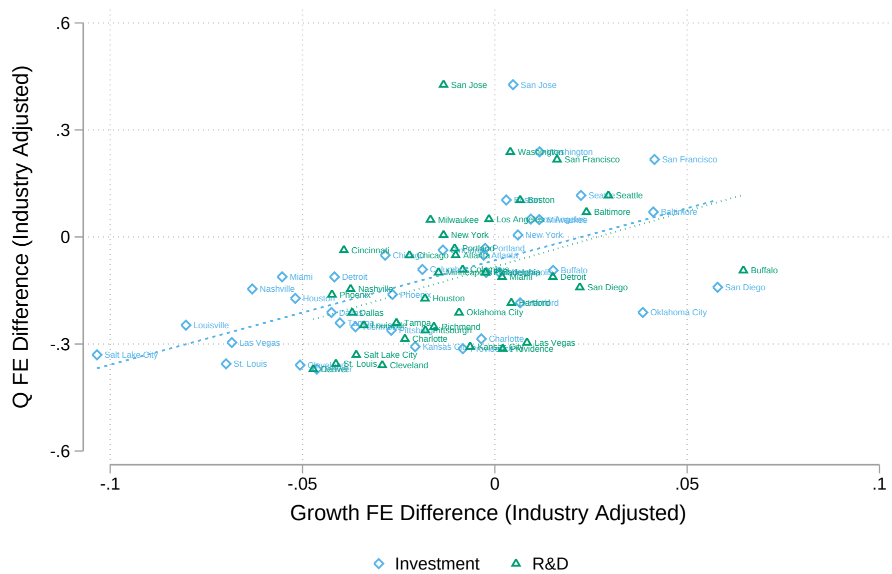


Figure 6: Area Q Versus Area Growth Opportunities Panel A of this plot shows each city's industry- and year-adjusted Tobin's q versus each city's industry and year-adjusted investment rates (blue diamonds) and R&D-to-assets (green triangles). Panel B plots each city's change in industry- and year-adjusted Tobin's q (as reported columns 5 and 6 of Table 2) versus each city's change in industry- and year-adjusted investment rates (blue diamonds) and R&D-to-assets (green triangles). In both panels, the top y-axis applies to operating income and the bottom to ROA.

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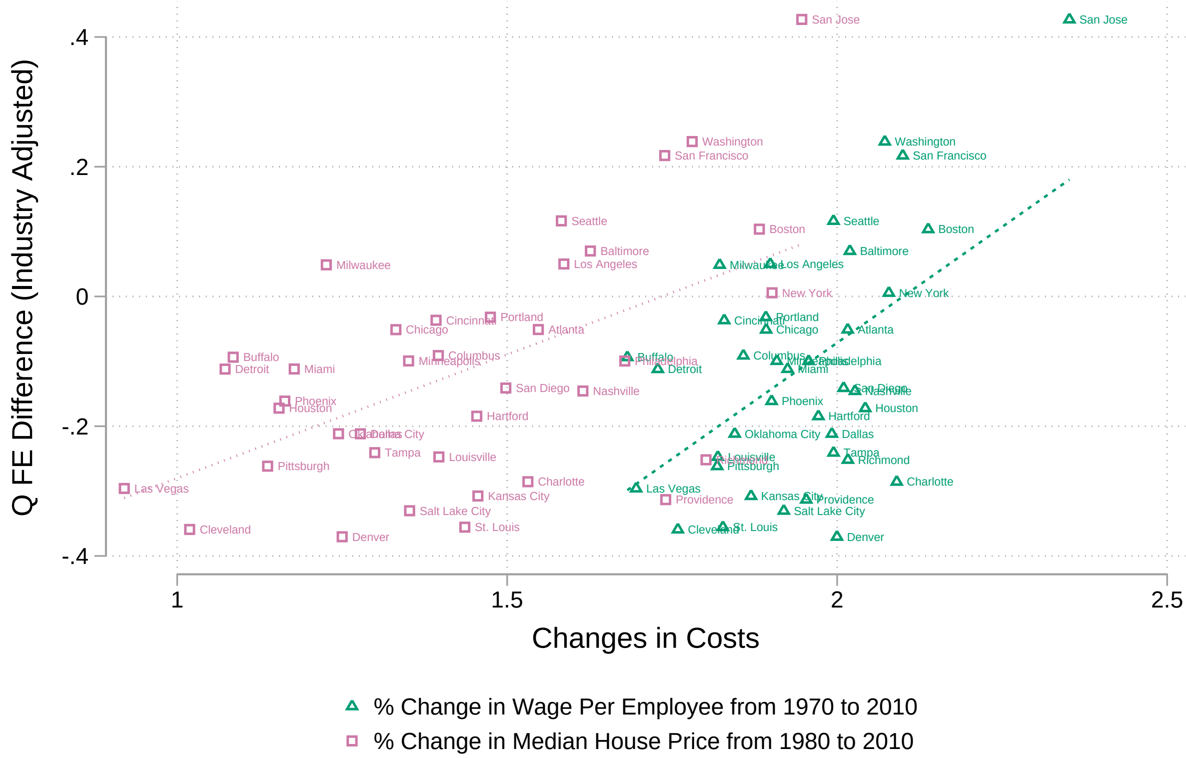

Figure 7: Crowding Out This figure plots each city's change in industry- and year-adjusted Tobin's q (as reported columns 5 and 6 of Table 2) versus the area's log change in the area's average wage per employee 1970, and the area's median house value in 1980.

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Figure 8: Cumulative Monthly Industry-Adjusted Area Returns This plot shows the cumulative monthly return of industry adjusted value-weighted portfolios formed by an index that sums the ranks of an area's percentage of college graduates in 1970 and average number of pleasant days per year. The top five areas by index rank are San Jose, San Francisco, San Diego, Seattle, and Los Angeles. The bottom five areas are Charlotte, Cincinnati, Nashville, St. Louis, and Louisville. The sample begins in January 1990 and ends in December 2000.

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Table 1: Summary Statistics

This table reports area-level averages for firms and areas over the years 1975-2015 for the following variables: area population in millions, area population growth rate, area percentage of college graduates in 1970, average area July temperature, average area July Heat Index, average area number of pleasant days per year, number of firms per area, market capitalization of area firms relative to total market capitalization, Tobin's Q, investment-to-lagged net PP&E, R&D-to-lagged assets, operating income-to-sales, ROA, and monthly stock returns (in percentages).

(1) Area	(2) Pop. (M)	(3) Growth	(4) Grads	(5) Temp.	(6) HI	(7) Days	(8) Firms	(9) % MC	(10) Q	(11) Inv.	(12) R&D	(13) OI/Sales	(14) ROA	(15) Ret.
Atlanta	3.95	2.57	0.12	80	100	62	74	4.52	1.90	0.36	0.07	0.06	0.02	1.31
Baltimore	2.48	0.63	0.10	77	92	67	24	0.36	2.04	0.38	0.08	−0.08	0.00	1.32
Boston	4.34	0.52	0.14	74	83	56	149	3.15	2.37	0.43	0.14	−0.30	−0.03	1.40
Buffalo	1.18	−0.30	0.10	71	81	73	11	0.05	1.50	0.25	0.08	0.00	0.03	1.38
Charlotte	1.27	2.27	0.10	80	98	55	22	0.51	1.51	0.26	0.03	0.09	0.04	1.28
Chicago	8.75	0.48	0.11	73	88	51	121	6.61	1.79	0.29	0.04	0.09	0.04	1.34
Cincinnati	1.93	0.62	0.10	76	94	44	24	2.08	1.62	0.25	0.03	0.13	0.04	1.39
Cleveland	2.13	−0.19	0.10	72	86	68	32	0.77	1.35	0.23	0.04	0.08	0.04	1.35
Columbus	1.57	1.19	0.12	75	90	55	20	0.53	1.83	0.28	0.04	0.02	0.06	1.42
Dallas	4.82	2.44	0.13	85	109	62	112	8.96	1.81	0.33	0.05	0.10	0.04	1.35
Denver	2.08	1.97	0.16	73	87	37	62	1.37	1.79	0.37	0.05	−0.08	−0.01	1.14
Detroit	4.34	−0.06	0.09	74	85	66	28	1.31	1.72	0.30	0.07	0.00	0.02	1.41
Hartford	1.13	0.36	0.13	74	88	59	13	0.64	1.46	0.28	0.05	0.11	0.05	1.62
Houston	4.67	2.32	0.13	84	110	81	126	4.82	1.59	0.31	0.05	0.07	0.02	1.18
Kansas City	1.77	0.94	0.11	79	101	58	18	0.40	1.84	0.34	0.07	0.06	0.05	1.40
Las Vegas	1.26	4.66	0.10	91	101	58	16	0.42	2.02	0.35	0.05	−0.08	0.01	1.64
Los Angeles	11.70	0.97	0.13	69	90	183	136	2.36	2.02	0.42	0.10	−0.07	0.00	1.34
Louisville	1.16	0.73	0.09	78	99	50	12	0.24	1.67	0.28	0.01	0.11	0.07	1.39
Miami	4.71	1.83	0.11	84	106	70	52	0.80	1.84	0.38	0.05	0.03	0.02	1.54
Milwaukee	1.48	0.31	0.11	72	82	66	26	0.74	1.53	0.27	0.03	0.10	0.05	1.37
Minneapolis	2.81	1.30	0.14	73	85	65	84	1.64	2.24	0.42	0.09	0.00	0.03	1.48
Nashville	1.28	1.95	0.10	79	98	50	23	0.53	1.64	0.30	0.01	0.09	0.05	1.66
New York	17.73	0.40	0.12	77	87	67	262	21.64	1.98	0.36	0.07	−0.08	0.02	1.40
Oklahoma City	1.07	1.25	0.13	82	105	54	9	0.30	1.57	0.35	0.01	0.30	0.04	1.17
Philadelphia	5.62	0.37	0.11	78	93	56	82	3.16	1.98	0.35	0.09	−0.18	0.00	1.44
Phoenix	3.03	3.13	0.13	93	107	59	34	0.63	1.79	0.38	0.06	0.09	0.04	1.56
Pittsburgh	2.46	−0.30	0.09	73	85	64	26	0.73	1.67	0.27	0.03	0.11	0.05	1.43
Portland	1.89	1.78	0.13	68	80	59	27	0.41	1.76	0.38	0.09	0.09	0.03	1.52
Providence	1.54	0.36	0.08	73	86	77	11	0.52	1.80	0.33	0.06	0.10	0.05	1.42
Richmond	0.90	1.49	0.11	78	100	57	15	1.71	1.61	0.20	0.03	0.14	0.07	1.47
St. Louis	2.67	0.35	0.10	80	98	47	32	1.37	1.73	0.26	0.03	0.12	0.04	1.34
Salt Lake City	0.92	1.88	0.15	77	90	38	18	0.17	2.47	0.35	0.07	−0.15	0.02	1.33
San Diego	2.77	1.45	0.14	71	75	182	56	0.79	2.75	0.51	0.18	−0.71	−0.11	1.17
San Francisco	4.07	0.96	0.17	63	68	129	120	5.02	2.80	0.50	0.19	−0.65	−0.09	1.15
San Jose	1.70	1.05	0.19	70	85	147	135	8.04	2.80	0.56	0.16	−0.11	−0.01	1.57
Seattle	2.98	1.62	0.15	65	75	83	43	3.49	2.67	0.47	0.16	−0.45	−0.05	1.40
Tampa	2.28	1.81	0.09	83	104	82	21	0.20	1.98	0.39	0.05	−0.06	0.02	1.48
Washington	3.38	1.34	0.21	79	95	63	75	2.21	2.20	0.43	0.11	−0.20	−0.02	1.26
All Areas	6.07	1.16	0.13	76	91	80	109	5.78	2.03	0.37	0.09	−0.08	0.01	1.37

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Table 2: Variation in Area Q Pre- and Post-1995.

This table reports estimates of area fixed-effects from regressions of firm-level Q on 2-digit SIC industry, area, and year fixed effects for the pre-1995 and post-1995 time period. The final two columns add firm age fixed effects which are a set of dummy variables corresponding to five year intervals of Compustat firm age up to age 25. Regression standard errors are robust to heteroscedasticity and clustered by firm. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) 75-94 Q	(2) 95-15 Q	(3) 75-94 Q	(4) 95-15 Q	(5) 75-94 Q	(6) 95-15 Q
Atlanta	0.09	0.04	0.02	−0.03	−0.03	−0.03
Baltimore	0.18	0.26	0.00	0.07	−0.06	0.06
Boston	0.33***	0.57***	0.22**	0.34***	0.11	0.27**
Buffalo	−0.15	−0.46**	−0.27	−0.36	−0.25	−0.29
Charlotte	−0.18	−0.37***	−0.04	−0.27**	−0.02	−0.25*
Cincinnati	−0.11	−0.22	−0.12	−0.20	−0.14	−0.13
Cleveland	−0.25***	−0.57***	−0.29***	−0.61***	−0.27***	−0.58***
Columbus	0.10	−0.07	0.16	0.03	0.07	0.03
Dallas	0.10	−0.11	0.13	−0.07	0.07	−0.09
Denver	0.16	−0.20*	0.16	−0.22**	0.02	−0.30***
Detroit	−0.08	−0.02	0.06	0.04	0.06	−0.00
Hartford	−0.12	−0.47***	−0.17	−0.43***	−0.18	−0.31**
Houston	−0.18***	−0.29***	−0.14*	−0.27**	−0.19***	−0.31***
Kansas City	0.19	−0.11	0.17	−0.21	0.10	−0.16
Las Vegas	0.40**	0.01	0.50***	0.13	0.35**	0.10
Los Angeles	0.17*	0.23**	0.13	0.17	0.02	0.13
Louisville	−0.01	−0.27	0.04	−0.22	−0.02	−0.22
Miami	0.08	−0.08	0.01	−0.13	−0.07	−0.13
Milwaukee	−0.25***	−0.33***	−0.28***	−0.26**	−0.33***	−0.23*
Minneapolis	0.48***	0.33**	0.41***	0.24*	0.30**	0.25**
Nashville	−0.12	−0.28**	−0.11	−0.27**	−0.18	−0.27**
New York	0.12*	0.25**	0.02	0.08	0.02	0.07
Oklahoma City	−0.13	−0.34**	−0.05	−0.32	−0.21	−0.37**
Philadelphia	0.17	0.18	0.07	0.00	0.05	−0.00
Phoenix	0.05	−0.12	0.08	−0.08	−0.04	−0.15
Pittsburgh	−0.01	−0.25**	0.07	−0.14	0.04	−0.17
Portland	−0.01	−0.21	0.00	−0.11	−0.18*	−0.16
Providence	0.22	−0.19	0.29	−0.06	0.22	−0.05
Richmond	0.03	−0.35	−0.02	−0.27	0.05	−0.15
St. Louis	0.06	−0.24*	0.03	−0.31**	−0.01	−0.32**
Salt Lake City	0.77**	0.52*	0.51*	0.19	0.41	0.13
San Diego	0.82***	0.86***	0.71***	0.55***	0.52**	0.43***
San Francisco	0.58***	0.98***	0.43***	0.65***	0.26**	0.53***
San Jose	0.60***	0.97***	0.50***	0.90***	0.30***	0.78***
Seattle	0.60***	0.85***	0.50**	0.61***	0.36*	0.53***
Tampa	0.27	0.04	0.28*	0.01	0.14	−0.05
Washington	0.03	0.44***	−0.05	0.28**	−0.09	0.20
Observations	31249	48598	31249	48598	31249	48598
R^2	0.08	0.08	0.13	0.14	0.18	0.15
City F-Stat	5.74	16.93	4.20	9.62	3.07	7.55
City P-value	0.00	0.00	0.00	0.00	0.00	0.00
Industry F-Stat			12.47	19.03	9.72	15.69
Industry P-value			0.00	0.00	0.00	0.00
Industry FE	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Age FE	No	No	No	No	Yes	Yes

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Table 3: Q Variation By Industry Agglomeration.

This table reports the same regressions as columns 5 and 6 of Table 2, but with firms sorted annually by whether they are located within or without an industry cluster. Panel A defines an industry cluster as 10% or more of the number of firms in the same industry being located in the same area, and Panel B defines an industry cluster as 10% or more of an industry's market cap being located in the same area. All industry cluster definitions require there be at least 10 firms in an industry for a potential cluster to exist. Area fixed effects are only estimated for areas which have at least 30 observations in each sort sample. Columns 1 and 2 of Panel C report the same results as those in columns 5 and 6 of Table 2, while columns 3 and 4 report the same excluding all firms located in California from the sample. Regression standard errors are robust to heteroscedasticity and clustered by firm. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Industry Clusters Defined By Percentage Of Firms

	(1) Inside 75-94 Q	(2) Inside 95-15 Q	(3) Outside 75-94 Q	(4) Outside 95-15 Q
Observations	9968	15844	20985	32443
R^2	0.16	0.16	0.18	0.15
City F-Stat	2.65	5.50	2.76	5.71
City P-value	0.00	0.00	0.00	0.00
Industry F-Stat	5.74	6.41	7.41	13.36
Industry P-value	0.00	0.00	0.00	0.00

Panel B: Industry Clusters Defined By Percentage Of Market Capitalization

	(1) Inside 75-94 Q	(2) Inside 95-15 Q	(3) Outside 75-94 Q	(4) Outside 95-15 Q
Observations	9686	14282	21343	33847
R^2	0.17	0.16	0.19	0.16
City F-Stat	1.58	2.32	2.63	5.79
City P-value	0.04	0.00	0.00	0.00
Industry F-Stat	5.90	5.99	6.54	16.21
Industry P-value	0.00	0.00	0.00	0.00

Panel C: Excluding California Firms

	(1) Full Sample 75-94 Q	(2) Full Sample 95-15 Q	(3) Excluding CA 75-94 Q	(4) Excluding CA 95-15 Q
Observations	31249	48598	26476	38190
R^2	0.18	0.15	0.17	0.13
City F-Stat	3.07	7.55	2.69	6.31
City P-value	0.00	0.00	0.00	0.00
Industry F-Stat	9.72	15.69	8.20	11.90
Industry P-value	0.00	0.00	0.00	0.00

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Table 4: Variation in Area Q Pre- and Post-1995.

This table reports the same regression specifications as Table 2 columns 5 and 6 with some slight variations. Panel A varies the timing of our tech boom breakpoint from 1995 to 1992 in columns 1 and 2 and to 1998 in columns 3 and 4, while columns 5 and 6 exclude the 1990 period entirely. Panel B varies our industry classification. Columns 1 and 2 classify industries by 3-digit SIC code, columns 3 and 4 by 4-digit SIC code, and columns 5 and 6 by the Fama-French 48 industry classification. Panel C varies our area definition. Columns 1 and 2 further restrict our area definition by limiting locations to only the core-counties surrounding a CBSA's principle city. Columns 3 and 4 expand our area definition to include all firms in a CBSA. Regression standard errors are robust to heteroscedasticity and clustered by firm. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Varying Tech Boom Timing Breakpoint

	(1) 75-91 Q	(2) 92-15 Q	(3) 75-97 Q	(4) 98-15 Q	(5) 75-89 Q	(6) 00-15 Q
Observations	24521	55326	39200	40647	20845	35394
R^2	0.17	0.15	0.19	0.15	0.18	0.14
City F-Stat	2.53	7.66	4.07	6.96	2.34	5.41
City P-value	0.00	0.00	0.00	0.00	0.00	0.00
Industry F-Stat	8.20	16.48	13.09	12.85	8.37	11.00
Industry P-value	0.00	0.00	0.00	0.00	0.00	0.00

Panel B: Varying Industry Definition

	(1) SIC3 75-94 Q	(2) SIC3 95-15 Q	(3) SIC4 75-94 Q	(4) SIC4 95-15 Q	(5) FF48 75-94 Q	(6) FF48 95-15 Q
Observations	31249	48598	31249	48598	31249	48598
R^2	0.18	0.17	0.15	0.12	0.19	0.17
City F-Stat	2.13	5.83	3.82	11.11	2.35	5.80
City P-value	0.00	0.00	0.00	0.00	0.00	0.00
Industry F-Stat	8.77	21.33	5.29	15.42	10.64	20.80
Industry P-value	0.00	0.00	0.00	0.00	0.00	0.00

Panel C: Varying Area Definition

	(1) Core 75-94 Q	(2) Core 95-15 Q	(3) CBSA 75-94 Q	(4) CBSA 95-15 Q
Observations	19000	28595	32493	50151
R^2	0.19	0.15	0.18	0.15
City F-Stat	2.83	7.56	2.91	6.79
City P-value	0.00	0.00	0.00	0.00
Industry F-Stat	8.19	9.88	9.06	16.05
Industry P-value	0.00	0.00	0.00	0.00

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Table 5: Q Variation By Firm Age and Industry R&D.

This table reports the same regressions as columns 5 and 6 of Table 2 (i.e., regressions of Q on area, industry, age, and year fixed effects), but with firms sorted annually by whether they have been in Compustat for greater or less than ten years (Panel A), and whether they belong to an industry with above or below median industry R&D calculated annually (Panel B). Area fixed effects are only estimated for areas which have at least 30 observations in each sort sample. Regression standard errors are robust to heteroscedasticity and clustered by firm. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Sorting On Firm Age

	(1) $\leq$ 10 years 75-94 Q	(2) $\leq$ 10 years 95-15 Q	(3) $>$ 10 years 75-94 Q	(4) $>$ 10 years 95-15 Q
Observations	15546	22774	15703	25824
R^2	0.16	0.15	0.14	0.14
City F-Stat	4.58	9.36	1.22	3.27
City P-value	0.00	0.00	0.18	0.00
Industry F-Stat	8.93	18.64	6.57	7.93
Industry P-value	0.00	0.00	0.00	0.00

Panel B: Sorting On Industry Median R&D

	(1) Above 75-94 Q	(2) Above 95-15 Q	(3) Below 75-94 Q	(4) Below 95-15 Q
Observations	14179	25746	17023	22685
R^2	0.19	0.16	0.18	0.12
City F-Stat	2.72	8.57	2.53	3.93
City P-value	0.00	0.00	0.00	0.00
Industry F-Stat	10.47	21.66	7.27	9.20
Industry P-value	0.00	0.00	0.00	0.00

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Table 6: Q Variation By Firm Size.

This table reports the same regressions as columns 5 and 6 of Table 2 using regression samples sorted on whether a firm has market capitalization above or below the median NYSE market capitalization (Panel A) or the median sample market capitalization (Panel B). Area fixed effects are only estimated for areas which have at least 30 observations in each sort sample. Regression standard errors are robust to heteroscedasticity and clustered by firm. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Sorting on Annual NYSE Median Market Capitalization

	(1) Below 75-94 Q	(2) Below 95-15 Q	(3) Above 75-94 Q	(4) Above 95-15 Q
Observations	23802	36690	7349	11835
R^2	0.18	0.15	0.30	0.33
City F-Stat	3.13	5.21	2.29	5.08
City P-value	0.00	0.00	0.00	0.00
Industry F-Stat	7.64	12.68	4.99	8.37
Industry P-value	0.00	0.00	0.00	0.00

Panel B: Sorting on Annual Sample Median Market Capitalization

	(1) Below 75-94 Q	(2) Below 95-15 Q	(3) Above 75-94 Q	(4) Above 95-15 Q
Observations	15632	24301	15617	24297
R^2	0.18	0.14	0.25	0.25
City F-Stat	3.31	4.40	3.23	7.15
City P-value	0.00	0.00	0.00	0.00
Industry F-Stat	6.02	11.33	8.00	12.37
Industry P-value	0.00	0.00	0.00	0.00

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Table 7: Determinants of Q Variation.

This table reports similar regressions to those reported in columns 5 and 6 of Table 2 with the exception that area fixed effects have been substituted by area level continuous regressors, and instead of estimating separate regressions for the pre- and post-1995 period a post-1995 interaction term is included as a regressor. Additionally, controls for log city population and log population growth are added to all specifications. Column 1 examines how Q-levels have changed over time as a function of an area's percentage of college graduates in 1970, column 2 as a function of an area's average July temperature, column 3 as a function of average July high temperature heat index, and column 4 as a function of the log of an area's number of pleasant days per year, where a pleasant day is defined as a day with the average temperature over 1992 - 2014 between 55 and 75 degrees Fahrenheit, a minimum temperature above 45 degrees Fahrenheit, a maximum temperature below 85 degrees Fahrenheit and no significant precipitation or snow depth. Regression standard errors are clustered at the firm level and are reported in parentheses. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) Q	(2) Q	(3) Q	(4) Q	(5) Q	(6) Q	(7) Q
% College Grad in 1970	2.42***				1.20	0.47	2.20***
	(0.75)				(0.78)	(0.78)	(0.77)
I[year>1994] × % College Grad in 1970	4.03***				2.01**	1.65	3.10***
	(0.86)				(1.00)	(1.01)	(0.91)
Avg. July Temperature		−0.01***			−0.01***		
		(0.00)			(0.00)		
I[year>1994] × Avg. July Temperature		−0.02***			−0.01***		
		(0.00)			(0.00)		
Avg. July Heat Index			−0.01***			−0.01***	
			(0.00)			(0.00)	
I[year>1994] × Avg. July Heat Index			−0.01***			−0.01***	
			(0.00)			(0.00)	
Log(Pleasant Days)				0.10*			0.07
				(0.06)			(0.06)
I[year>1994] × Log(Pleasant Days)				0.27***			0.19***
				(0.07)			(0.07)
Small Cities	0.03	−0.02	−0.02	−0.00	0.01	−0.01	0.04
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
I[year>1994]×Small Cities	−0.13**	−0.22***	−0.24***	−0.15***	−0.18***	−0.21***	−0.12**
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
Big Cities	−0.00	−0.05	−0.04	−0.05	−0.03	−0.04	−0.02
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)
I[year>1994]×Big Cities	−0.06	−0.04	−0.03	−0.07	−0.05	−0.03	−0.08
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Population Growth	2.64**	5.45***	6.62***	2.69**	4.71***	6.33***	2.15*
	(1.23)	(1.33)	(1.36)	(1.22)	(1.37)	(1.41)	(1.22)
I[year>1994] × Population Growth	−9.08***	2.07	2.78	−5.51***	−1.41	0.10	−7.39***
	(1.85)	(2.08)	(2.06)	(1.84)	(2.25)	(2.21)	(1.85)
Observations	79847	79847	79847	79847	79847	79847	79847
R^2	0.17	0.17	0.17	0.16	0.17	0.17	0.17
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Table 8: Glamour Versus Value Cities.

The first column of this table reports Fama-MacBeth regressions of firm returns on area Q fixed effects lagged one year and control variables, where area Q fixed effects are estimated using annual cross-sectional regressions of firm Q on area, industry, and firm age fixed effects. Control variables include firm-level log market equity, log market-to-book, log operating profitability–all measured at the firm's previous year end, and returns lagged six months. The remaining columns report Fama-MacBeth regressions of firm returns on these same controls and two dummy variables–one that equals 1 if a firm was located in an area with one of the top 5 largest Q FE estimate the previous year and is zero otherwise (I[Glamour City]), and one that equals 1 if a firm was located in an area with one of the 5 smallest Q FE estimate the previous year and is zero otherwise (I[Value City]). Columns 1 and 2 reports estimates using the full sample, while columns 3–5 use data from 1975–1989, 1990–1999, and 2000–2015, respectively. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) Ret	(2) Ret	(3) Ret	(4) Ret	(5) Ret
VW Ind Ret	0.56***	0.56***	0.54***	0.51***	0.60***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Q FE (Lagged One Year)	0.30***				
	(0.10)				
I[Glamour City]		0.21***	0.07	0.45**	0.16
		(0.08)	(0.11)	(0.19)	(0.10)
I[Value City]		−0.09	−0.18	−0.13	0.04
		(0.07)	(0.11)	(0.13)	(0.12)
Constant	2.01***	1.97***	2.44***	1.12**	2.15***
	(0.28)	(0.28)	(0.47)	(0.56)	(0.42)
Observations	512827	512827	152387	164233	196207
R^2	0.07	0.07	0.07	0.06	0.07

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Table 9: High Human Capital and Stock Returns.

Panel A of this table reports Fama-MacBeth regressions of firm-level returns on a dummy variable that equals 1 if the firm is located in one of the bottom five areas and a dummy variable that equals 1 if the firm is located in one of the top five areas as ranked by an area's percentage of college graduates in 1970, or the average number of pleasant days per year, or by the sum of these two rankings (index rank). The top five areas as ranked by the percentage of college graduates in 1970 are Denver, Salt Lake City, Washington, San Francisco, San Jose; and the bottom five areas are Louisville, Tampa, Pittsburgh, Providence, Detroit. The top five areas as ranked by the average number of pleasant days are San Jose, San Francisco, Seattle, Los Angeles, San Diego; and the bottom five ares are Nashville, Cincinnati, Salt Lake City, Denver, St. Louis. The top five areas by index rank are San Jose, San Francisco, San Diego, Seattle, and Los Angeles. The bottom five areas are Charlotte, Cincinnati, Nashville, St. Louis, and Louisville. Additional controls include firm-level log market equity from the previous year end, log market-to-book from the previous year end, log operating profitability from the previous year end, and returns lagged six months. Panel B reports regressions of Long-Short Portfolio Returns on the Fama-French Five Factors and a Momentum Factor, where the strategy is to go long on all firms located in one of the top 5 areas and short all firms located in cities in the bottom five areas as ranked by the percentage of college graduates in 1970 (Columns 1 and 2), the average number of pleasant days per year (Columns 3 and 4, and by the sum of these two rankings (Columns 5 and 6). Column 1, 3, and 5 form portfolios using raw returns, while columns 2, 4, and 6 form portfolios on industry adjusted returns, i.e. the firm return minus the firm's corresponding industry's value-weighted portfolio return. Panel B standard errors are Newey-West corrected using six lags. All returns are in percentage terms. The sample for both tables begins in January 1990 and ends in December 2000 to correspond to Figure 8. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Panel A: Fama-MacBeth Regressions

	(1) Ret	(2) Ret	(3) Ret	(4) Ret	(5) Ret	(6) Ret	(7) Ret	(8) Ret
VW Ind Ret	0.51***	0.51***	0.51***	0.51***	0.51***	0.51***	0.51***	0.51***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
% College Grad in 1970	7.67***	7.82***						
	(2.48)	(2.51)						
I[Top 5 Areas by College]			0.56***	0.27*				
			(0.18)	(0.16)				
I[High HC]				0.04				0.02
				(0.10)				(0.11)
I[Top 5 Areas by College] × I[High HC]				0.50*				
				(0.28)				
Log(Pleasant Days)					0.36**	0.37**		
					(0.16)	(0.16)		
I[Top 5 Areas by Pleasant Days]							0.44**	0.14
							(0.18)	(0.16)
I[Top 5 Areas by Pleasant Days] × I[High HC]								0.46*
								(0.24)
Population Growth		−3.18	−2.16	−1.40		0.03	0.67	0.66
		(4.03)	(3.92)	(3.76)		(3.81)	(3.69)	(3.70)
Constant	0.06	0.08	0.99*	0.98*	−0.53	−0.58	0.96*	0.96*
	(0.62)	(0.62)	(0.58)	(0.57)	(0.83)	(0.83)	(0.58)	(0.57)
Observations	158114	158114	158114	158114	158114	158114	158114	158114
R^2	0.06	0.07	0.07	0.07	0.06	0.07	0.07	0.07

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Table 9: High Human Capital and Stock Returns - Cont'd.

Panel B: Six Factor Model

Portfolio Formation:	(1) College LS VW Ret	(2) College LS VW Ret (Ind Adj)	(3) Pleasant Days LS VW Ret	(4) Pleasant Days LS VW Ret (Ind Adj)	(5) Index LS VW Ret	(6) Index LS VW Ret (Ind Adj)
MKTRF	−0.13	−0.07	−0.01	0.03	−0.02	0.05
	(0.09)	(0.06)	(0.09)	(0.06)	(0.10)	(0.06)
SMB	−0.07	0.00	0.12	0.05	0.02	0.03
	(0.08)	(0.08)	(0.09)	(0.06)	(0.09)	(0.05)
HML	−0.88***	−0.64***	−0.26	−0.22**	−0.20	−0.18
	(0.18)	(0.13)	(0.18)	(0.11)	(0.20)	(0.12)
RMW	−0.62***	−0.17*	−0.45**	−0.07	−1.01***	−0.35***
	(0.12)	(0.10)	(0.19)	(0.14)	(0.18)	(0.10)
CMA	0.08	0.24	−0.56***	−0.20	−0.85***	−0.33**
	(0.28)	(0.20)	(0.21)	(0.15)	(0.25)	(0.16)
MOM	0.20**	0.13**	0.21*	0.18*	0.24*	0.20**
	(0.08)	(0.07)	(0.12)	(0.09)	(0.12)	(0.09)
ALPHA	1.01***	0.72**	0.78***	0.40**	0.96***	0.58***
	(0.32)	(0.28)	(0.23)	(0.17)	(0.26)	(0.16)
Observations	132	132	132	132	132	132
R^2	0.71	0.54	0.56	0.43	0.70	0.61

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Appendix

Table A1: Ranking of Firms by 2015 Market Capitalization

This table reports the headquarter location (by CBSA principal city name), market capitalization, IPO year, and founding year for the 50 firms with the largest market capitalization (measured as of their 2015 fiscal year-end) which IPO'd after 1980 and were founded after 1975. Firms headquartered in San Jose, San Francisco, or Seattle are highlighted in gray.

Rank	Name	CBSA	Market Cap.	Founding	IPO
1	Apple Inc	San Jose	615336	1977	1980
2	Alphabet Inc	San Jose	534764	1998	2004
3	Microsoft Corp	Seattle	354392	1975	1986
4	Amazon.com Inc	Seattle	318344	1995	1997
5	Facebook Inc	San Francisco	297758	2004	2012
6	Oracle Corp	San Francisco	166066	1977	1986
7	Home Depot Inc. (The)	Atlanta	157452	1978	1981
8	Cisco Systems Inc	San Jose	144516	1984	1990
9	Gilead Sciences Inc	San Francisco	143892	1987	1992
10	Amgen Inc	Oxnard	122397	1980	1983
11	Unitedhealth Group Inc	Minneapolis	112111	1977	1984
12	Celgene Corp	New York	94203	1986	1987
13	Starbucks Corp	Seattle	84413	1985	1992
14	QUALCOMM Inc.	San Diego	81885	1985	1991
15	Biogen Inc	Boston	66968	1985	1991
16	Priceline Group Inc (The)	Bridgeport	63253	1997	1999
17	Costco Wholesale Corp	Seattle	61335	1983	1985
18	Express Scripts Holding Co	St. Louis	59168	1986	1992
19	Regeneron Pharmaceuticals Inc	New York	56811	1988	1991
20	Blackrock Inc	New York	56389	1988	1999
21	Time Warner Inc	New York	51413	1985	1992
22	EMC Corp	Boston	49896	1979	1986
23	Netflix Inc	San Jose	48948	1999	2002
24	NextEra Energy Inc	Miami	47893	1984	2014
25	salesforce.com Inc	San Francisco	45663	1999	2004
26	Adobe Systems Inc	San Jose	45530	1982	1986
27	Alexion Pharmaceuticals Inc	New Haven	43042	1992	1996
28	Cognizant Technology Solutions Corp	New York	36552	1994	1998
29	Las Vegas Sands Corp	Las Vegas	34837	1988	2004
30	Kinder Morgan Inc.	Houston	33260	1997	2011
31	eBay Inc.	San Jose	32536	1995	1998
32	T-Mobile US Inc	Seattle	32015	1994	2007
33	Tesla Inc	San Jose	31543	2003	2010
34	Altaba Inc	New York	31459	1995	1996
35	Vertex Pharmaceuticals Inc	Boston	30993	1989	1991
36	Intercontinental Exchange Inc	Atlanta	30495	1997	2005
37	LinkedIn Corp	San Jose	29722	2002	2011
38	Intuit Inc.	San Jose	29373	1983	1993

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39	Crown Castle International Corp	Houston	28855	1994	1998
40	Illumina Inc	San Diego	28136	1998	2000
41	DISH Network Corp	Denver	26542	1993	1995
42	Synchrony Financial	Bridgeport	25357	2003	2014
43	Boston Scientific Corp	Boston	24832	1979	1992
44	VMware Inc	San Jose	23870	1998	2007
45	Waste Management Inc.	Houston	23866	1985	1988
46	Ross Stores Inc	San Francisco	22636	1982	1985
47	AutoZone Inc	Memphis	21952	1979	1991
48	Fiserv Inc.	Milwaukee	20606	1984	1986
49	Cerner Corp	Kansas City	20455	1980	1986
50	Intuitive Surgical Inc	San Jose	20426	1995	2000

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Table A2: Fixed Effect Covariation: Growth Variables Versus Assets In Place.
This table reports regressions of the difference in area fixed effects estimates from columns 5 and 6 of Table 2 (Post-1995 minus Pre-1995 estimates) on the difference in area fixed effects from Table 3A and 3B. Regression standard errors are robust to heteroscedasticity and are reported in parentheses. Standard errors are bootstrapped with 1,000 repetitions to correct for using generated regressors. Statistical significance is indicated as follows: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

	(1) Q FE Diff	(2) Q FE Diff	(3) Q FE Diff	(4) Q FE Diff	(5) Q FE Diff
Investment FE Diff	2.93^{***}				
	(0.66)				
R&D FE Diff		3.12^{***}			
		(1.16)			
Equity Iss. FE Diff			3.67^{***}		
			(0.94)		
Op. Inccome/Sales FE Diff				-0.64^{***}	
				(0.17)	
ROA FE Diff					-2.11^{**}
					(0.97)
Constant	-0.07^{**}	-0.08^{***}	-0.08^{***}	-0.09^{***}	-0.10^{***}
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Observations	38	38	38	38	38
R^2	0.35	0.16	0.33	0.24	0.11

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Table A3: Variable Definitions.

This table reports variable definitions. Data sources include the 2006 National Center for Health Statistics Urban/Rural Classification (NCHS), the Bureau of Economic Analysis Regional Economic Accounts (BEA), the Decennial Census of Population and Housing by the U.S. Census Bureau (Census), Compustat North America Fundamentals Annual File (Compustat Annual), and the CRSP Monthly Stock File (CRSP Monthly).

Variable	Description	Source
Tobin's Q	Firm-level annual book debt plus market equity all divided by assets. Specifically, $(AT - LT - PreferredStock + TXDITC + CSHO * PRCC_C)/AT$, where Preferred Stock equals PSTKL or PSTKRV if PSTKL is missing, or PSTK if both PSTKL and PSTKRV are missing.	Compustat Annual
Investment	Firm-level annual capital expenditures divided by the previous year's net property, plant and equipment. Specifically, $CAPX/L.PPENT$.	Compustat Annual
R&D	Firm-level annual R&D expense divided by the previous year's assets. Specifically, $XRD/L.AT$.	Compustat Annual
Operating Income/Sales	Operating income before depreciation divided by revenue. Specifically, $OIBDP/SALE$.	Compustat Annual
ROA	Income before extrodinary items divided by lagged assets. Specifically, $IB/L.AT$.	Compustat Annual
Return	Firm-level monthly stock return.	CRSP Monthly
Area	Firms are classified by headquarter location zipcode (Compustat ADDZIP). Zipcodes are then matched to FIPS codes which are then classified by core-based statistical area (CBSA) and by county type. The areas used in this study correspond to the "large central metro" and "large fringe metro" counties (as classified by the 2006 National Center for Health Statistics Classification Scheme) surrounding the principal cities of CBSAs with at least five firm observations per year for each year of the sample. This results in 38 areas/principal cities.	Compustat Annual, NCHS, Census
2-Digit SIC Code	The first two digits of a firms historical Standard Industrial Classification (SIC) code as recorded by CRSP's SICCD. Industries with less than five observations per year across all years are classified as 2-Digit SIC Code 99, or "Nonclassifiable Establishments." This yields 27 industries.	CRSP Monthly
Population	Annual area population	BEA
Population Growth	Year-on-year log difference in area population.	BEA
Wage Per Employee	Annual area wages and salaries divided by annual area total wage and salary employment.	BEA

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% of College Graduates	Percentage of population 25 and over with at least 4 years of college.	Census
Median House Value	Median dollar value of owner occupied housing units.	Census
Avg. July Temperature	Average area July temperature over the years 19712000.	NOAA
Avg. July Heat Index	Average area July heat index over the years 19712000. The heat index combines the average July daily high air temperature and relative humidity in an attempt to determine the human-perceived equivalent temperature.	NOAA
Asset Pricing Factors	Fama-French 5 factors (Rm-Rf, SMB, HML, RMW, CMA) and the Carhart momentum factor (MOM).	Ken French's Data Library

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