Local Risk, Local Factors, and Asset Prices*

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July 2013

Abstract

This article provides a new link between firm location and stock returns. We show that the industrial composition of the local economy, in particular, how cyclical its industries are, affects firm risk. We propose a metric of this cyclicality, labeled "local beta", and demonstrate that local factor prices such as wages and real estate prices are more sensitive to aggregate shocks in areas with high local beta. While procyclical wages should lead to lower firm risk due to risk sharing with labor, procyclical prices of real estate, which is part of firm's assets, should increase firm risk. We confirm that firms located in *higher* beta areas have *lower* industry-adjusted returns and *lower* 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.

JEL classification: D24, G12, J21, R30

Keywords: Industry Composition, Local Factor Prices, Local Beta, Cross Section of Returns

*We have benefited from conversations with Ken Ahern, Sandra Black, Daniel Carvalho, Riccardo Colacito, Ed Coulson, Andres Donangelo, Wayne Ferson, Ayse Imrohoroglu, Chris Jones, Chang-Mo Kang, Oguzhan Ozbas, Vincenzo Quadrini, Clemens Sialm, Jiro Yoshido, and seminar participants at Penn State, USC, and the Econometric Society meetings. We thank Joseph Engelberg for sharing his data on firm headquarter location changes and Diego Garcia for providing data on geographic locations of firm operations.

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Most work in the finance literature treats labor and capital markets as perfectly competitive and homogenous at the aggregate level, where wages and rental rates equalize across different locations. In reality, workers face frictions when moving from place to place (transaction costs in real estate, labor search frictions, family coordination issues, etc.), and significant parts of physical capital, such as land and structures, are completely immobile. These local factors account for a large part of economic output[1], and fluctuations in their prices due to local economic conditions can have important effects on the firms using them.

In this paper, we show that the response of local factor prices to aggregate shocks varies across localities based on the types of industries that dominate these areas. If the major industries that drive the economy of an area are highly correlated with the aggregate economy, then factor prices in that area are likely to be fairly cyclical. If, on the other hand, an area is dominated by industries that do not comove with the aggregate economy, then factor prices are likely to move less in response to an aggregate shock. We find that the degree of cyclicality in local economies helps explain differences across areas in risk sharing between firms and the providers of local inputs (employees and lessors). This has important implications for asset pricing.

We propose a metric of how cyclical the local economy is, which we label "local beta." We compute local beta of an area (metropolitan statistical area, MSA) as the average of industry betas, weighted by the industry shares in the local market, where the industry beta is the beta of industry output on the aggregate GDP. We study how local beta affects the dynamics of wages and real estate prices in an MSA as well as the returns of the firms located there. We find that the sensitivity of wages to aggregate economic fluctuations increases in MSAs with high local beta over and above what would be expected given the industry composition of the area. This reflects risk sharing between firms and employees where cyclical firms shift part of the shock to their employees in the form of cyclical wages. Reflecting a more cyclical demand for real estate, we also find a greater sensitivity of real estate prices and rents to business cycles in high beta MSAs.

Two competing channels are at work on the firm's risk and equity returns. On the one hand, greater risk sharing with employees implies lower risk for firms in high beta MSAs relative to

[1] The estimates for the output share of labor range between 60% (Cooley and Prescott, 1995) to 75% (Imrohoroglu and Tuzel, 2012). Campbell (1996) uses 2/3. The output share of land and structures is roughly 15% (Tuzel, 2010). The two local factors jointly claim more than 75% of economic output.

firms in the same industry but located in low beta areas. On the other hand, real estate values are more sensitive to aggregate fluctuations in high beta areas. Since firm value is partly derived from the value of its capital, which includes real estate, this mechanism implies higher equity risk in high beta areas. So, for firms that hold real estate, the two channels have opposite effects on firm risk. We confirm that conditional equity betas and expected equity returns of firms that have few real estate holdings and that are located in high beta MSAs are indeed lower than their industry peers located in low beta areas. This relationship gets weaker as the real estate holdings of the firm increases.

In order to formalize these ideas, we develop a production-based equilibrium model with local markets. Firms belong to either a low beta or high beta industry, where beta is defined as the sensitivity of the firm's output to aggregate productivity shocks. Local markets have different compositions of low beta and high beta industries. Besides their industry affiliation, which determines their exposure to aggregate productivity shocks, firms are ex-ante identical, receive aggregate (economy-wide) and firm-level productivity shocks, and use three factors of production: labor, capital equipment, and land (immobile capital and real estate). Wages, land prices, and firms' investment and hiring decisions are determined endogenously.

The model generates the main empirical patterns observed in the data: High beta areas have more procyclical wages and real estate prices than low beta areas. On the other hand, due to endogenous risk sharing with labor, returns of firms in high beta areas are less sensitive to aggregate shocks, and their expected returns are lower relative to firms from the same industry but located in low beta areas. This is especially true for firms with relatively low land holdings.

In order to simplify our empirical and theoretical analysis, we assume that there is no local factor mobility (land and labor) between different markets. Though land is truly immobile, it is possible for labor to move across markets in response to shocks. Nevertheless, at annual frequency, job-related mobility is low. Kothari, Saporta-Eksten, and Edison (2012) report that only 1.2% of homeowners and 7.4% of renters moved due to job-related reasons in 2005, and that mobility actually further during the great recession. 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. Basic spatial equilibrium models (Rosen, 1979; Roback, 1982) suggest that a shock to a local labor market is both reflected in worker wages and capitalized into rents/housing prices. The movement in house prices discourages labor mobility. Consistent with this view, we find evidence that house prices, like wages, are also more sensitive to economy wide shocks in high beta areas. This demonstrates that inter-market labor mobility cannot fully absorb the differential effects of aggregate shocks, leaving relative factor prices unchanged.

We view the location choice of the firms as exogenous. Starting with Marshall (1920), there is a large urban economics literature that studies the causes and effects of agglomeration. Likewise, the issue of industrial clustering is well documented and studied in the literature.[2] Most of the work in this area is geared toward understanding the differences in clustering across industries, rather than the individual firm's location decision within its industry.[3] Our focus is the effect of location on the risk of the firm compared to its peers in its industry.[4]

While we focus on the geographic segmentation of the factors of production, we abstract from similar segmentation in the firms' product markets. This condition is satisfied for industries that produce *tradable* goods, where firms' products are not confined to be sold in the local markets where they are produced. However, the sales of certain industries, the retail sector in particular, are predominantly local (i.e., *nontradable*) and are naturally affected by local economic conditions.[5] Mian and Sufi (2012) document that job losses in the nontradable sector during the great recession are significantly higher in high leverage counties, implying that worsening household balance sheets in those areas led to sharp demand declines for nontradable goods. Therefore, local area characteristics such as local betas can impact both the input and the output prices for these nontradable industries, making inference about firm risk difficult. Consistent with our hypothesis, we confirm that the relationship between local betas and firm risk are indeed stronger for the firms that produce tradable goods.

We examine a variety of other predictions for how local betas are likely to impact labor and asset markets. In particular, we find that the positive relationship between local betas and the procyclicality of wages is stronger for industries with lower unionization rates, consistent with

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

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

[4] Since our focus is on the link between the firm location and its risk, in equilibrium, firms might be using this 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. Since we find the opposite, either the risk sharing mechanism is actually stronger than what we measure in the data, and we find these effects despite the firms' mitigating location choices; or the firm's location choice is exogenous to this mechanism.

[5] Identifying nontradable industries is not a trivial task. Even the retail sector, which is the prime example of nontradable sector, may not be completely nontradable due to non-local sales through the internet, catalog, ...

the view that unionization increases the frictions in wage adjustments. Also, we find that the negative relationship between local betas and expected equity returns are mainly found in firms with geographically focused operations, for which firm headquarter location is a better proxy for where the firm actually operates.

Our paper is related to a growing literature that studies how a firm's location affects its real and financial performance. Dougal, Parsons, and Titman (2012) document that firms' investments are sensitive to the investments of other firms headquartered in the same area. Engelberg, Ozoguz, and Wang (2010) find that fundamentals of firms in industry clusters have stronger 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 real estate portfolios of firms on those firms' investments. Specifically, they calculate the change in the real estate values based on the changes in property prices in firms' headquarter locations. Our analysis suggests that the changes in real estate prices are strongly linked to how cyclical the local economy is. Pirinky 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.

Finally, our paper is related to the growing body of work in asset pricing, in which asset returns are tied to the real production and investment decisions. Specifically, we contribute to two strands of literature, namely those on labor market frictions and capital heterogeneity. Several recent papers study the effects of labor market frictions on asset prices. Implications of labor adjustment costs are investigated in Merz and Yashiv (2007); Bazdresch, Belo, and Lin (2012); and Belo and Lin (2012). In the presence of labor adjustment costs, the firms' market values and expected returns are related to their hiring behavior. Gourio (2007); Berk and Walden (2013); and Favilikus and Lin (2012a, b) study the effects of wage rigidity. In an equilibrum setting, wage rigidity leads to volatile and cyclical profits, accompanied by high and countercyclical risk premia. Chen and Zhang (2011) and Kuehn, Petrosky-Nadeau, and Zhang (2013) study asset pricing with labor market search. Search frictions in the labor market endogeneously generates volatility in unemployment rates and wage rigidity and matches the dynamics of equity returns. Donangelo (2013) studies the implications of labor mobility on asset pricing, finding that industries that rely on more flexible labor force face greater risk. Our work adds to this literature by addressing heterogeneity in local labor markets and investigating its implications on the firms operating in these markets.

We also contribute to the literature on capital heterogeneity and asset pricing. Eisfeldt and Papanikolaou (2011) consider organization capital, Belo and Lin (2012) and Jones and Tuzel (2013) study the implications of having inventories as part of firms' productive assets. 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 the firms' returns. We show that in high beta areas real estate holdings of firms magnify the effects of aggregate shocks, hence adding to the "risky real estate" argument in Tuzel (2010).

The paper is organized as follows. Section 1 describes the data used in our empirical analysis and introduces our local beta measure. Section 2 presents our empirical results relating GDP shocks and local betas to wages, real estate returns, and firm returns. Section 3 presents our equilibrium model and quantitative results. Section 4 concludes.

1 Data

The central focus of this paper is on the beta of local economies, β^{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 industries. Specifically,

$$\beta^{local}_{a,t} = \sum_i s_{i,a,t}\beta^{ind}_{i,t}$$

for all areas a in year t, where $s_{i,a,t}$ represents the employment share of industry i in area a in year t, and $\beta^{ind}_{i,t}$ represents the beta of industry i in year t. Industry betas, $\beta^{ind}_{i,t}$, are calculated as the slope coefficients from the regressions of real industry value added growth on real GDP growth, using data up to year t.

We classify the local markets by Metropolitan Statistical Areas (MSA). MSAs are geographic entities defined by the Office of Management and Budget that contain a core urban area of 50,000 or more population. Consist of one or more counties, MSAs include the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core.[6] There are 373 unique MSAs in our sample.

Our employment data are from the County Business Patterns (CBP) data set published by the U.S. Census Bureau. CBP data are recorded in March of each year, published at annual frequency for each industry in each geographical unit, and span the years 1986-2011.[7] The industry classification is based on Standard Industrial Classification (SIC) codes until 1997 and North American Industry Classification System (NAICS) codes after that. Due to a poor match between SIC and NAICS, we keep the data in its original classification at the 2-digit SIC and 3-digit NAICS level rather than converting to one of the two classifications. CBP reports industry level employment at the county and MSA level. Until 2003, we use county level employment data from CBP and aggregate the data to the MSA level using the crosswalks from the Census Bureau. We directly use MSA level data after 2003.[8] We compute industry share $s_{i,a,t}$ as the ratio of each industry's employment in an MSA to the total reported MSA employment in year t. While most MSAs have diverse economic base featuring many industries, there is heterogeneity in industrial diversity of MSAs. Figure 1 plots a histogram of industrial dispersion of employment within each MSA, computed as a Herfindahl index of industry employment shares.

Industry output is measured as the value added by industry from the Bureau of Economic Analysis (BEA). Data are annual. SIC based data covers the 1947-1997 period whereas NAICS sample spans 1977-2011. Industry shock is the growth in the real industry value added where nominal data are deflated by GDP deflators to calculate real value added. Industry betas $\beta_{i,t}^{ind}$ are calculated as the slope coefficients from the regressions of industry shock (real industry value added growth) on aggregate shock (real GDP growth), using data up to year t. Table 1

[6] 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. For more information, see http://www.census.gov/population/metro/.

[7] Disaggregated data is at times suppressed for confidentiality reasons. However, in these situations, the Census Bureau provides a "flag" that tells us of 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 in such scenarios.

[8] Metropolitan statistical areas' geographic compositions have changed several times since the start of our sample period. In particular, the crosswalk between counties and MSAs is revised once every ten years, prior to each decennial census. The last major change happened in 2003 when the Census Bureau moved from the old MSA definitions to metro and micro CBSA definitions. In order to have consistency in area compositions, we use MSA definitions adapted in 2009.

reports the industries with highest and lowest betas in 2011. The industries with the lowest betas operate broadly 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 heavy manufacturing (primary metal, transportation equipment, nonmetallic mineral and wood) or the financial sector, with betas around 3.

Table 2 reports summary statistics for the lowest and highest beta MSAs to gain more perspective into local betas. For 2011, Elkhart/Goshen, Indiana is the highest beta MSA in our sample (local beta = 1.73). The biggest industry in the area, transportation equipment manufacturing, employs roughly a quarter of the workforce in Elkhart. The list of highest beta MSAs include other heavy manufacturing towns like Kokomo, IN, and Wichita, KS, and areas that rely heavily on tourism, such as Las Vegas, NV, and New London, CT. Many of the lowest beta MSAs, on the other hand, have economies based on food manufacturing, like Merced, CA, and Sioux City, IA. The lowest beta MSA in 2011 is St. Joseph, MO (local beta = 0.71). Other low beta areas include Rochester, MN, home to Mayo Clinic in the health care sector, and Ithaca, NY, where the education services industry (including Cornell University) employs more than one third of area employees. Table 2 also reports the number of employees and the employment rank for each MSA. There is no particular relationship between the local beta and size of an area (as measured by employment). The correlation between local beta and employment, computed using the sample of all MSAs in 2011, is less than 0.1.

To shed more light on the informativeness of the local beta measure, Figure 2 plots the recent economic performance of the highest and lowest beta MSAs over the 2001-2011 period. The top panel plots the average real GDP of the highest and lowest beta areas, together with national GDP, where 2001 levels are normalized to 1. The bottom panel plots annual GDP growth for the same areas. The real GDP data for the MSAs are from the BEA, the GDP by metropolitan area tables. The figures show that high beta areas experienced steady growth during the expansion years until 2007, but experienced a bigger reduction in GDP levels and growth during the great recession (2008-2009). The lowest beta areas, on the other hand, experienced neither a big increase nor a significant drop in value added over the same time period. These findings support the validity of our local betas, constructed from local industry shares and industry betas, and not directly from the measured GDPs of the MSAs.

Panel C of Table 2 tabulates the transition probabilities for an MSA moving from one local beta quintile to another in consecutive years. Since the employment base of the MSAs and industry betas do not change fast, local beta is persistent but not fixed. The probability for the MSAs in the lowest and highest local beta quintiles to stay in those quintiles next year is roughly 85%. Figure 3 plots the average local beta for the MSAs sorted into quintile portfolios every year over the sample period. The figure demonstrates that the dispersion of local betas got somewhat smaller over time, yet there is still significant spread between the betas of the lowest and highest beta areas. Figure 4 plots the histogram of MSA betas as of 2011. Most MSA betas are between 0.8 and 1.2, and there is positive skewness in MSA betas.

Our main MSA by industry wage data are from the Quarterly Workforce Indicators (QWI) dataset of the Longitudinal Employer - Household Dynamics (LEHD) program at the U.S. Census Bureau. We aggregate quarterly wages to annual wages as wages exhibit significant seasonality. The data starts in 1990, but the coverage for most states starts in the late 1990s. The main advantage of using QWI data over other sources, such as the CBP or 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.

We also study hourly occupational wages for metropolitan areas from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. The data starts in 1999.[9] We use both broad occupation definitions (22 major occupation groups) and detailed occupation definitions (854 detailed occupations).[10]

Housing returns are the percent changes in the house price indexes (HPI) from the Federal Housing Finance Agency (formerly known as OFHEO, Office of Federal Housing Enterprise Oversight, HPI). HPI data are available at quarterly frequency starting in 1975. Commercial real estate returns are the total returns (income + appreciation) for all commercial property types (office, retail, industrial, apartment, and hotel) from the National Council of Real Estate Investment Fiduciaries (NCREIF NPI). Data are available at the quarterly frequency starting in 1978. Even though HPI and NPI data start in 1975 and 1978, respectively, coverage is initially rather sparse and limited to bigger MSAs, increasing somewhat over the years. Commercial real estate rent data are from CoStar. The data starts in 1982, but the number of covered

[9] MSA level OES data coverage starts in 1997, but the occupation definitions are different from 1997-1998.

[10] Prior to 2005, OES MSA definitions were substantially different from the current definitions. This leads to an inconsistent match between our benchmark MSA betas (which are based on 2009 definitions) and OES wages prior to 2005. Since we cannot convert pre-2005 MSA definitions to current definitions, we reconstructed MSA betas with earlier MSA definitions to use with pre-2005 OES data.

MSAs remains fewer than 10 before 1997, increasing steadily afterwards. We use data on rents to office buildings, and we include MSAs in the sample if there are at least 500 rent observations from that area to reduce the noise in rent measurement.[11]

Our data source for the unionization rate of industries and occupations is from 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 used in the unionization dataset and NAICS industry classification codes in LEHD and Standard Occupational Classification (SOC) codes used in OES wage datasets.

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

We identify a firm's location with its headquarter location from Compustat, and supplement it with headquarter location change information from Compact Disclosure, compiled by Engelberg, Ozoguz, and Wang (2010).[12] Chaney, Sraer, and Thesmar (2012) argue that headquarters and production facilities tend to be clustered in the same state and MSA and headquarters represent an important fraction of corporate real estate assets. Therefore headquarter location is a reasonable proxy for firm location. They provide hand-collected evidence supporting this assumption.[13] To the extent that headquarter location is a noisy measure of where the firm operates and owns assets, we will underestimate the magnitude of the effect we find for firm returns. We confirm the validity of this argument by constructing a subsample of firms that focus most of their operations in their headquarter state. We measure geographic concentration

[11] HPI and CoStar rent data are available at the MSA level. NPI is available at the MSA level for most areas, and at the metropolitan division level for 11 MSAs, which are subgroups of MSAs. For those areas, we take the averages of HPI returns for metropolitan divisions and use that as a measure for the MSA return.

[12] Compustat reports only the most recent headquarter location of firms. Compact Disclosure discs provide current headquarter location of firms and covers the years 1990-2005. There are roughly 300 headquarter location changes over this time period.

[13] Chaney, Sraer, and Thesmar (2012) hand-collect information on firm headquarter ownership using their 10K files. They find that firms that report headquarter ownership also have positive real estate ownership based on Compustat data.

using the state name counts from the annual reports, organized by Garcia and Norli (2012). We classify firms as geographically focused if few state names are mentioned in the firms' annual report as in Garcia and Norli (2012).

In firm level regressions, we make all comparisons within the industry. Therefore, it is critical to have considerable dispersion in firm locations within the same industry. To do this investigation, we compute a measure of industry concentration over MSAs, which is a Herfindahl index of how the number of firms in an industry (from Compustat) are divided among the MSAs. Figure 5 plots the histogram of this industry concentration metric. The figure shows that most industries have large variation in firm locations, while few industries are more geographically focused, yet still include firms from several different MSAs.

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 beneficial interest. We match CRSP stock return data from July of year t to June of year $t+1$ with accounting information (Compustat) for fiscal year ending in year $t-1$ as in Fama and French (1992, 1993), allowing for a minimum of a six month gap between fiscal year-end and return tests.

2 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. In the second part, we study the relationship between local beta and firms' risk and returns.

2.1 Local Factor Prices

Our first hypothesis is that business cycles (shocks to aggregate GDP) will affect the wages in an area more if the local aggregate of industries that operate in that market is prone to business cycle shocks; i.e., if the area has a high beta. We test this hypothesis in Table 3. Specifically, we run pooled time series / cross sectional regressions of the form

$$\begin{aligned}\Delta wage_{ind,MSA,t} &= b_0 + b_1 shock_t \times \beta^{local}_{MSA,t-1} + b_2 \beta^{local}_{MSA,t-1} \\ &\quad + \text{MSA Dummies} + \text{Time} \times \text{Industry Dummies} + \epsilon_{ind,MSA,t},\end{aligned} \tag{1}$$

where $\Delta wage_{ind,MSA,t}$ is the (percent) change in wage per employee in each industry, MSA, and year triplet; $shock_t$ is the aggregate real GDP growth in that year; $\beta^{local}_{MSA,t-1}$ is the local beta inferred from the GDP betas of the industries operating in that area, computed as in Section 1.[14] Due to time×industry fixed effects, coeficient estimates reflect variation within the same industry and year. We expect to find a positive estimate for the interaction term, b_1, implying that wage growth in high beta areas covaries more with GDP shocks, relative to wage growth in the same industry but lower beta areas. We present results for several different specifications for the entire sample, subsamples, and different controls. Panel A uses data from LEHD, our main data source for wages at the MSA x industry level, and Panel B presents the results using MSA x occupation level hourly wage data from OES.[15] We cluster standard errors at the MSA 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 in Panel A), the estimates imply a roughly 15 basis points 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). We have similar findings based on occupational wage data. Columns 1 and 2 of Panel B present results for 22 major occupation groups, whereas columns 3 and 4 present results for 854 detailed occupation definitions, where estimates are both economically and statistically more significant.

An implicit assumption in our hypothesis 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 due to the prevalence of labor unions in certain industries. In the context of wages, Kimbell and Mitchell (1982) report that labor contracts in unionized industries are characterized

[14] The complete specification also includes $shock_t$ as an additional regressor, which drops due to time fixed effect in the regression.

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

by multi-year contracts with built-in inflation adjustments. Chen, Kacperczyk, and Ortiz-Molina (2011) argue that the presence of powerful unions substantially reduces firms' operating flexibility. In order to mitigate these potential concerns due to union involvement, we also consider subsamples of non-unionized industries and occupations where we define non-unionized industries (occupations) as industries (occupations) with unionization rates lower than the median unionization rate of all industries (occupations) in that year.[16] We expect our main findings to hold more strongly for non-unionized industries and occupations.[17] We report the regression results for non-unionized industries in columns 3 and 4 of Panel A and the non-unionized occupations in columns 5 and 6 of Panel B. We find that excluding highly unionized industries and occupations from our main sample strenghtens the results and slightly increases the magnitudes of the coefficients for the cross terms.

In our benchmark sample, we do not distinguish industries based on the geographic segmentation in their product markets. Our implicit assumption is that local beta does not have a substantial effect on the output demand/prices of the firms, which may not hold for industries that produce *nontradable* goods that are sold to locals. Therefore, we consider a subsample that excludes the nontradable industries. Following Mian and Sufi (2012), we define nontradable industries as the retail sector and restaurants (SIC 52-59, NAICS 44-45, and 722) and create a subsample of *tradable* industries excluding these. The results, presented in columns 5 and 6 of Panel A, show that our main results hold, and even get slightly more significant for the sample of tradable industries.

Overall, Table 3 demonstrates that local wages are more sensitive to systematic shocks in local markets with higher betas. This implies that employees in high beta areas are more exposed to aggregate shocks than their counterparts in low beta areas. Even though we take the location choice of the employees exogenous, in equilibrium, employees should be indifferent between locating to different areas, at least in the long run. To the extent that employees care about their labor income risk, they should require to earn higher wages in high beta areas. The last columns of Table 3 (columns 7 and 8) investigate this hypothesis. In Panel A, we regress the level of annual wages on local betas controlling for year×industry fixed effects; in Panel B, we regress hourly wages and control for year×occupation fixed effects. We find that wages

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

[17] OES and unionization data use different occupation classifications. We can match roughly 2/3 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.

rise with local beta and most estimates are highly significant. Wages in the MSAs in highest beta quintile are approximately \$1000 to \$2700 higher (annually) than their counterparts in the lowest beta quintile MSAs, in 1990 dollars.

Beside wages, aggregate shocks should have a bigger impact on real estate prices and rents in high beta areas. Commercial real estate is a major local input to the firms, so good (bad) shocks would lead to increased (decreased) demand for this type of assets. Since the supply of commercial real estate is inelastic in the short run, change in demand should have an impact on the prices and market rents, and variations in demand will be bigger in high beta areas. Beside commercial real estate, systematic shocks could also have a bigger effect on house prices in high beta areas due to two separate channels. The first channel is due to increased (decreased) demand for housing from households as a result of increasing (decreasing) wages in the area. The second channel is due to spillovers from the increasing (decreasing) commercial real estate prices, since both types of real estate share a common input, land.

In order to test the effect of aggregate shocks on real estate returns, we run pooled time series / cross sectional regressions of the form

$$\begin{aligned} r^{re}_{MSA,t} &= b_0 + b_1 shock_t \times \beta^{local}_{MSA,t-1} + b_2 \beta^{local}_{MSA,t-1} \\ &\quad + \text{MSA Dummies} + \text{Time Dummies} + \epsilon_{ind,MSA,t}. \end{aligned} \tag{2}$$

The results are presented in Table 4. $r^{re}_{MSA,t}$ represents housing returns in columns 1 and 2, commercial real estate returns in columns 3 and 4, and commercial real estate (office buildings) rent growth in columns 5 and 6 of Table 4. Like wage regressions, we cluster the standard errors at the MSA level. We expect to find a positive estimate for the interaction term, b_1, implying that real estate returns in high beta areas are more sensitive to GDP shocks relative to their counterparts in low beta areas. Table 4 presents results with and without MSA fixed effects. 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, 2.5% difference in commercial real estate returns, and 1.5% difference in commercial real estate rent growth, respectively, between MSAs in the highest and lowest beta quintiles, in response to a one standard deviation change in real GDP.

2.2 Firm Level Results

Section 2.1 demonstrates that GDP shocks have a bigger impact on local factor prices such as the wages and real estate prices in high beta areas compared to low beta areas. Since wages and commercial real estate are major inputs to the firms, the differential effect of the aggregate shocks on the local input prices should be an additional channel for how these shocks affect firms. We next study the effect of this mechanism on the returns of the firms located in areas with different local betas.

The greater sensitivity of wages to aggregate shocks in high beta areas implies endogenous risk sharing between firms and employees in response to systematic shocks, mitigating the effect of the shocks on the firms. Risk sharing with labor would lead to lower risk for firms in high beta areas. At the same time, real estate values are more sensitive to shocks in those areas. Since the firm value is partly derived from the value of its capital, including corporate real estate, this mechanism would imply higher risk in high beta areas. So, for the firms that own real estate, the two channels have opposite effects on the relationship between local beta and expected equity returns.[18]

We begin to investigate the implications of local betas for firm risk by estimating conditional equity betas for firms as in Lewellen and Nagel (2006). Conditional equity betas are estimated using short-window regressions (one year) and monthly returns, and do not require the specification of conditioning information. We correct for non-synchronous trading following the medhodology described in Lewellen and Nagel (2006).[19] We use conditional equity beta as a proxy for the firm's risk, and examine the effect of local betas on the conditional equity betas by running pooled time series / cross sectional regressions of the form

$$\begin{aligned} \beta^{cond}_{firm,t} &= b_0 + b_1 \beta^{local}_{MSA,t-1} \\ &\quad + \text{Time} \times \text{Industry Dummies} + \text{controls}_{firm,t} + \epsilon_{firm,t} \end{aligned} \tag{3}$$

where $\beta^{cond}_{firm,t}$ represents the conditional equity beta . We expect the regression coefficient

[18] For firms that do not own but lease real estate, leasing will create an additional risk sharing mechanism between the firms and their lessors (assuming that market rent changes will be reflected to their leases, which would be true if they are signing a new lease aggreement). The effect would be similar to the labor effect.

[19] 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.

$b_1 < 0$, reflecting lower risk of firms in high beta areas.[20] In order to tease out the effects of the labor and 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 risk due to risk sharing with labor. As the real estate exposure of the firms increase, we expect this mechanism to get weaker, and maybe switch sign.

Table 5 reports the results for the entire sample of firms, and subsamples based on the real estate ratio (RER), defined as the real estate holdings scaled by the number of employees of the firm. This ratio attempts to quantify the relative importance of the real estate versus the labor channel for the firm. Columns 1 and 2 report the results for the entire sample, columns 3 to 6 sort the firms into low (below median) and high (above median) RER subsamples based on firm level RER.[21] In columns 7 to 10, subsamples are formed by calculating the average RER for each industry and sorting industries based on this ratio (below - above median).[22] We present results with and without controlling for well known firm level predictors of returns, such as size and book-to-market ratio. Standard errors are clustered at the firm level. We find that in the entire sample, and especially in the low RER subsamples (columns 3, 4, 7, and 8), b_1 is negative and significant, implying that firms in high beta areas have lower risk, as measured by their conditional equity betas, than their industry peers in lower beta areas.[23] Using the entire sample of firms, our b_1 estimates imply that conditional equity betas for the firms located in the highest MSA beta quintile are roughly 0.1 lower compared to the 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 the firms increase (in columns 5, 6, 9, and 10), the difference in the equity betas declines in magnitude, and loses its statistical significance, implying that the real estate channel starts to dominate and cancels out the effect of the labor channel for this subsample. The results are both qualitatively and quantitatively similar whether we sort on the basis of firm level RER or industry level RER, so they are robust

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

[21] In Tables 5 to 8, all firms in our Compustat sample with valid real estate ratios are sorted into subsamples before the Compustat sample is merged with returns from CRSP. This leads to variations in the sizes of the subsamples after the return data is merged.

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

[23] 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, hence essentially have negative real estate exposure.

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 serve as a proxy for expected returns. We examine the effect of local betas on future firm returns by running pooled time series / cross sectional regressions of the form

$$\begin{aligned} r^e_{firm,t+1} &= b_0 + b_1 \beta^{local}_{MSA,t} \\ &\quad + \text{Time} \times \text{Industry Dummies} + \text{controls}_{firm,t} + \epsilon_{firm,t} \end{aligned} \tag{4}$$

where $r^e_{firm,t+1}$ is the excess firm return from July of year $t+1$ to June of year $t+2$. We expect the regression coefficient $b_1 < 0$, reflecting lower expected returns of firms in high beta areas. This should especially be the case for the firms with low real estate exposure, since the labor channel is likely to dominate in those firms. As the real estate exposure of the firms increase, we expect this mechanism to get weaker due to the effects of the real estate channel.

Table 6 reports the results for the entire sample of firms, and subsamples based on the real estate ratio (RER). Columns 1 and 2 report the results for the entire sample, columns 3 to 6 sort the firms into low (below median) and high (above median) RER subsamples based on firm level RER. In columns 7 to 10, subsamples are formed based on the industry-level RER. We present results with and without controlling for size and book-to-market ratio. Standard errors are clustered at the firm level. We find that in the entire sample, and especially in the low RER subsamples (columns 3, 4, 7, and 8), b_1 is negative and significant, implying that firms in high beta areas have lower expected returns than their industry peers in lower beta areas.[24] Using the entire sample of firms, our b_1 estimates imply roughly 1% lower expected returns for the 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. As the real estate holdings of the firms increase (in columns 5, 6, 9, and 10), the difference in the expected returns declines in magnitude, and loses its statistical significance, implying that the real estate channel starts to dominate and cancels out the effect

[24] 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.

of the labor channel for this subsample. The results are both qualitatively and quantitatively similar whether we sort on the basis of firm level RER or industry level RER, so they are robust to measuring real estate exposure in different ways.

In Table 7, we consider various refinements to our baseline sample of low real estate firms. In the first 4 columns of Panel A, we study firms from the tradable sectors, which are the sectors whose output are traded in the entire market, and not limited to the local market. For nontradable industries local betas can impact both the input and the output prices, making inference about firm risk difficult.[25] Consistent with this prediction, we confirm that the difference in the expected returns of firms located in low and high beta areas is slightly bigger for the sample of tradable firms. In columns 5 through 8 of Panel A, we consider firms from tradable industries with low unionization rates. It is widely accepted that unionization increases the frictions in wage adjustments and reduces firms' operating flexibility. Therefore, we expect that risk sharing with labor, and the resulting lower risk and expected returns of firms in high beta areas would be more prevalent for firms from industries with lower unionization rates. Also consistent with this prediction, our b_1 estimates from non-unionized industries are higher in absolute value, implying a bigger spread between the expected returns of firms located in high and low beta areas.

Panel B of Table 7 considers subsamples of firms with geographically focused operations, for which firm headquarter location is a better proxy for where the firm operates. Following Garcia and Norli (2012), we classify firms as geographically focused if few state names are mentioned in the firms' annual reports.[26] Garcia and Norli (2012) report that the median firm mentions five states in its 10-K, and the average state count for the firms in the highest geographical focus quintile is two. We use these two state counts (2 and 5) as our cutoffs for our "local firm" subsamples.[27] Our prediction is that firm headquarter location will be a less noisy measure

[25] 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 disperse 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, headquarter location would be a poor proxy for where the firm operates. By excluding firms from the retail sector, we improve the match between a firm's headquarter location and the market where it mainly operates.

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

[27] These subsamples have many fewer observations than our baseline sample. The lower cutoff in particular (1 or 2 states) leads to a sample size that is about 1/10th of the original sample size. Consequently, we consider a higher cutoff as well (5 or fewer state mentions), which triples the size of the local firm observations.

of firm location in these subsamples; hence, we expect a stronger relationship between local beta and expected returns. We confirm that the b_1 estimates go up significantly (in absolute value), more than doubling the size of the original coefficients in most specifications, though their statistical significance is somewhat lower due to much 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 investigate their future returns. We report the average industry-adjusted returns of the portfolios in Table 8. In order to form the portfolios, we simultaneously sort the firms based on their local betas and real estate ratios. Sorting on local betas is performed within each industry to account for within-industry variation in local betas. Industry-adjusted returns are computed by subtracting mean returns of each industry from individual firm returns. In addition to industry-adjusted returns, we present their alphas estimated as intercepts from the Fama-French 3-factor model. Results are presented for portfolios constructed form the entire sample, tradable sectors, non-unionized tradable sectors, and geographically focused firms that mention 5 or fewer states in their annual reports. Panel A measures real estate exposure with firm-level real estate ratio, Panel B uses industry-level real estate ratio.

We find, within the firms with low real estate exposure, that industry-adjusted portfolio returns decline monotonically as the beta of the local market increases, while 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%.[28] The spreads in portfolio returns get somewhat larger for the subsamples we consider.[29] 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 3-factor alphas. These results are both qualitatively and quantitatively consistent with the panel regression results presented in Tables 5 and 6.

Overall, our results confirm our hypothesis that aggregate shocks have differential effects on

[28] We present equal weighted portfolio returns. Value weighted return spreads are smaller and not statistically significant. Like firms from the retail sector, larger firms tend to operate in dispersed geographic areas, for which headquarter location is a weaker proxy for where the firm operates. Therefore we expect, and confirm that the relationship between expected returns and local beta is stronger for smaller firms.

[29] Due to much smaller sample size, there is considerably more noise, and larger standard errors, in the portfolios formed from the geographically focused firms, measured as firms that mention 5 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.

the firms based on the local beta of the area and the real estate exposure of the firms. Among the firms with low real estate exposure, firms in low beta areas have higher risk and hence higher expected returns. Firms located in high beta areas are less effected by the systematic shocks, and have lower expected returns, due to offsetting effects in labor costs. For firms with high real estate exposure, changes in labor costs and real estate prices cancel each other; hence, there is no differential location effect on risk and returns.

3 Model

We consider asset pricing in a simple production economy with three types of inputs, where two of the inputs (land, representing real estate, and labor) are local inputs in limited supply. We build heterogeneity into the industry composition (hence, risk) of the local markets. Our main questions are: (i) How does local risk affect local factor prices? (ii) How does local risk affect the risk of the firms operating in those markets? For firms that have high exposure to land, which channel (land or real estate) dominates in firm returns?

3.1 Firms

There are many firms that produce a homogeneous good using labor, land, and equipment. These firms are subject to aggregate and firm level productivity shocks and belong to either a low risk or a high risk industry.

The production function for firm i is given by:

$$\begin{aligned} Y_{ijt} &= F(A_t, Z_{it}, I_j, L_{it}, S_{it}, K_{it}) \\ &= A_t^{I_j} Z_{it} L_{it}^{\alpha_l} S_{it}^{\alpha_s} K_{it}^{\alpha_k}. \end{aligned}$$

L_{it} denotes the labor used in production by firm i during period t. S_{it} denotes the beginning of period t land holdings (real estate) of firm i. K_{it} 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, and α_k where $\alpha_l+\alpha_s+\alpha_k \in (0,1)$. Aggregate productivity is denoted by $a_t = \log(A_t)$.

a_t has a stationary and monotone Markov transition function, given by $p_a\left(a_{t+1}|a_t\right)$, as follows:

$$a_{t+1} = \rho_a a_t + \varepsilon^a_{t+1} \tag{5}$$

where $\varepsilon^a_{t+1} \sim$ i.i.d. $\mathrm{N}\big(0, \sigma_a^2\big)$. $I_j \in \{I_{low}, I_{high}\}$ is a scaler that represents the industry risk and scales the effect of the aggregate productivity on the firm's production. The firm productivity, $z_{it} = \log(Z_{it})$, has a stationary and monotone Markov transition function, denoted by $p_{z_i}(z_{i,t+1}|z_{it})$, as follows:

$$z_{i,t+1} = \rho_z z_{it} + \varepsilon^z_{i,t+1} \tag{6}$$

where $\varepsilon^z_{i,t+1} \sim$ i.i.d. $\mathrm{N}\big(0, \sigma_z^2\big)$. $\varepsilon^z_{i,t+1}$ and $\varepsilon^z_{j,t+1}$ are uncorrelated for any pair of firms (i, j) with $i \neq j$.

Local labor markets are competitive and labor is free to move between firms in the same area; therefore, the marginal product of labor is equalized among firms in the same area.[30] Hiring decisions are made after firms observe the productivity shocks and labor is adjusted freely; hence, for each firm, marginal product of labor equals the wage rate:

$$\begin{aligned} F_{L_{it}} &= F_L(A_t, Z_{it}, I_j, L_{it}, S_{it}, K_{it}) \\ &= W_t \end{aligned} \tag{7}$$

where W_t is the wage that clears the local labor market at time t.

The capital accumulation rule for equipment is:

$$K_{i,t+1} = (1 - \delta)K_{it} + I_{it}$$

where I_{it} denotes investment in equipment and δ denotes the depreciation rate of installed equipment.

Purchases and sales of land, and equipment investment are subject to quadratic adjustment

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

costs given by g_{it}:

$$g^{s}\left(S_{i,t+1},S_{it}\right) = \frac{1}{2}\eta_{s}\frac{\left(S_{i,t+1}-S_{it}\right)^{2}}{S_{it}} \tag{8}$$

$$g^{k}\left(I_{it},K_{it}\right) = \frac{1}{2}\eta_{k}\left(\frac{I_{it}}{K_{it}}-\delta\right)^{2}K_{it} \tag{9}$$

with $\eta_k, \eta_s > 0$. In this specification, investors incur no adjustment cost when net investment is zero, i.e., when the firm replaces its depleted equipment stock and maintains its equipment level, and when the firm does not change its land holdings.

Firms are equity financed. Dividends to shareholders are equal to:

$$D_{ijt} = Y_{ijt} - W_t L_{it} - P_t\left(S_{i,t+1}-S_{it}\right) - I_{it} - g^{s}_{it} - g^{k}_{it} \tag{10}$$

where P_t is the land price that clears the local land market at time t. At each date t, firms choose $\{S_{i,t+1}, I_{it}, L_{it}\}$ to maximize the net present value of their expected dividend stream, which is the firm value:

$$V_{ijt} = \max_{\{I_{i,t+k},S_{i,t+k+1},L_{i,t+k}\}} E_t\left[\sum_{k=0}^{\infty} M_{t,t+k} D_{ij,t+k}\right], \tag{11}$$

subject to (Eq.5-8), where $M_{t,t+k}$ is the stochastic discount factor between time t and $t+k$. V_{it} is the cum-dividend value of the firm.

The first order conditions for the firm's optimization problem leads to two pricing equations:

$$1 = \int\int M_{t,t+1} R^{S}_{i,t+1} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a \tag{12}$$

$$1 = \int\int M_{t,t+1} R^{K}_{i,t+1} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a \tag{13}$$

where the returns to land and equipment investment are given by:

$$R^{S}_{i,t+1} = \frac{F_{S_{i,t+1}} + q^{s}_{i,t+1} + \frac{1}{2}\eta_s\left(\frac{S_{i,t+1}-S_{it}}{S_{it}}\right)^{2}}{q^{s}_{it}} \tag{14}$$

$$R^{K}_{i,t+1} = \frac{F_{K_{i,t+1}} + (1-\delta)q^{k}_{i,t+1} + \frac{1}{2}\eta_k\left(\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^{2} - \delta^{2}\right)}{q^{k}_{it}} \tag{15}$$

and where

$$
\begin{aligned}
F_{S_{it}} &= F_S(A_t, Z_{it}, I_j, L_{it}, S_{it}) \\
F_{K_{it}} &= F_K(A_t, Z_{it}, I_j, L_{it}, S_{it}).
\end{aligned}
$$

Tobin's marginal q, value of a newly purchased unit of land, and newly installed unit of equipment, are:

$$
q_{it}^s = P_t + \eta_s \left(\frac{S_{i,t+1} - S_{it}}{S_{it}} \right) \tag{16}
$$

$$
q_{it}^k = 1 + \eta_k \left(\frac{I_{it}}{K_{it}} - \delta \right). \tag{17}
$$

The pricing equations (Eq.12-13) establish the links between the marginal cost and benefit of investing in land and equipment. The terms in the denominators of the right hand side of the equations, q_{it}^s and q_{it}^k, measure the marginal cost of investing. The terms in the numerator represent the discounted marginal benefit of investing. The firm optimally chooses $S_{i,t+1}$ and I_{it} such that the marginal cost of investing equals the discounted marginal benefit.

The returns to the firm are defined as:[31]

$$
R_{i,t+1}^F = \frac{V_{ij,t+1}}{V_{ijt} - D_{ijt}}. \tag{18}
$$

3.2 Local Markets

Firms have access to the local labor and land markets. All land is owned and utilized by the local firms, and all labor is employed by these firms. Each local market has a large number of firms operating in that area, and is endowed with the same large number of employees and amount of land. We assume that labor is not mobile between local labor markets.

There is heterogeneity in the industry composition (high or low risk) of local markets. The

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

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

3.3 The Stochastic Discount Factor

Since the purpose of our model is to examine the cross sectional variation across firms, we use a framework where time series properties of returns are matched by using an exogenous pricing kernel. Following Berk, Green, and Naik (1999) and Zhang (2005), we directly parameterize the pricing kernel without explicitly modeling the consumer's problem. As in Jones and Tuzel (2012) and Imrohoroglu and Tuzel (2013), the pricing kernel is given by:

$$\begin{aligned} \log M_{t+1} &= \log\beta - \gamma_t \epsilon^a_{t+1} - \frac{1}{2}\gamma_t^2\sigma_a^2 \\ \log\gamma_t &= \gamma_0 + \gamma_1 a_t \end{aligned} \tag{19}$$

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 as the result.

This pricing kernel shares a number of similarities with Zhang (2005). M_{t+1}, the stochastic discount factor from time t to $t+1$, 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 as the result.[32] In the absence of countercyclical price of risk, the risk premia generated in the economy does not change with economic conditions. Empirically, existence of time varying risk premia is well documented (Fama and Schwert (1977); Fama and Bliss (1987); Fama and French (1989); Campbell and Shiller (1991); Cochrane and Piazzesi (2005); Jones and Tüzel (2013); among many others).

[32] 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 Tüzel (2007) from time varying consumption composition risk.

3.4 Equilibrium and Calibration

Solving our model generates the pricing functions for local land prices P_t and local wages W_t as well as firms' investment and hiring decisions as functions of the state variables. Since the stochastic discount factor is specified exogenously, the solution does not require economy-wide aggregation. However, local land prices and wages are determined endogenously; so the solution requires aggregation at the local market level. The aggregate *local* state is (Γ, A), where Γ is the current 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_{it}, S_{it}), its firm level productivity Z_{it}, and the aggregate local state (Γ_t, A_t). The role of the aggregate local state is to allow the firms to predict future land prices and wages.

A recursive competitive equilibrium is a law of motion H, where $\Gamma' = H(\Gamma, A, A')$; individual policy functions ϕ and φ, where $K_i' = \phi(K_i, S_i, Z_i; \Gamma, A)$ and $S_i' = \varphi(K_i, S_i, Z_i; \Gamma, A)$; and pricing functions (P, W), such that:

(i) (ϕ, φ) solves the firm's investment problem,

(ii) P and W clear the local land and labor markets, and

(iii) H is generated by ϕ and φ.

We solve for the equilibrium prices and allocations recursively using the approximate aggregation idea of Krusell and Smith (1998).

We calibrate the model at annual frequency. Table 9 presents the parameters used in the calibration. We adapt the parameters of the firm level productivity process from the production function estimations in Imrohoroglu and Tuzel (2013). The persistence of the firm 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 typical values used in the literature. The share of labor α_l is 0.6 following Cooley and Prescott (1995). The shares of equipment and land, α_k and α_s, are set to 0.18 and 0.12, respectively. The relative shares of equipment and land in the capital aggregate follows Tuzel (2010). We model technology as slightly decreasing returns to scale, with $\alpha_l + \alpha_s + \alpha_k = 0.9$.

We take the parameters of the aggregate productivity from King and Rebelo (1999) and annualize them. Their point estimates for ρ_a and σ_a are 0.979 and 0.0072, respectively, using quarterly data, implying annual parameters of 0.922 and 0.014. The depreciation rate for fixed capital, δ is set to 8% annually, which is roughly the midpoint of 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} to $exp(-0.4)$ and I_{high} to $exp(0.4)$ to roughly match the interquartile range for the industry betas computed in section 1, which is $(0.66, 1.52)$. We solve and simulate the model for two local markets representing the low and high beta markets. s_m, the fraction of firms from the high risk industry, is set to 0.4 and 0.6, respectively, for the low and high beta areas. We can interpret the high (low) beta area in the model as an area with local beta roughly one standard deviation above (below) the average local beta in the data.

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 (2013). The discount factor β is 0.99, which implies an annual risk free rate of roughly 1%. γ_0 and γ_1 are 3.2 and -13, respectively, and 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 (2013).[33]

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

3.5 Quantitative Results

In this economy, firms optimally make their investment and hiring decisions to maximize firm value. The optimality conditions (equations 7, 12, 13) dictate that firms invest (hire) until the marginal cost of investing (hiring) equals the marginal benefit. The marginal benefit of investing and hiring increase in productivity. Therefore, everything else equal, the demand for labor and land will be 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 investing in land (affine in land prices) are also increasing in aggregate

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

productivity. So, a good (bad) aggregate productivity shock leads to increases (decreases) in wage rate and land prices. This effect is more pronounced in areas where a larger fraction of firms belong to the high risk industry ($I_j = I_{high}$) since the aggregate productivity shocks have bigger effects on the marginal benefit of investing and hiring of firms that belong to the high risk industry.

Table 10 demonstrates this result by running regressions similar to the ones we run in section 2.1, using simulated data from the model economy. We run regressions of the form:

$$\Delta \log(W_{area,t}) = b_0 + b_1 \Delta a_t \times \beta^{local}_{area} + b_2 \beta^{local}_{area} + \text{Time dummy} + \epsilon_{area,t} \quad (20)$$

$$\Delta \log(P_{area,t}) = b_0 + b_1 \Delta a_t \times \beta^{local}_{area} + b_2 \beta^{local}_{area} + \text{Time dummy} + \epsilon_{area,t} \quad (21)$$

where $W_{area,t}$ and $P_{area,t}$ are wage rate and land prices in each area, and a_t is log aggregate productivity, as defined in section 3.1. β^{local}_{area} is the beta of local area[34], computed as

$$\beta^{local}_{area} = I_{low} \times (1 - s_m) + I_{high} \times s_m.$$

The first column of Table 10 reports the wage regression, 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 productivity shocks, relative to 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 implies endogenous risk sharing between firms and employees in response to systematic shocks, mitigating the effect of the shocks on the firms. Risk sharing with labor leads to lower sensitivity of returns to aggregate shocks for firms in high beta areas, lower overall risk, and lower expected returns for the firm.

In order to clarify this channel, we derive an expression for the profit of the firm (abstacting from the capital adjustment costs):

$$\Pi_{it} = A_t^{I_j} Z_{it} L_{it}^{\alpha_l} S_{it}^{\alpha_s} K_{it}^{\alpha_k} - W_t L_{it}$$

[34] Unlike the data, model generates static rather than time varying β^{local}_{area}.Therefore, we drop area fixed effects from the regression.

where firms choose labor intra-temporally

$$
\begin{aligned}
L_{it} &= \arg\max_{L} \Pi_{it} \\
&= \left(\frac{\alpha_l A_t^{I_j} Z_{it} S_{it}^{\alpha_s} K_{it}^{\alpha_k}}{W_t}\right)^{\frac{1}{1-\alpha_l}}.
\end{aligned}
$$

We do not have a closed form solution for wage rate, W_t, but we know that it will be a function of the aggregate state variables (Γ, A), and monotonically increasing in aggregate productivity, A_t. Furthermore, sensitivity of wage rate to A_t increases with s_m, the fraction of firms from the high beta industry. Let's assume that log wage rate follows a linear functional form[35],

$$\log W_t = \lambda + \omega(s_m) a_t + f(\Gamma_t)$$

where $\omega(s_m)$ is positive and increasing in s_m. So, firm profits are

$$\Pi_{it}^{*} = (\kappa x_t)\, A_t^{\frac{I_j - \omega(s_m)\alpha_l}{1-\alpha_l}} \left(Z_{it} K_{it}^{\alpha_k}\right)^{\frac{1}{1-\alpha_l}} \tag{22}$$

where $\kappa = (1-\alpha_l)\, \alpha_l^{\frac{\alpha_l}{1-\alpha_l}} e^{-\frac{\lambda \alpha_l}{1-\alpha_l}}$ and $x_t = e^{-\frac{f(\Gamma_t)\alpha_l}{1-\alpha_l}}$. $\frac{I_j - \omega(s_m)\alpha_l}{1-\alpha_l}$ determines the sensitivity of firm profits to aggregate productivity A_t, and is decreasing in s_m. Since risk is defined as (the inverse of the) covariation of returns with the pricing kernel (equation 19), and the pricing kernel is monotonically decreasing in shocks to aggregate productivity, lower sensitivity of profits to productivity implies lower risk.

While the labor mechanism lowers the risk of the firms in high beta areas, land values are more sensitive to aggregate shocks in those areas. Since the firm value is partly derived from the value of its land holdings, greater variation in land prices would imply higher sensitivity of firm returns to aggregate shocks in high beta areas. So, the two channels (labor and land) have opposite effects on firm risk.

The model does not have a rental market. All capital (equipment and land) is owned by the firms. All firms optimally own some land since the marginal product of land goes to infinity as land ownership approaches zero. Nevertheless, there is heterogeneity in the firms' exposures to

[35] In order to solve the model, we conjecture a similar functional form for the wage rate and land prices and iterate on its parameters and the functional form until the market clearing conditions are satisfied in simulated data.

the two channels since the firms do not maintain a constant ratio of land and labor. Firms incur adjustment costs when they change their land ownership, while labor can be adjusted freely. Moreover, labor is an intratemporal choice, whereas land investments have to be implemented one period in advance. Therefore, firms exhibit heterogeneity in their ratio of land to labor[36], which makes it possible to observe the differential effects of the two channels in simulated data.

In order to test these predictions in the model, we replicate the firm-level analysis presented in Section 2.2 using simulated data from the model economy. The results are presented in Table 11. In Panels A and B we run regressions of the form:

$$\beta^{cond}_{firm,t} = b_0 + b_1 \beta^{local}_{area} + \text{Industry} \times \text{Time dummy} + \epsilon_{firm,t} \tag{23}$$

$$r^e_{firm,t+1} = b_0 + b_1 \beta^{local}_{area} + \text{Industry} \times \text{Time dummy} + \epsilon_{firm,t} \tag{24}$$

separately for firms with low and high land exposure, measured by their ratio of land to labor. $r^e_{firm,t}$ is the excess firm return, where raw firm returns are defined by equation 18. $\beta^{cond}_{firm,t}$ is the conditional beta of the firm, estimated by running short-window (10-period) regressions of the excess firm returns on the excess market return. Both regressions include industry×time fixed effects; therefore, all comparisons are within the firms in the same industry and same year.

Panels A and B of Table 11 present the results of the firm conditional beta and return regressions described in equations 23 and 24. The first column runs the regressions using the entire sample of firms, whereas columns 2 and 3 use low and high land/labor subsamples, respectively. Labor channel implies lower risk, and lower expected returns for firms in high beta areas, which would lead to negative b_1 estimates. Land price channel implies positive b_1 estimates. It is not clear ex-ante which channel would dominate the regression coefficient; however, b_1 is expected to be lower (more negative, or less positive) in the low land/labor subsample compared to the estimate from the high land/labor subsample. We find that b_1 is negative in all specifications and samples, implying that, overall, the labor channel dominates the land price channel. These results are consistent with our empirical results described in section 2.2, where we find that the labor channel overall dominates the real estate price channel in the data. Moreover, we find that the coefficient estimates are somewhat less negative for the high land/labor subsample, confirming that the land price channel -to some extent- mitigates

[36] As in Tuzel (2010), firms that experience negative firm level productivity shocks end up being high real estate (land) firms as these firms find it difficult to adjust their land holdings relative to their labor.

the effect of the labor channel.

Panel C presents the industry-adjusted returns of $\beta_{area}^{local}-$sorted portfolios for low and high land/labor subsamples. Consistent with our findings in Panels A and B, we find that the returns of firms in low beta areas exceed the returns of firms in high beta areas within the same industry, and the spread in returns is larger for the firms with lower relative land holdings.

4 Conclusion

We show that the industrial composition of local markets, and in particular, how cyclical the major industries in an area are, matter for how the systematic shocks affect the firms located in those areas. We calculate the "local beta," which is the average of the industry betas, weighted by the industry shares in the local market, for the metropolitan areas in the U.S. Aggregate GDP shocks have more pronounced effects on local factor prices such as wages and real estate returns in high beta areas compared to the lower beta areas. These local factors account for more than 75% of the economic output produced in the area, so fluctuations in their prices are relevant for the firms in the area. Larger effect of systematic shocks on wages in high beta areas leads to greater endogenous risk sharing between the firm and its employees and therefore mitigates the effect of these shocks on firm's returns. In addition to wages, high beta areas experience bigger fluctuations in local real estate prices due to aggregate shocks, as the demand for these assets changes more drastically. Since firms have different exposures to real estate, the implication of this real estate channel for firms varies. In high beta areas, the real estate channel increases the sensitivity of the firm returns with high real estate exposure (long position in real estate) to aggregate shocks, offsetting the effect of the labor channel.

We develop a theoretical model where firms belong to either a high risk (more cyclical) or a low risk (less cyclical) industry, and local markets vary in their composition of industry makeup. Each market features a continuum of firms that use labor, land (real estate), and equipment in their production. 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. Superior risk sharing with labor reduces the sensitivity of firm returns to systematic shocks in high beta areas, leading to lower risk for these firms. These results are stronger for firms with low real estate exposure.

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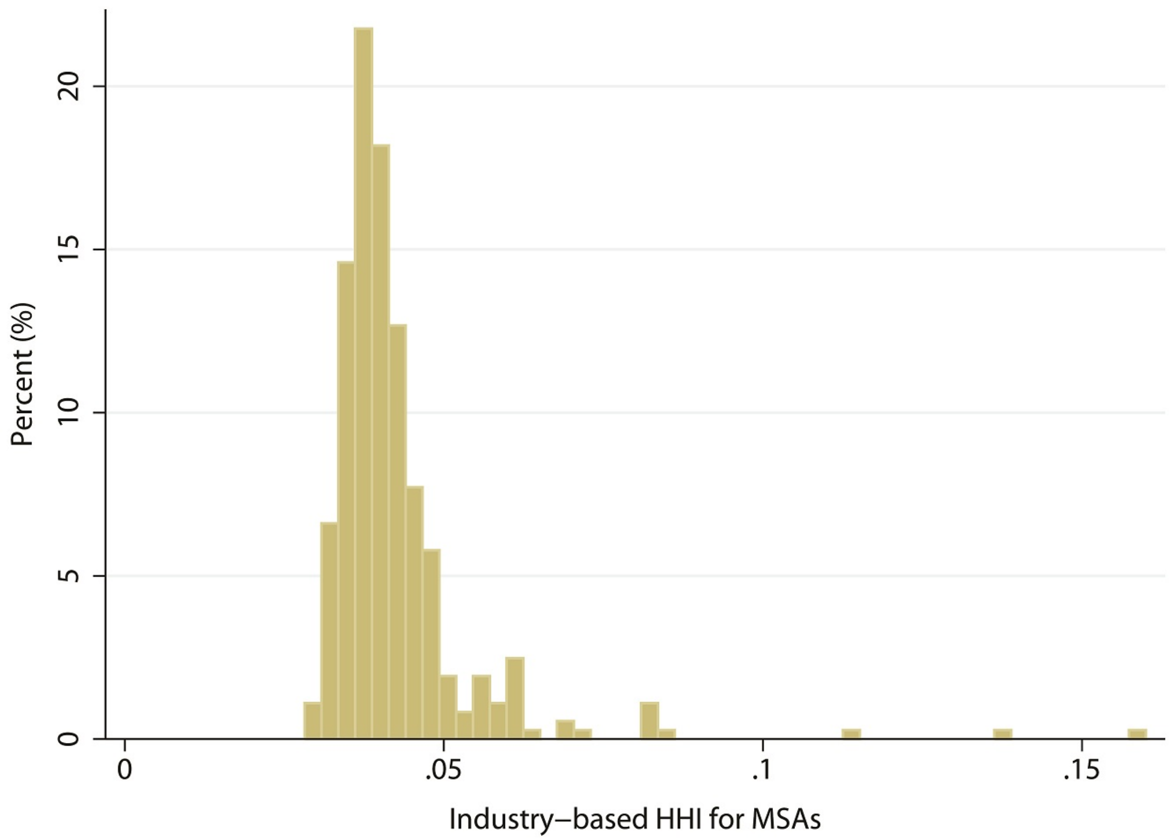

Figure 1. Histogram of Industrial Dispersion of Employment within MSAs. The figure illustrates the distribution of industrial dispersion of employment within each MSA, calculated as the Herfindahl-Hirschman Index (HHI) of industry employment shares in 2011.

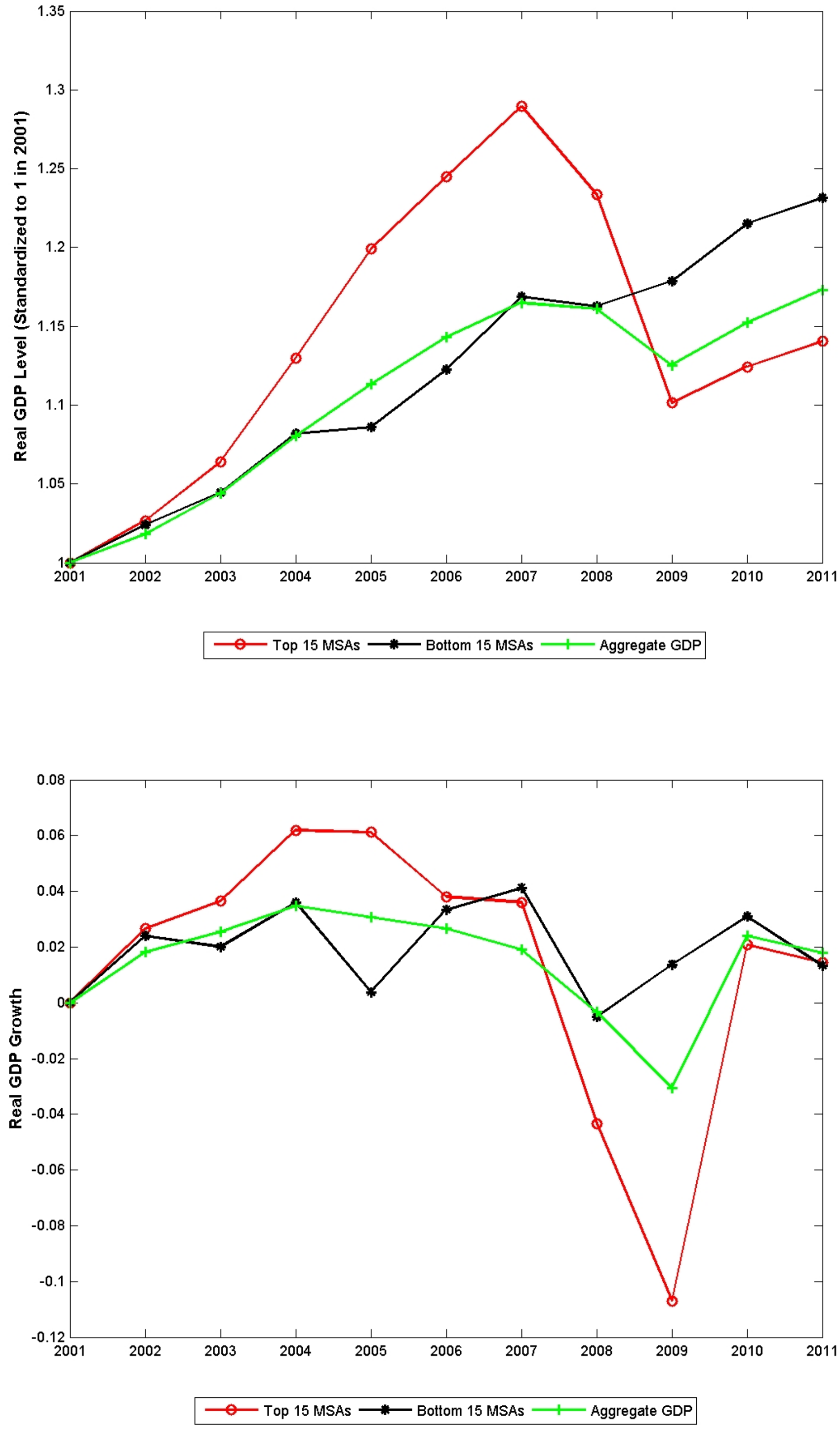

Figure 2. Local Beta and Fluctuations in Local GDP. The figure illustrates the average real GDP and GDP growth of the top and bottom 15 MSAs based on their local betas over the 2001-2011 period. MSAs are classified based on local betas in 2011. Top panel plots average real GDP, normalized to 1 in 2001, bottom panel plots the average real GDP growth.

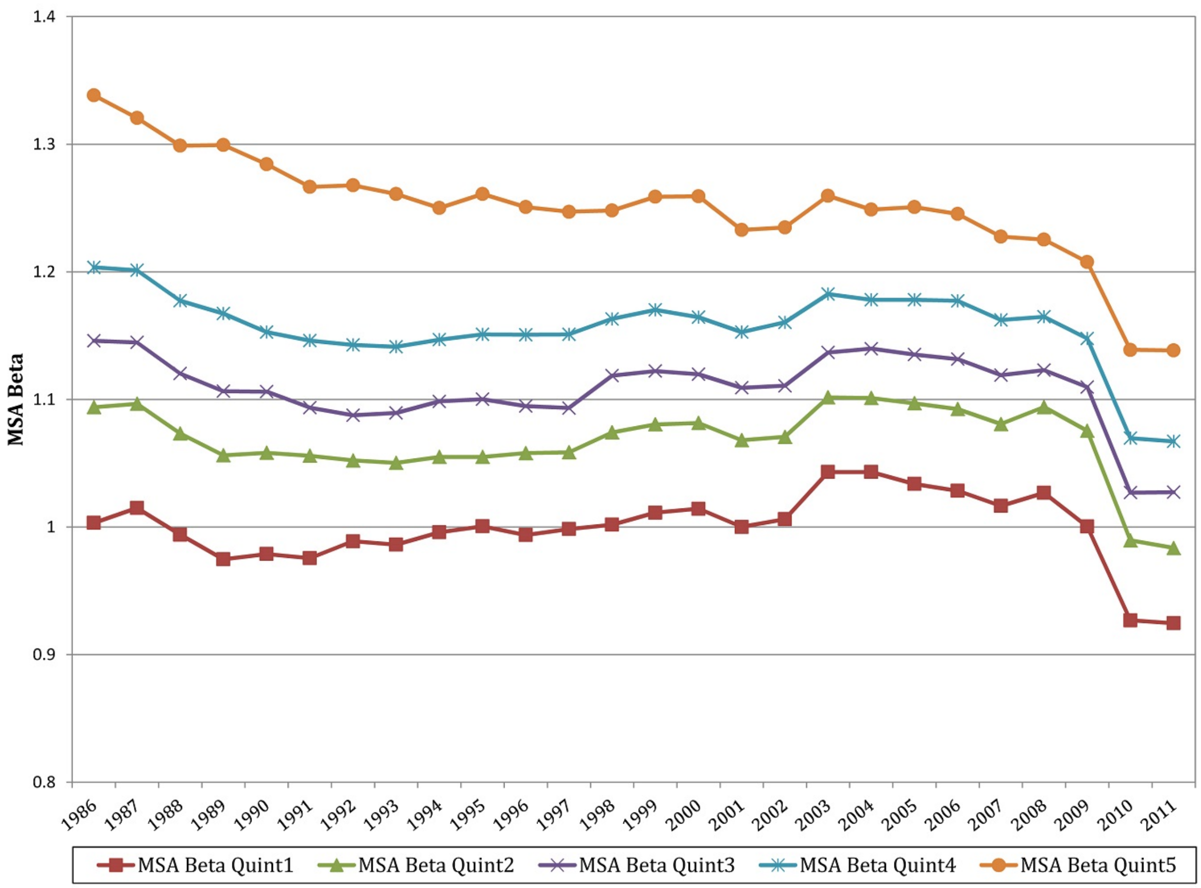

Figure 3. Time Series of MSA Betas. The figure illustrates the median local beta for the MSAs sorted into five beta quintiles over the 1986-2011 period. Portfolios are rebalanced every year.

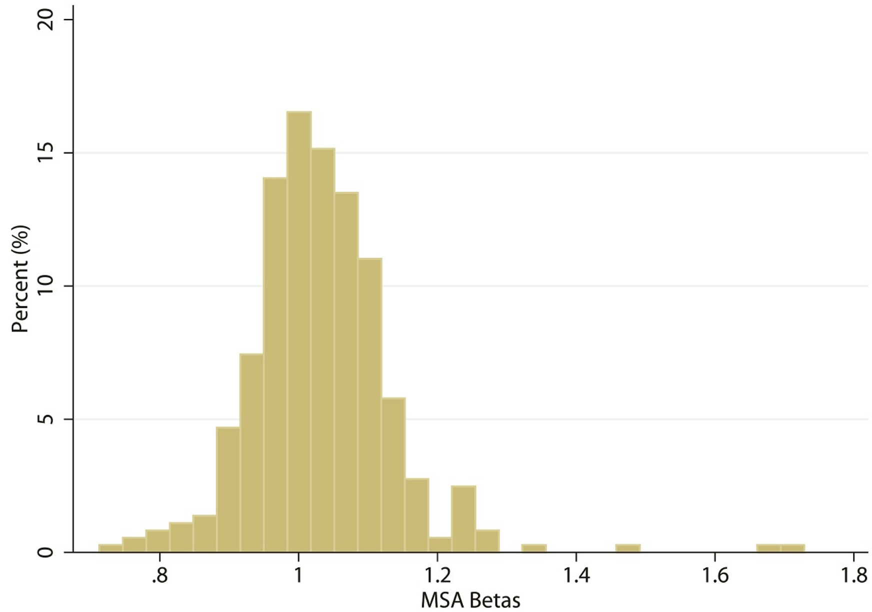

Figure 4. Histogram of MSA Betas. The figure illustrates the distribution of MSA Betas as of 2011.

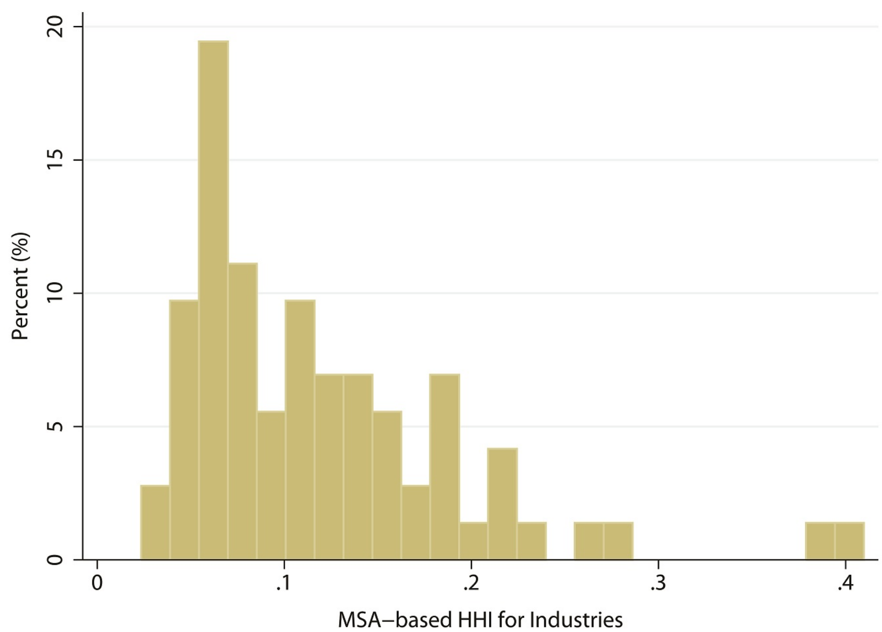

Figure 5. Histogram of MSA Dispersion of Firms within Industries. The figure illustrates the distribution of the dispersion of Compustat firm locations within each industry in 2011. For each industry we count the number of firms located in each MSA. The dispersion of firm locations is calculated as the HHI of MSA firm-count shares in each industry.

Table 1
Highest and Lowest Beta Industries

The table presents the 3-digit NAICS industries with lowest (Panel A) and highest (Panel B) betas as of 2011. The industry betas, β^{ind}, are calculated as the slope coefficients from the regressions of industry shock (real industry value added growth) on aggregate shock (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

Table 2
Highest and Lowest Beta MSAs

The table presents the summary statistics for the MSAs with lowest (Panel A) and highest (Panel B) betas as of 2011 and the transition probability matrix of MSA beta quintiles. Local betas, β^{local} are calculated as the average of the industry betas operating in that area, weighted by the employment share of industries. Representative industry is the industry that has the highest employment share in that MSA among all industries with location quotient above 3.5. 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. Panel C tabulates the transition probabilities of an MSA moving from one β^{local} quintile to another in consecutive years.

CBSA	MSA Title	β^{Local}	Representative Ind.	% of Emp.	# Emp.	Emp. Rank
			Panel A. Lowest β^{local} MSAs			
41140	St. Joseph, MO-KS	0.71	Food Manuf.	14.9%	48762	261
32900	Merced, CA	0.75	Food Manuf.	15.8%	39914	302
34900	Napa, CA	0.76	Bevg. & Tobac. Manuf.	11.9%	56022	230
27060	Ithaca, NY	0.78	Educ. Service	37.6%	45545	281
25260	Hanford-Corcoran, CA	0.79	Food Manuf.	13.8%	22896	359
23580	Gainesville, GA	0.81	Food Manuf.	14.5%	59760	223
40340	Rochester, MN	0.82	Hospitals	21.6%	86211	178
33260	Midland, TX	0.83	Supp. Mining	13.1%	65689	215
43580	Sioux City, IA-NE-SD	0.83	Food Manuf.	13.2%	65462	216
34060	Morgantown, WV	0.84	Chemical Manuf.	7.9%	45865	277
24140	Goldsboro, NC	0.86	Food Manuf.	7.2%	34069	327
26980	Iowa City, IA	0.86	Truck Transport.	5.7%	65159	217
38220	Pine Bluff, AR	0.87	Food Manuf.	6.6%	25139	355
47580	Warner Robins, GA	0.87	Food Manuf.	10.6%	34278	326
40660	Rome, GA	0.87	Food Manuf.	5.2%	32780	333
			Panel B. Highest β^{local} MSAs			
21140	Elkhart-Goshen, IN	1.73	Transp. Equip. Manuf.	24.9%	102109	160
37700	Pascagoula, MS	1.48	Transp. Equip. Manuf.	34.2%	49793	253
29020	Kokomo, IN	1.33	Transp. Equip. Manuf.	22.6%	31770	337
19140	Dalton, GA	1.29	Textile Product Mills	24.7%	54824	236
18020	Columbus, IN	1.28	Transp. Equip. Manuf.	6.9%	40314	299
43900	Spartanburg, SC	1.26	Transp. Equip. Manuf.	6.8%	110969	149
25860	Hickory-Lenoir-Morganton, NC	1.24	Furniture Manuf.	11.8%	123517	136
11500	Anniston-Oxford, AL	1.24	Fabric. Metal Manuf.	5.1%	36093	320
48620	Wichita, KS	1.24	Transp. Equip. Manuf.	10.6%	242354	76
34740	Muskegon-Norton Shores, MI	1.23	Prim. Metal Manuf.	6.6%	49204	259
29820	Las Vegas-Paradise, NV	1.23	Accommodation	23.3%	730747	34
29140	Lafayette, IN	1.23	Transp. Equip. Manuf.	7.5%	65748	214
35980	Norwich-New London, CT	1.23	Accommodation	16.6%	105276	152
31900	Mansfield, OH	1.20	Fabric. Metal Manuf.	4.4%	42132	295
26100	Holland-Grand Haven, MI	1.20	Fabric. Metal Manuf.	4.4%	90369	176

Panel C. Transition Probability Matrix of β^{local} Quintiles

	Next Year				
Current Year	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Quintile 1	0.847	0.138	0.015	0.001	0.000
Quintile 2	0.135	0.669	0.170	0.024	0.002
Quintile 3	0.014	0.174	0.656	0.146	0.008
Quintile 4	0.004	0.018	0.150	0.725	0.103
Quintile 5	0.000	0.001	0.009	0.103	0.887

Table 3
Local Wages and Local Beta

Panel A reports the effect of aggregate shocks on the industry wage growth in an MSA, conditional on the local beta, β^{local}_{MSA}. Panel B reports the effect of aggregate shocks on the occupational wage growth in an MSA, conditional on β^{local}_{MSA}. Calculation of β^{local}_{MSA} is described in Table 2. Wage growth is annual in Panel A, hourly in Panel B, all in real terms. Aggregate shock (*Shock*) is the aggregate real GDP growth in that year, in %. Regression sample period is 1990-2011 in Panel A (LEHD Data), 1999-2011 in Panel B (OES Data). Non-unionized 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, presented in parantheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Panel A. Annual Wage for Industries

	Wage Growth (%)						Wage Level	
	All Industries		Non-Union Industries		Tradable Industries		(1990 $)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β^{local}_{MSA}	-1.70^{***}	-0.45	-1.82^{***}	-0.23	-1.83^{***}	-0.40	1276.13	2734.57^{***}
	(0.29)	(0.76)	(0.35)	(0.90)	(0.31)	(0.81)	(996.47)	(480.78)
$Shock \times \beta^{local}_{MSA}$	0.24^{**}	0.24^{*}	0.34^{**}	0.34^{**}	0.30^{**}	0.30^{**}		
	(0.12)	(0.13)	(0.16)	(0.17)	(0.13)	(0.14)		
Constant	2.53^{***}	1.32^{**}	2.49^{***}	0.81	2.73^{***}	1.44^{**}	22723.25^{***}	18204.57^{***}
	(0.26)	(0.58)	(0.29)	(0.70)	(0.27)	(0.63)	(1103.41)	(438.15)
Ind.×Year FE	X	X	X	X	X	X	X	X
MSA FE		X		X		X		X
Observations	409294	409294	222549	222549	343477	343477	442591	442591
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 Non-Union Occ.		(1990 $)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β^{local}_{MSA}	-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)
$Shock \times \beta^{local}_{MSA}$	0.44^{***}	0.38^{***}	0.29^{***}	0.24^{***}	0.31^{***}	0.27^{***}		
	(0.14)	(0.13)	(0.07)	(0.06)	(0.08)	(0.08)		
Constant	1.39^{***}	-1.04	1.83^{***}	0.86^{*}	1.86^{***}	0.70	11.26^{***}	10.00^{***}
	(0.35)	(0.66)	(0.20)	(0.45)	(0.20)	(0.47)	(0.40)	(0.10)
Occ.×Year FE	X	X	X	X	X	X	X	X
MSA FE		X		X		X		X
Observations	76986	76986	1028541	1028541	758607	758607	1349174	1349174
R^2	0.08	0.09	0.04	0.05	0.04	0.04	0.83	0.86

Table 4
Real Estate Returns and Local Beta

The table reports the effect of aggregate shocks on the real estate returns in the MSA, conditional on the MSA beta, β^{local}_{MSA}. Calculation of β^{local}_{MSA} is described in Table 2. Housing returns are the annualized changes in the FHFA house price indexes in each MSA. Commercial real estate returns are the total annualized returns to all property types in each MSA, from NCREIF. Rent growth is the annualized growth in office building rents in each MSA, from CoStar. Aggregate shock (*Shock*) is the aggregate real GDP growth in that year, in %. Regression sample period is 1986-2011. Regressions are at the quarterly basis. The commercial real estate regression includes property type fixed effect (Office, Industrial, Retail, Apartment, Hotel). All standard errors are clustered at the MSA level, presented in parantheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

	Housing Returns		Commercial Real Estate Returns		Rent Growth	
	(1)	(2)	(3)	(4)	(5)	(6)
β^{local}_{MSA}	-1.87^{***}	3.82^{***}	-2.68	9.25	-4.36	0.18
	(0.56)	(1.18)	(4.38)	(6.17)	(2.77)	(7.54)
$Shock \times \beta^{local}_{MSA}$	1.16^{***}	1.09^{***}	4.16^{*}	3.52^{*}	2.72^{**}	1.98^{*}
	(0.25)	(0.26)	(2.14)	(2.08)	(1.13)	(1.14)
Constant	-0.04	-8.19^{***}	-8.32^{**}	-24.92^{**}	-0.19	-32.44^{***}
	(0.37)	(1.41)	(3.62)	(11.73)	(2.57)	(8.66)
Time FE	X	X	X	X	X	X
MSA FE		X		X		X
Observations	36268	36268	10267	10267	5411	5411
R^2	0.45	0.46	0.52	0.53	0.18	0.21

Table 5
Panel Regression of Conditional Equity Betas and Local Beta

The table reports the relationship between the conditional equity betas (β^{cond}_{firm}) of the firms located in an MSA and the MSA beta, β^{local}_{MSA}. Calculation of β^{local}_{MSA} is described in Table 2. Subsamples are sorted based on RER, defined as (buildings + capital leases) / Employees. Columns 3-6 use firm level RER, columns 7-10 use industry-level RER, computed as the average RER of firms in each industry. Conditional equity betas for firms are computed each calendar year from short window regressions using monthly data, correcting for non-syncronous trading, as in Lewellen and Nagel(2006). Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

	All Firms		Low RER Firms		High RER Firms		Low RER Industries		High RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β^{local}_{MSA}	−0.36***	−0.33**	−0.39**	−0.37**	−0.21	−0.16	−0.49***	−0.47***	−0.20	−0.13
	(0.14)	(0.14)	(0.18)	(0.18)	(0.22)	(0.22)	(0.16)	(0.16)	(0.24)	(0.23)
Log *Size*		−0.06***		−0.04***		−0.09***		−0.06***		−0.07***
		(0.01)		(0.01)		(0.01)		(0.01)		(0.02)
Log *BM*		−0.07***		−0.05**		−0.09***		−0.05**		−0.11***
		(0.02)		(0.02)		(0.03)		(0.02)		(0.03)
Constant	1.93***	2.61***	1.98***	2.41***	1.84***	2.79***	2.04***	2.71***	1.78***	2.48***
	(0.15)	(0.19)	(0.20)	(0.23)	(0.25)	(0.33)	(0.17)	(0.20)	(0.27)	(0.35)
Ind.×Time FE	X	X	X	X	X	X	X	X	X	X
Observations	97157	97157	41623	41623	48758	48758	56570	56570	40587	40587
R^2	0.08	0.08	0.11	0.11	0.08	0.08	0.10	0.10	0.06	0.07

Table 6
Panel Regression of Equity Returns and Local Beta

The table reports the relationship between the future returns of the firms located in an MSA and the MSA beta, β^{local}_{MSA}. Calculation of β^{local}_{MSA} is described in Table 2. Subsamples are sorted based on RER, defined as (buildings + capital leases) / Employees. Columns 3-6 use firm level RER, columns 7-10 use industry level RER, computed as the average RER of firms in each industry. Future returns are measured in the year following the portfolio formation, from July of year *t+1* to June of year *t+2*, and annualized (%). Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

	All Firms		Low RER Firms		High RER Firms		Low RER Industries		High RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β^{local}_{MSA}	−4.98**	−4.31*	−10.46***	−9.13***	−0.55	−0.72	−8.23***	−7.05**	−0.81	−0.80
	(2.22)	(2.37)	(3.40)	(3.54)	(3.37)	(3.66)	(3.04)	(3.15)	(3.36)	(3.65)
Log *Size*		−1.14***		−1.33***		−1.19***		−1.36***		−0.86***
		(0.12)		(0.19)		(0.18)		(0.15)		(0.19)
Log *BM*		5.29***		5.99***		4.63***		5.64***		4.85***
		(0.30)		(0.48)		(0.42)		(0.40)		(0.45)
Constant	15.55***	31.96***	20.90***	38.75***	11.18***	29.25***	18.53***	37.10***	11.74***	25.40***
	(2.46)	(2.98)	(3.74)	(4.45)	(3.76)	(4.58)	(3.35)	(3.90)	(3.76)	(4.74)
Ind.×Time FE	X	X	X	X	X	X	X	X	X	X
Observations	1163237	1163237	498699	498699	583826	583826	677701	677701	485536	485536
R^2	0.15	0.15	0.16	0.16	0.17	0.17	0.15	0.15	0.15	0.15

Table 7
Panel Regression of Equity Returns and Local Beta for Subsamples

The table reports the relationship between the future returns of the firms located in an MSA and the MSA beta, β^{local}_{MSA}, for various subsamples. Calculation of β^{local}_{MSA} is described in Table 2. 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. Non-unionized industries are industries with unionization rates lower than the median unionization rate of all industries in that year. Geographically focused firms are firms that mention five (two) or fewer states in their annual reports. Future returns are measured in the year following the portfolio formation, from July of year *t+1* to June of year *t+2*, and annualized (%). Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Panel A. Subsamples by Tradable Industries and Non-Union Industries

	Tradable Industries				Tradable, Non-Union Industries			
	Low RER Firms		Low RER Industries		Low RER Firms		Low RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β^{local}_{MSA}	-11.57^{***}	-10.42^{***}	-8.82^{***}	-7.70^{**}	-14.67^{***}	-13.89^{***}	-10.74^{***}	-9.75^{***}
	(3.40)	(3.54)	(3.05)	(3.16)	(4.09)	(4.20)	(3.50)	(3.60)
Log Size		-1.39^{***}		-1.40^{***}		-1.52^{***}		-1.58^{***}
		(0.19)		(0.15)		(0.22)		(0.17)
Log BM		6.09^{***}		5.63^{***}		5.85^{***}		5.54^{***}
		(0.48)		(0.40)		(0.57)		(0.45)
Constant	22.30^{***}	41.11^{***}	19.22^{***}	38.32^{***}	25.83^{***}	46.33^{***}	21.73^{***}	42.95^{***}
	(3.74)	(4.45)	(3.36)	(3.91)	(4.49)	(5.24)	(3.86)	(4.44)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	484727	484727	664878	664878	369898	369898	542717	542717
R^2	0.16	0.16	0.15	0.15	0.16	0.16	0.15	0.15

Panel B. Subsamples by Geographically Focused Firms

	Tradable, Geographically Focused ($\leq$ 5 States)				Tradable, Geographically Focused ($\leq$ than 2 States)			
	Low RER Firms		Low RER Industries		Low RER Firms		Low RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β^{local}_{MSA}	-16.33^{**}	-12.44^{*}	-21.50^{***}	-19.09^{***}	-31.83^{*}	-29.72	-24.50^{*}	-23.58^{*}
	(7.05)	(7.34)	(5.75)	(6.15)	(17.81)	(18.09)	(13.46)	(13.96)
Log Size		-2.68^{***}		-2.86^{***}		-3.43^{***}		-2.59^{***}
		(0.49)		(0.36)		(0.92)		(0.62)
Log BM		6.46^{***}		6.46^{***}		5.69^{***}		7.94^{***}
		(1.18)		(0.94)		(2.11)		(1.55)
Constant	30.11^{***}	62.14^{***}	35.05^{***}	71.72^{***}	50.40^{**}	91.96^{***}	40.24^{***}	75.74^{***}
	(7.83)	(9.74)	(6.39)	(7.96)	(19.87)	(22.95)	(15.02)	(17.45)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	118366	118366	173045	173045	42962	42962	60084	60084
R^2	0.21	0.21	0.19	0.19	0.27	0.27	0.22	0.22

Table 8
Industry-Adjusted Returns for Local Beta Sorted Portfolios

The table presents the average industry-adjusted returns and their alphas from the Fama-French 3-factor model for portfolios sorted on the MSA beta, β^{local}_{MSA}. At the end of each June, firms are simultaneously sorted based on their local betas and real estate ratios (RER). 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. Calculation of β^{local}_{MSA} is described in Table 2, RER is defined in Table 5. Panel A uses firm level RER, Panel B uses Industry RER. Results are presented for the entire sample, tradable industries, non-unionized industries and geographically focused firms (five or fewer states), which are explained in Table 6. Newey-West standard errors with 1 lag are presented in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, respectively.

Panel A. Portfolios Sorted by Local Beta and Firm Level RER

		Low RER Firms						High RER Firms					
		Low β^{local}_{MSA}	2	3	4	High β^{local}_{MSA}	Low-High	Low β^{local}_{MSA}	2	3	4	High β^{local}_{MSA}	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 Non-union 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 Geog. focused firms	Ind-adjusted return	−0.22	2.00	0.41	0.61	−3.49***	3.27	0.11	2.73	0.99	−1.24	−0.97	1.07
		(1.73)	(1.74)	(1.61)	(1.94)	(1.32)	(2.21)	(1.77)	(1.72)	(1.22)	(1.33)	(1.41)	(2.38)
	FF 3-factor alpha	0.16	2.41	0.89	0.22	−4.16***	4.32**	0.73	2.69	1.06	−1.31	−1.34	2.07
		(1.74)	(1.68)	(1.49)	(1.79)	(1.25)	(2.17)	(1.66)	(1.66)	(1.18)	(1.31)	(1.20)	(2.23)

Table 8 – *Continued*
Industry-Adjusted Returns for Local Beta Sorted Portfolios

Panel B. Portfolios Sorted by Local Beta and Industry Level RER

		Low RER Industry						High RER Industry					
		Low β^{local}_{MSA}	2	3	4	High β^{local}_{MSA}	Low-High	Low β^{local}_{MSA}	2	3	4	High β^{local}_{MSA}	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	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
Non-union firms		(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	Ind-adjusted return	1.42	2.15	−0.29	−0.06	−2.45**	3.88**	−2.32	2.49	1.35	−0.75	−0.69	−1.63
Geog. focused firms		(1.41)	(1.31)	(1.08)	(1.17)	(1.17)	(1.96)	(2.08)	(2.22)	(1.43)	(1.56)	(1.56)	(2.92)
	FF 3-factor alpha	1.85	2.21*	0.13	−0.15	−3.00***	4.85***	−1.79	2.72	1.37	−1.05	−0.95	−0.84
		(1.36)	(1.30)	(1.04)	(1.09)	(0.96)	(1.85)	(2.05)	(2.07)	(1.42)	(1.55)	(1.52)	(2.87)

Table 9
Model Parameter Values

Parameter	Description	Value
α_l	Labor share	0.60
α_s	Land share	0.12
α_k	Equipment share	0.18
I_{low}, I_{high}	Industry risk scalers	$e^{-0.4}, e^{0.4}$
β	Discount factor	0.99
γ_0	Constant price of risk parameter	3.2
γ_1	Time varying price of risk parameter	-13
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

Table 10
Model-Implied Factor Price Regressions

The table reports the effect of aggregate TFP shocks, Δa_t, on the wage and land price growth in an area, conditional on the local beta, β^{local}_{area}. β^{local}_{area} is computed as $I_{low} \times (1 - s_m) + I_{high} \times (s_m)$. 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, while 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 3 and 4, regressions include time fixed effects.

Dependent variable:	$\Delta \log(W_{area,t})$	$\Delta \log(P_{area,t})$
const	0.00	0.91
	(-0.12,0.09)	(-0.48,2.67)
$\Delta a_t \times \beta^{local}_{area}$	1.06	0.79
	(1.04,1.08)	(0.72,0.86)
β^{local}_{area}	0.03	0.15
	(-0.01,0.06)	(0.06,0.26)

Table 11
Model-Implied Equity Betas and Firm Returns

The table reports the relationship between the conditional betas (β^{cond}_{firm}) and expected returns of the firms located in an area and the local beta, β^{local}_{area}. Panel A presents the panel regression results for equity betas, Panel B presents the panel regression results for expected equity returns, Panel C presents the expected returns for the portfolio sorts. β^{cond}_{firm} is estimated running regressions of excess firm returns on the market returns using 10-period windows. Calculation of β^{local}_{area} is described in Table 10. Results presented in the table are based on regressions run on (portfolios constructed from) data generated from 100 simulations of 2,000 firms for 50 periods. Point estimates are simulation medians of regression coefficients (portfolio averages), while 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 5, 6, and 7, panel regressions include industry × time fixed effects.

Panel A: Conditional Beta Regressions

Dependent Variable: $\beta^{cond}_{firm,t}$

	All Firms	Low Land/Emp	High Land/Emp
const	1.08	1.09	1.07
	(1.05,1.16)	(1.03,1.23)	(1.05,1.09)
β^{local}_{area}	-0.07	-0.08	-0.07
	(-0.15,-0.05)	(-0.15,-0.05)	(-0.13,-0.04)

Panel B: Firm Return Regressions

Dependent Variable: $r^{e}_{firm,t+1}$

	All Firms	Low Land/Emp	High Land/Emp
const	6.21	5.74	6.76
	(1.82,15.06)	(1.40,14.26)	(2.33,15.88)
β^{local}_{area}	-0.67	-0.75	-0.66
	(-1.31,-0.26)	(-1.35,-0.32)	(-1.25,-0.32)

Panel C: $\beta^{local}_{area}-$Sorted Portfolio Returns

	Industry-Adjusted Returns	
	Low Land/Emp	High Land/Emp
low β^{local}_{area}	0.06	0.05
	(0.03,0.10)	(0.02,0.09)
high β^{local}_{area}	-0.06	-0.05
	(-0.10,-0.03)	(-0.09,-0.02)
low-high	0.12	0.10
	(0.05,0.21)	(0.05,0.20)