Urban Density and Firms' Stock Returns

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Abstract

Firms located in dense urban areas experience higher productivity due to the flow of ideas and innovation in these areas. Through this productivity channel, the urban density characteristics of the areas in which firms are located affect their stock returns. We use high-resolution satellite images from Google Earth to develop an exogenous measure of potential density increases (PDIs) for the 95 most populated metropolitan statistical areas (MSAs) in the US. This measure represents the proportion of the total area within a one-hour drive from the center of the MSA that could rapidly increase its building density. We find that firms located in areas with high PDIs present lower stock returns. On average, a 10% higher PDI for an MSA results in 0.33% lower excess stock returns for firms located in that MSA.

Keywords: Stock returns; productivity; urban density.

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1 Introduction

Agglomeration –the productivity gains that arise from clustering production and workers– is one of the main reasons for the existence of cities. Agglomeration advantages result in firms and workers being more productive in dense urban areas than elsewhere (Marshall (1890); Sveikauskas (1975); Rauch (1993); Rosenthal and Strange (2004); Combes et al. (2012)). These productivity gains are driven by knowledge spillovers that accelerate the adoption of new technologies, the increase in opportunities from specialization, and the existence of economies of scale and low transportation costs (Davis et al. (2014)). As a result, firms invest and grow more (Dougal et al. (2015)), and they can generate more revenue (Glaeser et al. (2001)) by locating closer to the center of dense urban areas. Although there is evidence of this location–productivity relationship and as well as a link between firms' productivity and stock returns, there is no study in the asset pricing literature that analyzes whether and how the urban density characteristics of the areas in which firms are located affect stock returns.

In order to address this gap in the literature, we explore the effects of the density characteristics of the urban areas in which firms are located on their expected excess stock returns. We use density of buildings at the micro level as our main measure of urban density. Throughout the paper, we use "density", "urban density", and "building density" indistinctively. Using high–resolution satellite images from Google Earth we develop an exogenous measure of potential density increase (PDI) for the 95 largest metropolitan statistical areas (MSA) in the US. MSAs are geographical entities defined by the U.S. Office of Management and Budget that contain a core urban area with a population of 500,000 or more. Each MSA consists of a core urban area as well a set of adjacent counties that exhibit a high degree of social and economic integration with the urban core (i.e., counties with a large number of commuters to the urban core). We estimate the PDI as the proportion of the total area within a one–hour drive from the center of the MSA that could rapidly increase its building density. Furthermore, we develop a measure of the non–potential density increase (NDI) for each of the 95 MSAs in order to control for land availability. The NDI for a specific

MSA is defined as the proportion of the total area within a one–hour drive from the center of the MSA that cannot rapidly increase its building density, either because it is already highly dense or because it cannot be developed due to natural conditions (e.g., highly sloped terrain, lakes, rivers).

We use firm–level data for 2,711 firms to investigate whether urban density characteristics cause an increase or a decrease in firms' expected stock returns. Our characterization of urban density goes beyond extant measures of urban density in the literature, such as total population, population density, and population–weighted density (Glaeser et al. (2005); Maantay et al. (2007); Mennis (2003); Sutton et al. (2003)), which is concerned with the current level of density and do not account for flexibility in building and increasing the urban density of an MSA. Moreover, is captures the expected future change in density of the area. We show that there is a statistically significant cross section of stock returns for firms located in these MSAs.

Our main findings can be summarized in two sets of results. First, we study the link between firms' productivity and the cross section of stock returns following İmrohoroğlu and Tuzel (2014). We provide statistically significant evidence of this link by showing that firms located in fast–growing MSAs with high PDIs exhibit higher productivity. Second, we analyze the relationship between urban density characteristics and the cross section of stock returns, and we present new evidence regarding this relationship. We find that firms located in areas with high PDI present lower stock returns. This result demonstrates the importance of being located in an MSA that can grow and quickly increase its density. We empirically show that a 10% higher PDI results in 0.33% lower excess stock returns for firms located in that MSA.

We show that by increasing innovation, productivity at the firm level is the channel that drives the causal effect between the urban density characteristics of the area in which a firm is located and its stock return. We demonstrate that there is a link between firms' innovation – measured, for example, as firms' R&D expenditures – and their productivity.

This mechanism is explained through the large flow of ideas and innovation in dense urban areas and, therefore, it is linked to higher R&D expenditures – for firms located in these areas (Sun et al. (2017)). We document a positive and statistically significant influence of firms' R&D expenditure on their productivity.

Our empirical results indicate that building a portfolio with a long position on firms with low productivity and a short position on highly productive firms provides a positive annualized alpha of 7.83% in a four–factor model using value–weighted portfolios. We obtain lower and not statistically significant return spreads for equal–weighted portfolios.

Our goal is to identify the causality between the urban characteristics of the areas in which firms are located and firms' stock returns, which is consistent with the idea that location influences firms' productivity and expected stock returns. Therefore, we require an exogenous source to capture the characteristics of urban density in different areas. Our measure of PDI is exogenous because the urban density characteristics of an MSA do not change as fast as stock returns over time. However, we adapt the instrumental variable (IV) approach developed by Himmelberg et al. (2005) and Mian and Sufi (2011) to address potential concerns about the endogeneity of the PDI measure in our estimations. We instrument our measure of PDI using the interaction between local housing supply elasticity and long–term interest rates to identify changes in housing demand. We also control for the interaction between the supply constraint and time, in both first and second stage regressions of our IV specification to address the criticism of this instrument (see Davidoff et al. (2016)). Our results are robust to this identification strategy.

Our paper contributes to two growing strands of literature that study the connections among firms' location, their economic activity, and their financial performance. First, we contribute to the urban economics literature that studies the importance of geographic proximity and externalities in specialized workers, suppliers, and infrastructure (Krugman (1991)) and the effect of previous urbanization in new development (Burchfield et al. (2006)). Henderson (2003), Combes et al. (2012), and Roca and Puga (2017) find a positive relationship between the size of the city and the higher productivity of establishments located in them, as well as higher workers' earnings. Building on the classical urban economics theory, Duranton and Puga (2004) define the city as the equilibrium outcome of the trade–off between the gains from sharing the fixed costs of a facility (e.g., real–estate assets and infrastructure) among a larger number of consumers, which increases the returns through agglomeration economies and the costs through urban congestion. Consequently, a larger workforce leads to a more than proportionately higher level of output because of the constant elasticity of substitution aggregation among final producers. This happens in dense areas because the sharing of indivisible facilities is more efficient (i.e., lower risks; gains from variety and specialization; better matching among employers and employees, buyers and suppliers, partners in joint projects, or entrepreneurs and financiers; and facilitated learning about new technologies, market evolution, or new forms of organization.) Moreover, Carlino et al. (2007) find that patent intensity – the per capita invention rate – is positively related to the density of employment in highly urbanized portions of metropolitan areas. This result suggests that density is a key component of the knowledge spillovers and innovation that power economic development and growth. Building upon this empirical finding, Davis et al. (2014) study the effect of local agglomeration on aggregate growth by modeling agglomeration as an externality in which the total factor productivity (TFP) at a location increases with the location's output density (i.e., the total output per acre of finished land). Denser, more productive acres of land present greater variety because more intermediate service producers can break even. This connection between density and variety yields an expression for the production of composite services in which labor productivity increases with variety. With density leading to variety and variety leading to productivity, Davis et al.'s (2014) model provides a reduced–form relationship between density and productivity.

Second, our paper is related to the asset pricing literature that investigates the factors that affect firms' expected stock returns. Gomes et al. (2003); Zhang (2005); Belo and Lin (2012); Novy-Marx (2013); and Belo et al. (2014) study how firms are exposed to firm–

level TFP shocks, which lead to different firm characteristics and, consequently, to different expected returns. İmrohoroğlu and Tuzel (2014) is the closest paper to our study. They provide evidence of a negative link between the firm–level TFP and the cross section of expected stock returns. Building on this body of literature, we show that the part of TFP explained by PDI has a negative effect on firms' stock returns. In summary, the urban density characteristics of the area in which the firm is located – in terms of potential for building density increase which is the focus of this paper – influences the firm's innovation and, eventually, its productivity. Subsequently, the characteristics of urban density affect the firm's stock return through this productivity channel.

2 Hypotheses Development

The focus of this paper is primarily empirical. However, in the Appendix, we present a stylized conceptual framework to illustrate the key effects of urban density on firms' stock returns and to develop testable hypotheses.

The first prediction builds on the literature that analyzes the effects of density on innovation and suggests that the effects of creative capital on innovation (i.e., creative spillovers) increase with the density of the metropolitan area. For example, Carlino et al. (2007) and Knudsen et al. (2008) document a positive relationship between the density of creative workers and the metropolitan patenting activity. Their results show that density is a key component of the knowledge spillovers and innovation that power economic development and growth. Moreover, recent general equilibrium models of cities show the effect of local characteristics of density on aggregate growth and provide a reduced–form relationship between density and productivity. Davis et al. (2014) model agglomeration as an externality in which the TFP at any location increases with the location's output density. They show that denser, higher–productivity acres of land have greater variety and provide a reduced–form relationship between density and productivity.

Building on this literature, we expect that firms located in dense areas with high potential for density increase have higher TFP and are more productive. Hypothesis 1 outlines this prediction. Moreover, we empirically explain this effect on firms productivity through firm-level R&D, which represents the level of innovation in the corresponding area.

Hypothesis 1 (H1) *Firms located in fast-growing areas with high potential for an increase in urban density are more productive.*

There is a negative relationship between firm–level productivity and expected returns, as in İmrohoroğlu and Tuzel (2014). The mechanism behind this negative relationship works as follows. In our model, shocks in aggregate productivity drive the business cycle. When aggregate productivity is low, firms invest less and hire less. Even though firms can freely adjust their labor, they incur adjustment costs when they change their capital stock. Hence, an inability to adjust firms' capital following shocks to aggregate and firm–level productivity makes firms riskier. As adjustment costs are convex, low TFP firms must pay a higher cost (relative to their output) when reducing their capital stocks in periods of low aggregate productivity than high TFP firms.[1] In contrast, a positive shock in aggregate productivity drives a larger decrease in adjustment costs for low TFP firms than for high TFP firms. Therefore, the returns of low TFP firms covary more with changes in economic conditions during periods of low aggregate productivity.

As the volatility of the stochastic discount factor is a decreasing function of aggregate productivity, discount rates are higher during periods of low aggregate productivity. The covariance between returns and the stochastic discount factor defines the level of risk. Higher volatility in the stochastic discount factor implies higher covariance between returns and the stochastic discount factor and, as such, higher risk in periods of low aggregate productivity. Low productive firms are riskier because they invest less during recessions when discount

[1] Low TFP firms are on a steeper part of the convex adjustment costs curve. Hence, in periods of low aggregate productivity, a bad shock tends to have a larger negative effect on the low TFP firms than on the high TFP firms. As a result, low TFP firms should have lower investment rates and reduce their capital stocks relatively more.

rates are high. Therefore, low productivity firms present the higher expected returns during periods of low aggregate productivity. In contrast, high TFP firms tend to invest more during periods of high aggregate productivity when discount rates are low. Hence, their expected stock returns are lower. Hypothesis 2 summarizes this prediction.

Hypothesis 2 (H2) *Firms located in fast–growing areas with high potential for a density increase have lower expected stock returns.*

The second prediction builds on the literature that studies the role of human capital and education in innovation (see Sun et al. 2017). We show how firms benefit from knowledge spillovers in these areas and become more productive. Consistent with the previous literature, we use TFP as a measure of firm productivity and we test whether the addition to a firm's R&D caused by the potential density increase of the area in which the firm is located results in a higher level of productivity for that firm.

Our conceptual model and the obtained numerical results confirm our theoretical hypotheses and certify the importance of taking into account the urban density characteristics in terms of potential for density increase of the MSA in which the firm is located when studying its productivity and stock return (see Appendix A). We now empirically test these hypotheses.

3 Data

In this section, we describe the data that we use for our empirical analysis. First, we explain how we create our measure of potential density increase (PDI). Second, we characterize the firm–level data that we use in our empirical analyses. Finally, we provide details about the MSA–level data.

3.1 Measure of potential density increase

There is a body of literature on capturing urban characteristics and studying changes in physical appearances at the city level. The static measure of land availability has recently been used in the urban economics literature was created by Saiz (2010). Saiz (2010) uses satellite–generated data on terrain elevation to develop a measure of the amount of developable land based on the presence of water bodies and steep–sloped terrain in US MSAs. He demonstrates that topographical constraints correlate positively and strongly with regulatory barriers to development, and that both types of constraints negatively affect supply elasticity. Other recent papers also propose dynamic measures. Naik et al. (2016) study changes in the physical appearance of neighborhoods using street–level imaginary. Their results show how computer vision techniques in combination with traditional methods can be used to explore the dynamics of urban change. Furthermore, Henderson et al. (2016) argue that durable formal–sector buildings can be built high, unlike informal ones, which are malleable. They study this idea using the average height of buildings by grid square in the formal and slum sectors.

In this subsection, we develop a computer vision method to measure characteristics of urban density in the sense of potential density increase in US metropolitan areas taking geographical constraints into consideration. We define density as the density of buildings in a given area and We segment images into four geometric classes: undevelopable areas, highly developed areas, developed areas, and low developed areas.

First, we define the whole polygon in each MSA that is estimated to be within one–hour driving distance by car from the MSA's center [2] along the main existing roads. We allow for maximum time variation based on the current traffic information available from Google Maps. This captures the willingness to spend about one hour commuting between work and residential placements, which leads to a distinct polygon for each city based on

[2] We consider as the center of the MSA the city hall of the largest city of that MSA as the headquarters of the city or town's administration or the town council.

traffic congestion and geographical disturbances. Afterwards, we name water bodies, natural reserves, and steep–sloped terrain as fully restricted parts for any further construction. The highly developed areas account for the fully packed areas and are usually located around the central business district of the MSA. Developed areas represent the parts that have already been developed to some extent but still offer more opportunities for further growth in density. Finally, low developed areas within each MSA polygon are plain and empty lands.

The development of our measure of potential density increase (PDI) for 95 US MSAs consists of two main steps: (1) the definition of the areas within the MSA; and (2) the calculation of the PDI measure. In the following, we describe these steps.

We use high–resolution satellite images from Google Earth in order to define four types of subareas within each MSA.

- Highly developed (HD) areas. These are fully packed urban areas that are characterized by the substantial existence of tall buildings, residential areas, or commercial areas, where the observable available space for new developments is negligible.

- Developed (D) areas. These areas correspond to semi–urban areas that are characterized by the existence of residential or commercial areas surrounded by some observable available space for new constructions.

- Low developed (LD) areas. These correspond to zones of empty land that are available for construction, accounting for a large amount of the total space analyzed. This area is mainly characterized by plains.

- Undevelopable (U) areas. These are fully restricted areas and natural reserves. Protected areas include lakes, rivers, and in many cases mountains as well as national parks.

Figure 1 shows some examples of aerial views of these types of areas.

[Insert Figure 1 around here]

First, we exclude undevelopable areas from the area of study to obtain an input image for each MSA. We use a computer vision algorithm in Matlab to determine the exact number of square kilometers for each type of area (i.e., HD, D, and LD). This algorithm classifies the different types of areas using a process of image segmentation by color using an input image of the MSA from Google Earth. Input images for each MSA are manually prepared by determining the whole polygon within a one–hour drive from the center of the MSA using Google Earth, excluding undevelopable areas. Figure 2 provides an example of input and output images for New York.

[Insert Figure 2 around here]

We then define and estimate our measure of potential density increase (PDI) for each MSA. We assume that developed areas (D) within each MSA present more opportunities for a quick increase in urban density. This is due to the fact that existing infrastructure and services make land development and construction cheaper and faster. Accordingly, PDI is estimated by dividing the total developed area (D) in the MSA by the sum of the total developed (D) plus low developed (LD) areas:

$$PDI = \frac{area_D}{area_D + area_{LD}}. \tag{1}$$

Cities with high PDIs, such as Chicago and Los Angeles, have many developable areas where density could be increased quickly and easily. On the other hand, a low PDI is found for cities with a large amount of empty land, like Charlotte and Louisville. Column 1 of Table 1 reports the PDI values for all 95 MSAs.

3.2 Firm–level data

At the firm level, we use data on company names and zip codes from Compustat. Then, we link this data to the MSA in which each company is located. Using the mapping table between zip codes and MSA codes developed by the U.S. Department of Labor's Office of

Workers' Compensation Programs (OWCP), we match the zip codes from the two files to obtain the company's location.

To estimate firms' productivity, which is the dependent variable in our first hypothesis, we use several key variables, such as firm–level value added, employment, and capital. We compute the firm–level value added using Compustat data on sales, operating income, and employees, deflated using the output deflator. The stock labor is given by the number of employees (EMP), while firm–level capital stock is given by the gross plant, property, and equipment (PPEGT), both from Compustat. The detailed explanation of our estimates of firms' productivity is provided in section 4.1.

We use data on monthly stock returns – the dependent variable in our second hypothesis – from the Center for Research in Security Prices (CRSP). In calculating future returns, we match the CRSP stock–return data from July of year t to June of year t+1 with accounting information for the fiscal year ending in t–1, as in Fama and French (1992) and Fama and French (1993). We do so in order to ensure that the accounting information is already reflected in the stock prices. Then, we compute the excess expected stock returns by considering four Fama and French factors: the excess market returns (MKT); the return of the portfolio that is long in small firms and short in big firms (SMB); the return of the portfolio that is long in high–B/M firms and short in low–B/M firms (HML); and the momentum factor (MOM), which is the return of the portfolio that is long in short–term winners and short in short–term losers.

Moreover, in line with the finance literature, we control for several important variables at the firm and MSA levels. At the firm level, we control for the firm size, computed as the market capitalization (number of outstanding shares multiplied by the share price). We calculate corporate real–estate holdings as the sum of building plus capitalized leases, all divided by net property, plant, and equipment (PPE), in accordance with Tuzel (2010). Leverage is computed as long–term debt (DLTT) divided by the sum of DLTT and the market value of equity. We calculate asset growth as the percentage change in total assets, and inventory growth as the percentage change in total inventories. The hiring rate is defined as the difference between the current and the lagged stock of labor (EMP) divided by the lagged stock of labor (EMP). R&D expenditure is computed as research and development expenses (XRD) divided by the gross PPE. We calculate ROA as net income (IB) minus dividend on preferred (DVP) plus income statement deferred taxes (TXDI), all divided by total assets (TA). ROE is calculated as income before extraordinary items (IB) over total stockholders' equity (CEQ), while the market–to–book ratio is calculated as the firm's market value over its value. We use data from Compustat for all of these variables. Finally, we measure the firm's age as the number of years since the firm's first year of observation in Compustat.

3.3 MSA–level data

At the MSA level, we control for population density as a proxy for agglomeration used in the extant literature (Glaeser et al. 2005; Maantay et al. 2007; Mennis 2003; Sutton et al. 2003). We use the data from the US Census Bureau to compute population density as the number of inhabitants in the MSA divided by the total MSA area (in square kilometers). In order to control for real–estate prices, we obtain the residential home price index (HPI) from the Federal Housing Finance Association (FHFA). We use the 30–year conventional mortgage rate from the St. Louis Federal Reserve Bank (FRED) as a measure of the long-term interest rate for the real–estate market. We also use the local housing supply elasticities provided by Glaeser et al. (2008) and Saiz (2010), which are available for 95 MSAs. These elasticities capture the amount of developable land in each metro area, and are estimated using satellite–generated data on elevation and the presence of water bodies. Moreover, we create a measure to control for the amount of land for which it is very costly or impossible to increase its density, which is equivalent to the areas that are either highly developed or undevelopable (i.e., highly sloped terrains, lakes, rivers). This measure refers to the fraction of non–potential density increase (NDI) in each MSA and is calculated as the sum of all highly developed areas in the MSA, $area_{HD}$, plus all undevelopable areas, $area_U$, as a proportion of the total area of the polygon within a one–hour drive from the city center. Therefore, cities with a lot of highly developed or/and undevelopable areas present high values of NDI, as they are dense cities with substantial geographical constraints on further construction, such as San Francisco.

Table 1 reports our two measures of urban density for all MSAs in the US. with more than 500,000 inhabitants. The MSAs are sorted by PDI measure from high to low.

[Insert Table 1 around here]

We use our measure of PDI as the main independent variable. Our sample is comprised of all firms in Compustat that have positive data on sales, total assets, number of employees, gross property, plant, and equipment, depreciation, accumulated depreciation, and capital expenditures. As is standard in the literature (see Chaney et al. 2012; Cvijanović 2014), we omit firms active in the finance, insurance, real–estate, non–profit, government, construction, or mining industries. This leaves us with an unbalanced panel containing 2,711 distinct firms spanning the years from 2010 to 2014.

Table 2 provides the summary statistics of all variables in our empirical analyses.

[Insert Table 2 around here]

4 Empirical Strategy and Empirical Results

In this section, we present and discuss our empirical strategy and our main empirical results. First, we estimate total factor productivity at the firm level. Second, we show that potential for density increase in an area has an effect on productivity at the firm level. Finally, we study the causal effect of PDI on asset prices.

4.1 Estimating total factor productivity (TFP)

TFP is a measure of the overall effectiveness with which capital and labor are used in the production process. It provides a broader gauge of firm–level performance than some of the more conventional measures, such as labor productivity or firm profitability.[3] We estimate the production function given in:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \nu_{it}, \tag{2}$$

where y_{it} is the log of value added for firm i in period t. Let l_{it} and k_{it} be the log values of the firm's labor and capital, respectively; ω_{it} is the productivity; and ν_{it} is the error term, which is not known by the firm or the econometrician. We employ the semi–parametric procedure suggested by Pakes and Olley (1995) to estimate the parameters of this production function. The major advantages of this approach over more traditional estimation techniques, such as ordinary least squares (OLS), are its ability to control for selection and simultaneity biases, and to deal with the within–firm serial correlation in productivity that plagues many production function estimates.

After we have estimated the production function parameters ($\widehat{\beta}_0$, $\widehat{\beta}_l$, and $\widehat{\beta}_k$), we obtain the firm–level (log) TFP from:

$$w_{it} = y_{it} - \widehat{\beta}_0 - \widehat{\beta}_l l_{it} - \widehat{\beta}_k k_{it}, \tag{3}$$

in which firm–level data are supplemented with the price index for the gross domestic product as a deflator for the value added, the price index for private fixed investment as a deflator for investment and capital (both from the Bureau of Economic Analysis), and the national average wage index from the Social Security Administration. Value added is computed as (sales

[3] Profitability captures only the part of the value added that is distributed to shareholders, and labor productivity can be an adequate measure of overall efficiency, especially in capital–intensive industries. See Lieberman and Kang (2008) for a case study of a Korean steelmaker showing the differences between TFP and profitability in measuring firm performance.

– materials), deflated by the GDP price deflator. Materials are calculated as (total expenses – labor expenses), which is equal to (sales – operating income before depreciation (OIBDP) – total stuff expense (XLR)). Therefore, we compute value added as (operating income before depreciation (OIBDP) + total stuff expense (XLR)), all gathered from Compustat. Stock labor, calculated as the number of employees (EMP), is available from Compustat. Capital stock is computed as property, plant, and equipment total – gross (PPEGT), deflated by the price deflator for investment, following Hall (1993). In the estimation, we use industry-specific time dummies. Hence, our firms' TFPs are free from the effects of industry or aggregate TFP in any given year.

4.2 Urban density characteristics and firms' productivity

In this section, we show that by increasing innovation, productivity at the firm level is the channel that drives the causal effect between the potential for density increase of the area in which a firm is located and its stock return. We demonstrate that there is a link between firms' innovation – measured, for example, as firms' R&D expenditures – and its productivity. This mechanism is explained through the large flow of ideas and innovation in dense urban areas and, therefore, it is linked to higher R&D expenditures for firms located in these areas (Sun et al. 2017). We confirm that firms' R&D expenditures have a positive and statistically significant influence on their productivity. Consequently, we estimate TFP, that is $Productivity_{it}^{l}$ of firm i with headquarters located in area l at time t as:

$$Productivity_{it}^{l} = \alpha_i + \beta.PDI/R\&D(PDI)_{it}^{l} + Controls_{it}^{l} + i.year + i.industry + i.state + \epsilon_{it}. \tag{4}$$

Table 3 provides the summary results for the effects of our urban density measures and R&D on firms' productivity. The dependent variable, productivity, is measured as a firm's TFP, which is explained in the previous section. $Controls_{it}$ denotes two sets of controls: firm–level controls and MSA–level controls. In line with the extant literature on productivity, at the firm level, we control for: (1) leverage; (2) firm size; (3) asset growth; (4) inventory growth; (5) hiring rate; (6) return on assets (ROA); (7) return on equity (ROE); (8) market–to–book ratio; (9) corporate real estate holdings; and (10) company age. At the MSA level, we control for: (1) NDI measure; (2) residual housing price index; and (3) population density. We also control for the year fixed effect, the industry fixed effect, and the state fixed effect. Standard errors clustered at the month–year level to account for the high persistent of PDI due to the the short time period of our study.

In Column [1] of Table 3, we find that, on average, a 10% higher PDI of an MSA results in 2.18% higher productivity among firms located in that MSA. Column [2] shows the results for the specification in column [1], while controlling for land availability using the NDI measure. An additional analysis that helps explain the mechanism is reported in column [3]. We find that a firm's R&D expenditure has a positive and statistically significant effect on its productivity through our measure of PDI. To show this effect, we calculate the part of the firm's R&D that comes from urban density by estimating the fitted values of the firm's R&D on PDI: R&D (PDI). We also control for the fitted values of the firm's R&D on NDI: R&D (NDI). Accordingly, we obtain a positive and statistically significant effect of R&D (PDI) on the firm's productivity. We find that, on average, a 10% increase in R&D (PDI) results in 4.39% increase in the firm's productivity (see column [3]).[4]

To address potential concerns about the PDI measure being endogenous to real–estate prices, we adapt the IV approach developed by Himmelberg et al. (2005) and Mian and Sufi (2011). We instrument our measure of potential density increase, PDI, using the interaction between the elasticity of supply of the local housing market and the long–term interest rate to pick up changes in the housing demand. The economic intuition behind this interaction goes as follows. When interest rates decrease, demand for housing increases. As markets can adjust prices and quantities, this increase in demand leads to higher real estate prices

[4]Note that urban density characteristics, geographical constraints, and the limitations of an MSA change rapidly over time. Therefore, we use our two measures, PDI and NPI, as approximately constant proxies for urban density characteristics of each MSA in a reasonable period of five years (2010 to 2014).

in areas where supply is more inelastic. On the other hand, very constrained land supply MSAs are the areas where present low values of local housing supply elasticity (i.e., they are inelastic.) Therefore, we expect that a decline in interest rates will produce a higher increase in house prices in MSAs with lower elasticity of supply which means less potential for the density increase. We use the local housing supply elasticities provided by Glaeser et al. (2008) and Saiz (2010), which are available for 95 MSAs. These elasticities capture the amount of developable land in each metro area, and are estimated using satellite–generated data on elevation and the presence of water bodies. As a measure of long–term interest rates for the real–estate market, we use the 30–year fixed conventional mortgage rate from the St. Louis Federal Reserve Bank (FRED) website between 2010 and 2014.

This instrument has been used widely to address endogeneity issues related to real–estate prices in the finance and real estate economics literature. To study housing bubbles, Himmelberg et al. (2005) instrument local house prices using the interaction of local housing-supply elasticity and long-term interest rates. Mian and Sufi (2011) use the same instrument for house prices to analyze household leverage. Moreover, Chaney et al. 2012 and Cvijanović 2014 use this instrument for commercial real estate prices in their study of firms investments and leverage.

This is a good instrument for our empirical strategy for two reasons. First, the IV is correlated with our measure of potential density increase. The results of the first–stage regression shows the instrument is statistically significant at the 5% level and, as expected, has a negative effect on both PDI and TFP(PDI). Second, this IV doesn't have any relationship with firms' productivity or stock returns.

We estimate the following first–stage regression to predict PDI measure, PDI^l, for location l:

$$PDI^l = \alpha_i + \gamma.Elasticity^l.IR + Controls^l_{it} + i.year + i.industry + i.state + \epsilon_{it}. \tag{5}$$

where $Elasticity^l$ measures the constraints on the land supply at the MSA level and IR measures the nationwide real interest rate at which banks refinance home loans. $Controls_{it}$ is the same as in previous specifications. We also control for the year fixed effect, the industry fixed effect, and the state fixed effect. Standard errors clustered at the month–year level to account for the high persistent of PDI. Moreover, we address the criticism of this instrument in Davidoff et al. (2016) by controlling for the interaction between the supply constraint and year in the first stage as well as in the second stage IV specification. [5]

Columns [4] and [5] in Table 3 show the results of the implementation of our IV strategy. We consistently find that, on average, a 10% higher PDI for an MSA results in 4.39% higher productivity for firms located in that MSA (column [4]). Finally, column [5] confirms the positive and statistically significant effect of R&D on firms' productivity through PDI while using our IV strategy. We find that, on average, a 10% increase in firms' R&D (PDI) results in 6.20% higher productivity.

[Insert Table 3 around here]

4.3 Asset–pricing implications of urban density

Our empirical strategy adapts the analyses undertaken by İmrohoroğlu and Tuzel (2014) to study the link between firms' productivity and the cross–section of expected excess stock returns. We create ten portfolios sorted by the part of firms' productivity that comes from potential for density increase, that is, the TFP fitted values on PDI, TFP (PDI).[6] In this section, we investigate whether widely used asset–pricing models, such as the capital asset–pricing model (CAPM) and the Fama–French (FF) four–factor (MKT, SMB, HML, and

[5] Davidoff et al. (2016) mentions that the housing supply elasticity in the study by Saiz (2010) could be an invalid instrument, as it reflects both supply and demand factors. He argues that the orthogonality condition of supply of elasticity is unlikely to be satisfied because land availability and land-use regulations are likely to be correlated with local demand for real estate assets. To address this concern, we control for the interaction of the supply constraint and time, as discussed in his paper.

[6] The regression analysis of TFP on PDI, considering all the other controls including NDI, is used to predict the TFP (PDI).

MOM)[7] model, capture the variation in excess returns of the TFP fitted value on PDI, TFP (PDI)–sorted portfolios. Table 4 presents the alphas and betas of TFP (PDI)–sorted portfolios for the CAPM and FF four–factor models. The betas are estimated by regressing the portfolio's excess stock returns on the factors. The alphas are estimated as intercepts from the regressions of excess portfolio returns. The top half of the table reports the results for the equal–weighted portfolios, and the bottom half reports the value–weighted portfolio results.

[Insert Table 4 around here]

In the top half of the table, which focuses on equal–weighted portfolios, we find that low–TFP portfolios load heavily on SMB, whereas the loadings of the high–TFP portfolios are low. The loadings on HML are non–monotonic and not always statistically significant. The equal–weighted low portfolios have a significantly lower loading on MKT than the high–TFP portfolios, whereas the value–weighted portfolios show this effect non–monotonically. Neither the CAPM nor the Fama–French four–factor model completely explain the return spread: the high–low TFP portfolio has an annualized alpha of –7.83% (–10.16%) in a four– (one–) factor model using value–weighted portfolios, and both spreads are statistically significant. Overall, these results indicate that, building a portfolio with a long position on firms with low productivity and a short position on highly productive firms provides a positive annualized alpha of 7.83% (10.16%) in a four– (one–) factor model using value–weighted portfolios. The spread in the average returns across these portfolios is explained by the risk premium associated with the higher risk of low TFP firms. We obtain lower and statistically non–significant return spreads for equal–weighted portfolios.[8]

[7] MKT is the excess market return; SMB is the return on a portfolio that is long in small firms and short in big firms; HML is the return on a portfolio that is long in high B/M firms and short in low B/M firms; and MOM is the average return on two high prior return portfolios minus the average return on two low prior return portfolios (Fama and French 1992 and Fama and French 1993, among others).

[8] Harvey et al. 2016 claim that "a new factor needs to clear a much higher hurdle rate, with a t-statistic greater than 3.0." All the t-statistics for the beta when sorting portfolios according to our new factor are higher than 4.9 for equally-weighted portfolios and higher than 4.3 for value-weighted portfolios, except for the lowest decile portfolio coefficient, which presents a t-statistic of 2.6.

We also run regressions of monthly expected excess stock returns on the lagged firm–level TFP and urban density as well as other control variables. The estimates of the slope coefficients in these regressions allow us to determine the magnitude of the effect of potential density increase on excess stock returns. In all of the specifications, the dependent variable is the residual of regressing excess monthly stock returns on the four Fama–French factors.

We run our analysis by considering PDI as a proxy for potential density increase of each MSA. Accordingly, we run the following specification for a firm's expected excess stock return, Ret^{l}_{it+1}:

$$\begin{aligned} Ret^{l}_{it+1} = \alpha_i + \beta.PDI/TFP(PDI)^{l}_{it} + Controls^{l}_{it} + i.year + i.industry + \\ i.state + \epsilon_{it}. \end{aligned} \tag{6}$$

Table 5 presents the results of the analysis of the effect of our PDI measure on firms' stock returns. $Controls_{it}$ denotes two sets of controls: firm–level controls and MSA–level controls. At the firm level, we control for: (1) leverage; (2) firm size; (3) asset growth; (4) inventory growth; (5) hiring rate; (6) return on assets (ROA); (7) return on equity (ROE); (8) market–to–book ratio; (9) corporate real–estate holdings; (10) the firm's R&D expenditure; and (11) company age. At the MSA level we control for (1) NDI measure; (2) residual housing price index; and (3) population density. We also control for the year fixed effect, the industry fixed effect, and the state fixed effect. Standard errors clustered at the MSA level.

In Column [1] of Table 5, we study the effect of PDI while controlling for firms' TFP to capture firms' productivity and NDI to capture land availability. The coefficient of PDI is negative and statistically significant. Furthermore, we provide empirical evidence that productivity is the channel that drives this effect by increasing innovation. Column [2] shows the effect of PDI on stock returns through the productivity channel. The coefficient of the part of productivity caused by PDI, TFP (PDI), is negative and statistically significant at the 1% level. We obtain this result by calculating the fitted values of TFP on PDI. We predict the estimated fitted values of TFP on PDI of the MSA in which the firm is located by regressing a firm's TFP on our measure. Moreover, columns [3] and [4] report the results when we implement the IV strategy in the regressions in columns [1] and [2]. We instrument PDI measure by the interaction between the local constraints on land supply and interest rate, and we control for the interaction between the supply constraint and year in both first and second stage regressions following the detailed explanation of our IV strategy in section 4.2. Eventually,to account for the high persistent of PDI in the short time period of the study, in columns [5] and [6] we re run our regressions of columns [3] and [4] clustering the standard errors at the month–year level and we confirm that our results stay robust addressing this concern.

[Insert Table 5 around here]

Columns [3] and [4] show that our results are robust to using this IV strategy. Specifically, we find that, on average, a 10% higher PDI for an MSA results in 0.33% lower excess stock returns among firms located in that MSA (column [5]). We obtain a statistically significant and negative effect of the part of TFP caused by a potential density increase, TFP (PDI), on firms' excess stock returns. The results show that, on average, a 10% higher TFP (PDI) for a firm results in 1.76% lower excess stock return for that firm. And finally in columns [5] and [6] we report that the magnitude and the statistical significance of these variables remain unchanged.

5 Robustness Tests

In this section, we provide robustness tests for the main results presented in section 4. First, we address concerns regarding the identification of the firm's location, and the fact that firms with higher growth and productivity expectations choose to locate in denser or high–tech cities, which could bias our results. We perform a robustness test by excluding from our analysis firms that changed their headquarters' location at the city level during the period of study. We run a second robustness test to address the concern that big global firms may choose to locate their R&D center in a different area than their headquarters. The results of these two robustness checks are reported in Tables 6 and 7. Finally, we perform a third robustness check in which we examine whether industry affiliation affects firms' needs regarding the innovation, flow of ideas, and spillovers in the area in which they are located. Table 8 reports the results for different industry classifications.

5.1 Choice of headquarters' location

In our firm–level analysis, we identify a firm's location using its headquarters' location as listed in Compustat due to the fact that relevant decisions at the firm level are made at the headquarters. At least three studies validate this fact.

First, Tuzel and Zhang (2017) link their Compustat–CRSP sample to the ReferenceUSA U.S. Businesses Database and collect employment data for all headquarters, branch, and subsidiary locations of the firms in the sample. This allows them to create an employment map for each of roughly 2,000 firms in their linked sample. They find that 63% of the firms in that sample have at least 50% of their employment in the MSA of their headquarters and, for the median firm in their sample, the headquarters' location accounts for 72% of total employment. Consequently, they use the headquarters' location as a proxy for the location of real estate and they identify a firm's location based on its headquarters' location as listed in Compustat. Second, Chaney et al. (2012) argue that headquarters and production facilities tend to be clustered in the same state and MSA, and that headquarters represent an important fraction of corporate real–estate assets. They provide hand–collected information on firms' headquarters ownership using their 10–K files as evidence supporting this assumption and they conclude that headquarters' location is a reasonable proxy for firm location. Third, Garcia and Norli (2012) measure the degree of firms' geographical concentration by extracting state name counts from annual reports filed with the SEC on 10–K files. They report that the activities of U.S. firms tend to be clustered in the same U.S. states as their headquarters.

Although the literature offers some empirical evidence about the validity of identifying the firm's location using its headquarters' location, we perform a robustness test. We run our analyses after excluding all firms that moved their headquarters to a different city during the period of study. Compustat reports the current state and county of firms' headquarters but not their past locations. In order to track headquarters moves during the time of our study, we cross–check the historical SEC records of firms' headquarters using the Edgar fast search program[9] for all companies in our database from 2009 to 2015. We search for all 10–K files and 10–K/A files for all firms in the sample from 2009 to 2015. These files contain the address of the headquarters.[10] Therefore, we can identify all headquarters moves in our sample. We create a dummy variable that takes a value of one if the company has ever moved its headquarters. Less than 22% of the firms in our sample moved their headquarter from one city to another between 2009 and 2015 (i.e., 594 out of 2,711 firms).

Columns [1] and [2] of Table 6 show the results of our main specifications for the entire sample, while columns [1] and [2] of Table 7 report the results after implementing our IV strategy. Columns [3] and [4] of Table 6 show that our results remain robust to excluding these firms. Columns [3] and [4] of Table 7 report these results after implementing our IV strategy. We find that, on average, a 10% higher PDI for an MSA results in 0.39% lower excess stock returns among firms located in that MSA, after excluding all firms that changed their headquarters' location. Similarly, we find a negative and statistically significant effect of the part of TFP caused by the potential density increase (PDI) effect, TFP (PDI), on firms' excess stock returns for this subsample of firms.

We also address the concern that firms with better growth and productivity choose to locate in denser or high–tech cities which experience high growth. To address this potentail

[9]https://www.sec.gov/edgar/searchedgar/companysearch.html

[10]Edgar downloads the "Complete submission text file", which is submitted by all of the companies. It includes the following data: company data (company name, CIK, industrial classification, IRS number, state of incorporation, fiscal year end); filing values, (form type, sec act, sec file number, film number); business address (street 1, city, state, zip, business phone); mail address (street 1, city, state, zip); and former company (former conformed name, date of name change). From this header, we can grab the company data, (company name, CIK) as well as the business and mail address information for that specific year. After all of the information is gathered, the procedure is repeated until the data for all of the companies is complete.

endogeneity problem we follow Almazan et al. (2010). We argue that, given that the unobserved characteristics that may influence a firm's location choice become less important over time, the observed effect on the productivity of older firms that chose locations many years ago is unlikely to arise because of a selection effect. For this reason, it is interesting to explore whether the relationship between firms' stock returns and older firms' locations is consistent with what we observe for the entire sample. In line with Almazan et al. (2010), we report the results of this test in columns [5] and [6] of Table 6 for the subsample of firms that have been public for at least 10 years. The results are similar in magnitude to the results for the entire sample. Columns [5] and [6] of Table 7 report these results after implementing our IV strategy. Consistent with the previous findings, for the subsample of firms that are at least 10 years old, a 10% higher PDI for an MSA results in 0.41% lower excess stock returns among firms located in that MSA. Moreover, to account for the high persistent of PDI, in Table 7, we clustered the standard errors at the month–year level and we confirm that our results remain unchanged – in terms of the magnitude and the statistical significance of the reported variables – in all these regressions.

5.2 Location of firms' R&D centers

There could be a concern that some companies (e.g., global firms) could locate their R&D centers in a different areas than their headquarters. To confirm our argument, we run a robustness test by splitting the sample into small and large firms. We follow Chaney et al. (2012) and define small firms as the subsample of firms in the bottom three quartiles in terms of size and in the top 20 MSAs. Small firms are more likely to be geographically concentrated than large firms. Therefore, we run regressions using only the subsample of small firms.

We show that the effect is statistically significant for the subsample of small firms. The results of this robustness test are reported in Table 6 and Table 7. Columns [1] and [2] of Table 6 report the results for the whole sample, while columns [7] and [8] show the results for the subsample of small firms. In columns [7] and [8] of Table 7, we implement the IV strategy in these regressions. Overall, our results remain robust to this identification strategy. These results also confirm that the effect is statistically significant for the subsample of small as low–value firms in comparison to the big as high–value and global firms that may locate their R&D centers in a different areas than their headquarters. Similarly, we show that after clustering the standard errors at the month–year level to account for the high persistent of PDI our results remain unchanged in terms of the magnitude and the statistical significance of the reported variables.

[Insert Tables 6 and 7 around here]

5.3 Industry classification according to innovation

In this section, we focus on high–tech industries (i.e., innovation firms), which benefit more from the innovation, flow of ideas, and spillovers of the areas in which they are located. Consistent with the literature, we define high–tech firms as those that are active in the electronic computers, electrical machinery, transportation equipment, instruments, software and data processing services industries (see Cortright and Mayer 2001).

We study the effect of potential density increase on the productivity of high–tech firms and their stock returns. Table 8 reports the results of our main specification for different industry classifications. Columns [1] and [2] show the main results for the entire sample, while columns [3] and [4] show the results for the group of firms belonging to the electronic computers, electrical machinery, transportation equipment, instruments, software and data processing services industries (i.e., innovative firms), consistent with the literature. In columns [5] and [6], we see these results for the group of firms that are not in the sample of innovative firms (i.e., less innovative firms). Columns [7], [8], [9], and [10] display the same regressions as columns [1], [2], [3], and [4] when implementing our IV strategy. Similarly, in Table 8, we show that after clustering the standard errors at the month–year level to account for the high persistent of PDI our results remain unchanged in terms of the magnitude and the statistical significance of the reported variables.

Overall, our results show that these effects are stronger for the subsample of high–tech firms, which are the firms that benefit more from innovation and spillover effects. We also show that this effect is not statistically significant for the subsample of less–innovative firms. These results reinforce the finding that by increasing innovation, productivity at the firm level is the channel that drives the causal effect between the urban density characteristics of the area in which a firm is located and its stock return.

[Insert Table 8 around here]

6 Conclusions

The positive effect of agglomeration on productivity has long been documented and quantified by studying spatial patterns in wages and land rents. This positive effect on productivity is driven by knowledge spillovers that accelerate the adoption of new technologies, the increase in opportunities from specialization, and the existence of economies of scale and low transportation costs. In this paper, we present new evidence regarding the relationship between firms' stock returns and the urban density characteristics (i.e., the urban development potential–in terms of building density–in the MSA where each firm is located). To do so, we create a measure of potential density increase (PDI) using high–resolution satellite images from Google Earth with a computer vision algorithm. This measure of PDI reflects the proportion of the area within a one–hour drive from the center of the MSA that could rapidly increase its building density. Our measure of PDI captures the fact that developed areas with low urban density (i.e., areas with existing facilities and infrastructure, but low density) can potentially increase their density faster than low developed areas and undevelopable areas.

We show that neither the CAPM nor the Fama–French four–factor model completely explain the return spread. These results indicate that building a portfolio with a long position on firms with low productivity and a short position on highly productive firms provides a positive annualized alpha of 7.83% (10.16%) in a four– (one–) factor model using value–weighted portfolios. The spread in the average returns across these portfolios is explained by the risk premium associated with the higher risk of low TFP firms. We obtain lower and statistically non–significant return spreads for equal–weighted portfolios. Moreover, we run regressions of monthly expected excess stock returns on PDI while controlling for the lagged firm–level TFP as well as other control variables. We find that, on average, a 10% higher PDI for an MSA results in 0.33% lower excess stock returns among firms located in that MSA. We argue that R&D is the mechanism behind this effect, and we show that a firm's R&D has a positive and statistically significant effect on the firm's productivity. In order to confirm these results, we demonstrate that the effect of firms' productivity on stock returns is caused by the potential density increase. Through this productivity channel, the urban development potential in the MSA where each firm is located affect their stock returns. Our results remain robust to the use of instrumental variables, as well as to several checks addressing potential concerns.

Our results have important implications for managers, entrepreneurs, investors, and local authorities. Managers and entrepreneurs must consider the fact that the urban density characteristics of the area in which they decide to locate their firms affect firms' stock returns. The location of the firm in an MSA that can quickly increase its density is perceived as a low risk – when compared to the location of the firm in an MSA with a low potential for density increase – and, therefore, leads to lower excess stock returns. Investors can optimize their portfolios using measures of PDI in order to improve their performance. Finally, local authorities can develop urban plans to provide areas that can rapidly increase the density of MSAs.

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Table 1: Measures of urban density characteristics

Rank	MSA	PDI	NDI
1	Chicago, IL	0.8160	0.1603
2	Los Angeles–Long Beach, CA	0.8109	0.5617
3	San Diego, CA	0.5766	0.5809
4	Riverside–San Bernardino, CA	0.5306	0.0843
5	San Francisco, CA	0.5100	0.6345
6	New York, NY	0.4855	0.1375
7	Oakland, CA	0.4339	0.6191
8	Seattle–Bellevue–Everett, WA	0.3924	0.0274
9	Ventura, CA	0.3888	0.8056
10	San Jose, CA	0.3638	0.6997
11	Newark, NJ	0.3625	0.5967
12	Salt Lake City–Ogden, UT	0.3577	0.6335
13	Fort Worth–Arlington, TX	0.3298	0.1645
14	Denver, CO	0.3174	0.2676
15	New Orleans, LA	0.3123	0.3540
16	Charleston–North Charleston, SC	0.3087	0.3375
17	Tacoma, WA	0.3019	0.2292
18	Boston–Worcester–Lawrence–Lowell–Brockton, MA–NH	0.2894	0.1147
19	Fresno, CA	0.2852	0.4631
20	Sarasota–Bradenton, FL	0.2635	0.1970
21	Vallejo–Fairfield–Napa, CA	0.2623	0.4482
22	Tampa–St. Petersburg–Clearwater, FL	0.2616	0.2080
23	Portland–Vancouver, OR–WA	0.2583	0.2367
24	New Haven–Bridgeport–Stamford–Danbury–Waterbury, CT	0.2243	0.0697
25	West Palm Beach–Boca Raton, FL	0.2222	0.3202
26	Providence–Warwick–Pawtucket, RI	0.2198	0.1057
27	Omaha, NE-IA	0.2139	0.0653
28	Raleigh–Durham–Chapel Hill, NC	0.2003	0.0712
29	Dallas, TX	0.1991	0.0862
30	Indianapolis, IN	0.1976	0.0358
31	St. Louis, MO-IL	0.1948	0.0658
32	Detroit, MI	0.1934	0.0762
33	Wilmington-Newark, DE-MD	0.1912	0.1418
34	Nashville, TN	0.1822	0.0603
35	Jersey City, NJ	0.1779	0.1258
36	Gary, IN	0.1773	0.1297
37	Greensboro–Winston–Salem–High Point, NC	0.1697	0.0672
38	Norfolk–Virginia Beach–New Port News, VA–NC	0.1683	0.3477
39	Atlanta, GA	0.1678	0.0702
40	Columbia, SC	0.1672	0.1092
41	Columbus, OH	0.1632	0.0258
42	Fort Lauderdale, FL	0.1583	0.1276
43	Philadelphia, PA–NJ	0.1527	0.0978
44	San Antonio, TX	0.1493	0.0254
45	Baltimore, MD	0.1464	0.1076
46	Miami, FL	0.1440	0.1781
47	Mobile, AL	0.1412	0.1519
48	Phoenix–Mesa, AZ	0.1361	0.4348
49	Minneapolis–St. Paul, MN-WI	0.1341	0.0593
50	Springfield, MA	0.1288	0.0298

Table 1: Measures of urban density characteristics (cont.)

Rank	MSA	PDI	NDI
51	Hartford, CT	0.1248	0.1080
52	Tucson, AZ	0.1245	0.2660
53	Cleveland–Lorain–Elyria, OH	0.1241	0.0550
54	Knoxville, TN	0.1234	0.0929
55	Cincinnati, OH–KY–IN	0.1230	0.0439
56	Akron, OH	0.1136	0.0478
57	Harrisburg–Lebanon–Carlisle, PA	0.1117	0.0354
58	Dayton–Springfield, OH	0.1114	0.1765
59	Birmingham, AL	0.1082	0.0990
60	Kansas City, MO–KS	0.1059	0.0501
61	Memphis, TN–AR–MS	0.1047	0.1145
62	Tulsa, OK	0.1026	0.0604
63	Jacksonville, FL	0.1015	0.0855
64	Rochester, NY	0.1007	0.0319
65	Las Vegas, NV–AZ	0.1001	0.4208
66	Albany–Schenectady–Troy, NY	0.0962	0.0865
67	Grand Rapids–Muskegon–Holland, MI	0.0914	0.1415
68	Baton Rouge, LA	0.0904	0.1075
69	Washington, DC–MD–VA–WV	0.0823	0.0574
70	Allentown–Bethlehem–Easton, PA	0.0810	0.0267
71	Orlando, FL	0.0797	0.1291
72	Pittsburgh, PA	0.0776	0.0375
73	Austin, San Marcos, TX	0.0765	0.0206
74	Ann Arbor, MI	0.0745	0.1735
75	Richmond–Petersburg, VA	0.0725	0.0682
76	El Paso, TX	0.0688	0.1780
77	Milwaukee–Waukesha, WI	0.0666	0.1522
78	Colorado Springs, CO	0.0606	0.2887
79	Greenville–Spartanburg–Anderson, SC	0.0592	0.0260
80	Houston, TX	0.0592	0.2292
81	Wichita, KS	0.0590	0.0234
82	Oklahoma City, OK	0.0576	0.0323
83	Syracuse, NY	0.0548	0.0513
84	Stockton–Lodi, CA	0.0491	0.0972
85	Bakersfield, CA	0.0441	0.2884
86	Youngstown, Warren, OH	0.0423	0.0330
87	Toledo, OH	0.0419	0.0479
88	Little Rock–North Little Rock, AR	0.0405	0.0817
89	Albuquerque, NM	0.0370	0.2279
90	McAllen–Edinburg–Mission, TX	0.0359	0.0492
91	Scranton–Wilkes–Barre–Hazleton, PA	0.0319	0.0555
92	Fort Wayne, IN	0.0295	0.0251
93	Louisville, KY–IN	0.0272	0.1446
94	Buffalo-Niagara Falls, NY	0.0230	0.0934
95	Charlotte–Gastonia–Rock Hill, NC–SC	0.0147	0.0232

Note: Measures of potential density increase (PDI), and non–potential density increase (NDI) are calculated for metropolitan statistical areas (MSAs) with populations of more than 500,000 inhabitants in the year 2010. Data is sorted by PDI.

Table 2: Summary statistics

Variable	Mean	Median	Std dev.	25th percent.	75th percent.	Obs.
Measures of urban density, geography, regulation, and macroeconomic variables:						
PDI	0.3184	0.2616	0.2321	0.1341	0.4855	110,296
NDI	0.2395	0.1375	0.2241	0.0762	0.3373	110,296
Saiz	0.3379	0.3390	0.2224	0.1269	0.4733	110,296
Population density	674.49	493.08	1,049.63	264.89	739.03	110,296
Real–estate price index	212.78	218.33	40.18	182.18	235.34	107,358
Firm–level variables:						
Expected excess returns	0.0086	0.0046	0.1376	-0.0555	0.0631	110,296
Firm size	173,852.70	718.05	5,478,799	181.21	2,776.58	110,296
Value added	8.50	0.75	34.80	0.06	3.93	110,296
Labor	13.37	2.02	41.01	0.41	8.60	110,296
Capital stock	31.25	2.07	159.71	0.34	11.27	110,296
Asset growth	0.14	0.05	0.58	-0.02	0.16	107,248
Inventory growth	0.16	0.06	0.99	-0.05	0.21	84,315
Leverage	0.2778	0.1824	1.2754	0	0.4372	109,734
ROA	-0.0241	0.0372	0.7372	-0.0250	0.7727	107,677
ROE	0.0302	0.0790	2.9323	-0.0414	0.1559	110,296
Hiring rate	0.0947	0.0335	0.8538	-0.0230	0.1195	107,248
Inventory growth	0.1626	0.06173	0.9892	-0.0490	0.2054	84,315
Market–to–book ratio	3.05	3.05	54.57	1.29	3.79	108,114
Company age	22.73	18	16.71	10	30	110,296
Real–estate ratio	0.6071	0.4972	0.7345	0.1784	0 .8209	110,296
Measures of R&D at the firm level:						
R&D	1.19	1	5.97	0.19	1	110,296

Note: This table provides the summary statistics for the main variables used in the paper with a short description. PDI, the measure of potential density increase, is the proportion of the area within a one–hour drive from the center of the MSA that could rapidly increase its density, NDI is the measure of non–potential density increase, is the proportion of the total area within a one–hour drive from the center of the MSA that cannot rapidly increase its density, either because it is already highly dense or because it is undevelopable. Saiz is the measure of geographical constraints from Saiz (2010), population density is the number of inhabitants in the MSA divided by the total MSA area in square kilometers. Distances are measured to the city hall or similar municipal building of the metro area's first–named principal city. Real–estate price index is the residential home price index (HPI) gathered from the website of the Federal Housing Finance Association (FHFA), firm size is calculated as market capitalization (common shares outstanding multiplied by the price bid/ask average in USD), value added is defined as the operating income before depreciation plus total staff expenses, all divided by the gross domestic product implicit price deflator. Labor is the number of employees, firm's capital stock calculated as total firm–year PPE total divided by the gross private domestic investment implicit price deflator, and asset growth is defined as the difference in the current and the lagged total assets divided by the lagged total assets. Inventory growth is defined as the difference in the current and the lagged total inventories divided by the lagged total inventories. Leverage is the total long–term debt divided by the total long–term debt plus the common/ordinary equity total. ROA is the income before extraordinary items minus dividends preferred plus income taxes, deferred, all divided by the total assets, and ROE is the income before extraordinary items, available for common stock divided by total stockholders' equity. Hiring rate is calculated as the difference between the current and the lagged number of employees divided by the lagged number of employees, company age is calculated as the number of years since the firm's first year of observation in Compustat, real–estate ratio is defined as the buildings plus capitalized leases divided by the net PPE, and firm's R&D is the research and development expenses divided by total PPE.

Table 3: Potential density increase and firms' productivity

	OLS [1]	OLS [2]	OLS [3]	IV [4]	IV [5]
PDI	0.2176***	0.2672***		0.4394***	
	(0.03915)	(0.0441)		(0.0666)	
R&D (PDI)			0.4396***		0.6204***
			(0.0842)		(0.1346)
Controlling for NDI	No	Yes	No	Yes	No
Controlling for R&D (NDI)	No	No	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
Controlling for housing supply elasticity*year	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
US state FE	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the month–year level	Yes	Yes	Yes	Yes	Yes
Observations	103,199	103,199	103,199	103,199	103,199
R^2	0.1018	0.1019	0.1019	0.1019	0.1021

Note: This table shows the effect of our measure of potential density increase (PDI) on firms' productivity. The dependent variable is the TFP estimated by the production function. Column [1] shows the effect of our PDI measure on firms' productivity. Column [2] shows the effect of PDI on firms' productivity when controlling for NDI. Column [3] shows the effect of firms' R&D caused by urban density on firms' productivity. Our main independent variable here is the fitted value of regressing R&D on PDI. We also control for the fitted value of regressing R&D on NDI. Standard errors are reported in parentheses. Columns [4] and [5] represent the same regressions as columns [2] and [3] plus the implementation of the instrumental variable (IV) strategy in which PDI is instrumented using the interaction of the interest rate and local constraints on the land supply. Consistent with the literature, we control for the interaction between housing supply elasticity and year in our instrumental regressions to capture the time trend of interest rates, which explains most of the correlation between home prices. Other controls refer to leverage; firm size; asset growth; inventory growth; hiring rate; return on assets (ROA); return on equity (ROE); market–to–book ratio; corporate real–estate holdings; firm's R&D expenditure; company age; residual housing price index; and population density. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Potential density increase and the cross–section of stock returns

	Low	2	3	4	5	6	7	8	9	High	High–Low	Low–High annual %
Equal–weighted portfolios												
Alpha	0.0125***	0.0136***	0.0112***	0.0097***	0.0085***	0.0095***	0.0107***	0.0075***	0.0103***	0.0107***	-0.0018	2.18
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0014)		
MKT	0.0131***	0.0160***	0.0150***	0.0197***	0.0157***	0.0201***	0.0211***	0.0167***	0.0212***	0.0182***		
	(0.0027)	(0.0024)	(0.0023)	(0.0021)	(0.0024)	(0.0022)	(0.0021)	(0.0019)	(0.002)	(0.0018)		
Alpha	0.0137***	0.0154***	0.0132***	0.0116***	0.0102***	0.0115***	0.0128***	0.0094***	0.0122***	0.0126***	-0.0011	1.33
	(0.0014)	(0.0013)	(0.0013)	(0.0013)	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0014)	(0.0014)		
MKT	0.0179***	0.0240***	0.0218***	0.0243***	0.0225***	0.0248***	0.0285***	0.0199***	0.0214***	0.0178***		
	(0.0036)	(0.0032)	(0.003)	(0.0028)	(0.0032)	(0.0029)	(0.0028)	(0.0025)	(0.0026)	(0.0024)		
SMB	0.0090***	0.0106***	0.0089***	0.0097***	0.0087***	0.0079***	0.0083***	0.0103***	0.0097***	0.0076***		
	(0.0016)	(0.0014)	(0.0013)	(0.0013)	(0.0014)	(0.0013)	(0.0012)	(0.0011)	(0.0012)	(0.0011)		
HML	0.0136*	0.0195***	0.0204***	0.0117**	0.0160***	0.0158***	0.0189***	0.0038	-0.0004	-0.0019		
	(0.0054)	(0.0047)	(0.0044)	(0.0042)	(0.0048)	(0.0043)	(0.0041)	(0.0037)	(0.0039)	(0.0035)		
MOM	0.0032	0.0059**	0.0048**	0.0028	0.0047*	0.0028	0.0052**	0.0017	-0.0010	-0.0014		
	(0.0021)	(0.0019)	(0.0017)	(0.0016)	(0.0019)	(0.0017)	(0.0016)	(0.0015)	(0.0015)	(0.0014)		
Value–weighted portfolios												
Alpha	0.0151***	0.0111***	0.0086***	0.0095***	0.0111***	0.0125***	0.0126***	0.0102***	0.0065***	0.0070***	-0.0081***	10.16***
	(0.0018)	(0.0015)	(0.0013)	(0.001)	(0.0009)	(0.0007)	(0.0009)	(0.0013)	(0.0016)	(0.0019)		
MKT	0.0090**	0.0115***	0.0169***	0.0184***	0.0217***	0.0171***	0.0180***	0.0180***	0.0241***	0.0198***		
	(0.0035)	(0.0027)	(0.0022)	(0.0018)	(0.0014)	(0.0011)	(0.0014)	(0.0019)	(0.0024)	(0.0028)		
Alpha	0.0162***	0.0129***	0.0108***	0.0113***	0.0126***	0.0135***	0.0141***	0.0121***	0.0092***	0.0099***	-0.0063**	7.83**
	(0.0018)	(0.0015)	(0.0013)	(0.001)	(0.0009)	(0.0007)	(0.0009)	(0.0013)	(0.0017)	(0.0019)		
MKT	0.0121**	0.0219***	0.0215***	0.0267***	0.0269***	0.0207***	0.0235***	0.0201***	0.0220***	0.0239***		
	(0.0046)	(0.0036)	(0.0029)	(0.0024)	(0.0018)	(0.0014)	(0.0018)	(0.0024)	(0.0032)	(0.0036)		
SMB	0.0044*	0.0098***	0.0119***	0.0117***	0.0076***	0.0035***	0.0071***	0.0086***	0.0137***	0.0117***		
	(0.0021)	(0.0016)	(0.0013)	(0.0011)	(0.0008)	(0.0006)	(0.0008)	(0.0011)	(0.0014)	(0.0016)		
HML	0.0133*	0.0258***	0.0136**	0.0183***	0.0118***	0.0086***	0.0114***	0.004	-0.0046	0.0106*		
	(0.0068)	(0.0053)	(0.0043)	(0.0036)	(0.0027)	(0.0021)	(0.0027)	(0.0036)	(0.0047)	(0.0054)		
MOM	0.0018	0.0078***	0.0026	0.0062***	0.0035**	0.0026**	0.0040***	0.0007	-0.0037*	0.0017		
	(0.0027)	(0.0021)	(0.0017)	(0.0014)	(0.0011)	(0.0008)	(0.0011)	(0.0014)	(0.0019)	(0.0021)		

Note: This table presents the regressions of equal–weighted and value–weighted expected excess portfolio returns on various factor returns. Alphas of portfolios are sorted on TFP. They are all reported monthly except for those in the last column, which are annualized. The MKT, SMB, HML, and MOM factors are taken from Ken French's website (http://mba.tuck.darmouth.edu). The portfolios are sorted on the part of TFP that comes from potential density increase: the fitted values of regressing estimated productivity on PDI considering all other control variables including NDI. Returns are measured from July 2011 to June 2015. Other controls refer to leverage; firm size; asset growth; inventory growth; hiring rate; return on assets (ROA); return on equity (ROE); market–to–book ratio; corporate real–estate holdings; firm's R&D expenditure; company age; residual housing price index; and population density. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Potential density increase and firms' stock returns

	OLS [1]	OLS [2]	IV [3]	IV [4]	IV [5]	IV [6]
PDI	-0.0101**		-0.0326**		-0.0326**	
	(0.0039)		(0.0171)		(0.0161)	
TFP	-0.0016**		-0.0015**		-0.0015**	
	(0.0007)		(0.0007)		(0.0007)	
TFP (PDI)		-0.0609***		-0.1759**		-0.1759**
		(0.0203)		(0.0855)		(0.0828)
Controlling for NDI	Yes	No	Yes	No	Yes	No
Controlling for TFP (NDI)	No	Yes	No	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Controlling for housing supply elasticity*year	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
US state FE	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the MSA level	Yes	Yes	Yes	Yes	No	No
Standard errors clustered at the month–year level	No	No	No	No	Yes	Yes
Observation	103,199	103,199	103,199	103,199	103,199	103,199
R^2	0.0102	0.0101	0.0101	0.0099	0.0101	0.0099

Note: This table studies the effect of our measure of potential density increase (PDI) on firms' stock returns. The dependent variable is the residuals of the expected excess stock returns, excluding Fama–French factors. Column [1], shows the effect of PDI on stock returns while controlling for firms' TFP to capture firms' productivity and NDI to capture land availability. Column [2], shows the effect of PDI on stock returns through the productivity channel. The independent variable here is the fitted value of regressing TFP on PDI, while we control for the fitted value of regressing TFP on NDI. Columns [4] and [5] represent the same regressions as columns [1] and [2] after implementing the instrumental variable (IV) strategy, in which PDI is instrumented using the interaction of the interest rate and the local constraints on the land supply. Consistent with the literature, we control for the interaction between housing supply elasticity and year in our instrumental regressions to capture the time trend of interest rates, which explains most of the correlation between home prices. Other controls refer to leverage; firm size; asset growth; inventory growth; hiring rate; return on assets (ROA); return on equity (ROE); market–to–book ratio; corporate real–estate holdings; firm's R&D expenditure; company age; residual housing price index; and population density. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Choice of headquarters' location and R&D centers. OLS strategy: Robustness tests 1 and 2

	OLS [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [6]	OLS [7]	OLS [8]
PDI	-0.0101**		-0.0093**		-0.0106**		-0.0120***	
	(0.0039)		(0.0045)		(0.0041)		(0.0042)	
TFP(PDI)		-0.0609***		-0.0578**		-0.0714***		-0.0706***
		(0.0203)		(0.0269)		(0.0183)		(0.0216)
Controlling for NDI	Yes	No	Yes	No	Yes	No	Yes	No
Controlling for TFP (NDI)	No	Yes	No	Yes	No	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controlling for housing supply elasticity*year	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the MSA level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firms in the sample	Full sample	Full sample	Without firms that changed HQ city	Without firms that changed HQ city	Age >10	Age >10	Small firms	Small firms
Observations	103,199	103,199	81,391	81,391	78,438	78,438	77,406	77,406
R^2	0.0102	0.0101	0.0103	0.0102	0.0118	0.0117	0.0108	0.0108

Note: This table studies the robustness of our results in relation to the choice of firm location; excluding the firms that changed their headquarters' location at the city level; and firm size. The dependent variable is the residuals of the expected excess stock returns, excluding Fama–French factors. Columns [1] and [2] show our main results for the entire sample. In Columns [3] and [4], we see the main results for the subsample of firms after excluding those that changed their headquarters' location. Columns [5] and [6] show the consistency of the relation between a firm's stock return and its location for older firms. We also address the concern that firms with better growth and productivity choose to locate in more agglomerated or high–tech cities. However, given that the unobserved characteristics that may influence a firm's location choice become less important over time, the observed effect on the productivity of older firms that chose locations many years ago is unlikely to arise because of a selection effect. For this reason, we explore whether the relation between a firm's stock return and its location for older firms is consistent with what we observe for the entire sample. These columns report the baseline regressions for the subsample of firms that are at least 10 years old. Columns [7] and [8] show the results for the subsample of small firms after splitting our sample into small and large firms. We define small firms as the subsample of firms in the bottom three quartiles in terms of size and in the top 20 MSAs. Other controls refer to leverage; firm size; asset growth; inventory growth; hiring rate; (ROA); (ROE); market–to–book ratio; corporate real–estate holdings; firm's R&D expenditure; company age; residual housing price index; and population density. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Choice of headquarters' location and R&D centers. Instrumental variable (IV) strategy: Robustness tests 1 and 2

	IV [1]	IV [2]	IV [3]	IV [4]	IV [5]	IV [6]	IV [7]	IV [8]
PDI	-0.0326**		-0.0391**		-0.0408**		-0.0359*	
	(0.0171)		(0.0189)		(0.0167)		(0.0202)	
TFP(PDI)		-0.1759**		-0.239**		-0.2159***		-0.1899*
		(0.0855)		(0.1133)		(0.0812)		(0.0999)
Controlling for NDI	Yes	No	Yes	No	Yes	No	Yes	No
Controlling for TFP (NDI)	No	Yes	No	Yes	No	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controlling for housing supply elasticity*year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the MSA level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the month–year level	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Firms in the sample	Full sample	Full sample	without firms that changed HQ city	without firms that changed HQ city	Age >10	Age >10	Small firms	Small firms
Observations	103,199	103,199	81,391	81,391	78,438	78,438	77,406	77,406
R^2	0.0101	0.0099	0.0099	0.0097	0.0115	0.0114	0.0106	0.0106

Note: This table studies the robustness of our results in relation to the choice of firm location; excluding the firms that changed their headquarter location at the city level; and firm size. The dependent variable is the residuals of the expected excess stock returns, excluding Fama–French factors. Basically, the table represents the same regressions as in Table 6 plus the implementation of the instrumental variable (IV) strategy in which PDI is instrumented using the interaction of the interest rate and the local constraints on the land supply. Consistent with the literature, we control for the interaction between housing supply elasticity and year in our instrumental regressions to capture the time trend of interest rates, which explains most of the correlation between home prices. Other controls refer to leverage; firm size; asset growth; inventory growth; hiring rate; return on assets (ROA); return on equity (ROE); market–to–book ratio; corporate real–estate holdings; firm's R&D expenditure; company age; residual housing price index; and population density. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Industry classification: Robustness test 3

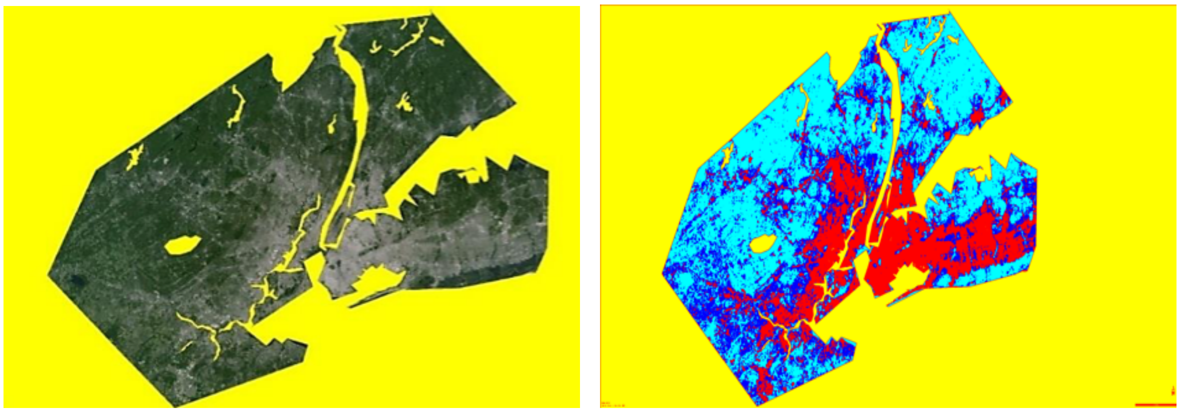
	OLS [1]	OLS [2]	OLS [3]	OLS [4]	OLS [5]	OLS [6]	IV [7]	IV [8]	IV [9]	IV [10]
PDI	-0.0101**		-0.0185***		-0.0068		-0.0326**		-0.0444**	
	(0.0039)		(0.0066)		(0.0047)		(0.0171)		(0.0224)	
TFP (PDI)		-0.0609***		-0.1279***		-0.0354		-0.1759**		-0.2580**
		(0.0203)		(0.0284)		(0.0238)		(0.0855)		(0.1127)
Controlling for NDI	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Controlling for TFP (NDI)	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controlling for housing supply elasticity*year	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the MSA level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors clustered at the month–year level	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust	Robust
Firms in the sample	Full sample	Full sample	High–tech	High–tech	Less–innovative	Less–innovative	Full sample	Full sample	High–tech	High–tech
Observation	103,199	103,199	28,880	28,880	74,319	74,319	103,199	103,199	28,880	28,880
R^2	0.0102	0.0101	0.0138	0.0137	0.0096	0.0095	0.0101	0.0099	0.0136	0.0135

Note: This table studies our results for different industry classifications. The dependent variable is the residuals of the expected excess stock returns, excluding Fama–French factors. Columns [1] and [2] show our main results for the entire sample. Columns [3] and [4] show the results for the group of firms belong to electronic computers, electrical machinery, transportation equipment, instruments, software and data processing services industries, which we define as high–tech firms consistent with the literature. In columns [5] and [6], we see these results for the subsample of non–innovative firms. Columns [7], [8], [9], and [10] represent the same regressions as columns [1], [2], [3], and [4] plus the implementation of the instrumental variable (IV) strategy in which PDI is instrumented using the interaction of the interest rate and the local constraints on the land supply. Consistent with the literature, we control for the interaction between housing supply elasticity and year in our instrumental regressions to capture the time trend of interest rates, which explains most of the correlation between home prices. Other controls refer to leverage; firm size; asset growth; inventory growth; hiring rate; return on assets (ROA); return on equity (ROE); market–to–book ratio; corporate real–estate holdings; firm's R&D expenditure; company age; residual housing price index; and population density. Standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Figure 1: Examples of types of areas according to their potential for urban development

Note: This figure shows examples of aerial views of highly developed (HD) areas (top left), developed (D) areas (top right), low developed (LD) areas (middle left and middle right), and undevelopable (U) areas (bottom left and bottom right). Source: Google Earth.

Figure 2: Input and output images for the MSA of New York



Note: The left figure shows the input image for the MSA of New York. It contains the Google Earth aerial view of the area within a maximum of one–hour drive from the center of the city (i.e., Times Square). This area is equal to 6,724.35 km^2. The right figure shows the corresponding output image after being processed by the computer vision algorithm. The area in red represents highly developed (HD) areas, dark blue corresponds to developed (D) areas with the potential to increase their density, and light blue represents low developed (LD) areas, which are almost entirely open land with some existing facilities. In this specific case of New York, the numeric output of the analysis is as follows: HD areas account for 1,540.46 km^2; D areas account for 2,868.85 km^2; LD areas account for 1,659.48 km^2; and undevelopable (U) areas account for 655.56 km^2.

Appendix

A Conceptual framework

In this Appendix, we present a stylized conceptual framework to illustrate the key effects of urban density on firms' stock returns and to develop testable hypotheses. We build upon a standard produced–based asset pricing model with many firms that produce a good using capital, labor, and real–estate assets (i.e., land). in a classic real option framework for land-use decisions as in Titman et al. (1985) and subsequent literature (see Clarke and Reed (1988); Williams (1991); Capozza and Li (1994)).

Firms. The production function for firm i is given by:

$$Y_{it} = A_t Z_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} T_{it}^{\alpha_T}, \tag{7}$$

where K_{it} denotes the capital stock, L_{it} denotes the labor used in production and T_{it} is the land used in production, by firm i at time t. Let α_K, α_L, and α_T denote the capital, labor, and land shares, respectively, with $0 < (\alpha_K + \alpha_L + \alpha_T) < 1$. Let A_t denote aggregate productivity, $a_t = log(A_t)$, and assume that a_t follows the AR(1) process $a_{t+1} = \rho_a a_t + \epsilon^a_{t+1}$, where ϵ^a_{t+1} follows a $N(0, \sigma_a^2)$ i.i.d. process. The productivity of firm i, $z_{it} = log(Z_{it})$, follows the AR(1) process $z_{i,t+1} = \rho_{z,i} z_{it} + \epsilon^z_{i,t+1}$, where $\epsilon^z_{i,t+1}$ follows a $N(0, \sigma_z^2)$ i.i.d. process, with $correlation(\epsilon^z_{i,t+1}; \epsilon^z_{j,t+1}) = 0$, for any $i \neq j$. Capital follows the process $K_{i,t+1} = (1-\delta)K_{it} + I_{it}$, where δ is the depreciation rate. I_{it} denotes investment, which has quadratic adjustment costs, $g_{it} = g(I_{it}, K_{it}) = 0.5\eta(I_{it}/K_{it} - \delta)^2 K_{it}$, with $\eta > 0$. Moreover, labor supply is perfectly elastic at a given stochastic wage, W_t.

Cities and Urban Development. Each firm i is located in a city c, which has two types of land as in Capozza and Li (1994): (i) urbanized or developed land, D, and, (ii) vacant land for conversion or low developed, LD. Real estate generates net cash flows (net rents) $R = [R_D, R_{LD}]$ per unit of rentable space in the D and LD areas, respectively. Let $q^T(K^T) = [q^T_D(K^T_D), q^T_{LD}(K^T_{LD})]$ denote the rentable space in each area, where K^T is the capital–land ratio. At any time t, a social planner has the option to convert LD areas to D areas (i.e., from capacity q_{LD} and net cash flows R_{LD} to capacity q_D and net cash flows R_D) by replacing capital K^T_{LD} with new capital K^T_D. There is a cost of conversion, c^T, per unit capital K^T_D. Without a loss of generality, we assume that the area LD is initially vacant. In other words, $R_{LD} = 0$ and $q_{LD} = 0$. We also assume that net cash flows follow a the process $dR_D = g_D dt + \sigma_D dB_t$, where g_D and σ_D are constants and B_t is a Wiener process. Finally, we assume that $q_D(K^T_D) = [K^T_D]^\gamma$, with $0 < \gamma < 1$.

Stochastic discount factor. We consider an exogenous time–varying pricing kernel as in Berk et al. (1999), Jones and Tuzel (2013), and İmrohoroğlu and Tuzel (2014). The stochastic discount factor in our economy, M_t, is given by $logM_{t+1} = log\beta - \gamma_t \epsilon^a_{t+1} - 0.5\gamma_t^2 \sigma_a^2$, and $log\gamma_t = \gamma_0 + \gamma_1 a_t$, where β, γ_0, and γ_1 are constants, $\gamma_0 > 0$, and $\gamma_1 < 0$. The real interest rate, r_t, is $r_t = E(M_{t+1})$.

Equilibrium. We normalize the size of cities to 1 and assume that cities are circle–shaped and monocentric. A circle of radius b^* with its center in the center of the city defines the boundary of the developed area within the city, where vacant land is converted to developed land. Therefore, the area of the developed D land is $\pi(b^*)^2$ and the area of low developed LD land is $(1 - \pi(b^*)^2)$. Hence, our measure of potential density increase (PDI) is $area_D/(area_D + area_{LD}) = \pi(b^*)^2$.

Proposition 1 *In equilibrium, at the boundary b^*, the optimal capital intensity is given by:*

$$K^* = \left[\frac{\gamma}{(1-\gamma)\alpha r_t c}\right]^{1/(1-\gamma)}. \tag{8}$$

The value of the developed land is:

$$V_D = \frac{q(K^*)}{\alpha r_t} + \frac{\gamma q(K^*)}{\alpha r_t(1+\gamma)} + \frac{q(K^*)d(b^*-b)}{r_t}, \tag{9}$$

where $\alpha = \frac{1}{\sigma_D}(-g_D + \sqrt{g_D^2 + 2\sigma_D^2 r})$.

There is a positive relationship between PDI and b^* because $PDI = \pi(b^*)^2$. At the same time, there is a positive relation between b^* and V_D from equation (9), as $q(K^*)$ is increasing in b^*. Each firm i is located at a distance, b, from the center of the city. As a result, $V_{D,i}$ is the value of developed land in equilibrium that firm i uses in production, T_{it}. Therefore, we expect firms located in dense areas with high PDI to present higher TFP and to be more productive. Hypothesis A outlines this prediction.

Firms located in fast–growing areas with high potential for an increase in urban density are more productive.

Proposition 2 *Firm i's returns in equilibrium are given by:*

$$R_{i,t+1} = \frac{\alpha_K A_t Z_{it} K_{it}^{(\alpha_K - 1)} L_{it}^{\alpha_L} V_{D,i}^{\alpha_T} + (1-\delta)(1 + \eta(I_{it}/K_{it}) - \delta) + 0.5\eta((I_{i,t+1}/K_{i,t+1})^2 - \delta^2)}{1 + \eta(I_{it}/K_{it}) - \delta}. \tag{10}$$

There is a negative relationship between firm–level productivity and expected returns, as in İmrohoroğlu and Tuzel (2014). The mechanism behind this negative relationship works as follows. In our model, shocks in aggregate productivity drive the business cycle. When aggregate productivity is low, firms invest less and hire less. Even though firms can freely adjust their labor, they incur adjustment costs when they change their capital stock. Hence, an inability to adjust firms' capital following shocks to aggregate and firm–level productivity makes firms riskier. As adjustment costs are convex, low TFP firms must pay a higher cost (relative to their output) when reducing their capital stocks in periods of low aggregate productivity than high TFP firms.[11] In contrast, a positive shock in aggregate productivity drives a larger decrease in adjustment costs for low TFP firms than for high TFP firms. Therefore, the returns of low TFP firms covary more with changes in economic conditions during periods of low aggregate productivity.

As the volatility of the stochastic discount factor is a decreasing function of aggregate productivity, discount rates are higher during periods of low aggregate productivity. The covariance between returns and the stochastic discount factor defines the level of risk. Higher volatility in the stochastic discount factor implies higher covariance between returns and the stochastic discount factor and, as such, higher risk in periods of low aggregate productivity. Low productive firms are riskier because they invest less during recessions when discount rates are high. Therefore, low productivity firms present the higher expected returns during periods of low aggregate productivity. In contrast, high TFP firms tend to invest more during periods of high aggregate productivity when discount rates are low. Hence, their expected stock returns are lower. Hypothesis A summarizes this prediction.

Firms located in fast–growing areas with high potential for a density increase have lower expected stock returns.

Calibration. To make the equilibrium relationships explicit, we next present numerical results. We first choose the values for the model parameters. For the parameters related to the firms, we follow İmrohoroğlu and Tuzel (2014). We set the parameters of aggregate productivity $\rho_a = 0.922$ and $\sigma_a = 0.014$, and firm's productivity $\rho_z = 0.7$ and $\sigma_z = 0.27$. We set depreciation $\delta = 8\%$, the parameter related to adjustment costs $\eta = 4.45$, and the parameters of the stochastic discount factor $\beta = 0.988$, $\gamma_0 = 3.27$, and $\gamma_1 = -13.32$. Finally, we set the urban development parameters $\gamma = 0.02$, $g_D = 2\%$, and $\sigma_D = 15\%$.

We first present the numerical results related to Hypothesis 1. Figure A.1 exhibits firms' TFPs in equilibrium for areas with different values of PDI (left graph). We observe that firms located in areas with higher PDIs exhibit higher TFPs.[12] We also find that the equilibrium value of developed land decreases with the value of PDI (right graph). These graphs also show that both TFP and the value of developed land decrease as the distance from the center of the MSA increases.

[11] Low TFP firms are on a steeper part of the convex adjustment costs curve. Hence, in periods of low aggregate productivity, a bad shock tends to have a larger negative effect on the low TFP firms than on the high TFP firms. As a result, low TFP firms should have lower investment rates and reduce their capital stocks relatively more.

[12] Different values of g_D equal to 1%, 2%, 3%, and 4%, provide PDI values of 0.09, 0.20, 0.30, and 0.49, respectively.

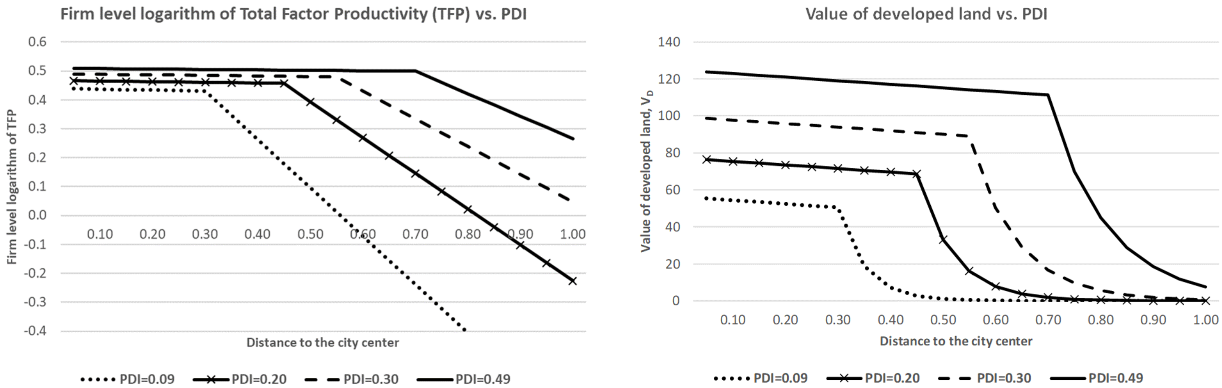
[Insert Figure A.1 around here]

Finally, we present the numerical results related to Hypothesis 2. Figure A.2 exhibits firms' returns in equilibrium as a function of PDI. We observe that firms located in areas with a higher value of PDI present lower returns.

[Insert Figure A.2 around here]

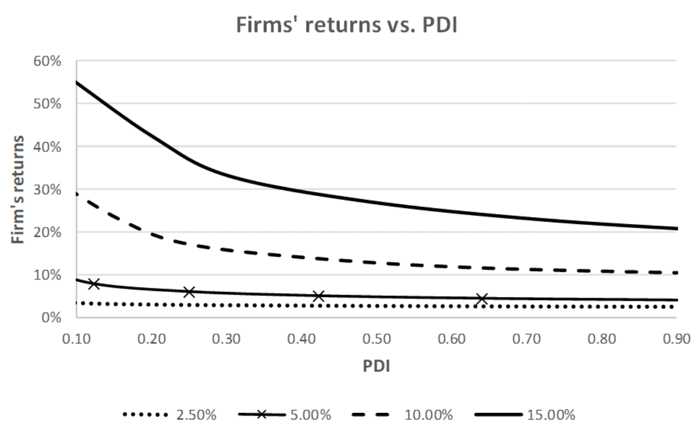
These numerical results confirm the theoretical hypotheses of the model and certify the importance of taking into account the urban density characteristics in terms of potential for density increase of the MSA in which the firm is located when studying its productivity and stock return.

Figure A.1: Modeled TFP and value of developed land for cities with different PDI values



Note: This figure displays the equilibrium results of the model. The left figure shows the equilibrium logarithm of total factor productivity (TFP) at the firm level as a function of the distance to the city center and for cities with different PDI values. The right figure shows the equilibrium value of developed land as a function of the distance to the city center and for cities with different PDI values.

Figure A.2: Modeled firms' returns as a function of PDI



Note: This figure displays the equilibrium firms' returns of the model as a function of PDI for different values of σ_D ranging from 2.50% to 15.0%.