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Local Risk, Local Factors, and Asset Prices

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ABSTRACT

Firm location affects firm risk through local factor prices. We find more procyclical factor prices such as wages and real estate prices in areas with more cyclical economies, namely, high "local beta" areas. While procyclical wages provide a natural hedge against aggregate shocks and reduce firm risk, procyclical prices of real estate, which are part of firm assets, increase firm risk. We confirm that firms located in higher local beta areas have lower industry-adjusted returns and conditional betas, and show that the effect is stronger among firms with low real estate holdings. A production-based equilibrium model explains these empirical findings.

MOST WORK IN THE FINANCE literature treats labor and capital markets as perfectly competitive and homogeneous at the aggregate level, where wages and rental rates equalize across locations. In reality, workers face frictions when moving from place to place (e.g., transaction costs in housing, job search frictions, family coordination issues, etc.). Moreover, a significant part of physical capital, such as land and structures, is immobile. Production factors that are subject to such geographical immobility, namely, local factors, account for a large part of economic output.[1] Fluctuations in factor prices due to local economic conditions can thus have important effects on the firms using them.

In this paper, we show that local factor prices respond to aggregate shocks differently across localities based on the types of industries that dominate

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[1] The estimates for the output share of labor range from 60% (Cooley and Prescott (1995)) to 75% (Imrohoroglu and Tuzel (2014)). Campbell (1996) uses two-thirds. The output share of land and structures is roughly 15% (Tuzel (2010)). The two local factors jointly claim more than 75% of total economic output.

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those areas. Conceptually, if local factors are immobile across areas, the market for these factors clears *within* each area. As a result, local factor prices—for example, wages and real estate rents—aggregate the shocks to the firms in the area since all firms tap into the same local labor pool and real estate market. If the major industries that drive the economy of an area covary highly with the aggregate economy, local factor prices in that area are likely to be procyclical. Take, for example, the accommodation industry, which is fairly cyclical. It is the main industry in three metropolitan areas: Las Vegas, Norwich-New London, and Atlantic City. Given its significant weight in these economies, these areas have some of the most cyclical economies in the United States. Thus, during the 2009 economic downturn, real wages in these three metropolitan areas declined more than twice the national average. More importantly, the excess wage decline in these areas relative to the national average occurred not only in the accommodation sector but also in unrelated sectors such as plastics, nonmetallic minerals, and transportation equipment manufacturing. These areas also experienced much larger declines in rents and real estate prices compared to other metropolitan areas in 2009. Larger fluctuations in input prices during economic cycles have implications for the risk and returns of firms located in these areas. We explore these implications in two steps.

To capture the cyclicality of the local economy, we begin by constructing a measure of local risk, which we refer to as "local beta." Specifically, we compute the local beta of a metropolitan statistical area (MSA) as the average of industry betas weighted by the industry shares in the local market, where an industry's beta is the beta of the industry's output on aggregate GDP. We confirm that the sensitivity of wage growth (within industry or occupation) to aggregate shocks is higher in MSAs with high local beta. Similarly, we find more procyclical house prices, commercial real estate prices, and rents in MSAs with high local beta, which suggests that demand for real estate is more cyclical in high local beta areas. These findings support the view that industry composition is an important driver of the heterogeneous fluctuations in local factor prices.

We next explore the implications of heterogeneous fluctuations in local factor prices for firm risk by comparing firms *in the same industry* that are located in different areas. Intuitively, if all firms in an industry are subject to the same aggregate productivity shocks, their location will affect their risk and equity returns only through local production factors. Two competing channels are at work here. On the one hand, more cyclical wages absorb part of the aggregate shocks. This provides a natural hedge for firms in high beta areas and lowers their risk relative to industry peers located in low beta areas. On the other hand, real estate values also respond more strongly to aggregate shocks in high beta areas than in low beta areas. Since firm value is derived in part from the value of its capital, which includes real estate, this mechanism implies higher equity risk for firms in high beta areas than for firms in low beta areas. Therefore, for firms that hold real estate, the two channels are expected to have opposite effects on firm risk.

We find that local beta negatively predicts conditional equity betas and future equity returns. We also show that this predictability is particularly strong for the subsample of firms with few real estate holdings and gets weaker and insignificant for the subsample of firms with high real estate holdings. These results are obtained in both panel regressions with time-industry fixed effects and also in portfolio sorting. Taken together, these findings suggest that both the labor and the real estate channels are at work, but the labor hedging channel dominates for the average firm.

To formalize these ideas, we develop a production-based equilibrium model with local markets. In this model, firms belong to either a low beta industry or a high beta industry, where the industry beta is determined by the sensitivity of the industry's output to aggregate productivity shocks. Local markets have different compositions of low beta and high beta industries. We also introduce heterogeneity to the real estate intensity of industries to capture their varying real estate needs. All firms produce a homogeneous good, receive aggregate (economy-wide) and firm-level productivity shocks, and use three factors of production: labor, capital equipment, and land (i.e., immobile capital and real estate). Labor and land are local factors of production with limited supply, whereas equipment is not. Firms are ex-ante identical except for their location, which determines the mix of firms active in their local factor markets, and their industry affiliation, which determines their exposure to aggregate productivity shocks and real estate intensity. Wages and land prices clear the local markets and are determined endogenously, conditional on the industry composition of the local market. Firms' investment and hiring decisions are also endogenously determined in equilibrium.

The calibration of the model generates the main empirical patterns observed in the data: high beta areas have more procyclical wages and real estate prices (i.e., higher covariance between aggregate productivity and local factor prices) than low beta areas. In addition, more procyclical wages act as a natural hedge against shocks, making the returns of firms in high beta areas less sensitive to aggregate shocks. Therefore, their expected returns are lower relative to peer firms in the same industry but located in low beta areas. This is especially true for firms that belong to industries with low real estate intensity.

To simplify our empirical and theoretical analysis, we make several assumptions that merit some discussion. First, we assume that there is no local factor mobility (labor and land) between local markets. Though land is truly immobile, it is possible for labor to move across markets in response to shocks. Nevertheless, at an annual frequency, job-related mobility is low. Between 2012 and 2013, for instance, only 3.8% of households moved across county lines, with job-related moves making up roughly one-third of these moves.[2] Several

[2] Estimates are from the Census Bureau report, Reason for Moving: 2012 to 2013. The other two major reasons for moves—family-related (e.g., change in marital status) and housing-related (e.g., wanted better neighborhood) reasons—each account for one-third of intercounty moves. Chen and Rosenthal (2008) investigate individual migration decisions using IPUMS (Integrated Public Use Microdata Series) data. Consistent with the Census statistics, they find that, among movers, an important reason for moving is the availability of local amenities (e.g., climate, temperature, nonmetropolitan areas, etc.), which is not directly related to wages. In addition, Kennan and Walker (2011) develop an econometric model of optimal migration and estimate moving costs to

factors contribute to low labor mobility, especially at a higher (business cycle) frequency. Moretti (2011) argues that, in the short run, frictions in labor mobility and in the housing supply constrain the ability of workers and housing stock to fully adjust to shocks. Frictions in land and housing supply play an important role in the basic spatial equilibrium models (Rosen (1979), Roback (1982)). These models suggest that a shock to a local labor market is not only reflected in worker wages but also capitalized into rents/housing and land prices. In this case, movement in house prices discourages labor mobility.[3] Consistent with this view, we find evidence that house prices, like wages, are also more sensitive to economy-wide shocks in high beta areas.[4] Therefore, intermarket labor mobility cannot fully absorb the differential effects of aggregate shocks, leaving relative factor prices unchanged.

We also assume that firms' location choice is exogenous. Starting with Marshall (1920), a large urban economics literature studies the causes and effects of agglomeration. Likewise, the issue of industrial clustering is well documented in the literature.[5] Most of the work in this area is geared toward understanding differences in clustering across industries rather than an individual firm's location decision within its industry.[6] Our focus here is the effect of location on the risk of the firm compared to its industry peers.[7]

While we focus on the geographic segmentation of the factors of production, we abstract from similar segmentation in firms' product markets. This condition is satisfied for industries that produce *tradable* goods, that is, products that can be sold outside the local markets in which they are produced. However, sales of certain industries—the retail sector in particular—are predominantly local (i.e., *nontradable*) and hence are naturally affected by local economic conditions. Mian and Sufi (2012) document that job losses in the nontradable sector during the Great Recession (2008 to 2009) are significantly higher in

be $312,146 for the average hypothetical mover and $80,768 for the average actual mover. These figures exceed expected income gains for most people, and thus Kennan and Walker (2011) argue that many of the moves that do occur are motivated by factors other than income gains.

[3] Sharp declines in house prices and a breakdown of the Beveridge Curve (historically strong negative relationship between job vacancies and unemployment rate) during the Great Recession sparked a debate about whether the two observations are related. Sterk (2015) develops a general equilibrium model in which declines in house prices lower households' home equity levels, reducing the geographic mobility of unemployed homeowners.

[4] We do not model the household side and therefore do not consider feedback effects between house prices and wages. Nevertheless, the differential effect of aggregate shocks on local good prices such as housing would work as an additional mechanism amplifying the relationship between local betas and the cyclicality of wages.

[5] See Ellison, Glaeser, and Kerr (2010) for a recent contribution to this area.

[6] Almazan, Motta, and Titman (2007) present a model of a firm's location choice in this category.

[7] While we assume that firms' location choice is exogenous, in reality firms may use the local beta mechanism to manage their risk. Specifically, inherently risky firms may locate in high beta areas to mitigate their risk. However, this would result in higher risk for the firms located in high beta areas, which goes against our findings. Since we find the opposite, either the hedging effect of cyclical wages in high beta areas is stronger than what we measure in the data, so that we find these effects despite firms' mitigating endogenous location choices, or firms' location choice is exogenous to our mechanism.

high leverage counties, implying that worsening household balance sheets in those areas led to sharp decreases in demand for nontradable goods. Therefore, local area characteristics such as local betas can impact both input and output prices for nontradable industries, making inference about firm risk difficult. Consistent with our hypothesis, we confirm that the relationship between local betas and firm risk is indeed stronger for firms that produce tradable goods.

In additional analysis, we examine other predictions for how local betas are likely to impact labor and asset markets. We find that the positive relationship between local betas and the procyclicality of wages is stronger for industries with lower unionization rates, consistent with the view that unionization increases the frictions in wage adjustments. We also find that the negative relationship between local betas and expected equity returns mainly concentrated in firms with geographically focused operations for which firm headquarters location is a better proxy for where the firm actually operates.

We perform several robustness checks of our main findings. First, we test the robustness of our results to two alternative measures of local beta. The first measure aggregates industry betas, which are computed as the beta of industry total factor productivity (TFP) on aggregate TFP, and the second measure is estimated directly using MSA GDPs. Next, we test the asset pricing implications using an expanded sample period, which starts in 1970, to ensure that our results hold beyond the main sample period of 1986 to 2011. Third, we change the asset pricing test assets from individual firm returns to industry-MSA portfolio returns to ensure that our results are not driven by a few outlier firms. Finally, we check the robustness of the regression results to various assumptions for the correlation structure of the residuals. We confirm that the results are robust to these variations.

Our paper is related to a growing strand of the literature that studies the connection between firms' location, economic activity, and financial performance. On the real side, Dougal, Parsons, and Titman (2015) document that firms' investments are sensitive to the investments of other firms headquartered in the same area. They argue that shared local vibrancy facilitates positive externalities among firms in the same area. Engelberg, Ozoguz, and Wang (2010) find that fundamentals of firms in industry clusters have strong comovement. They interpret this finding as a possible outcome of firms' exposure to the same local labor markets. Chaney, Sraer, and Thesmar (2012) study the effect of changes in the value of firms' real estate portfolios on those firms' investments. Specifically, they calculate the change in real estate values based on changes in property prices in firms' headquarters locations. Our analysis proposes a source for heterogeneity in real estate prices by exploring the cyclicality of the local economy.

On the financial side, several papers investigate the relationship between firms' location and stock returns. Pirinsky and Wang (2006) study the correlations between stock returns of firms headquartered in the same area and find that their returns move together. Garcia and Norli (2012) show that the returns of geographically focused firms exceed the returns of geographically dispersed firms. Korniotis and Kumar (2013) document that local economic conditions are useful in predicting the returns of firms in that area. The common theme in these studies is that firms in the same area share the same group of investors. Our paper complements this literature by exploring a channel through which firms in the same area share the same factors of production.

Our paper is also related to the growing body of work in asset pricing that ties asset returns to labor market frictions. Danthine and Donaldson (2002), Gourio (2007), Berk and Walden (2013), and Favilukis and Lin (2016a, 2016b) among others study the effects of wage rigidity. In an equilibrium setting, wage rigidity leads to labor-induced operating leverage that results in volatile and cyclical profits accompanied by high and countercyclical risk premia. While there is no exogenously imposed wage rigidity in our model, there is endogenous variation in wage fluctuations across local labor markets, which leads to a more subtle form of operating leverage.

Implications of labor adjustment costs are investigated by Merz and Yashiv (2007), Belo, Lin, and Bazdresch (2014), and Belo et al. (2015) among others. In the presence of labor adjustment costs, firms' market values and expected returns are related to their hiring behavior. Chen and Zhang (2011) and Kuehn, Petrosky-Nadeau, and Zhang (2013) study asset pricing with labor market search. Search frictions in the labor market endogenously generate volatility in unemployment rates and wage rigidity, and match the dynamics of equity returns. Donangelo (2014) studies the implications of labor mobility on asset pricing and finds that industries that rely on a more flexible labor force face greater risk. Our work adds to this literature by incorporating a previously unexplored friction, namely, the local nature of labor markets. In particular, we explore the heterogeneity in local labor markets and investigate its implications for the firms operating in these markets.

Finally, our paper contributes to the literature on capital heterogeneity and asset pricing. Eisfeldt and Papanikolaou (2013) consider organization capital, Hansen, Heaton, and Li (2005) and Li and Liu (2012) investigate intangible capital, and Belo and Lin (2012) and Jones and Tuzel (2013a) study the implications of having inventory as part of firms' productive assets. Zhang (2016) explores heterogeneity of firms in terms of their human capital that can be replaced by machines, namely, routine-task labor, and finds that firms with a higher share of routine-task labor earn lower expected returns, since routine-task labor proxies for a hedging option for the firms. Tuzel (2010) studies the asset pricing implications of firms' real estate holdings, finding that firms that own more structures (real estate) are less flexible, hence riskier, and earn higher risk premia. In this paper, we study the implications of local beta on the propagation of aggregate shocks to local real estate prices and examine how this mechanism affects firms' returns. We show that, in high beta areas, real estate holdings of firms magnify the effects of aggregate shocks and thus support the "risky real estate" argument of Tuzel (2010).

The paper is organized as follows. Section I presents a simplified version of the model with closed-form solutions to build intuition. Section II describes the data used in our empirical analysis and introduces our local beta measure. Section III presents our empirical results relating GDP shocks and local betas to wages, real estate returns, and firm returns. Section IV presents our full model and quantitative results. Section V concludes.

I. Simplified Model

In this section, we discuss the basic intuition in the context of a simplified version of the model in which labor is the only factor of production. Section IV develops the full model.

Each local market, m, is populated by a measure one of workers and a continuum of measure one of infinitely lived firms producing a homogeneous good using labor. There are two industries in the economy, with one more cyclical than the other, $j \in \{1, 2\}$. Local markets differ in their composition of the two types of industries. Let $s_m \in (0, 1)$ denote the fraction of firms that belong to the high cyclicality industry in market m.

The output of firm i in industry j of market m during time t is given by

$$Y_{ijm,t} = A_t^{I_j} Z_{it} L_{ijm,t}^{\alpha_l}, \tag{1}$$

where $L_{ijm,t}$ denotes the labor used in production by firm i. Labor share in the firm's production function is given by α_l, where $\alpha_l \in (0, 1)$. Aggregate productivity, denoted by $a_t = \log(A_t)$, follows the AR(1) process

$$a_{t+1} = \rho_a a_t + \varepsilon_{t+1}^a, \tag{2}$$

where $\varepsilon_{t+1}^a \sim$ i.i.d. $N(0, \sigma_a^2)$. In equation (1), I_j is a scaler that represents the degree of industry cyclicality and scales the effect of aggregate productivity on the firm's production, where $I_1 = I_{\text{high}} > 1$ and $I_2 = I_{\text{low}} < 1$. The idiosyncratic firm productivity, $z_{it} = \log(Z_{it})$, follows the AR(1) process

$$z_{i,t+1} = \rho_z z_{it} + \varepsilon_{i,t+1}^z, \tag{3}$$

where $\varepsilon_{i,t+1}^z \sim$ i.i.d. $N(0, \sigma_z^2)$ and uncorrelated across firms.

Firms have access to the local labor markets, which are competitive. Labor is free to move between firms in the same area, but not across different labor markets.[8] The marginal product of labor is therefore equalized among firms in the same area. Hiring decisions are made after firms observe the productivity shocks and labor is adjusted freely. Each period the firm chooses the amount of labor, $L_{ijm,t}$, to maximize operating profits, which are given as output minus labor expenses:[9]

$$\Pi_{ijm,t} = Y_{ijm,t} - W_{m,t} L_{ijm,t}, \tag{4}$$

where $W_{m,t}$ denotes the wage rate in local labor market m at time t.

[8] We use the terms "local market" and "local area" interchangeably throughout the paper.

[9] In this setting, the firm's problem is a static profit maximization problem. Maximizing period profits is equivalent to maximizing firm value.

The first-order condition for the firm's optimization problem leads to the firm's labor choice

$$W_{m,t} = \alpha_l A_t^{I_j} Z_{it} L_{ijm,t}^{\alpha_l - 1}, \tag{5}$$

$$L_{ijm,t} = Z_{it}^{\frac{1}{1-\alpha_l}} \left(\frac{\alpha_l A_t^{I_j}}{W_{m,t}} \right)^{\frac{1}{1-\alpha_l}}. \tag{6}$$

The aggregate labor supply in each market m is normalized to be one. In equilibrium, the aggregate labor demand in each market equals the supply,

$$\sum_j \int L_{ijm,t} di = 1, \tag{7}$$

where $j \in \{1, 2\}$. Using lognormality of Z_{it}, we can derive the equilibrium wage rate as

$$W_{m,t}^* = \kappa \left(s_m A_t^{\frac{I_{\text{high}}}{1-\alpha_l}} + (1 - s_m) A_t^{\frac{I_{\text{low}}}{1-\alpha_l}} \right)^{1-\alpha_l}, \tag{8}$$

where $\kappa = \alpha_l e^{\frac{\sigma_z^2}{2(1-\rho_z^2)(1-\alpha_l)}}$ is a constant.

The wage rate increases in aggregate productivity, A_t, and therefore is procyclical. More importantly, wage cyclicality increases with s_m, the fraction of firms that belong to the high-risk industry. Replacing $W_{m,t}$ and $L_{ijm,t}$ in equation (4) leads to maximized firm profits

$$\Pi_{ijm,t}^* = \theta A_t^{\frac{I_j}{1-\alpha_l}} Z_{it}^{\frac{1}{1-\alpha_l}} \left(s_m A_t^{\frac{I_{\text{high}}}{1-\alpha_l}} + (1 - s_m) A_t^{\frac{I_{\text{low}}}{1-\alpha_l}} \right)^{-\alpha_l}, \tag{9}$$

where $\theta = (1 - \alpha_l) e^{-\frac{1}{2(1-\rho_z^2)} \frac{\sigma_z^2 \alpha_l}{(1-\alpha_l)^2}}$ is a constant.

Define the elasticity of firm profits to aggregate productivity, $\beta_{ijm,t}$, as a measure of firm risk as follows:[10]

$$\beta_{ijm,t} = \frac{\frac{\partial \Pi_{ijm,t}^*}{\partial A_t}}{\frac{\Pi_{ijm,t}^*}{A_t}} = \frac{\left[s_m \left(\frac{I_j - \alpha_l I_{\text{high}}}{1-\alpha_l} \right) A_t^{\frac{I_{\text{high}}}{1-\alpha_l}} + (1 - s_m) \left(\frac{I_j - \alpha_l I_{\text{low}}}{1-\alpha_l} \right) A_t^{\frac{I_{\text{low}}}{1-\alpha_l}} \right]}{\left(s_m A_t^{\frac{I_{\text{high}}}{1-\alpha_l}} + (1 - s_m) A_t^{\frac{I_{\text{low}}}{1-\alpha_l}} \right)}. \tag{10}$$

Equation (10) shows that $\beta_{ijm,t} > I_{\text{high}} > 1$ for firms with $I_j = I_{\text{high}}$ (i.e., firms from the high-risk industries), and $\beta_{ijm,t} < I_{\text{low}} < 1$ for firms with $I_j = I_{\text{low}}$,

[10] Donangelo (2014) defines a similar risk measure and refers to it as labor-induced operating leverage.

regardless of the local markets. Wages in the local market, which is a mix of high-risk and low-risk industries, are less cyclical than the output of high-risk industries and more cyclical than the output of low-risk industries. This leads to even higher (lower) cyclical variation in the profits of high (low) risk industries.

Now let us define the sensitivity of firm risk, $\beta_{ijm,t}$, to the share of high-risk industries in a local market, s_m, as follows:

$$\frac{\partial \beta_{ijm,t}}{s_m} = \frac{\frac{\alpha_l}{1-\alpha_l}(I_{\text{low}} - I_{\text{high}}) A_t^{\frac{I_{\text{low}}+I_{\text{high}}}{1-\alpha_l}}}{\left(s_m A_t^{\frac{I_{\text{high}}}{1-\alpha_l}} + (1-s_m) A_t^{\frac{I_{\text{low}}}{1-\alpha_l}}\right)^2}. \tag{11}$$

Note that higher s_m implies a riskier local market. Since $I_{\text{low}} - I_{\text{high}} < 0$ and all other terms are positive, we have that $\frac{\partial \beta_{ijm,t}}{s_m} < 0$. Thus, in areas with a higher share of high-risk industries, the risk of individual firms is lower than that of their industry peers located in areas with a lower share of high-risk industries. This geographical comparison holds for firms in both high-risk and low-risk industries. Wages are more cyclical in local markets where the majority of firms belong to the high-risk industry, that is, areas with higher s_m, and hence serve as a hedge against fluctuations in aggregate productivity. In contrast, local markets where the majority of firms belong to the lower risk industry, that is, areas with lower s_m, experience smaller fluctuations in wages, which amplifies the effect of aggregate shocks on firm profits relative to industry peers and hence results in higher risk. Thus, the industrial composition of the local market leads to a novel operating leverage channel.

It is useful to emphasize that, while the risk of individual firms, conditional on their industry, is lower in markets with a higher share of high-risk industry, on an unconditional basis, firms in these areas are still riskier than firms elsewhere.[11] Therefore, throughout the paper, all firm-level analysis is performed conditional on the firm's industry.

The static nature of the simplified model with only labor allows us to make predictions, based on closed-form expressions, on how the riskiness of a local economy affects wage cyclicality and the risk of the firms operating in that economy. In the dynamic full model presented in Section IV, firms own and use land—another local factor—and equipment, in addition to labor. The full model generates additional predictions based on firms' input composition, with a focus on land holdings, and quantifies the qualitative insights of this section.

[11] To show this, we write the total profits of local markets as the sum of the profits of individual firms located in that area, Π^*_m, and we define $\beta_m = \frac{\frac{\partial \Pi^*_m}{\partial A_t}}{\frac{\Pi^*_m}{A_t}}$. The result that $\frac{\partial \beta_m}{\partial s_m} = \frac{A_t^{\frac{I_{\text{high}}+I_{\text{low}}}{1-\alpha_l}}(I_{\text{high}}-I_{\text{low}})}{(s_m A_t^{\frac{I_{\text{high}}}{1-\alpha_l}} + [1-s_m] A_t^{\frac{I_{\text{low}}}{1-\alpha_l}})^2} > 0$ implies that, unconditionally, firms are riskier in areas with a higher share of high-risk industries.

II. Data and Measurement

In this section, we describe the data used in the paper and discuss the measurement of key variables. To conduct the empirical analysis, we combine a number of data sets. Appendix Table A.I summarizes all data sets used in the paper. The Internet Appendix provides more details on data sources and variable construction.[12]

Local Beta. The key explanatory variable in this paper is the beta of local economies, β_m^{local}. We compute local beta as the average of the GDP betas of the industries operating in that area, weighted by the employment share of the industries. Specifically,

$$\beta_{m,t}^{\text{local}} = \sum_i w_{i,m,t} \beta_{i,t}^{\text{ind}}, \tag{12}$$

where $w_{i,m,t}$ represents the employment share of industry i in market m in year t, and $\beta_{i,t}^{\text{ind}}$ represents the beta of industry i in year t.

We classify local markets by MSA, geographic entities defined by the Office of Management and Budget that contain a core urban area with a population of 50,000 or more as well as adjacent counties that have a high degree of social and economic integration with the urban core measured by work commutes.[13] Our sample contains 373 unique MSAs.

To calculate the weight of the industries in an MSA, we collect MSA-level industry employment data from the County Business Patterns (CBP) data set published by the U.S. Census Bureau.[14] We then compute an industry's share (weight) $w_{i,m,t}$ as the ratio of the industry's employment in the MSA to the total reported employment in the MSA in year t. While most MSAs have a diverse economic base featuring many industries, there is heterogeneity in the degree of industrial diversity across MSAs. Figure 1 plots the distribution of MSA-level industrial employment dispersion, computed as the Herfindahl-Hirschman index (HHI) of industry employment shares as of 2011, the last observation year in our sample.

To calculate industry betas, we obtain annual data on industry value-added, as a measure of industry output, from the Bureau of Economic Analysis (BEA). Industry shocks are given as the growth in real industry value-added, where nominal data are deflated by GDP deflators to calculate real value-added. Industry betas, $\beta_{i,t}^{\text{ind}}$, are calculated as the slope coefficients of regressions of industry shocks (i.e., real industry value-added growth) on aggregate shocks

[12] The Internet Appendix is available in the online version of this article on the *Journal of Finance* website.

[13] The term "Core Based Statistical Area" (CBSA) refers to both metro and micro areas. Currently, the Census Bureau uses the MSA and metro CBSA terms interchangeably. See http://www.census.gov/population/metro/.

[14] Disaggregated data are at times suppressed for confidentiality reasons. However, in these cases, the Census Bureau provides a "flag" that tells us the range within which the employment number lies. Like Mian and Sufi (2012), we take the mean of this range as a proxy for the missing employment number.

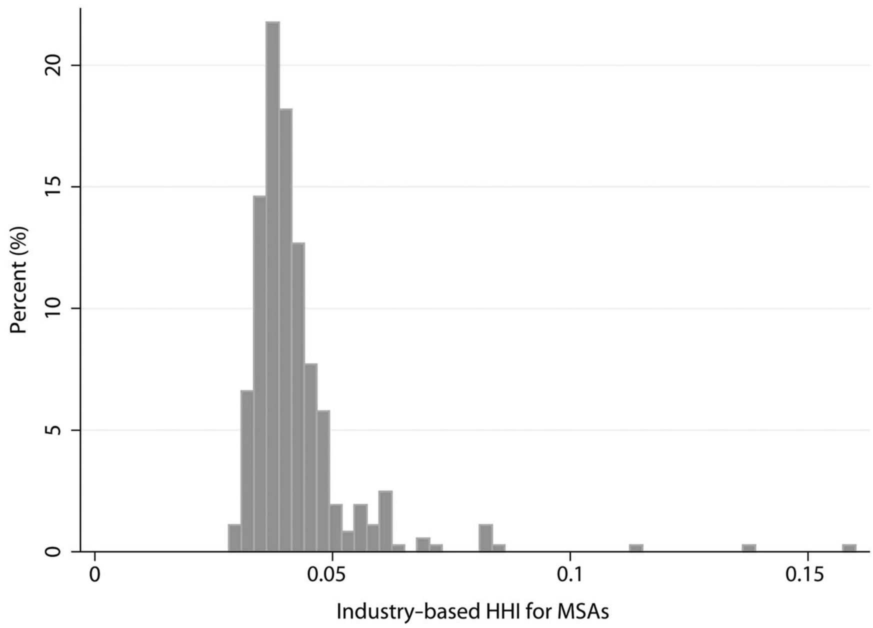

Figure 1. Distribution of industrial employment dispersion within MSAs. The figure plots the distribution of industrial employment dispersion on a within-MSA basis, calculated as the Herfindahl-Hirschman Index (HHI) of industry employment shares in 2011.

(i.e., real GDP growth), using data up to year t. Table I lists the industries with the highest and lowest betas in 2011. Broadly speaking, the industries with the lowest betas operate in the food manufacturing, health care, and oil sectors. These industries have negative or near-zero betas in our sample. The industries with the highest betas operate in the heavy manufacturing (primary metal, transportation equipment, nonmetallic mineral, and wood) and financial sectors, with betas around three. Replacing industry employment weights, $w_{i,m,t}$, and industry betas, $\beta_{i,t}^{\text{ind}}$, in equation (12), we obtain MSA betas over 1986 to 2011.

Figure 2 plots the distribution of MSA betas as of 2011. Most MSA betas are between 0.8 and 1.2, and betas are positively skewed. Table II lists the MSAs with the lowest and highest betas as of 2011 to shed more light on local betas. MSAs with the highest local betas are typically dominated by the heavy manufacturing industries and accommodation sector, while those with the lowest local betas are dominated by food manufacturing, health care, and education service industries. There is no particular relationship between local beta and the size of an MSA (as measured by employment): the correlation coefficient between local beta and employment, computed using the sample of all MSAs in 2011, is less than 0.1.

Figure 3 compares the economic performance of the MSAs with the highest and lowest local betas over the period 2001 to 2011. We obtain data on

Table I

Highest and Lowest Beta Industries

The table presents the three-digit NAICS industries with the lowest (Panel A) and highest (Panel B) betas as of 2011. The industry betas, β^{ind}, are calculated as the slope coefficients from regressions of industry shocks (real industry value-added growth) on aggregate shocks (real GDP growth) from 1978 to 2010.

NAICS	Industry Title	β^{ind}
	Panel A: Lowest β^{ind} Industries	
211	Oil and Gas Extraction	−0.757
311	Food Manufacturing	−0.712
312	Beverage and Tobacco Product Manufacturing	−0.712
213	Support Activities for Mining	−0.245
622	Hospitals	−0.067
	Panel B: Highest β^{ind} Industries	
331	Primary Metal Manufacturing	3.623
525	Funds, Trusts, and Other Financial Vehicles	3.479
321	Wood Product Manufacturing	3.259
336	Transportation Equipment Manufacturing	3.104
327	Nonmetallic Mineral Product Manufacturing	2.863

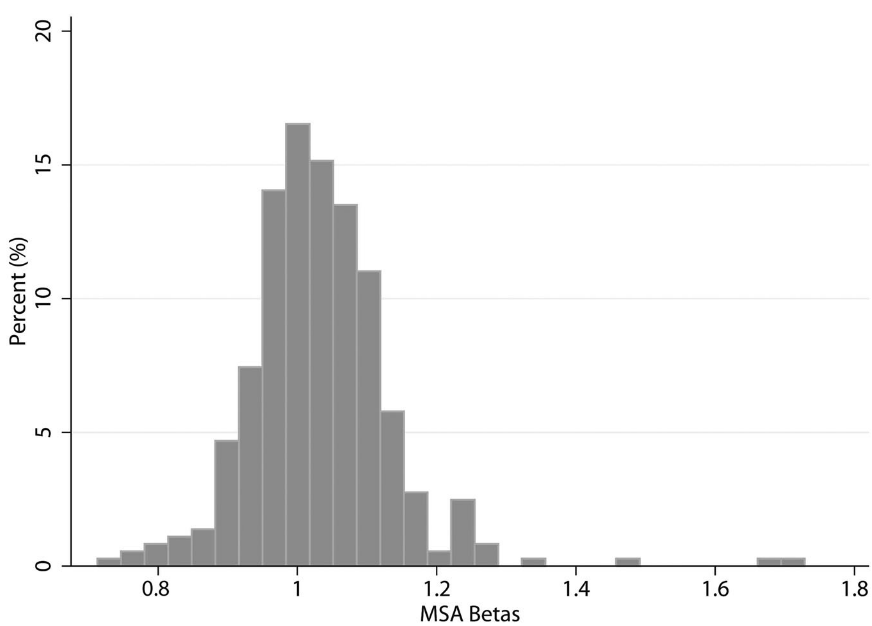

Figure 2. Distribution of MSA betas. The figure plots the distribution of MSA betas as of 2011.

Table II

Highest and Lowest Beta MSAs

The table presents summary statistics for the MSAs with the lowest (Panel A) and highest (Panel B) betas as of 2011 and the transition probability matrix of local beta quintiles. Local betas, β_m^{local}, are calculated as the average of the industry betas for industries operating in that area, weighted by the employment share of industries. The representative industry is the industry with the highest employment share in the MSA among all industries with a location quotient above 3.5. The location quotient is the ratio of an industry's share of regional employment to its share of the entire economy. % of Employment reports the fraction of jobs from the representative industry in that MSA. # Employment reports the number of employees in 2011 for the MSA and the employment rank among all MSAs.

CBSA	MSA Title	β_m^{Local}	Representative Ind.	% of Emp.	# Emp.	Emp. Rank
		Panel A: Lowest β_m^{local} MSAs				
41140	St. Joseph, MO-KS	0.71	Food Manuf.	14.9%	48,762	261
32900	Merced, CA	0.75	Food Manuf.	15.8%	39,914	302
34900	Napa, CA	0.76	Bevg. & Tobac. Manuf.	11.9%	56,022	230
27060	Ithaca, NY	0.78	Educ. Service	37.6%	45,545	281
25260	Hanford-Corcoran, CA	0.79	Food Manuf.	13.8%	22,896	359
23580	Gainesville, GA	0.81	Food Manuf.	14.5%	59,760	223
40340	Rochester, MN	0.82	Hospitals	21.6%	86,211	178
33260	Midland, TX	0.83	Supp. Mining	13.1%	65,689	215
43580	Sioux City, IA-NE-SD	0.83	Food Manuf.	13.2%	65,462	216
34060	Morgantown, WV	0.84	Chemical Manuf.	7.9%	45,865	277
24140	Goldsboro, NC	0.86	Food Manuf.	7.2%	34,069	327
26980	Iowa City, IA	0.86	Truck Transport.	5.7%	65,159	217
38220	Pine Bluff, AR	0.87	Food Manuf.	6.6%	25,139	355
47580	Warner Robins, GA	0.87	Food Manuf.	10.6%	34,278	326
40660	Rome, GA	0.87	Food Manuf.	5.2%	32,780	333
		Panel B: Highest β_m^{local} MSAs				
21140	Elkhart-Goshen, IN	1.73	Transp. Equip. Manuf.	24.9%	102,109	160
37700	Pascagoula, MS	1.48	Transp. Equip. Manuf.	34.2%	49,793	253
29020	Kokomo, IN	1.33	Transp. Equip. Manuf.	22.6%	31,770	337
19140	Dalton, GA	1.29	Textile Product Mills	24.7%	54,824	236
18020	Columbus, IN	1.28	Transp. Equip. Manuf.	6.9%	40,314	299
43900	Spartanburg, SC	1.26	Transp. Equip. Manuf.	6.8%	110,969	149
25860	Hickory-Lenoir-Morganton, NC	1.24	Furniture Manuf.	11.8%	123,517	136
11500	Anniston-Oxford, AL	1.24	Fabric. Metal Manuf.	5.1%	36,093	320

(*Continued*)

Table II—*Continued*

CBSA	MSA Title	β_m^{Local}	Representative Ind.	% of Emp.	# Emp.	Emp. Rank
48620	Wichita, KS	1.24	Transp. Equip. Manuf.	10.6%	242,354	76
34740	Muskegon-Norton Shores, MI	1.23	Prim. Metal Manuf.	6.6%	49,204	259
29820	Las Vegas-Paradise, NV	1.23	Accommodation	23.3%	730,747	34
29140	Lafayette, IN	1.23	Transp. Equip. Manuf.	7.5%	65,748	214
35980	Norwich-New London, CT	1.23	Accommodation	16.6%	105,276	152
31900	Mansfield, OH	1.20	Fabric. Metal Manuf.	4.4%	42,132	295
26100	Holland-Grand Haven, MI	1.20	Fabric. Metal Manuf.	4.4%	90,369	176

MSA-level real GDP from the BEA.[15] The top panel plots the average real GDP of the two groups of MSAs along with national GDP. The bottom panel plots annual real GDP growth. The figures show that high beta areas experienced steady growth during the 2001 to 2007 expansion, but experienced a larger reduction in GDP in terms of both levels and growth during the Great Recession of 2008 and 2009. The lowest beta areas, in contrast, experienced neither a large increase nor a significant drop in output over the same period. These findings support the validity of our local betas, constructed from local industry shares and industry betas, as measures of the economic risk of local areas.

Factor Prices. We measure local factor prices—wages and real estate prices—using data from several different sources. We obtain wage data at the MSA × industry level from the Quarterly Workforce Indicators (QWI) data set of the Longitudinal Employer-Household Dynamics (LEHD) program of the U.S. Census Bureau.[16] We also obtain hourly occupational wages for metropolitan areas from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. We use both broad occupation definitions, with 22 major occupation groups, and detailed occupation definitions, with 854 detailed occupation categories.

We capture MSA-level housing prices using the house price indexes (HPIs) from the Federal Housing Finance Agency. Commercial real estate returns account for the income and appreciation of all commercial property types (office, retail, industrial, apartment, and hotel) and are provided by the National

[15] To the best of our knowledge, there are no publicly available data before 2001. This is one of our main motivations for constructing our benchmark measure of local beta from industry betas as in equation (12).

[16] The main advantage of QWI data over other sources, such as the CBP or Quarterly Census of Employment and Wages (QCEW), is that QWI reports average wages for virtually all industries in all areas, whereas CBP and similar programs do not disclose wages for many industry-area combinations for confidentiality reasons.

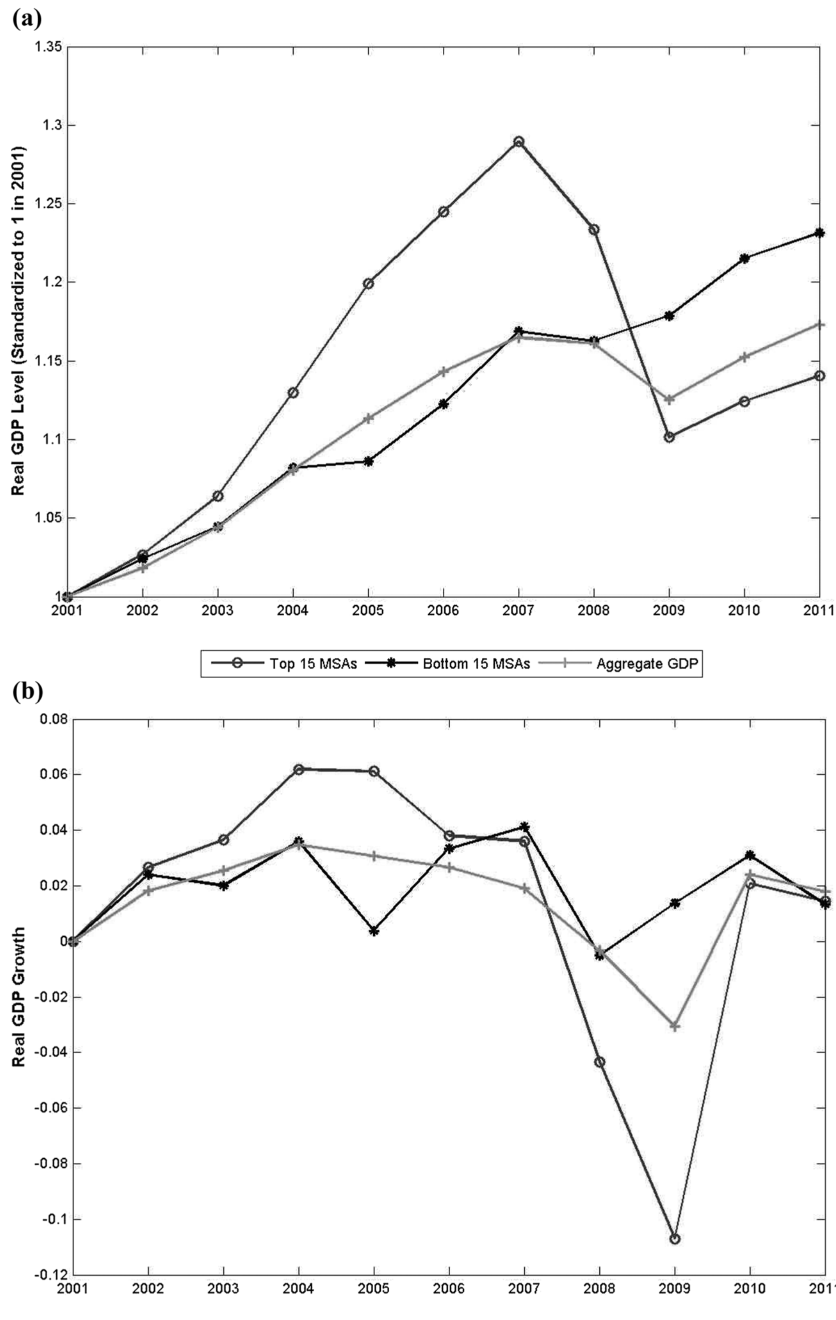

Figure 3. Local beta and fluctuations in local GDP. The figure plots the average real GDP and GDP growth of the top and bottom 15 MSAs based on their local betas over the 2001 to 2011 period. MSAs are classified based on local betas in 2011. The top panel plots average real GDP, normalized to one in 2001, while the bottom panel plots average real GDP growth.

Council of Real Estate Investment Fiduciaries (NCREIF NPI). Commercial real estate rent data come from CoStar.[17]

Firm Location. For our firm-level analysis, we identify a firm's location using its headquarters location from Compustat.[18] We supplement these data with headquarters location change information from Compact Disclosure, compiled by Engelberg, Ozoguz, and Wang (2010).[19]

To further assess the validity of this identification, we link our 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 our sample.[20] This allows us to create an employment map for each of roughly 2,000 firms in the linked sample.[21] We find that 63% of the firms in our linked sample have at least 50% of their employment in their headquarters MSA. For the median firm in our sample, headquarters location accounts for 72% of total employment. However, while 60% of sample firms have more than half of their employees in their headquarters MSA, there is significant heterogeneity across firms of different size (market capitalization). Appendix Table A.II shows that headquarters MSA is a much better proxy for location for smaller firms. Sorting firms into size quintiles, we find that almost 80% of firms in the smallest size quintile have more than half of their employment in their headquarters MSA, and of these firms, about 55% have virtually all their employment in their headquarters MSA. For the firms in the largest size quintile, the comparable statistics are approximately 50% and 10%. To address the concern that headquarters location may be a noisy measure of where the firm operates and owns assets, we also run our firm-level tests on a subsample of smaller firms.

In the firm-level regressions, all comparisons are conducted on a within-industry basis. To check whether the headquarters of firms in an industry are clustered in one or few MSAs, for each industry, we compute a measure of the

[17] House Price Index (HPI) and CoStar rent data are available at the MSA level. The NCREIF Property Index (NPI) is available at the MSA level for most areas, and at the metropolitan division level, which are subgroups of MSAs, for 11 MSAs. For those areas, we take the average HPI returns for metropolitan divisions as a proxy for the MSA return.

[18] Chaney, Sraer, and Thesmar (2012) argue that headquarters and production facilities tend to cluster in the same state and MSA, and headquarters represent an important fraction of corporate real estate assets. They hand-collect information on firm headquarters ownership using 10K files and find that firms that report headquarters ownership also have positive real estate ownership based on Compustat data. They therefore conclude that headquarters location is a reasonable proxy for firm location.

[19] Compustat reports only the most recent headquarters location of firms. Compact Disclosure discs provide firms' current headquarters location and cover the period 1990 to 2005. There are roughly 300 headquarters location changes over this time period.

[20] We collect the most recent employment numbers from ReferenceUSA U.S. Businesses Database in November 2014 for businesses that are active at that time.

[21] Note that this is the employment map created from the ReferenceUSA database. If ReferenceUSA misses any firm establishments, employees of those establishments do not show up in our employment map. Since ReferenceUSA reports only domestic establishments, international employees of sample firms are not included in the employment map.

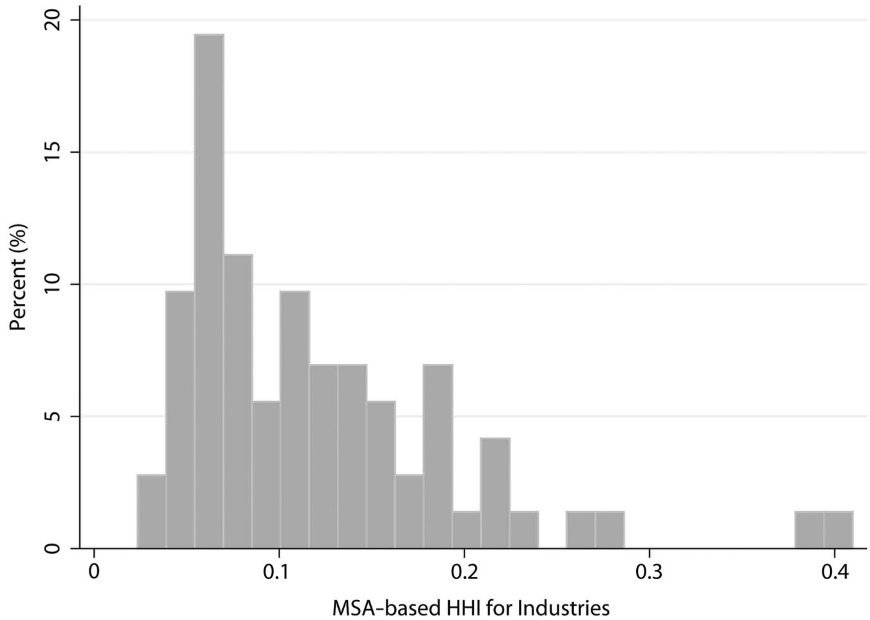

Figure 4. Distribution of MSA dispersion of firms within industries. The figure plots the distribution of the dispersion of Compustat firm locations on a within-industry basis in 2011. For each industry, we count the number of firms located in each MSA. The dispersion of firm locations is then calculated as the HHI of MSA firm-count shares in each industry.

geographic dispersion of firms in the industry.[22] Figure 4 plots the distribution of this geographic dispersion measure. The figure shows that most industries have large variation in firm locations, but a few industries are more geographically focused, though still include firms in several different MSAs.

Financial and Accounting Data. Data on real estate holdings and firm employees come from Compustat. We apply the standard filters to the Compustat data and exclude firms without positive sales (SALE) and assets (AT). Following Fama and French (1993), to avoid survivorship bias in the data, we include firms in our sample after they have appeared in Compustat for two years. Following Tuzel (2010), we measure firms' real estate holdings as the sum of their buildings (FATB) and capitalized leases (FATL). We replace missing values with zero. To calculate a firm's real estate ratio (RER), we scale its real estate holdings with the number of employees (EMP) at the firm.

Monthly stock returns are from the Center for Research in Security Prices (CRSP). Similar to Fama and French (1993), our sample includes firms with ordinary common equity as classified by CRSP, excluding ADRs, REITs, and units of beneficial interest. We match CRSP stock return data from July of year t to June of year $t+1$ with accounting information (Compustat) for the fiscal

[22] Specifically, the geographic dispersion measure is constructed as the HHI of how the number of firms in an industry (from Compustat) are divided among the MSAs.

year ending in year $t-1$ as in Fama and French (1992, 1993), to allow for a minimum gap of six months between fiscal year-end and return tests.

III. Empirical Analysis

In the first part of our empirical analysis, we study the effect of aggregate GDP shocks on local factor prices—in particular on wages and real estate prices—conditional on the beta of the local market. We then study the relationship between local beta and firms' risk and returns.

A. Local Factor Prices

Our first hypothesis is that business cycles (i.e., shocks to aggregate GDP) affect wages in an area more if in aggregate the industries that operate in that market are prone to business cycle shocks (i.e., if the area has a high local beta). We derive this prediction theoretically in equation (8). To test this hypothesis, we run panel regressions with fixed effects as follows:

$$\Delta wage_{\mathrm{ind},m,t} = b_0 + b_1 shock_t \times \beta^{\mathrm{local}}_{m,t-1} + b_2 \beta^{\mathrm{local}}_{m,t-1} + \mathrm{Time} \times \mathrm{Industry\ FE} + \mathrm{MSA\ FE} + \epsilon_{\mathrm{ind},m,t}, \tag{13}$$

where $\Delta wage_{\mathrm{ind},m,t}$ is the percent change in wage per employee in industry ind, market (MSA) m, and year t, $shock_t$ is aggregate real GDP growth in year t, and $\beta^{\mathrm{local}}_{m,t-1}$ is the local beta constructed from the GDP betas of the industries operating in market m, computed as in Section II.[23] The specifications include time-industry fixed effects, and hence the coefficient estimates account for cross-sectional variation within industry and year. We expect to find a positive estimate for the interaction term, b_1, which would imply that wage growth in high beta areas covaries more with GDP shocks than wage growth in the same industry in lower beta areas.

Table III presents results for several different specifications for the full sample, subsamples, and different controls. Panel A uses data from LEHD, our main data source for wages at the MSA-industry level, and Panel B presents the results using MSA-occupation-level hourly wage data from OES.[24] We cluster standard errors at the MSA-industry level.

Consistent with our hypothesis, we find that the interaction term is uniformly positive and significant. In our main specification using LEHD data (columns (1) and (2) of Panel A), the estimates imply a roughly 15 bp difference in wage growth for a one-standard-deviation increase in real GDP (2.5%) between MSAs in the highest and lowest beta quintiles (0.25 beta spread).

[23] The complete specification also includes $shock_t$ as an additional regressor, but it drops out to time fixed effects in the regression.

[24] Both samples have their advantages. LEHD data are disaggregated at the industry level, whereas OES data are disaggregated at the occupation level, and hence include occupation controls rather than industry controls. Another difference between the two data sets is that LEHD includes total wages for the period, whereas OES includes hourly wages.

Table III

Local Wages and Local Beta

Panel A reports the effect of aggregate shocks on industry wage growth in an MSA, conditional on the local beta, β_m^{local}. Panel B reports the effect of aggregate shocks on occupational wage growth in an MSA, conditional on β_m^{local}. The calculation of β_m^{local} is described in Table II. Wage growth is annual in Panel A and hourly in Panel B, all in real terms. The aggregate shock (*Shock*) is aggregate real GDP growth in that year, in %. The regression sample period is 1990 to 2011 in Panel A (LEHD Data), and 1999 to 2011 in Panel B (OES Data). Nonunionized industries (occupations) are industries (occupations) with unionization rates lower than the median unionization rate of all industries (occupations) in that year. Tradable industries are all industries excluding the retail sector and restaurants. All standard errors are clustered at the MSA level and presented in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Annual Wage for Industries

	Wage Growth (%)						Wage Level	
	All Industries		Nonunion Industries		Tradable Industries		(1990 $)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−1.70***	−0.45	−1.82***	−0.23	−1.83***	−0.40	1,276.13	2,734.57***
	(0.29)	(0.76)	(0.35)	(0.90)	(0.31)	(0.81)	(996.47)	(480.78)
Shock × β_m^{local}	0.24**	0.24*	0.34**	0.34**	0.30**	0.30**		
	(0.12)	(0.13)	(0.16)	(0.17)	(0.13)	(0.14)		
Ind.×Year FE	X	X	X	X	X	X	X	X
MSA FE		X		X		X		X
Observations	409,294	409,294	222,549	222,549	343,477	343,477	442,591	442,591
R^2	0.05	0.05	0.06	0.06	0.04	0.04	0.57	0.64

Panel B: Hourly Wage for Occupations

	Wage Growth (%)						Wage Level	
	Broad Occupations		Detailed Occupations		Detailed Nonunion Occ.		(1990 $)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−1.30***	−1.12*	−1.22***	0.12	−1.25***	0.53	0.77**	0.47***
	(0.33)	(0.67)	(0.20)	(0.46)	(0.21)	(0.50)	(0.35)	(0.11)
Shock × β_m^{local}	0.44***	0.38***	0.29***	0.24***	0.31***	0.27***		
	(0.14)	(0.13)	(0.07)	(0.06)	(0.08)	(0.08)		
Occ.×Year FE	X	X	X	X	X	X	X	X
MSA FE		X		X		X		X
Observations	76,986	76,986	1,028,541	1,028,541	758,607	758,607	1,349,174	1,349,174
R^2	0.08	0.09	0.04	0.05	0.04	0.04	0.83	0.86

We obtain similar findings using occupational wage data. Columns (1) and (2) of Panel B present results based on the 22 major occupation groups, and columns (3) and (4) present results based on the 854 detailed occupation definitions. Estimates are both economically and statistically more significant using the detailed occupation definitions.

An implicit assumption in our analysis above is that labor markets are competitive and there are no major frictions to the adjustment of employment or wages. A violation of this condition may arise, however, due to the existence of labor unions in certain industries. For instance, in the context of wages, Kimbell and Mitchell (1982) report that labor contracts in unionized industries are characterized by multiyear contracts with built-in inflation adjustments. Chen, Kacperczyk, and Ortiz-Molina (2011) further argue that the presence of powerful unions substantially reduces firms' operating flexibility. To mitigate concerns due to union involvement, we also consider subsamples of nonunionized industries and occupations.[25] We define nonunionized industries (occupations) as industries (occupations) with unionization rates lower than the median unionization rate of all industries (occupations) in that year.[26] We expect our main findings to be more pronounced for nonunionized industries and occupations.[27] We report the regression results using nonunionized industries in columns (3) and (4) of Panel A and using nonunionized occupations in columns (5) and (6) of Panel B. We find that excluding highly unionized industries and occupations from our main sample strengthens the results and slightly increases the magnitudes of the coefficients on the cross terms.

Note that, in our benchmark sample, we do not distinguish industries based on geographic segmentation in their product markets. The implicit assumption here is that local beta does not have a substantial effect on firms' output demand/prices. But this assumption may not hold for industries that produce *nontradable* goods that are sold only to locals. To address this concern, we also consider a subsample that excludes nontradable industries, where following Mian and Sufi (2012), we define nontradable industries as the retail sector and restaurants (SIC 52-59, NAICS 44-45, and 722).[28] The results, presented in columns (5) and (6) of Panel A, show that our main results continue to hold, and indeed are even slightly more significant for the subsample of tradable industries.

Overall, Table III demonstrates that local wages are more sensitive to systematic shocks in local markets with higher betas. The significant weight of risky industries in high local beta areas amplifies the effects of aggregate shocks to the wages of all employees in the area, regardless of their industry and occupation affiliation. This implies that employees in high beta areas are more exposed to aggregate shocks than their counterparts in low beta areas. While we take the location choice of employees to be exogenous, in equilibrium,

[25] We obtain data on the unionization rate for industries and occupations from http://www.unionstats.com, compiled by Barry Hirsch and David Macpherson from the Current Population Survey and updated annually. The database is described in Hirsch and Macpherson (2003). The industry and occupations are based on Census codes. We use crosswalks between the Census industry and occupation codes, which are used in the unionization data set, and NAICS industry classification codes in LEHD and Standard Occupational Classification (SOC) codes, which are used in OES wage data sets.

[26] Our results are qualitatively similar when we use different cutoffs for unionized industry definitions.

[27] OES and unionization data use different occupation classifications. We can match roughly two-thirds of the 854 detailed occupation definitions in OES to the unionization data. The unmatched occupations are included in the low unionization subsample for a conservative estimate.

[28] Identifying nontradable industries is not a trivial task. Even the retail sector, which is a classic example of a nontradable sector, may not be completely nontradable due to nonlocal sales through the Internet, catalogs, etc.

employees should be indifferent to different locations, at least in the long run. To the extent that employees care about labor income risk, they should require higher wages in high beta areas. The last columns of Table III (columns (7) and (8)) investigate this hypothesis. In Panel A, we regress annual wages at industry-MSA level on local beta controlling for year-industry fixed effects; in Panel B, we regress hourly wages at occupation-MSA level on local beta controlling for year-occupation fixed effects. We find that wages increase with local beta and that most estimates are highly significant. Wages in MSAs in the highest beta quintile are approximately $1,000 to $2,700 higher (annually) than their counterparts in the lowest beta quintile, in 1990 dollars.

In addition to wages, aggregate shocks should have a larger impact on real estate prices and rents in high beta areas. Commercial real estate is a major local input for firm production, so good (bad) shocks should lead to increased (decreased) demand for this type of asset. Since the supply of commercial real estate is inelastic in the short run, a change in demand should affect real estate prices and rents, with the variation in demand greater in high beta areas than in low beta areas. Systematic shocks could also have a larger effect on house prices in high beta areas due to two separate channels. The first channel is through increased (decreased) demand for housing from households as a result of increasing (decreasing) wages in the area. The second channel is through spillovers from increasing (decreasing) commercial real estate prices, since both types of real estate share a common input, land.

To test the effect of aggregate shocks on real estate returns, in Table IV, we run the following panel regressions with fixed effects:

$$\begin{aligned} r^{\mathrm{re}}_{m,t} &= b_0 + b_1 shock_t \times \beta^{\mathrm{local}}_{m,t-1} + b_2 \beta^{\mathrm{local}}_{m,t-1} \\ &\quad + \text{Time FE} + \text{MSA FE} + \epsilon_{\mathrm{ind},m,t}. \end{aligned} \tag{14}$$

where $r^{\mathrm{re}}_{m,t}$ represents housing returns in columns (1) and (2), commercial real estate returns in columns (3) and (4), and commercial real estate rent growth in columns (5) and (6). All specifications include time fixed effects, and we present results with and without MSA fixed effects. As in the wage regressions, we cluster the standard errors at the MSA level. We expect to find a positive estimate for the interaction term, b_1, which implies that real estate returns in high beta areas are more sensitive to GDP shocks than real estate returns in low beta areas. Consistent with our hypothesis, we find that the interaction terms are positive and significant in all specifications. The coefficient estimates imply roughly a 0.6% difference in housing returns, a 2.5% difference in commercial real estate returns, and a 1.5% difference in commercial real estate rent growth between MSAs in the highest and lowest beta quintiles in response to a one-standard-deviation change in real GDP.

Taken together, our panel regression results in Tables III and IV show that prices of local factors of production—wages and real estate—are more sensitive to aggregate shocks in areas with more cyclical economies. In the Internet Appendix, we also adopt an alternative methodology where we test the hypotheses above using two-stage cross-sectional regressions. We find consistent results.

Table IV

Real Estate Returns and Local Beta

The table reports the effect of aggregate shocks on real estate returns in an MSA, conditional on the local beta, β_m^{local}. The calculation of β_m^{local} is described in Table II. Housing returns are annualized changes in the FHFA house price indexes in each MSA. Commercial real estate returns are total annualized returns to all property types in each MSA, from NCREIF. Rent growth is annualized growth in office building rents in each MSA, from CoStar. The aggregate shock (*Shock*) is aggregate real GDP growth in that year, in %. The regression sample period is 1986 to 2011. Regressions are conducted on a quarterly basis. The commercial real estate regression includes property-type fixed effects (office, industrial, retail, apartment, and hotel). All standard errors are clustered at the MSA level, presented in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

	Housing Returns		Commercial Real Estate Returns		Rent Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
β_m^{local}	−1.87***	3.82***	−2.68	9.25	−4.36	0.18
	(0.56)	(1.18)	(4.38)	(6.17)	(2.77)	(7.54)
$Shock \times \beta_m^{\text{local}}$	1.16***	1.09***	4.16*	3.52*	2.72**	1.98*
	(0.25)	(0.26)	(2.14)	(2.08)	(1.13)	(1.14)
Time FE	X	X	X	X	X	X
MSA FE		X		X		X
Observations	36,268	36,268	10,267	10,267	5,411	5,411
R^2	0.45	0.46	0.52	0.53	0.18	0.21

B. Firm-Level Results

Section III.A demonstrates that GDP shocks have a larger impact on local factor prices such as wages and real estate prices in high beta areas than in low beta areas. Since labor and commercial real estate are major firm inputs, the differential effect of aggregate shocks on local input prices should be an additional channel through which these shocks affect firms. We next study the effect of this mechanism on the returns of firms located in areas with different local betas.

The greater sensitivity of wages to aggregate shocks in high beta areas provides a natural hedge for firms, mitigating the effect of the shocks and thus leading to lower firm risk. At the same time, however, real estate values are more sensitive to shocks in high beta areas. Since firm value is derived in part from the value of its capital, including corporate real estate, this mechanism implies higher firm risk in high beta areas. So, for firms that own real estate, these two channels should have opposite effects on the relationship between local betas and firm risk.[29]

[29] For firms that do not own but instead lease real estate, leasing will create an additional hedging mechanism in the presence of procyclical rents (assuming that market rent changes are reflected in their leases, which would be true if firms are signing a new lease agreement or renegotiating their existing lease). The effect would be similar to the labor effect.

To investigate the implications of local betas for firm risk, we first estimate firms' conditional equity betas as in Lewellen and Nagel (2006). Conditional equity betas are estimated using short-window regressions (one year) and monthly returns, and do not require that the conditioning information be specified. We correct for nonsynchronous trading following the methodology described in Lewellen and Nagel (2006).[30] We use conditional equity beta as a proxy for firm risk, and we examine the effect of local betas on firms' conditional equity betas by running the following panel regressions with fixed effects[31]

$$\beta^{\text{cond}}_{\text{firm},t} = b_0 + b_1 \beta^{\text{local}}_{m,t-1} + \text{Time} \times \text{Industry FE} + \text{controls}_{\text{firm},t} + \epsilon_{\text{firm},t}, \tag{15}$$

where $\beta^{\text{cond}}_{\text{firm},t}$ represents the conditional equity beta. We expect $b_1 < 0$, which would imply lower risk of firms located in high beta areas.[32] To distinguish the effects of the labor and the real estate channels, we create subsamples based on firm real estate exposure. The idea is that firms with low exposure to real estate should not be affected by the real estate channel, so firms in high beta areas should have lower industry-adjusted risk due to the labor channel. As the real estate exposure of firms increases, we expect this mechanism to weaken and possibility switch sign.

Table V reports the results for the full sample of firms as well as subsamples based on the RER, defined as a firm's real estate holdings scaled by the number of employees at the firm. This ratio attempts to quantify the relative importance of the real estate channel versus the labor channel for the firm. Panel A reports the results for the full sample, while Panel B sorts the firms into low (below-median) and high (above-median) RER subsamples. In columns (1) to (4) of Panel B, subsamples are formed based on firm-level RER.[33] In columns (5) to (8), subsamples are formed by calculating the average RER for each industry and then sorting industries based on this ratio (below or above median).[34] We present results with and without controls for well-known firm-level predictors of returns, such as size, book-to-market ratio, leverage, profitability, and investment ratio. Standard errors are clustered at the firm level.

[30] Specifically, we regress monthly excess stock returns on the excess returns of the market and one lag of the market portfolio. Conditional beta is the sum of the coefficients for the contemporaneous and lagged market returns.

[31] In panel regressions of equity betas (equation (15)) and firm returns (equation (16)), we equally weight the observations. We show that larger firms tend to operate in dispersed geographic areas, for which headquarters location is a weaker proxy from where the firm operates. Local betas should have a larger effect among small firms since betas are more precisely estimated for these firms.

[32] This is true if the labor channel dominates the real estate channel for the full sample of firms.

[33] In Tables V to VIII, all firms in our Compustat sample with valid RERs are sorted into subsamples before the Compustat sample is merged with returns from CRSP. This leads to variation in the size of the subsamples after the return data are merged.

[34] It is well known that some industries need and thus hold more real estate than others (Tuzel (2010)). Sorting firms based on industry RER helps reduce the measurement errors individual firms face.

Table V

Panel Regression of Conditional Equity Betas and Local Beta

The table reports the relationship between the conditional equity betas ($\beta_{\text{firm}}^{\text{cond}}$) of firms located in an MSA and local beta, β_m^{local}. The calculation of β_m^{local} is described in Table II. Conditional equity betas for firms are computed each calendar year from short window regressions using monthly data, correcting for nonsynchronous trading as in Lewellen and Nagel (2006). All independent variables are lagged one year. In Panel A, we regress conditional equity beta on local beta and other firm-level control variables. *Log BM* and *Log Size* are the log of the firm's book-to-market ratio and market equity constructed following Fama and French (1992). *Leverage* is the firm's market leverage as in Fan, Titman, and Twite (2012). *Profitability* is gross profit measured as in Novy-Marx (2013). *Investment* is the investment ratio as in Dougal, Parsons, and Titman (2015). In Panel B, the subsamples are sorted based on RER, defined as (buildings + capital leases)/employees. Columns (3) to (6) use firm-level RER, and columns (7) to (10) use industry-level RER, computed as the average RER of firms in each industry. Regression sample period is 1986 to 2011. Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_m^{local}	−0.35***	−0.35***	−0.33***	−0.34***	−0.33***	−0.36***	−0.30**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Log *BM*		−0.03*					−0.10***
		(0.01)					(0.01)
Log *Size*			−0.04***				−0.05***
			(0.01)				(0.01)
Leverage				0.30***			0.34***
				(0.05)			(0.05)
Profitability					−0.37***		−0.36***
					(0.05)		(0.05)
Investment						0.46**	0.58***
						(0.18)	(0.18)
Ind.×Time FE	X	X	X	X	X	X	X
Observations	105,334	105,334	105,334	105,334	105,334	105,334	105,334
R^2	0.09	0.09	0.09	0.09	0.09	0.09	0.09

Panel B: Subsample by Real Estate Holdings

	Low RER Firms		High RER Firms		Low RER Industries		High RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−0.45***	−0.40**	−0.18	−0.12	−0.48***	−0.44***	−0.19	−0.11
	(0.16)	(0.16)	(0.19)	(0.18)	(0.14)	(0.14)	(0.20)	(0.19)
Log *BM*		−0.08***		−0.10***		−0.09***		−0.10***
		(0.02)		(0.02)		(0.02)		(0.02)
Log *Size*		−0.03***		−0.07***		−0.06***		−0.05***
		(0.01)		(0.01)		(0.01)		(0.01)
Leverage		0.41***		0.25***		0.43***		0.23***
		(0.08)		(0.08)		(0.07)		(0.08)
Profitability		−0.15*		−0.59***		−0.07		−0.64***
		(0.08)		(0.06)		(0.07)		(0.07)
Investment		0.31		0.84***		0.39		0.77***
		(0.29)		(0.25)		(0.24)		(0.28)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	44,851	44,851	52,760	52,760	61,162	61,162	44,167	44,167
R^2	0.11	0.11	0.09	0.10	0.10	0.10	0.08	0.08

We find that, in the full sample, and especially in the low RER subsamples (columns (1), (2), (5), and (6) of Panel B), b_1 is negative and significant. These results imply that firms in high beta areas have lower risk, as measured by their conditional equity betas, than their industry peers in lower beta areas.[35] Focusing on the full sample of firms, our b_1 estimates imply that the conditional equity betas for the firms located in the highest MSA beta quintile are roughly 0.1 lower than those for firms in the lowest MSA beta quintile. The implied spread is slightly higher in the sample of firms with low real estate exposure. As the real estate holdings of firms increase (in columns (3), (4), (7), and (8) of Panel B), the difference in the conditional equity betas declines in magnitude and loses statistical significance, implying that the real estate channel starts to dominate and cancels out the effect of the labor channel for this subsample. Notably, the results are both qualitatively and quantitatively similar whether we sort on the basis of firm-level or industry-level RER, which implies that they are robust to measuring real estate exposure in different ways.

Next, we investigate the relationship between local betas and firm returns. Since low risk implies low expected returns, we expect to find a negative relationship between local betas and future stock returns, which proxy for expected returns. Similar to our tests for conditional equity betas, we examine the effect of local betas on future firm returns by running the following panel regressions with fixed effects:

$$\begin{aligned} r^e_{\mathrm{firm},t+1} = {} & b_0 + b_1 \beta^{\mathrm{local}}_{m,t} \\ & + \mathrm{Time} \times \mathrm{Industry\ FE} + \mathrm{controls}_{\mathrm{firm},t} + \epsilon_{\mathrm{firm},t}, \end{aligned} \tag{16}$$

where $r^e_{\mathrm{firm},t+1}$ is the firm's excess return from July of year $t+1$ to June of year $t+2$. We expect $b_1 < 0$, which would imply lower expected returns for firms in high beta areas. This should especially be the case for firms with low real estate exposure, since the labor channel is likely to dominate in those firms. As the real estate exposure of firms increases, we expect this mechanism to weaken due to the effects of the real estate channel.

Table VI follows the same format as Table V, reporting results for firm returns using the full sample of firms as well as subsamples based on the RER. We find that in the full sample, and especially in the low RER subsamples, b_1 is negative and significant, which implies that firms in high beta areas have lower expected returns than their industry peers in lower beta areas. Focusing on the full sample of firms, our b_1 estimates imply roughly 1% lower expected returns for firms located in the highest MSA beta quintile compared to the lowest beta quintile. The implied spread doubles to approximately 2% and is highly significant in the sample of firms with low real estate exposure. Like our findings in Table V, the difference in expected returns declines and loses

[35] Many firms in the low RER subsample have zero real estate holdings. Since virtually all firms need some real estate to operate, these firms are most likely leasing substantial amounts of real estate and hence essentially have negative real estate exposure.

Table VI

Panel Regression of Equity Returns and Local Beta

The table reports the relationship between the future returns of firms located in an MSA and local beta, β_m^{local}. The calculation of β_m^{local} is described in Table II. In Panel A, we regress future monthly returns on local beta and other firm-level control variables. *Log BM* and *Log Size* are the log of the firm's book-to-market ratio and market equity constructed following Fama and French (1992). *Leverage* is the firm's market leverage as in Fan, Titman, and Twite (2012). *Profitability* is gross profit measured as in Novy-Marx (2013). *Investment* is the investment ratio as in Dougal, Parsons, and Titman (2015). Future returns are measured in the year following portfolio formation, from July of year $t+1$ to June of year $t+2$, and annualized (%). In Panel B, the subsamples are sorted based on RER, defined as (buildings + capital leases)/employees. Columns (1) to (4) use firm-level RER, and columns (5) to (8) use industry-level RER, computed as the average RER of firms in each industry. Regression sample period is 1986 to 2011. Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Controlling for Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_m^{local}	−5.13**	−5.24**	−4.09*	−4.77**	−5.64**	−4.89**	−5.19**
	(2.23)	(2.33)	(2.31)	(2.25)	(2.22)	(2.25)	(2.37)
Log *BM*		6.52***					5.92***
		(0.28)					(0.33)
Log *Size*			−1.97***				−1.22***
			(0.11)				(0.12)
Leverage				6.68***			−1.85*
				(0.99)			(1.09)
Profitability					7.84***		9.76***
					(0.91)		(0.97)
Investment						−19.63***	−9.73**
						(4.12)	(4.17)
Ind.×Time FE	X	X	X	X	X	X	X
Observations	1,138,028	1,138,028	1,138,028	1,138,028	1,138,028	1,138,028	1,138,028
R^2	0.15	0.15	0.15	0.15	0.15	0.15	0.15

Panel B: Subsample by Real Estate Holdings

	Low RER Firms		High RER Firms		Low RER Industries		High RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−10.29***	−10.38***	−1.13	−1.32	−7.90**	−8.06**	−1.70	−1.58
	(3.45)	(3.55)	(3.39)	(3.68)	(3.08)	(3.15)	(3.36)	(3.65)
Log *BM*		6.88***		4.99***		6.84***		4.92***
		(0.52)		(0.45)		(0.45)		(0.48)
Log *Size*		−1.34***		−1.35***		−1.30***		−1.02***
		(0.19)		(0.18)		(0.15)		(0.19)
Leverage		−3.93**		−1.75		−2.30		−0.40
		(1.72)		(1.63)		(1.41)		(1.75)
Profitability		10.21***		9.43***		15.27***		4.39***
		(1.52)		(1.32)		(1.41)		(1.32)
Investment		−4.81		−18.52***		−10.21*		−10.11*
		(6.82)		(5.59)		(5.68)		(6.04)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	484,464	484,464	576,199	576,199	658,523	658,523	479,505	479,505
R^2	0.16	0.16	0.17	0.17	0.15	0.15	0.15	0.15

statistical significance as the real estate holdings of firms increase, and the results are robust to measuring real estate exposure at the firm or industry level.

In Table VII, we consider various refinements to our baseline sample of low real estate firms. In the first four columns of Panel A, we focus on firms in the tradable sectors, that is, sectors whose output can be traded beyond the local market. For firms in nontradable industries, local betas can impact both input and output prices, making inference about firm risk difficult.[36] Consistent with this view, we find that the difference in the expected returns of firms located in low and high beta areas is slightly larger for the sample of tradable firms. In columns (5) through (8) of Panel A, we consider firms in tradable industries with low unionization rates. It is widely accepted that unionization increases frictions in wage adjustments and reduces firms' operating flexibility. We therefore expect the strength of the labor channel, and the resulting decreasing risk and expected returns of firms in high beta areas, to be more pronounced for firms in industries with lower unionization rates. Consistent with this prediction, our b_1 estimates from nonunionized industries are higher in absolute value, implying a larger spread between the expected returns of firms located in high and low beta areas.

Panel B of Table VII considers subsamples of firms with geographically focused operations, for which firm headquarters location is a better proxy for where the firm operates. We use two instruments for geographical focus. The first instrument is based on firm size. Using the employment map of firms created from the ReferenceUSA database, we find that smaller firms are more likely to concentrate their operations and employment in the headquarters MSA (Table A.II). Our first subsample thus consists of firms with a market value below the median market value of all firms in that year. To construct our second instrument, we follow Garcia and Norli (2012) and classify firms as geographically focused if few state names are mentioned in their annual reports.[37] Garcia and Norli (2012) report that the median firm mentions five states in its 10K, and the average state count for firms in the highest geographical focus quintile is two. We therefore classify firms that mention two or fewer states as geographically focused.[38] Our prediction is that, for geographically focused firms, firm headquarters location is a less noisy measure of firm location, and hence, the relationship between local beta and expected returns should

[36] Following Mian and Sufi (2012), we define nontradable industries as the retail sector and restaurants. The retail sector poses additional challenges for our empirical analysis. Most public retail firms operate in dispersed geographic areas. For example, Garcia and Norli (2012) report that retailers such as Sears, Darden Restaurants, Barnes & Noble, Office Max, and many others operate in more than 45 states each. For such firms, headquarters location would be a poor proxy from where the firm operates. By excluding firms from the retail sector, we improve the match between a firm's headquarters location and the market where it mainly operates.

[37] This is a noisy measure of geographic focus as state names can be mentioned for reasons besides being the physical location of firm operation. The main advantage of this measure is that it is available for a large cross section of firms.

[38] This subsample has many fewer observations (approximately 1/10th) than our baseline sample.

Table VII

Panel Regression of Equity Returns and Local Beta for Subsamples

The table reports the relationship between the future returns of firms located in an MSA and local beta, β_m^{local}, for various subsamples. The calculation of β_m^{local} is described in Table II. RER subsamples are sorted based on RER, defined as (buildings + capital leases)/employees. Industry-level RER is computed as the average RER of firms in each industry. Tradable industries are all industries excluding the retail sector and restaurants. Nonunionized industries are industries with unionization rates lower than the median unionization rate of all industries in that year. Geographically focused firms comprise firms with below-median market capitalization, and firms that mention two or fewer states in their 10Ks. *Log BM* and *Log Size* are the log of the firm's book-to-market ratio and market equity constructed following Fama and French (1992). *Leverage* is the firm's market leverage as in Fan, Titman, and Twite (2012). *Profitability* is gross profit measured as in Novy-Marx (2013). *Investment* is the investment ratio as in Dougal, Parsons, and Titman (2015). Future returns are measured in the year following portfolio formation, from July of year $t+1$ to June of year $t+2$, and annualized (%). The regression sample period is 1986 to 2011. Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Subsamples for Tradable and Nonunion Industries

	Tradable Industries				Tradable, Nonunion Industries			
	Low RER Firms		Low RER Industries		Low RER Firms		Low RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−11.57***	−11.91***	−8.58***	−8.91***	−15.09***	−16.01***	−10.54***	−10.95***
	(3.45)	(3.55)	(3.08)	(3.16)	(4.14)	(4.23)	(3.56)	(3.65)
Log *BM*		6.97***		6.82***		7.07***		7.03***
		(0.52)		(0.45)		(0.63)		(0.51)
Log *Size*		−1.41***		−1.35***		−1.50***		−1.45***
		(0.19)		(0.15)		(0.23)		(0.18)
Leverage		−4.06**		−2.26		−5.18***		−3.30**
		(1.74)		(1.42)		(2.00)		(1.55)
Profitability		10.20***		15.56***		10.89***		16.04***
		(1.55)		(1.43)		(1.86)		(1.59)
Investment		−5.88		−9.77*		−9.10		−9.77
		(6.87)		(5.71)		(8.55)		(7.06)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	470,862	470,862	646,084	646,084	345,218	345,218	513,762	513,762
R^2	0.16	0.16	0.15	0.15	0.15	0.15	0.15	0.15

Panel B: Subsamples for Geographically Focused Firms

	Tradable, Market Size Below Median				Tradable, Two or Fewer States in 10K			
	Low RER Firms		Low RER Industries		Low RER Firms		Low RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−16.76***	−17.38***	−13.14***	−12.44**	−32.94*	−31.07*	−27.29**	−25.68*
	(5.38)	(5.55)	(5.00)	(5.15)	(17.92)	(18.13)	(13.65)	(14.13)
Log *BM*		7.02***		6.87***		6.45***		8.65***
		(0.73)		(0.66)		(2.31)		(1.70)
Log *Size*		−6.05***		−5.25***		−3.39***		−2.71***

(*Continued*)

Table VII—*Continued*

Panel B: Subsamples for Geographically Focused Firms

	Tradable, Market Size Below Median				Tradable, Two or Fewer States in 10K			
	Low RER Firms		Low RER Industries		Low RER Firms		Low RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		(0.60)		(0.52)		(0.93)		(0.63)
Leverage		−7.37***		−4.41**		−5.58		−2.26
		(2.58)		(2.10)		(6.37)		(4.81)
Profitability		6.94***		11.40***		5.71		11.18**
		(2.06)		(1.98)		(6.67)		(5.21)
Investment		−0.28		−1.93		47.68		−5.99
		(10.33)		(8.74)		(33.33)		(24.55)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	258,646	258,646	325,705	325,705	41,460	41,460	58,436	58,436
R^2	0.16	0.16	0.14	0.14	0.26	0.27	0.21	0.22

be stronger. We find that the b_1 estimates do indeed increase significantly (in absolute value) to more than double the original coefficients in some specifications, although their statistical significance is somewhat weakened due to smaller sample sizes.

In the last part of our firm-level analysis, we form portfolios of firms based on the beta of their local markets and examine their future returns. We report the average industry-adjusted returns of the portfolios in Table VIII. We construct equal-weighted, rather than value-weighted portfolios. As we discuss in Section II, larger firms tend to operate in more dispersed geographic areas, for which headquarters location is a weaker proxy for where the firm operates.[39] Since local betas are more precisely measured for smaller firms, we expect the relationship between expected returns and local betas to be stronger for these firms. To form the portfolios, we simultaneously sort firms based on their local betas and RERs. Sorting on local betas is performed on a within-industry basis to account for within-industry variation in local betas. Industry-adjusted returns are computed by subtracting the mean returns of each industry from individual firm returns each month. In addition to industry-adjusted returns, we present their alphas estimated as intercepts from the Fama-French three-factor model. Results are presented for portfolios constructed from the full sample, tradable sectors, nonunionized tradable sectors, and small firms, which are more geographically focused. Panel A measures real estate exposure using the firm-level RER, while Panel B uses the industry-level RER.

For firms with low real estate exposure, we find that industry-adjusted portfolio returns decline monotonically as the beta of the local market increases.

[39] Almost 80% of the firms in the smallest size quintile have more than half of their employment in their headquarters MSA, and of these firms about 55% have virtually all of their employment in their headquarters MSA. For the firms in the largest size quintile, those statistics are roughly 50% and 10% (see Appendix Table A.II).

Table VIII
Industry-Adjusted Returns for Local Beta-Sorted Portfolios

The table presents average industry-adjusted returns and their alphas from the Fama-French three-factor model for portfolios sorted on local beta, β_m^{local}. At the end of each June, firms are simultaneously sorted based on their local betas and real estate ratios (RERs). Sorting on local betas is performed within each industry. Industry-adjusted returns are computed by subtracting mean returns of each industry from individual firm returns. The calculation of β_m^{local} is described in Table II, and RER is defined in Table V. Panel A uses firm-level RER, and Panel B uses industry-level RER. Results are presented for the full sample, tradable industries, nonunionized industries, and geographically focused firms (market cap below median), as explained in Table VII. The sample period is 1986 to 2011. Newey-West-adjusted standard errors with one lag are presented in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Portfolios Sorted by Local Beta and Firm-Level RER

		Low RER Firms						High RER Firms					
		Low β_m^{local}	2	3	4	High β_m^{local}	Low-High	Low β_m^{local}	2	3	4	High β_m^{local}	Low-High
All firms	Ind-adjusted return	0.36	0.32	0.14	−0.39	−1.91**	2.28*	−0.01	−0.01	0.91	1.06	−0.25	0.24
		(0.93)	(0.91)	(0.73)	(0.64)	(0.75)	(1.26)	(0.81)	(0.66)	(0.61)	(0.67)	(0.69)	(1.15)
	FF 3-factor alpha	0.49	0.59	0.40	−0.50	−1.96***	2.45*	−0.02	0.08	0.81	0.86	−0.53	0.51
		(0.92)	(0.86)	(0.64)	(0.63)	(0.73)	(1.26)	(0.80)	(0.65)	(0.58)	(0.65)	(0.63)	(1.13)
Tradable firms	Ind-adjusted return	0.47	0.33	0.34	−0.28	−2.10***	2.57**	−0.19	0.18	1.08*	0.77	−0.47	0.27
		(0.91)	(0.92)	(0.76)	(0.67)	(0.76)	(1.26)	(0.87)	(0.71)	(0.64)	(0.73)	(0.78)	(1.25)
	FF 3-factor alpha	0.57	0.62	0.59	−0.39	−2.18***	2.75**	−0.18	0.33	0.98	0.58	−0.86	0.67
		(0.91)	(0.86)	(0.65)	(0.66)	(0.73)	(1.26)	(0.86)	(0.70)	(0.61)	(0.71)	(0.70)	(1.23)
Tradable nonunion firms	Ind-adjusted return	0.87	0.57	0.32	−0.66	−2.60***	3.46**	0.35	1.06	1.19	0.90	−0.63	0.98
		(1.05)	(0.96)	(0.91)	(0.78)	(0.89)	(1.50)	(1.25)	(1.02)	(0.88)	(0.93)	(1.09)	(1.80)
	FF 3-factor alpha	0.95	0.71	0.73	−0.75	−2.76***	3.71**	0.19	0.92	1.10	0.84	−0.86	1.05
		(1.04)	(0.92)	(0.79)	(0.76)	(0.87)	(1.49)	(1.23)	(1.02)	(0.85)	(0.92)	(0.99)	(1.77)
Tradable small Firms	Ind-adjusted return	−0.26	0.36	0.86	−0.88	−3.53***	3.27*	0.04	1.54	0.96	2.48**	−1.28	1.32
		(1.48)	(1.21)	(1.02)	(1.10)	(1.06)	(1.86)	(1.49)	(1.30)	(1.17)	(1.08)	(1.08)	(1.91)
	FF 3-factor alpha	0.20	1.25	1.04	−1.24	−3.59***	3.79**	0.39	1.41	0.47	2.09*	−1.49	1.88
		(1.45)	(1.10)	(0.94)	(1.07)	(1.04)	(1.81)	(1.48)	(1.28)	(1.14)	(1.08)	(1.02)	(1.88)

(*Continued*)

Table VIII—*Continued*

Panel B: Portfolios Sorted by Local Beta and Industry-Level RER

		Low RER Industry						High RER Industry					
		Low β_m^{local}	2	3	4	High β_m^{local}	Low-High	Low β_m^{local}	2	3	4	High β_m^{local}	Low-High
All firms	Ind-adjusted return	1.14	0.03	0.43	−0.07	−1.16*	2.31**	−1.14	0.22	0.58	1.15*	−0.52	− 0.62
		(0.73)	(0.61)	(0.57)	(0.55)	(0.62)	(1.08)	(0.84)	(0.87)	(0.59)	(0.62)	(0.71)	(1.16)
	FF 3-factor alpha	1.08	0.08	0.64	−0.12	−1.36**	2.44**	−0.97	0.54	0.49	0.87	−0.53	−0.44
		(0.72)	(0.60)	(0.52)	(0.54)	(0.57)	(1.06)	(0.83)	(0.79)	(0.59)	(0.60)	(0.70)	(1.16)
Tradable firms	Ind-adjusted return	1.04	0.08	0.61	−0.03	−1.36**	2.40**	−1.15	0.53	0.79	0.90	−0.69	−0.47
		(0.74)	(0.62)	(0.58)	(0.56)	(0.64)	(1.10)	(0.89)	(0.96)	(0.63)	(0.67)	(0.78)	(1.26)
	FF 3-factor alpha	0.96	0.16	0.83	−0.06	−1.59***	2.55**	−0.92	0.93	0.70	0.63	−0.80	−0.11
		(0.74)	(0.61)	(0.53)	(0.56)	(0.59)	(1.08)	(0.87)	(0.87)	(0.62)	(0.66)	(0.77)	(1.26)
Tradable nonunion firms	Ind-adjusted return	0.99	0.32	0.63	−0.12	−1.45**	2.44**	−0.82	2.29	1.77	0.72	−2.20	1.38
		(0.82)	(0.66)	(0.69)	(0.61)	(0.73)	(1.21)	(1.98)	(1.58)	(1.20)	(1.35)	(1.38)	(2.59)
	FF 3-factor alpha	0.96	0.37	0.89	−0.22	−1.66**	2.63**	−0.96	2.33	1.50	0.85	−2.12	1.16
		(0.81)	(0.66)	(0.64)	(0.61)	(0.68)	(1.20)	(1.96)	(1.51)	(1.19)	(1.34)	(1.35)	(2.59)
Tradable small Firms	Ind-adjusted return	1.48	0.62	1.07	0.17	−2.55**	4.02**	−2.52	2.40	0.69	1.68	−1.64	−0.88
		(1.16)	(0.90)	(0.86)	(0.89)	(1.00)	(1.68)	(1.84)	(1.52)	(1.18)	(1.15)	(1.18)	(2.19)
	FF 3-factor alpha	1.76	0.91	1.14	-0.03	−2.87***	4.63***	−1.86	2.76*	0.17	1.16	−1.38	−0.48
		(1.14)	(0.87)	(0.85)	(0.88)	(0.91)	(1.61)	(1.79)	(1.45)	(1.16)	(1.14)	(1.17)	(2.16)

In contrast, there is no significant relationship between the returns and local betas of the firms with high real estate exposure. For the baseline sample, the spread between the returns of low and high beta portfolios is 2.3%.[40] The spreads in portfolio returns are somewhat larger for the subsamples we consider.[41] Though future returns decline almost monotonically as local betas rise, most of the spread in returns comes from the low industry-adjusted expected returns of the highest local beta portfolio. We see similar patterns in the three-factor alphas. These results are both qualitatively and quantitatively similar to the panel regression results presented in Tables VI and VII.

Overall, the results support the hypothesis that aggregate shocks have differential effects on firms based on the local beta of the area and on firms' real estate exposure. For firms with low real estate exposure, those located in high local beta areas are less affected by systematic shocks and have lower expected returns than their industry peers located in low local beta areas, due to hedging effects in labor costs. For firms with high real estate exposure, changes in labor costs and real estate prices offset each other, and thus we do not find differential location effects on risk and returns.

In the Internet Appendix, we present results of a number of additional robustness tests. We begin by testing the robustness of our results to two alternative measures of local beta. The first measure aggregates industry betas, which are computed as the beta of industry TFP on aggregate TFP. The second measure is estimated directly using MSA-level GDP. Next, we test the asset pricing implications using an expanded sample period that starts in 1970 to examine whether our results hold beyond our main sample period, 1986 to 2011. Third, in the asset pricing tests, we replace individual firm returns with industry-MSA portfolio returns to ensure that our results are not driven by a few outlier firms. Finally, we check the robustness of the regression results to various assumptions on the correlation structure of the residuals. We find that the results are robust to all of these variations.

IV. Full Model

In this section, we generalize the simple model presented in Section I, where labor is the only factor of production to consider asset pricing in a production economy with three types of inputs. Two of the inputs (land, which represents real estate, and labor) are local inputs in limited supply. We build heterogeneity into the industry composition (and, in turn, risk) of the local markets. The main questions we address here are: how does local risk affect local factor prices, how does local risk affect the risk of the firms operating in those markets, and for

[40] We present equally weighted portfolio returns. As expected, value-weighted return spreads are smaller and not statistically significant.

[41] Due to the much smaller sample size, there is considerably more noise and larger standard errors in the portfolios formed from geographically focused firms (measured as firms that mention five or fewer states in their annual reports). We do not consider the subsample of firms that mention one or two states as this restriction makes the sample too small to construct meaningful within-industry portfolios.

firms that have high exposure to land, which channel (labor or real estate) dominates in firm returns?

A. Firms

Similar to the simplified model, there exists a continuum of measure one of infinitely lived firms in each local market m that are subject to aggregate and firm-level productivity shocks and that produce a homogeneous good. However, in addition to using labor, firms own and use equipment and land. Moreover, firms belong to one of four industries categorized by both risk (high or low) and real estate intensity (high or low).

The production function for firm i is given by

$$\begin{aligned} Y_{ijm,t} &= F(A_t, Z_{it}, L_{ijm,t}, S_{ijm,t}, K_{ijm,t}) \\ &= A_t^{I_j} Z_{it} L_{ijm,t}^{\alpha_l} S_{ijm,t}^{\alpha_s^j} K_{ijm,t}^{\alpha_k^j}, \end{aligned} \tag{17}$$

where $L_{ijm,t}$ denotes the labor used in production by firm i in industry j and local market m during period t, $S_{ijm,t}$ denotes the beginning-of-period t land holdings (i.e., real estate) of firm i, and $K_{ijm,t}$ denotes the beginning-of-period t equipment holdings of firm i. Labor, land, and equipment shares in the firm's production function are given by α_l, α_s^j, and α_k^j, where $\alpha_l + \alpha_s^j + \alpha_k^j = \overline{\alpha} \in (0, 1)$. All firms have the same labor share α_l. To capture heterogeneity in industries' real estate intensity, we assume that firms belong to either a low real estate industry (α_s^{low}, α_k^{high}) or a high real estate industry (α_s^{high}, α_k^{low}). We further assume that half of the firms belong to high real estate intensity industries, and half belong to low real estate industries.[42] The processes for aggregate and firm productivity, A_t and Z_{it}, and the industry risk scaler, I_j, are described in Section I.

Local labor markets are competitive and labor is free to move between firms in the same area. The marginal product of labor therefore equals the wage rate,[43]

$$\begin{aligned} F_{L_{ijm,t}} &= F_L(A_t, Z_{it}, L_{ijm,t}, S_{ijm,t}, K_{ijm,t}) \\ &= W_{m,t}, \end{aligned} \tag{18}$$

where $W_{m,t}$ is the wage that clears local labor market m at time t.

The capital accumulation rule for equipment is

$$K_{ijm,t+1} = (1 - \delta)K_{ijm,t} + I_{ijm,t}, \tag{19}$$

[42] In total, we have four industries, $j \in \{1, 2, 3, 4\}$, categorized by two orthogonal characteristics: industry risk scaler, $I_j \in \{I_{\text{high}}, I_{\text{low}}\}$, and real estate intensity $(\alpha_s^j, \alpha_k^j) \in \{(\alpha_s^{\text{low}}, \alpha_k^{\text{high}}), (\alpha_s^{\text{high}}, \alpha_k^{\text{low}})\}$.

[43] This is an assumption we make for convenience. Frictions could be introduced through labor adjustment costs, as in Belo, Lin, and Bazdresch (2014), wage rigidity, as in Favilukus and Lin (2012b), or a labor market search mechanism, similar to Kuehn, Petrosky-Nadeau, and Zhang (2013).

where $I_{ijm,t}$ denotes investment in equipment and δ denotes the depreciation rate of installed equipment.

Purchases and sales of land and equipment are subject to quadratic adjustment costs given by $g^s_{ijm,t}$ and $g^k_{ijm,t}$

$$g^s(S_{ijm,t+1}, S_{ijm,t}) = \frac{1}{2}\eta_s \frac{(S_{ijm,t+1} - S_{ijm,t})^2}{S_{ijm,t}}, \tag{20}$$

$$g^k(I_{ijm,t}, K_{ijm,t}) = \frac{1}{2}\eta_k \left(\frac{I_{ijm,t}}{K_{ijm,t}} - \delta\right)^2 K_{ijm,t}, \tag{21}$$

where $\eta_k, \eta_s > 0$. In the above specifications, investors incur no adjustment costs when net investment is zero, that is, when the firm replaces depleted equipment stock to maintain its equipment level or when the firm does not change its land holdings.

Firms are equity financed. Dividends to shareholders are equal to

$$D_{ijm,t} = Y_{ijm,t} - W_{m,t}L_{ijm,t} - P_{m,t}(S_{ijm,t+1} - S_{ijm,t}) - I_{ijm,t} - g^s_{ijm,t} - g^k_{ijm,t}, \tag{22}$$

where $P_{m,t}$ is the land price that clears local land market m at time t. At each date t, firms choose $\{S_{ijm,t+1}, I_{ijm,t}, L_{ijm,t}\}$ to maximize the equity value of the firm, which can be computed as the solution to the dynamic program

$$V_{ijm,t} = \max_{\{I_{ijm,t}, S_{ijm,t+1}, L_{ijm,t}\}} \{D_{ijm,t} + E_t(M_{t,t+1}V_{ijm,t+1})\} \tag{23}$$

subject to equations (2) to (20), where $M_{t,t+1}$ is the stochastic discount factor between time t and $t+1$. The first-order conditions for the firm's optimization problem lead to two pricing equations, which are derived in the Internet Appendix. The returns to the firm are given as[44]

$$R^F_{ijm,t+1} = \frac{V_{ijm,t+1}}{V_{ijm,t} - D_{ijm,t}}. \tag{24}$$

B. Local Markets

Firms have access to the local labor and land markets. All land is owned and used by local firms, and all labor is employed by these firms. Each local market m is populated by a measure one of firms and a measure one of workers, and is endowed with a measure one of land. We assume that labor is not mobile across local labor markets.

[44] We do not assume constant returns to scale in the production function, that is, $\alpha_l + \alpha_s + \alpha_k \in (0, 1)$. In the presence of constant returns to scale, firm returns would be equivalent to the weighted average of returns to land and equipment investment, $R^S_{i,t+1}$ and $R^K_{i,t+1}$, where weights are the shares of land and equipment in the firm's total capital stock. With slightly decreasing returns to scale, firm returns diverge slightly from the weighted average of investment returns.

There is heterogeneity in the industry composition (high or low risk) of local markets. The fraction of firms in high-risk industries in each market is denoted by $s_m \in (0, 1)$. Apart from their industry composition, local markets are ex-ante identical. In equilibrium, local wages and land prices clear the local labor and land markets.

C. The Stochastic Discount Factor

Since the purpose of our model is to examine the cross-sectional variation across firms, we use a framework where the time-series properties of returns are matched using an exogenous pricing kernel. Following Berk, Green, and Naik (1999) and Zhang (2005), we parameterize the pricing kernel directly without explicitly modeling the consumer's problem. As in Jones and Tuzel (2013a) and Imrohoroglu and Tuzel (2014), the pricing kernel is given by

$$\log M_{t+1} = \log \beta - \gamma_t \epsilon^a_{t+1} - \frac{1}{2}\gamma_t^2 \sigma_a^2, \tag{25}$$

$$\log \gamma_t = \gamma_0 + \gamma_1 a_t, \tag{26}$$

where β, $\gamma_0 > 0$, and $\gamma_1 < 0$ are constant parameters. The volatility of M_{t+1} is time-varying, driven by the γ_t process. This volatility takes higher values following business cycle contractions and lower values following expansions, implying a countercyclical price of risk.

The above pricing kernel shares a number of similarities with Zhang (2005). The stochastic discount factor from time t to $t+1$, M_{t+1} is driven by ϵ^a_{t+1}, the shock to the aggregate productivity process in period $t+1$. The volatility of M_{t+1} is time-varying, driven by the γ_t process. This volatility takes higher values following business cycle contractions and lower values following expansions, implying a countercyclical price of risk.[45] In the absence of a countercyclical price of risk, the risk premia generated in the economy do not change with economic conditions. Empirically, the existence of time-varying risk premia is well documented (e.g., Fama and Schwert (1977), Fama and Bliss (1987), Fama and French (1989), Campbell and Shiller (1991), Cochrane and Piazzesi (2005), Jones and Tuzel (2013b), among many others).

D. Equilibrium and Calibration

Solving our model generates the pricing functions for local land prices $P_{m,t}$ and local wages $W_{m,t}$ as well as firms' investment and hiring decisions

[45] A countercyclical price of risk is endogenously derived in Campbell and Cochrane (1999) from time-varying risk aversion, in Barberis, Huang, and Santos (2001) from loss aversion, in Constantinides and Duffie (1996) from time-varying cross-sectional distribution of labor income, in Guvenen (2009) from limited participation, in Bansal and Yaron (2004) from time-varying economic uncertainty, and in Piazzesi, Schneider, and Tuzel (2007) from time-varying consumption composition risk.

as functions of the state variables, namely, firms' industry and local industry shares, s_m. Since the stochastic discount factor is specified exogenously, the solution does not require economy-wide aggregation. However, since local land prices and wages are determined endogenously, the solution requires aggregation at the local market level, m. The aggregate *local* state is (Γ_m, A), where Γ_m is the distribution of local firms over holdings of capital (equipment and land) and firm-level productivity. For the individual firm, the relevant state variables are its capital holdings $(K_{ijm,t}, S_{ijm,t})$, its firm-level productivity Z_{it}, and the aggregate local state $(\Gamma_{m,t}, A_t)$. The role of the aggregate local state is to allow firms to predict future land prices and wages. Let $\Omega_{ijm,t}$ denote the state $(K_{ijm,t}, S_{ijm,t}, Z_{it}; \Gamma_{m,t}, A_t)$ faced by firm i in industry j and local market m at time t.

A recursive competitive equilibrium is a law of motion H_m, where $\Gamma'_m = H_m(\Gamma_m, A)$, local market and industry-specific individual policy functions ϕ_{jm} and φ_{jm}, where $K'_{ijm} = \phi_{jm}(\Omega_{ijm})$ and $S'_{ijm} = \varphi_{jm}(\Omega_{ijm})$, and pricing functions $P_m(\Gamma_m, A)$ and $W_m(\Gamma_m, A)$, such that:

(i) $(\phi_{jm}, \varphi_{jm})$ solve firms' investment problem,

(ii) P_m clears the local land market

$$\sum_j \int S'_{ijm} di = 1, \tag{27}$$

and W_m clears the local labor market

$$\sum_j \int L_{ijm} di = 1, \tag{28}$$

where aggregate labor and land supply in each market m is normalized to one, and $j \in \{1, 2, 3, 4\}$.

(iii) H_m is generated by ϕ_{jm} and φ_{jm}.

We solve for the equilibrium prices and allocations recursively using the approximate aggregation idea of Krusell and Smith (1998). The Internet Appendix provides details on the model solution.

We calibrate the model at the annual frequency. Table IX presents the parameters used in the calibration. The parameters of the firm-level productivity process come from the production function estimations in Imrohoroglu and Tuzel (2014). Specifically, the persistence of the firm-level productivity process, ρ_z, is 0.7, and the conditional volatility of firm productivity, σ_z, is 0.27. The parameters of the production function are values commonly used in the literature: the share of labor, α_l, is set to 0.6 following Cooley and Prescott (1995), and the shares of equipment and land, α_k^j and α_s^j, are set to 0.21 and 0.09 in low real estate intensity industries and 0.11 and 0.19 in high real estate intensity industries, which we calibrate to match the interquartile

Table IX
Model Parameter Values

Parameter	Description	Value
α_l	Labor share	0.60
$\alpha_s^{\text{high}}, \alpha_s^{\text{low}}$	Land share	0.19, 0.09
$\alpha_k^{\text{low}}, \alpha_k^{\text{high}}$	Equipment share	0.11, 0.21
$I_{\text{low}}, I_{\text{high}}$	Industry risk scalers	$e^{-0.9}, e^{0.9}$
β	Discount factor	0.99
γ_0	Constant price of risk parameter	3.2
γ_1	Time varying price of risk parameter	-12
η_k	Adjustment cost parameter for equipment	1
η_s	Adjustment cost parameter for land	1
δ	Equipment depreciation rate	0.08
ρ_a	Persistence of aggregate productivity	0.922
σ_a	Conditional volatility of aggregate productivity	0.014
ρ_z	Persistence of firm productivity	0.7
σ_z	Conditional volatility of firm productivity	0.27

range for the structures/(structures+equipment) ratio of NIPA industries.[46] We model technology as having slighting decreasing returns to scale, with $\alpha_l + \alpha_s^j + \alpha_k^j = \overline{\alpha} = 0.9$.

We take the parameters for aggregate productivity from King and Rebelo (1999) and annualize them. Their point estimates for ρ_a and σ_a using quarterly data are 0.979 and 0.0072, respectively, implying annual parameters of 0.922 and 0.014. We set the depreciation rate for fixed capital, δ, to 8% annually, which is roughly the midpoint of the values used in other studies—Cooley and Prescott (1995) use 1.6%, Boldrin, Christiano, and Fisher (2001) use 2.1%, and Kydland and Prescott (1982) use a 2.5% quarterly depreciation rate.

We set the industry risk parameters I_{low} and I_{high} to exp(-0.9) and exp(0.9), respectively.[47] To solve and simulate the model for the low and high beta markets, we set the fraction of firms from the high-risk industry, s_m, to 0.1 and 0.9 for the low and high beta areas, respectively. We compute local betas, β_m^{local}, as the average of industry output growth betas weighted by the employment share of industries, similar to equation (12). Our parameters lead to a β_m^{local} of 0.9 for low beta areas, and 1.1 for high beta areas. We can interpret a high (low) beta area in the model as an area with local beta roughly one standard

[46] The data come from NIPA Private Fixed Assets by Industry tables. We construct the ratio of current cost structures/(structures+equipment) for each industry. The ratios are quite stable over time. The time-series average for the 25$^{\text{th}}$ percentile is 0.42 and for the 75$^{\text{th}}$ percentile is 0.76 over the 1955 to 2013 period.

[47] Even though industry risk scalers vary significantly between low and high beta industries, their output betas (computed as the slope coefficient from the regression of industry output growth on aggregate output growth) vary much less. The main reason for this is procyclical fluctuations in capital stock (due to the time-varying price of risk), which dominate the procyclical fluctuations in industry and aggregate output. Therefore, modest differences in industry output betas require relatively stark differences in industry scalers.

deviation above (below) the average local beta in the data. In each area, half of the firms belong to high real estate intensity industries and half belong to the low real estate intensity industries, where real estate intensity and industry risk scalers are orthogonal industry attributes.[48]

We choose the pricing kernel parameters β, γ_0, and γ_1 to match the average riskless rate and the first two moments of aggregate value-weighted excess stock returns reported in Imrohoroglu and Tuzel (2014). The discount factor β is 0.99, which implies an annual risk-free rate of roughly 1%. The parameters γ_0 and γ_1 are 3.2 and -12, respectively, which generate annual excess mean returns and standard deviation of 6.2% and 17%, respectively. The adjustment cost parameters, η_s and η_k, are both set to 1 to replicate the value-weighted average (annual) volatility of investment to capital ratio of 16% reported in Imrohoroglu and Tuzel (2014).[49]

To compute the model statistics, we perform 100 simulations of the model economy with 2,000 firms over 50 periods (years).

E. Quantitative Results

In this economy, firms optimally make their investment and hiring decisions to maximize firm value. The optimality conditions dictate that firms invest (hire) until the marginal cost of investing (hiring) equals the marginal benefit. The marginal benefit of investing and hiring increases in productivity. Therefore, everything else held equal, the demand for labor and land is increasing in aggregate productivity. Since both land and labor are in limited supply, in equilibrium, the market-clearing condition can only be satisfied if the marginal cost of hiring (wage rate) and the marginal cost of investing in land (affine in land prices) are also increasing in aggregate productivity. So, a good (bad) aggregate productivity shock leads to increases (decreases) in the wage rate and land prices. This effect is more pronounced in areas where a larger fraction of firms belong to the high-risk industry ($I_j = I_{\text{high}}$) since aggregate productivity shocks have a greater effect on the marginal benefits of investing and hiring for firms that belong to a high-risk industry.

Table X demonstrates this result by running regressions similar to those that we run in Section II using simulated data from the model economy. Specifically, we run regressions of the form

$$\Delta \log(W_{m,t}) = b_0 + b_1 \Delta output_t \times \beta_m^{\text{local}} + b_2 \beta_m^{\text{local}} + \text{Time FE} + \epsilon_{m,t} \tag{29}$$

$$\Delta \log(P_{m,t}) = b_0 + b_1 \Delta output_t \times \beta_m^{\text{local}} + b_2 \beta_m^{\text{local}} + \text{Time FE} + \epsilon_{m,t}, \tag{30}$$

[48] In a robustness test, we added another area with a more diversified economy to our analysis and solved the model for three areas. We confirmed that our quantitative results are almost the same when we use observations from all three areas or from any two of the areas. Therefore, adding more areas with different industry shares is unlikely to have a material effect on our results.

[49] The investment to capital ratio in the data is not separately calculated for equipment and land as investment data are not available in disaggregated form. Setting parameter values $\eta_s = \eta_k = 1$ leads to 15% volatility in I/K for equipment and 16% volatility for land.

Table X

Model-Implied Factor Price Regressions

The table reports the effect of aggregate output shocks, $\Delta output_t$, on wage ($W_{m,t}$) and land price ($P_{m,t}$) growth in an area, conditional on the local beta, β_m^{local}. β_m^{local} is computed as the average of the industry output betas operating in that area, weighted by the employment share of industries. All values are based on regressions run on data generated from 100 simulations of 2,000 firms for 50 periods (years). Point estimates are simulation medians of regression coefficients, and confidence intervals (in parentheses) for the estimates are constructed from the 5th and 95th percentiles of the simulated distributions of those estimates. Like the specifications presented in Tables III and IV, regressions include time fixed effects.

Dependent variable:	$\Delta\log(W_{m,t})$	$\Delta\log(P_{m,t})$
$\Delta output_t \times \beta_m^{\text{local}}$	0.56	0.39
	(0.25, 0.91)	(0.16, 0.62)
β_m^{local}	0.00	−0.01
	(−0.88, 0.88)	(−0.43, 0.43)

where $W_{m,t}$ and $P_{m,t}$ are the wage rate and land prices in each area, and $output_t$ is the log aggregate output of all the firms in the economy.

The first column of Table X reports the wage regression results, and the second column reports the land price regression results. Both regressions produce positive and highly significant estimates for b_1, implying that wage growth and land price growth in high beta areas covary more with aggregate output shocks than their counterparts in lower beta areas.

We next investigate the effect of local risk (local beta) on the risk and expected returns of the firms operating in those areas. The greater sensitivity of wages to aggregate shocks in high beta areas provides a natural hedge for the firms operating in those areas, mitigating the effect of the aggregate shocks on those firms. This mechanism leads to a lower sensitivity of returns to aggregate shocks for firms in high beta areas, lower overall risk, and lower expected returns. While the full model cannot be solved analytically, the results of the simple model presented in Section I allow us to derive closed-form expressions for the local wage rate and firm profits, and are useful for gaining intuition into this result. Equation (8) shows that, while the local wage rate is cyclical in all areas, the sensitivity of the wage rate to aggregate productivity A_t increases with s_m, the fraction of firms from the high beta industries. This, in turn, reduces the sensitivity of firm profits to aggregate shocks in high beta areas, as shown in equations (10) and (11). Since risk is defined as (the inverse of the) covariation of returns with the pricing kernel (equation (25)), and the pricing kernel is monotonically decreasing in shocks to aggregate productivity, a lower sensitivity of profits to productivity shocks implies lower risk.

While the labor mechanism lowers the risk of firms in high beta areas relative to their industry peers located elsewhere, the land mechanism leads to the opposite result. Given that land values are more sensitive to aggregate shocks in high beta areas, and firm value is derived in part from the value of its land holdings, greater variation in land prices implies higher sensitivity of firm returns to aggregate shocks in high beta areas.

Table XI

Model-Implied Equity Betas and Firm Returns

The table reports the relationship between conditional betas ($\beta_{\text{firm}}^{\text{cond}}$) and expected returns of the firms located in an area and the local beta, β_m^{local}. Panel A presents the panel regression results for equity betas, and Panel B presents the panel regression results for expected equity returns. $\beta_{\text{firm}}^{\text{cond}}$ is the estimated running regressions of excess firm returns on market returns using 50-period windows. The calculation of β_m^{local} is described in Table X. Results are based on regressions run on data generated from 100 simulations of 2,000 firms for 50 periods. Point estimates are simulation medians of regression coefficients (portfolio averages), and confidence intervals (in parentheses) for the estimates are constructed from the 5th and 95th percentiles of the simulated distributions of those estimates. Like the specifications presented in Tables V, VI, and VII, the panel regressions include industry × time fixed effects.

	All	Low RER Industries	High RER Industries
	(1)	(2)	(3)
Panel A: Conditional Beta Regressions (Dependent Variable: $\beta_{\text{firm},t}^{\text{cond}}$)			
β_m^{local}	−0.08	−0.10	−0.06
	(−0.38, −0.02)	(−0.45, −0.02)	(−0.31, −0.02)
Panel B: Firm Return Regressions (Dependent Variable: $r_{\text{firm},t+1}^{e}$)			
β_m^{local}	−0.44	−0.83	−0.05
	(−0.88,0.15)	(−1.44, −0.08)	(−0.30,0.38)

The model does not have a rental market. All capital (equipment and land) is owned by firms. All firms optimally own some land since the marginal product of land goes to infinity as land ownership approaches zero. However, firms that belong to high real estate intensity industries endogenously maintain a higher ratio of land to equipment than firms in low real estate intensity industries. As a result, there is cross-sectional heterogeneity in firms' exposures to the labor versus real estate channels.

To test these predictions in the model, we replicate the firm-level analysis presented in Section II using simulated data from the model economy. The results are presented in Table XI. In Panels A and B, we run regressions of the form

$$\beta_{\text{firm},t}^{\text{cond}} = b_0 + b_1\beta_m^{\text{local}} + \text{Industry} \times \text{Time FE} + \epsilon_{\text{firm},t}, \tag{31}$$

$$r_{\text{firm},t+1}^{e} = b_0 + b_1\beta_m^{\text{local}} + \text{Industry} \times \text{Time FE} + \epsilon_{\text{firm},t}, \tag{32}$$

respectively, where $r_{\text{firm},t}^{e}$ is a firm's excess returns, where raw firm returns are defined by equation (24), and $\beta_{\text{firm},t}^{\text{cond}}$ is a firm's conditional beta, which is estimated by running regressions of the firm's excess returns on the excess market returns. Both regressions include industry-time fixed effects and thus comparisons are among firms in the same industry and year.

In both panels of Table XI, the first column runs the regressions using the full sample of firms, whereas columns (2) and (3) report results using the low and high real estate intensity subsamples, respectively. The labor channel implies lower risk and lower expected returns for firms in high beta areas, which should lead to negative b_1 estimates. Conversely, the land price channel implies positive b_1 estimates. It is not clear ex-ante which channel should dominate. However, b_1 is expected to be lower (more negative, or less positive) in the low real estate subsample compared to the high real estate subsample. We find that b_1 is negative in all specifications and samples, which implies that, in general, the labor channel dominates the land price channel. However, the coefficients are much larger in absolute value terms for the firms from low real estate industries: -0.10 versus -0.06 in the conditional beta regressions (both statistically significant) and -0.83 versus -0.05 in the firm return regressions (only the former is statistically significant). These results are consistent with our empirical results described in Section II, where we find that the labor channel overall dominates the real estate price channel in the data.

V. Conclusion

We show that the industrial composition of local markets, and particularly the cyclicality of the major industries in local markets, influence the effect of systematic shocks on firms located in those markets. By calculating MSAs' "local beta"— the average of the industry GDP betas weighted by the industry shares in each MSA, we find that aggregate GDP shocks have more pronounced effects on local factor prices such as wages and real estate prices in high beta areas compared to lower beta areas. These local factors account on average for more than 75% of economic output, so fluctuations in their prices are relevant for firms' exposure to systematic risk.

The larger effect of aggregate shocks on wages in high beta areas provides a natural hedge for firms operating in those areas, compared to their industry peers operating in low beta areas, and thus mitigates the effect of these shocks on firm returns. The implication of the larger effect of aggregate shocks on local real estate prices in high beta areas, however, varies across firms with different exposures to real estate. For firms with high real estate holdings (i.e., a long position in real estate), being located in a high beta area means that firms' value is more exposed to aggregate shocks due to more procyclical real estate prices. In this case, the real estate channel offsets the labor channel, making the effect of local beta on firm risk less significant for firms with high real estate holdings.

We develop a theoretical model in which firms belong to either a high-risk (more cyclical) or a low-risk (less cyclical) industry, and local areas vary in their composition of industry makeup. Each area features a continuum of firms that use labor, land (real estate), and equipment in their production, and land and labor markets clear within each market. The model generates patterns similar to our main empirical results. Specifically, we confirm that land and labor prices are more procyclical in high beta areas. Larger fluctuations in wages reduce the sensitivity of firm returns to systematic shocks in high beta areas, leading to lower risk for firms in these areas. These results are stronger for firms with low real estate exposure.

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Appendix

Table A.I
List of Data Sets

Data Source	Time Period	Purpose/Target
Data Used in MSA β Construction		
BEA Industry GDP (SIC)	1947–1997	Calculate industry β for 1986 to 1997
BEA Industry GDP (NAICS)	1977–2011	Calculate industry β for 1998 to 2011
Census CBP	1986–2011	Obtain industry employment weights in each MSA
BEA MSA GDP	2001–2011	Calculate an alternative measure of local β: β_m^{Output}
BEA Ind. Fixed Assets (SIC)	1947–1997	Calculate an alternative measure of local β: β_m^{TFP} for 1986 to 1997
BEA Ind. Fixed Assets (NAICS)	1977–2011	Calculate an alternative measure of local β: β_m^{TFP} for 1998 to 2011
BEA Ind. FTPT Emp. (SIC)	1948–1997	Calculate an alternative measure of local β: β_m^{TFP} for 1986 to 1997
BEA Ind. FTPT Emp. (NAICS)	1977–2011	Calculate an alternative measure of local β: β_m^{TFP} for 1998 to 2011
Labor Data		
Census LEHD	1990–2011	Obtain the annual wage for each industry in each MSA
BLS OES	1999–2011	Obtain the hourly wage for each occupation in each MSA
www.unionstats.com	1983–2011	Obtain union coverage at the industry and occupation levels
Real Estate Data		
FHFA HPI	1975–2011	Obtain the housing price index in each MSA
NCREIF NPI	1978–2011	Obtain commercial real estate returns for each MSA
CoStar Rent	1982–2011	Obtain the average rent for office buildings in each MSA
Firm Location Data		
Compact Disclosure	1990–2005	Track the change in firms' headquarters locations
State counts from Garcia and Norli (2012)	1992–2008	Obtain a proxy for firms' geographic concentration
www.referenceusa.com	2013–2014	Obtain firms' employment distribution across MSAs
Financial and Accounting Data		
Compustat (annual)		Obtain firms' location, industry, and other characteristics
CRSP Stock (monthly)		Calculate monthly stock returns and equity βs

Table A.II

Employment Share of Headquarters MSA

The table reports the percentage of firms that have at least 50%, 75%, 90%, or 100% of their employment in their headquarters MSA. We create an employment map for firms by linking our Compustat-CRSP sample to the ReferenceUSA U.S. Businesses Database and collecting employment data for all headquarters, branch, and subsidiary locations of the firms in our sample. ReferenceUSA data are collected in November 2014 for businesses that are active at that time. We aggregate the employment counts of firm establishments at the MSA level. Employment share of the headquarters MSA is computed by dividing total employment in that MSA by the total number of employees in all MSAs. Firm size is measured using market capitalization in December 2013. The top panel divides the sample into two size groups (above versus below median), while the lower panel divides the sample into five groups (quintile portfolios).

		Percentage of Employees Working in the Headquarter MSA			
	# Firms	$\geq$ 50%	$\geq$ 75%	$\geq$ 90%	= 1
All Firms	2,008	62.75%	47.46%	37.60%	27.09%
Small Firms	1,004	71.81%	60.26%	51.89%	42.13%
Large Firms	1,004	53.69%	34.66%	23.31%	12.05%
All Firms	2,008	62.75%	47.46%	37.60%	27.09%
Small Firms	402	78.61%	69.90%	63.68%	55.22%
Q2 Firms	402	69.90%	58.96%	48.51%	36.57%
Q3 Firms	401	59.35%	41.90%	31.42%	20.95%
Q4 Firms	402	57.46%	39.05%	25.87%	13.43%
Large Firms	401	48.38%	27.43%	18.45%	9.23%

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.