Internet Appendix to

"Local Risk, Local Factors, and Asset Prices"

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This Internet Appendix presents material that is supplemental to the main analysis and tables in "Local Risk, Local Factors, and Asset Prices." We supplement the empirical analysis in the paper with detailed description of the data in Section I and additional robustness checks in Section II. We supplement the theoretical analysis with the derivation of the first-order conditions and details on our numerical solution method in Section III.

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I. Extended Version of Data and Measurement

This section extends Section II of the main text by providing a more detailed discussion of the data sources used in our empirical analysis. Some material in this section duplicates the main text.

To conduct the empirical analysis we combine a number of data sets. The key variable in this paper is the beta of local economies, β_m^{local}. We compute local beta as the average of the GDP betas of the industries operating in that area, weighted by the employment share of those industries. Specifically,

$$\beta_{m,t}^{local} = \sum_i w_{i,m,t} \beta_{i,t}^{ind} \tag{IA1}$$

for all areas (markets) m in year t, where $w_{i,m,t}$ represents the employment share of industry i in market m in year t and $\beta_{i,t}^{ind}$ represents the beta of industry i in year t. Industry betas, $\beta_{i,t}^{ind}$, are calculated as the slope coefficients from regressions of real industry value-added growth on real GDP growth, using data up to year t.

We classify 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 with a population of 50,000 or more as well as adjacent counties that have a high degree of social and economic integration (as measured by work commutes) with the urban core.[1] Our sample contains 373 unique MSAs.

To calculate the weight of the industries in an MSA, we collect MSA-level industry employment data from the County Business Patterns (CBP) data set published by the U.S. Census Bureau. CBP data are recorded in March of each year, are published at annual frequency for each industry in each geographical unit, and span the years 1986 to 2011.[2] The industry classification is based on Standard Industrial Classification (SIC) codes until 1997 and North American Industry Classification System (NAICS) codes thereafter. Due to a poor match between SIC

[1]The term "core based statistical area" (CBSA) refers to both metro and micro areas. Currently, the Census Bureau uses the MSA and metro CBSA interchangeably. For more information, see http://www.census.gov/population/metro/.

[2]Disaggregated data are at times suppressed for confidentiality reasons. In such cases, the Census Bureau provides a "flag" that indicates 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.

and NAICS, we employ the original classification at the two-digit SIC and three-digit NAICS level rather than converting to one of the two classifications. The CBP reports industry-level employment at the county and MSA level. For the period prior 2003, we use county-level employment data from CBP and aggregate the data to the MSA level using crosswalks from the Census Bureau. We directly use MSA-level data after 2003.[3] We compute the industry share, $w_{i,m,t}$, as the ratio of each industry's employment in an MSA to the total reported employment in the MSA in year t. While most MSAs have a diverse economic base featuring many industries, there is heterogeneity in the degree of industrial diversity across MSAs. Figure 1 plots the distribution of MSA-level industrial employment dispersion, computed as a Herfindahl index of industry employment shares.

To calculate industry betas, we obtain annual data on industry value-added, as a measure of industry output, from the Bureau of Economic Analysis (BEA). SIC-based data covers the 1947 to 1997 period whereas the NAICS sample spans 1977 to 2011. Industry shocks are given as 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 then calculated as the slope coefficients from regressions of industry shocks (real industry value-added growth) on aggregate shocks (real GDP growth), using data up to year t. Table I in the main text lists the industries with the highest and lowest betas in 2011. Broadly speaking, the industries with the lowest betas operate in the food manufacturing, health care, and oil sectors. These industries have negative or near-zero betas in our sample. The industries with the highest betas operate in the heavy manufacturing (primary metal, transportation equipment, nonmetallic mineral, and wood) and the financial sector, with betas around three. Replacing industry employment weights, $w_{i,m,t}$, and industry betas, $\beta_{i,t}^{ind}$, in equation (IA1), we obtain MSA betas over 1986 to 2011.

Table II in the main text reports summary statistics for the 15 lowest and the 15 highest beta MSAs as of 2011 to gain more perspective on local betas. in 2011, Elkhart/Goshen Indiana is the highest beta MSA in our sample (local beta = 1.73). The largest industry in the area, transportation equipment manufacturing, employs roughly a quarter of the workforce in Elkhart. The remaining high beta MSAs include other heavy manufacturing towns like

[3] 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.

Kokomo Indiana, and Wichita Kansas, as well and areas that rely heavily on tourism, such as Las Vegas Nevada, and New London Connecticut. Many of the lowest beta MSAs, in contrast, have economies based on food manufacturing, like Merced California, and Sioux City Iowa. The lowest beta MSA in 2011 is St. Joseph Missouri (local beta = 0.71). Other low beta areas include Rochester Minnesota, home to the Mayo Clinic in the health care sector, and Ithaca New York, where the education services industry (including Cornell University) employs more than one-third of area employees. Table II also reports the number of employees and the employment rank for each MSA. There is no particular relationship between the local beta and the 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. We find that MSAs in the first quintile of the local beta distribution contribute little to aggregate metropolitan GDP (6.2%), while the MSAs in the remaining quintiles all make sizable contributions: 22.7%, 16.5%, 32.3%, and 22.4% for quintiles 2 to 5, respectively.

To shed more light on the informativeness of the local beta measure, Figure 3 plots the recent economic performance of the highest and lowest beta MSAs over the 2001 to 2011 period. The top panel plots the average real GDP of the highest and lowest beta areas, together with national GDP, where levels are normalized to one in 2001. Real GDP data for MSAs come from the BEA, which reports GDP by metropolitan area since 2001.[4] The bottom panel plots annual GDP growth for the same areas. The panels show that high beta areas experienced steady growth during the expansion years until 2007, but experienced a larger reduction in terms of both GDP levels and growth during the Great Recession (2008 to 2009). The lowest beta areas, in contrast, experienced neither a large increase nor a significant drop in output over the same period. These findings support the validity of our local betas, constructed from local industry shares and industry betas, as measure of the economic risk of local areas.

To examine the time-series dynamics of local beta, Table IA.I tabulates the transition probabilities for an MSA moving from one local beta quintile to another between two consecutive years. Since the employment base of the MSAs and industry betas does not change fast, local beta is persistent but not fixed. The probability of MSAs in the lowest and highest local beta quintiles staying in those quintiles next year is roughly 85%. Figure IA.1 plots the average local beta for the MSAs sorted into quintile portfolios every year over the sample period. The

[4] To the best of our knowledge, there are no publicly available data before 2001. This is also one of our main motivations for constructing our benchmark measure of local beta from industry betas as in equation (IA1).

figure shows that the dispersion in local betas decreased somewhat over time, yet there is still a significant spread between the betas of the lowest and highest beta areas. Figure 4 plots the distribution of MSA betas as of 2011, the last observation year in our sample. Most MSA betas are between 0.8 and 1.2, and the betas are positively skewed.

We measure local factor prices using data from several different sources. We obtain wage data at the MSA $\times$ industry level from the Quarterly Workforce Indicators (QWI) data set of the Longitudinal Employer-Household Dynamics (LEHD) program of the U.S. Census Bureau. We aggregate quarterly wages to annual wages as wages exhibit significant seasonality. The data start in 1990, but 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. The data come from the Occupational Employment Statistics (OES) program of the Bureau of Labor Statistics. The data start in 1999.[5] We use both broad occupation definitions with 22 major occupation groups and detailed occupation definitions with 854 detailed occupation groups.[6]

To check the robustness of our wage analysis, we look at industries and occupations with high and low union coverage separately. We obtain data on the industry and occupation unionization ratesfrom http://www.unionstats.com, which is 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 data set and the NAICS industry classification codes in LEHD and Standard Occupational Classification (SOC) codes in the OES wage.

We calculate housing returns as the percent change in the house price indexes (HPI) from the Federal Housing Finance Agency (formerly known as OFHEO, Office of Federal Housing Enterprise Oversight). HPI data are available at the quarterly frequency starting in 1975.

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

[6] 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.

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 start in 1982, but the number of covered 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. [7]

For our firm-level analysis, we identify a firm's location using its headquarters location from Compustat, and we supplement the data with headquarters location change information from Compact Disclosure, compiled by Engelberg, Ozoguz, and Wang (2010).[8] Chaney, Sraer, and Thesmar (2012) argue that headquarterss and production facilities tend to be clustered in the same state and MSA and headquarterss represent an important fraction of corporate real estate assets. They provide hand-collected evidence supporting this assumption.[9] Therefore, they conclude that headquarters location is a reasonable proxy for firm location.

To assess the validity of this identification, we link our Compustat-CRSP sample to the ReferenceUSA U.S. Businesses Database and collect employment data for all headquarters, branch, and subsidiary locations of the firms in our sample.[10] This allows us to create an employment map for each of roughly 2,000 firms in the linked sample.[11] We find that 63% of the firms in our linked sample have at least 50% of their employment in their headquarters MSA. For the median firm in our sample headquarters location accounts for 72% of total employment. While headquarters MSA accounts for the majority of firms' employment for more than 60% of

[7]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.

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

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

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

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

the firms, there is significant heterogeneity across firms of different size (market capitalization). Appendix Table AII of the main text reports the percentage of firms that have at least 50%, 75%, 90%, or 100% of their employment in their headquarters MSA for all firms, and for firms sorted based on size. Not surprisingly, we find that headquarters MSA is a much better location proxy for smaller firms. Almost 80% of firms in the smallest size quintile have more than half of their employment in their headquarters MSA, and of these firms about 55% have virtually all of their employment in the same MSA. For the firms in the largest size quintile, the comparative statistics are roughly 50% and 10%. To the extent that headquarters location is a noisy measure of where a 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 two subsamples of firms that are geographically focused. The first subsample is the sample of smaller firms, for which headquarters location accounts for a large fraction of employment. The second subsample is based on a measure constructed from state name counts from annual reports, organized by Garcia and Norli (2012). We classify firms as geographically focused if one or two state names are mentioned in the firms' annual report, as in Garcia and Norli (2012)[12]

In firm-level regressions, we conduct all comparisons on a within-industry basis. It is therefore important that we considerable dispersion in firm locations within a given industry. Accordingly, we compute a measure of industry concentration across MSAs, which is a Herfindahl index of how the number of firms in an industry (from Compustat) are divided across MSAs. Figure 4 in the main text plots the distribution of this industry concentration measure. The figure shows that most industries have large variation in firm locations, but a few industries are more geographically focused, though still include firms from several different MSAs.

Data on real estate holdings and firm employees come 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), to avoid survivorship bias in the data, we include firms in our sample after they have appeared in Compustat for two years. Following Tuzel (2010), we measure 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 real estate ratio (RER), we scale the real estate holdings with the number of employees (EMP).

Monthly stock returns are from the Center for Research in Security Prices (CRSP). Similar

[12] Zhang (2016) conducts a similar subsample test.

to Fama and French (1993), our sample includes firms with ordinary common equity as classified by CRSP, excluding ADRs, REITs, and units of beneficial interest. We match CRSP stock return data from July of year t to June of year $t+1$ with accounting information (Compustat) for 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. Appendix Table AI of the main text summarizes all data sets used in the paper.

II. Additional Empirical Analysis

A. Local Factor Prices with Alternative Approach

Our panel regression results in Tables III and IV of the paper show that the prices of local factors of production—wages and real estate—are more sensitive to aggregate shocks in areas with more cyclical economies. Here we adopt an alternative methodology and test the same hypotheses using two-stage cross-sectional regressions. In the first stage we run time-series regressions of wage growth (in each industry-MSA) and real estate returns (in each MSA) on aggregate GDP growth to estimate factor price betas, β_m^{Factor}:

$$\Delta Factor\ Price_{m,t} = \alpha + \beta_m^{Factor} shock_t + \epsilon_{m,t}.$$

In second stage, we conduct a cross sectional regression of factor price betas, β_m^{Factor}, on local betas computed using our entire sample, $\beta_{m,2011}^{local}$:

$$\beta_m^{Factor} = b_0 + b_1 \beta_{m,2011}^{local} + \epsilon_m.$$

Table IA.II reports results of the second-stage regressions.[13] Columns (1) to (3) show that wages (for the entire sample of industries, non-unionized industries, and tradable industries) are more sensitive to aggregate shocks in MSAs with more cyclical economies ($\beta_{m,2011}^{local}$). Columns (4) to (6) report similar results for house prices, commercial real estate prices, and office rents, though results are only statistically significant for the former two.[14]

[13] We include industry fixed effects for wage regressions, and property type fixed effects for the commercial real estate regressions.

[14] The sparsity of commercial real estate and rent data in earlier years presents difficulties in running the first-stage regressions. To achieve some uniformity in sample periods we exclude years with very few observations and

B. Robustness Checks for Firm Level Results

In this section, we check the robustness of our main results to using alternative measures of local beta, an expanded sample period, alternative assumptions for the correlation structure of the residuals, and different regression specifications.

In our baseline results we compute local beta as the average of the GDP betas of the industries operating in an area, weighted by the employment share of the industries in the area. Table IA.III replicates our main tests using two alternative measures of local beta. The first measure is constructed as a weighted average of the total factor productivity (TFP) betas of the industries operating in the MSA. TFP growth is the source of exogenous variation in industry output and therefore it is a natural proxy for industry shocks. Industry TFP growth is computed as the Solow residual given by

$$\Delta \log \widehat{\xi}_{it} = \Delta \log VA_{it} - \alpha_L \Delta \log L_{it} - \alpha_K \Delta \log K_{it},$$

where VA_{it} denotes real value-added, L_{it} represents total labor input (total number of full-time and part-time employees, from BEA), and K_{it} represents total capital input (measured from the current-cost net stock of private fixed assets, from BEA) of each industry. The labor share, α_L, is computed as the share of compensation of employees in the value-added of the industry, where capital share, α_K, is $1 - \alpha_L$. Industry TFP betas are calculated as the slope coefficients from the regressions of industry TFP growth on aggregate TFP growth, using data up to year t. Local TFP betas, β_m^{TFP}, are computed as the average of industry TFP betas, weighted by employment shares of industries. The second measure is a more direct measure of local beta, calculated as the slope coefficient from regressions of real GDP growth of each MSA on real (aggregate) GDP growth (β_m^{Output}). MSA level GDP data is available annually from 2001 to 2011. Due to the short time-series, this measure does not allow us to lag MSA beta in our empirical tests. Instead, we calculate one β_m^{Output} for each MSA and use it as that MSA's local beta in all periods.

Table IA.III, Panel A presents results to pooled time-series / cross-sectional regressions for wages and real estate prices, given in equations (12) and (13) in the main text, and Panel B presents the results to firm return regressions given in equation (15) in the main text, using

start the sample in 2001.

alternative MSA beta measures. In both panels, results presented in columns (1) to (4) are based on β_m^{TFP}, while columns (5) to (8) use β_m^{Output}. Due to data availability, the sample period for regressions using β_m^{Output} is limited to 2001 to 2011. Consistent with our benchmark results, we find that the coefficients on $Shock \times \beta_m^{alter}$ in Panel A are positive and significant using both alternative MSA beta measures, implying that wages and house prices are more sensitive to aggregate shocks in areas with more cyclical economies. We also find that the coefficients on β_m^{alter} in Panel B remain uniformly negative and significant, implying that firms in higher beta areas (measured with alternative MSA betas) have lower returns after controlling for firms' industry. We therefore conclude that our main empirical results are not particularly sensitive to how MSA betas are calculated.

Our baseline firm-level return regressions cover the 1986 to 2011 period, which is dictated by the availability of employment data to compute MSA betas. Apart from the Great Recession of 2008 to 2009, the U.S. economy experienced relatively stable economic growth during this period, compared to the sample periods that are covered in most asset pricing studies, which go back to early 1970s. This raise the question of whether our main results would hold over a longer sample period that experienced several economic cycles. To address this concern, we expand the sample period for our firm return regressions back to 1970. Since we cannot compute MSA betas prior to 1986, we assign 1986 MSA betas to all years prior to 1986.[15] Table IA.IV presents the results using this longer sample period. We find that while the estimated regression coefficients on β_m^{local} are slightly smaller for the longer sample period, the statistical significance of the results remains unchanged.

In Table IA.V, we present our main return regression results under various assumptions for the correlation structure of the residuals. In Panel A, we run monthly cross-sectional regressions of future equity returns on MSA beta, firm-level control variables, and industry dummies, and report time-series averages of the coefficients (Fama and MacBeth (1973)). In Panel B, we double-cluster the standard errors by time (year-month) and firm following Petersen (2009). We find that the results are robust to these alternative specifications.

Finally, in Table IA.VI, we test the relationship between MSA beta and future returns of firms located in that area by aggregating firms into MSA-industry portfolios. We run panel

[15] MSA betas change slowly over time, as seen in Table IA.I. Thus, while they are imperfect, 1986 betas should provide a reasonable proxy to real-time MSA betas over this period.

regressions of future portfolio returns on β_m^{local} with industry-month fixed effects. The main advantage of this test relative to firm-level panel regressions is that it rules out any concerns related to outlier firms in our sample. However, unlike our firm-level regressions, this test does not allow us to control for various firm characteristics that are known to predict returns. We find that the coefficient on β_m^{local} is very similar to our earlier results from Tables VI and VII, confirming the negative and significant relationship between MSA beta and firm returns.

III. Additional Information for the Full Model

A. Pricing Equations

Here, we provide supplementary information about the pricing equations for both land and equipment, following the setup in Section IV.A of the main text. These equations provide guidance to our numerical solutions in next section.

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

$$1 = \int\int M_{t,t+1} R_{i,t+1}^{S} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a \tag{IA2}$$

$$1 = \int\int M_{t,t+1} R_{i,t+1}^{K} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a, \tag{IA3}$$

where the returns to land and equipment investment are given by

$$R_{i,t+1}^{S} = \frac{F_{S_{i,t+1}} + q_{i,t+1}^{s} + \frac{1}{2}\eta_s \left(\frac{S_{i,t+1}-S_{it}}{S_{it}}\right)^2}{q_{it}^{s}} \tag{IA4}$$

$$R_{i,t+1}^{K} = \frac{F_{K_{i,t+1}} + (1-\delta) q_{i,t+1}^{k} + \frac{1}{2}\eta_k \left(\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2 - \delta^2\right)}{q_{it}^{k}}, \tag{IA5}$$

with

$$F_{S_{it}} = F_S(A_t, Z_{it}, I_j, L_{it}, S_{it})$$

$$F_{K_{it}} = F_K(A_t, Z_{it}, I_j, L_{it}, S_{it}).$$

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

$$q_{it}^{s} = P_t + \eta_s \left(\frac{S_{i,t+1} - S_{it}}{S_{it}} \right) \tag{IA6}$$

$$q_{it}^{k} = 1 + \eta_k \left(\frac{I_{it}}{K_{it}} - \delta \right). \tag{IA7}$$

The pricing equations (equations (IA2)-(IA3)) 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 (IA4) and (IA5), 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.

B. Model Solution

Here, we supplement Section IV.D of the main text with a description of the algorithm that we use to solve the full model numerically.

Solving our model generates the pricing functions for local land prices $P_{m,t}$ and local wages $W_{m,t}$ as well as firms' investment and hiring decisions as functions of the state variables, firms' industry, j, and local industry shares, s_m. 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, m.

The solution algorithm is as follows:

1. Assume a parameterized functional form for local wages $W_{m,t}$ and local land prices $P_{m,t}$. Following the approximate aggregation idea of Krusell and Smith (1998), we assume that wages and land prices are functions of aggregate productivity, A_t, and aggregate equipment holdings, $\overline{K}_{m,t} = \sum_j \int K_{ijm,t} di$, of local firms.[16] Since $\overline{K}_{m,t}$ is determined

[16] Note that aggregate land holdings of local firms, which is the supply of available local land, is constant.

endogenously and requires aggregation of local firms' capital holdings, we also guess a parameterized functional form for $\overline{K}_{m,t}$.

2. Guess the initial parameter values for the wage, land price, and aggregate capital functions for each local market.

3. For firms in each industry, add the wage and price functions as inputs to firms' optimization problem (Equation (IA2) and (IA3)). Solve the optimization problem and derive firms' investment and hiring decisions using perturbation methods.

4. Use firms' investment rules to simulate the behavior of N firms over T periods for each local market.

5. Select the stationary region of the simulated data. Aggregate land holdings and employment decisions for each local market to check whether the land and labor markets clear at each period. Measure the forecast errors from the current wage, land price, and aggregate capital functions by comparing total land holdings and employees to the constant supply of land and employees, and simulated aggregate capital to the aggregate capital forecasts.

6. If the forecast errors are below the tolerance values, stop. If the forecast errors are greater than the tolerance, update the parameters for the functions, and go to step 3. If the parameters of the functional form have converged but forecast errors remain large, guess a different functional form and go to step 2.

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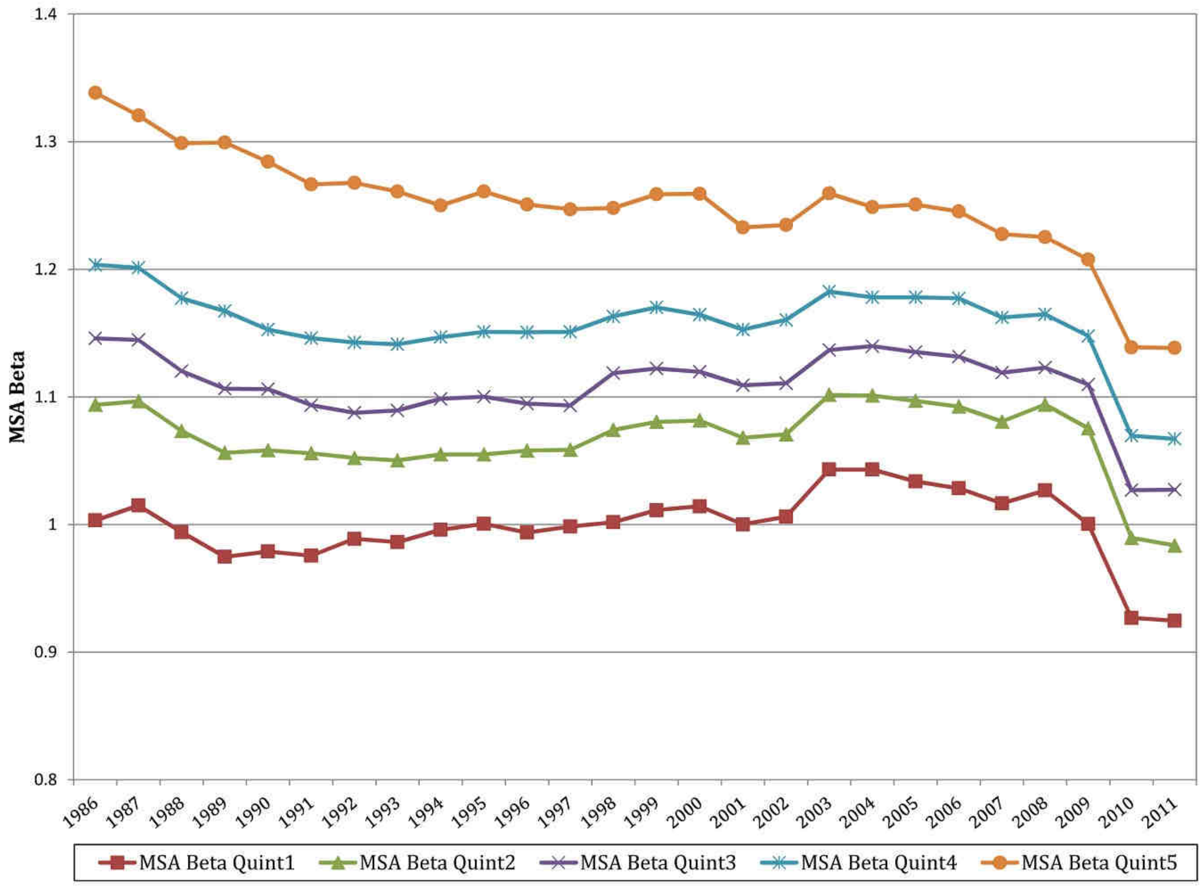

Figure IA.1. Time-series of MSA betas. The figure plots the median local beta for the MSAs sorted into five beta quintiles over the 1986 ot 2011 period. Portfolios are rebalanced every year.

Table IA.I
Transition Probability Matrix of β_m^{local} Quintiles

The table tabulates the transition probabilities of an MSA moving from one β_m^{local} quintile to another between two consecutive years. Local betas, β_m^{local} are calculated as the average betas of the industries operating in that area, weighted by the employment share of those industries.

	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 IA.II
Factor Price Sensitivity and Local Beta

The table reports results of (second-stage) cross-sectional regressions where local betas, β_m^{local}, are used to predict factor price betas, which are estimated in first-stage time-series regressions of wage growth and real estate returns on aggregate shocks (aggregate real GDP growth). The calculation of β_m^{local} is described in Table II, annual wage growth for industries is explained in Table III, and real estate returns are described in Table IV. First-stage regressions

$$\Delta Factor\ Price_{m,t} = \alpha + \beta_m^{Factor} \Delta GDP_t$$

for wages are estimated over 1990 to 2011, housing are estimated over 1986 ot 2011, commercial real estate and rent are estimated using available data over 2001 to 2011. We require each MSA to have at least 10 observations to run first-stage regressions. In second stage regressions,

$$\beta_m^{Factor} = b_0 + b_1 \beta_m^{local}$$

we regress wage and real estate return betas from first-stage regressions on MSA betas in 2011. The wage regressions include industry fixed effects, and commercial real estate regressions include property type fixed effects (office, industrial, retail, apartment, and hotel). Robust standard errors are reported in parentheses. *, **, and ***represent significance at the 10%, 5%, and 1% level, respectively.

	Wage Betas			Housing	Commercial RE	Rent
	All	Non-Union	Tradable	Beta	Beta	Beta
β_m^{local}	0.28***	0.26***	0.34***	0.54**	0.81**	0.05
	(0.07)	(0.10)	(0.09)	(0.26)	(0.39)	(0.24)
Constant	0.29***	0.30***	0.26***	0.55**	0.03	0.08
	(0.08)	(0.10)	(0.09)	(0.27)	(0.42)	(0.26)
Ind/Type FE	X	X	X		X	
Observations	25534	14122	21344	363	155	175
R^2	0.04	0.04	0.04	0.01	0.10	0.00

Table IA.III
Alternative Measures of Local Beta

Panel A reports the effect of aggregate shocks on industry wage growth and housing returns in an MSA, conditional on two alternative measures of local beta. Panel B reports the relationship between the future returns of the firms located in an MSA and the alternative measures of local beta. β_{MSA}^{TFP} is constructed as the average of the TFP betas of the industries operating in that MSA, weighted by the employment share of industries in the MSA. β_{MSA}^{Output} is calculated as the slope coefficient from the regression of real GDP growth of each MSA on real (aggregate) GDP growth. Wage growth is at the industry $\times$ MSA level from LEHD, housing returns are changes in the FHFA house price indexes in each MSA. Aggregate shock (*Shock*) is the aggregate real GDP growth in that year, in %. Firm level controls are described in Table V. Future returns are measured in the year following portfolio formation, from July of year $t+1$ to June of year $t+2$, and annualized (%). In Panel A, columns (1) to (3) and (5) to (7) have industry $\times$ time fixed effects, where time refers to a month in a year. Column 4 and 8 have only time fixed effect where time refers to a quarter in a year. Regression sample period is 1990 to 2011 in columns (1) to (3) of Panel A, 1986 to 2011 in column (4) of Panel A and columns (1) to (4) of Panel B, and 2001 to 2011 in columns (5) to (8) of Panels A and B. Standard errors are clustered at the MSA level in Panel A and by firms in Panel B, and are presented in parentheses. *, **, and ***represent significance at the of 10%, 5%, and 1% level, respectively.

Panel A. Local Factors and Alternative Local Beta Measures

	$\beta_{MSA}^{alter}=\beta_{MSA}^{TFP}$				$\beta_{MSA}^{alter}=\beta_{MSA}^{Output}$			
	Wage All	Wage Non-Union	Wage Tradable	Housing	Wage All	Wage Non-Union	Wage Tradable	Housing
β_{MSA}^{alter}	-1.03	-0.54	-0.51	1.04	-0.16^{***}	-0.18^{***}	-0.16^{***}	-0.94^{***}
	(1.01)	(1.15)	(1.09)	(1.61)	(0.04)	(0.04)	(0.04)	(0.14)
Shock $\times\ \beta_{MSA}^{alter}$	1.21^{***}	1.00^{***}	1.25^{***}	1.19^{**}	0.03^{**}	0.04^{**}	0.03^{**}	0.28^{***}
	(0.31)	(0.38)	(0.33)	(0.50)	(0.01)	(0.02)	(0.02)	(0.08)
Ind.$\times$Time/Time FE	X	X	X	X	X	X	X	X
MSA FE	X	X	X	X				
Observations	409294	220180	343477	36268	273582	145211	229612	14080
R^2	0.05	0.06	0.03	0.46	0.05	0.07	0.04	0.54

Panel B. Equity Returns and Alternative Local Beta Measures

	$\beta_{MSA}^{alter}=\beta_{MSA}^{TFP}$				$\beta_{MSA}^{alter}=\beta_{MSA}^{Output}$			
	All	All	Low RER Firms	Low RER Industries	All	All	Low RER Firms	Low RER Industries
β_{MSA}^{alter}	-5.42^{**}	-6.14^{**}	-12.38^{***}	-9.04^{**}	-1.47^{***}	-1.37^{***}	-2.04^{***}	-1.08^{*}
	(2.50)	(2.68)	(4.06)	(3.61)	(0.44)	(0.46)	(0.62)	(0.56)
Log *BM*		5.93^{***}	6.89^{***}	6.84^{***}		5.63^{***}	7.24^{***}	5.95^{***}
		(0.33)	(0.52)	(0.45)		(0.50)	(0.92)	(0.68)
Log *Size*		-1.22^{***}	-1.34^{***}	-1.30^{***}		-1.75^{***}	-1.55^{***}	-1.54^{***}
		(0.12)	(0.19)	(0.15)		(0.17)	(0.28)	(0.22)
Leverage		-1.85^{*}	-3.94^{**}	-2.30		5.89^{***}	-0.08	2.64
		(1.09)	(1.72)	(1.41)		(1.93)	(3.02)	(2.42)
Profitability		9.76^{***}	10.21^{***}	15.27^{***}		12.66^{***}	15.59^{***}	17.07^{***}
		(0.97)	(1.52)	(1.41)		(1.57)	(2.80)	(2.13)
Investment		-9.75^{**}	-4.83	-10.21^{*}		-8.01	-2.12	0.47
		(4.17)	(6.82)	(5.68)		(8.10)	(12.59)	(10.17)
Ind.$\times$Time FE	X	X	X	X	X	X	X	X
Observations	1138028	1138028	484464	658523	400100	400100	153487	244593
R^2	0.15	0.15	0.16	0.15	0.18	0.18	0.20	0.18

Table IA.IV
Panel Regression of Equity Returns and Local Beta over an Expanded Sample Period

The table reports the relationship between the future returns of the firms located in an MSA and local beta, β_m^{local}, over an expanded sample period, 1970 to 2011. The calculation of β_m^{local} is described in Table II. We assign 1986 β_m^{local} to all years prior to that. In Panel A, we regress future monthly returns on local beta, and other firm-level control variables. *Log BM* and *Log Size* are the log of the firm's book-to-market ratio and market equity constructed following Fama and French (1992). *Leverage* is firm's market leverage as in Fan, Titman, and Twite (2012). *Profitability* is gross profit measure as in Novy-Marx (2013). *Investment* is the investment ratio as in Dougal, Parsons, and Titman (2015). Future returns are measured in the year following portfolio formation, from July of year $t+1$ to June of year $t+2$, and annualized (%). In Panel B, the Subsamples are sorted based on RER, defined as (buildings + capital leases)/employees. Columns (3) to (6) use firm-level RER, columns (7) to (10) use industry-level RER, computed as the average RER of firms in each industry. Standard errors are clustered by firms and are presented in parentheses. *, **, and ***represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Controlling for Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_m^{local}	−3.92**	−3.89**	−3.24*	−3.51**	−4.44***	−3.60**	−4.06**
	(1.69)	(1.78)	(1.77)	(1.71)	(1.69)	(1.71)	(1.82)
Log *BM*		6.09***					5.30***
		(0.24)					(0.29)
Log *Size*			−2.14***				−1.45***
			(0.09)				(0.10)
Leverage				6.66***			−1.64*
				(0.79)			(0.90)
Profitability					7.54***		9.71***
					(0.79)		(0.85)
Investment						−23.89***	−12.07***
						(3.33)	(3.39)
Ind.×Time FE	X	X	X	X	X	X	X
Observations	1507591	1507591	1507591	1507591	1507591	1507591	1507591
R^2	0.16	0.16	0.16	0.16	0.16	0.16	0.16

Panel B: Subsample by Real Estate Holdings

	Low RER Firms		High RER Firms		Low RER Industries		High RER Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β_m^{local}	−8.50***	−8.34***	0.72	0.34	−6.56***	−6.97***	−0.81	−0.55
	(2.77)	(2.85)	(2.47)	(2.71)	(2.47)	(2.54)	(2.40)	(2.62)
Log *BM*		6.19***		4.43***		6.31***		4.20***
		(0.45)		(0.40)		(0.40)		(0.41)
Log *Size*		−1.56***		−1.59***		−1.49***		−1.35***
		(0.16)		(0.15)		(0.13)		(0.15)
Leverage		−3.60**		−1.38		−2.36*		−0.27
		(1.42)		(1.32)		(1.21)		(1.35)
Profitability		10.02***		9.36***		14.45***		5.47***
		(1.34)		(1.17)		(1.27)		(1.13)
Investment		−8.32		−20.38***		−12.12**		−12.96***
		(5.65)		(4.53)		(4.73)		(4.78)
Ind.×Time FE	X	X	X	X	X	X	X	X
Observations	632153	632153	764968	764968	826068	826068	681523	681523
R^2	0.18	0.18	0.18	0.19	0.16	0.17	0.16	0.17

Table IA.V
Robustness of Standard Errors for Panel Regressions of Equity Returns

The table reports two alternative regression analyses with different assumptions for the correlation structure of the residuals. In Panel A, we run cross-sectional Fama-MacBeth (1973) regressions of monthly future equity returns on local beta, firm level control variables, and industry dummies. In Panel B, we run the panel regressions as in Table VI and Table VII, but cluster the standard errors by both firm and time (year-month). We first demean all the variables for each industry at each month and then run the panel regression with double-clustered standard errors. Calculation of β_m^{local} is described in Table II. *Log BM* and *Log Size* are the log of the firm's book-to-market ratio and market equity constructed following Fama and French (1992). *Leverage* is firm's market leverage as in Fan, Titman and, Twite (2012). $Profitability$ is gross profit measure as in Novy-Marx (2013). $Investment$ is the investment ratio as in Dougal, Parsons, and Titman (2015). Future returns are measured in the year following portfolio formation, from July of year $t+1$ to June of year $t+2$, and annualized (%). In Panel B, the Subsamples are sorted based on RER, defined as (buildings + capital leases)/employees. Columns (3) to (6) use firm-level RER, columns (7) to (10) use industry-level RER, computed as the average RER of firms in each industry. Regression sample period is 1986 ot 2011. Standard errors are clustered by firms and are presented in parentheses. *, **, and ***represent significance at the of 10%, 5%, and 1% level, respectively.

Panel A: Fama-MacBeth Cross-Sectional Regressions

	All Firms	Low RER Firms			Low RER Industries		
		All	Tradable	Non-Union	All	Tradable	Non-Union
β_m^{local}	−5.58*	−8.39*	−9.83**	−14.73**	−8.04**	−8.93**	−11.78**
	(3.07)	(4.47)	(4.50)	(6.82)	(3.93)	(3.99)	(5.15)
Log *BM*	4.93***	5.95***	5.99***	6.08***	5.47***	5.42***	5.87***
	(0.81)	(0.93)	(0.94)	(1.02)	(0.99)	(0.99)	(1.04)
Log *Size*	−1.11	−1.15	−1.23	−1.07	−1.20*	−1.25*	−1.15
	(0.70)	(0.75)	(0.75)	(0.78)	(0.72)	(0.72)	(0.75)
Leverage	−2.65	−5.11	−5.14	−5.96*	−3.56	−3.54	−4.13
	(2.80)	(3.18)	(3.21)	(3.44)	(2.77)	(2.80)	(2.93)
Profitability	9.07***	10.21***	10.28***	10.24***	12.46***	12.75***	12.83***
	(2.49)	(2.39)	(2.43)	(2.51)	(2.17)	(2.18)	(2.30)
Investment	−11.63*	−8.33	−9.38	−10.97	−8.15	−8.31	−8.21
	(6.23)	(7.99)	(7.98)	(9.89)	(7.75)	(7.82)	(9.41)
Ind. Dummies	X	X	X	X	X	X	X
Observations	1138028	484464	470862	358426	658523	646084	526201
R^2	0.07	0.10	0.09	0.08	0.07	0.07	0.06

Panel B: Panel Regressions with Double-Clustered Standard Errors

	All Firms	Low RER Firms			Low RER Industries		
		All	Tradable	Non-Union	All	Tradable	Non-Union
β_m^{local}	−5.19*	−10.38***	−11.91***	−13.51***	−8.06**	−8.91**	−9.78**
	(2.81)	(3.64)	(3.67)	(5.09)	(3.54)	(3.60)	(4.25)
Log *BM*	5.92***	6.88***	6.97***	6.96***	6.84***	6.82***	7.06***
	(0.93)	(0.98)	(0.98)	(1.21)	(1.22)	(1.21)	(1.40)
Log *Size*	−1.22	−1.34*	−1.41*	−1.39	−1.30	−1.35*	−1.38
	(0.77)	(0.80)	(0.80)	(0.87)	(0.81)	(0.81)	(0.90)
Leverage	−1.85	−3.93	−4.06	−4.97	−2.30	−2.26	−3.33
	(2.89)	(3.08)	(3.13)	(3.15)	(2.74)	(2.76)	(2.82)
Profitability	9.76***	10.21***	10.20***	10.85***	15.27***	15.56***	15.68***
	(2.86)	(2.51)	(2.50)	(2.82)	(2.60)	(2.59)	(2.85)
Investment	−9.73	−4.81	−5.88	−7.20	−10.21	−9.77	−10.42
	(5.94)	(7.81)	(7.89)	(9.09)	(7.50)	(7.60)	(8.86)
Ind.×Time Demeaned	X	X	X	X	X	X	X
Observations	1138028	484464	470862	358426	658523	646084	526201
R^2	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Table IA.VI
Panel Regression of Local Industry Portfolios

The table reports the relationship between future returns of portfolios of firms located in an MSA and local beta, β_m^{local}. We form equal-weighted industry-MSA portfolios, and run panel regressions with industry-month fixed effects. The calculation of β_m^{local} is described in Table II. The sample period is 1986 to 2011. Standard errors are clustered by industries and are presented in parentheses. *, **, and ***represent significance at the 10%, 5%, and 1% level, respectively.

	All Firms	Low RER Firms			Low RER Industries		
		All	Tradable	Non-Union	All	Tradable	Non-Union
β_m^{local}	-6.16^{**}	-11.94^{**}	-13.71^{***}	-14.32^{***}	-8.90^{*}	-9.63^{**}	-11.66^{**}
	(3.08)	(4.63)	(4.61)	(4.13)	(4.59)	(4.65)	(4.97)
Ind.×Time FE	X	X	X	X	X	X	X
Observations	423765	214995	204527	140179	226105	218124	160625
R^2	0.22	0.23	0.23	0.22	0.22	0.22	0.21