Internet Appendix to: "Local Risk, Local Factors, and Asset Prices"

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Abstract

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 data and empirical robustness checks. We supplement the theoretical analysis with the derivation of the first order conditions and details of our numerical solution method.

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A Extended Version of Data and Measurement

This section extends Section 2 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 industries. Specifically,

$$\beta_{m,t}^{local} = \sum_i w_{i,m,t} \beta_{i,t}^{ind} \tag{A.1}$$

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 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. Each MSA consists of one or more counties that contain the core urban area, as well as adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core.[1] There are 373 unique MSAs in our sample.

To calculate the weight of industries in each MSA, we collect industry employment data at the MSA level from the County Business Patterns (CBP) dataset 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.[2] The industry classification is based on Standard Industrial Classification (SIC) codes until 1997 and North American Industry

[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 terms interchangeably. For more information, see http://www.census.gov/population/metro/.

[2] 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.

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.[3] We compute industry share $w_{i,m,t}$ 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.

To calculate industry betas, we obtain annual data on the industry value added, as a measure of industry output, from the Bureau of Economic Analysis (BEA). 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 reports the industries with the 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. Replacing industry employment weights, $w_{i,m,t}$, and industry betas, $\beta_{i,t}^{ind}$, in equation A.1, we obtain MSA betas over 1986-2011.

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

[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.

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. We find that MSAs in the first quintile of the local beta distribution have lower contribution to aggregate metropolitan GDP (6.2%), while the MSAs from the remaining quintiles all make sizable contributions: 22.7%, 16.5%, 32.3%, 22.4% for quintiles 2 to 5, respectively.

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 levels are normalized to 1 in 2001. The real GDP data for the MSAs are from the BEA, the GDP by metropolitan area tables, available since 2001.[4] The bottom panel plots annual GDP growth for the same areas. The figures show that high beta areas experienced steady growth during the expansion years until 2007, but experienced a bigger reduction in both 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 output over the same time period. These findings support the validity of our local betas, constructed from local industry shares and industry betas, to capture the economic risk of local areas.

To examine the time series dynamics of local beta, Table IA.1 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 IA.1 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

[4] To the best of our knowledge, there is 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 A.1.

still a significant spread between the betas of the lowest and highest beta areas. Figure 4 plots the histogram of MSA betas as of 2011, last year of observation in our sample. Most MSA betas are between 0.8 and 1.2, and betas are positively skewed.

We measure local factor prices using data from several different sources. We obtain wage data at MSA by industry level 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.[5] We use both broad occupation definitions with 22 major occupation groups and detailed occupation definitions with 854 detailed occupations.[6]

We perform a robustness check for our wage analysis by looking at industries and occupations with high and low union coverage separately. We obtain data on the unionization rate for industries and occupations 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.

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). HPI data are available at quarterly frequency starting in 1975. Commercial real estate returns are the total returns (income + appreciation) for all commercial

[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.

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 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 with its headquarter location from Compustat, and supplement it with headquarter location change information from Compact Disclosure, compiled by Engelberg, Ozoguz, and Wang (2010).[8] 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. They provide hand-collected evidence supporting this assumption.[9] Therefore, they conclude that headquarter location is a reasonable proxy for firm location.

To further assess the validity of this identification, we link our Compustat-CRSP sample to ReferenceUSA U.S. Businesses Database and collect employment data for all headquarter, branch, and subsidiary locations of firms in our sample.[10] This allows us to create an employment map for each of roughly 2000 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 headquarter MSA. For the median firm in our sample headquarter location accounts for 72% of total employment. While headquarter MSA accounts for the majority of firms' employment for more than 60% of the firms, there is significant heterogeneity among firms of different size (market capitaliza-

[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 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.

[9] 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.

[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.

tion). Appendix Table A2 reports the percentage of firms that have at least 50%, 75%, 90%, or 100% of their employment in their headquarter MSA for all firms, and for firms sorted based on size. Not surprisingly, we find that headquarter 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 headquarter MSA, and about 55% of these firms have virtually all their employment in the same MSA. For the firms in the biggest size quintile, those statistics are roughly 50% and 10%. 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 two subsamples of firms that are geographically focused. The first subsample is the sample of smaller firms, for which headquarter location accounts for a large fraction of employment. The second subsample is based on a measure constructed from state name counts from the 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).

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.

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).

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. Appendix Table A1 summarizes all datasets used in the paper.

B Additional Empirical Analysis

B.1 Local Factor Prices with Alternative Approach

Our panel regression results in Table 3 and 4 of the paper show that 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}:

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

The second stage is 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.2 reports the results of the second-stage regressions.[12] Columns 1-3 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 4-6 report similar results for house prices, commercial real estate prices, and office rents, though results are only statistically significant for the former two.[13]

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

[13] The sparsity of commercial real estate and rent data in earlier years present difficulties in running the first-stage regressions. To achieve some uniformity in sample periods we exclude years with very few observations and start the sample in 2001.

B.2 Robustness Checks for Firm Level Results

We check the robustness of our main results to alternative measures of local beta, expanded sample period, 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 that area, weighted by the employment share of industries. Table IA.3 replicates our main tests with two additional local beta measures. The first measure is constructed as a weighted average of the TFP (total factor productivity) betas of the industries operating in that MSA. TFP growth is the source of exogenous variation in industry output, therefore, it is a natural proxy for industry shocks. TFP growth for industries is computed as a 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 the total capital input (measured from the current-cost net stock of private fixed assets, from BEA) of each industry. α_L, labor share, is computed as the share of compensation of employees in the value added of the industry, where α_K, capital share, 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 coefficients from the regressions of real GDP growth of each MSA on real (aggregate) GDP growth (β_m^{Output}). MSA level GDP data is available annually from 2001-2011. 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.

Panel A of Table IA.3 presents the results to pooled time series / cross sectional regressions for wages and real estate prices, given in equations 12 and 13, and Panel B presents the results to firm return regressions given in equation 15, using alternative MSA beta measures. In both panels, results presented in columns 1-4 are based on β_m^{TFP}, while columns 5-8 use β_m^{Output}.

Due to data availability, the sample period for regressions using β_m^{Output} is limited to 2001-2011. Consistent with our benchmark results, we find that the coefficients for $Shock \times \beta_m^{alter}$ in Panel A are positive and significant for 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 confirm that the coefficients for β_m^{alter} in Panel B are uniformly negative and significant, implying that firms in higher beta areas (measured with alternative MSA betas) have lower returns after controlling for firms' industry. Therefore we conclude that our main empirical results are not particularly sensitive to how MSA betas are calculated.

Our baseline firm level return regressions cover 1986-2011 period, which is dictated by the availability of employment data to compute MSA betas. Except for the great recession of 2008-2009, 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, going back to early 1970s. This may be a source for concern in whether the 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 that.[14] Table IA.4 presents our results using this longer sample period. We find that while the estimated regression coefficients for β_m^{local} are slightly smaller in the longer sample period, the statistical significance of the results remain unchanged.

In Table IA.5, 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 average 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, Table IA.6 tests the relationship between MSA beta and future returns of firms located in that area by aggregating firms into MSA-industry portfolios. We run panel regressions of future portfolio returns on β_m^{local} with industry-month fixed effects. The main advantage of this test to firm-level panel regressions is ruling out any concerns related to outlier firms in

[14] MSA betas change slowly over time, as seen in Table IA.1. So, while they are imperfect, 1986 betas would provide a reasonable proxy to real-time MSA betas in this time period.

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 the coefficient for β_m^{local} to be very similar to our earlier results from Tables 6 and 7, confirming the negative and significant relationship between MSA beta and firm returns.

C Additional Information for the Full Model

C.1 Pricing Equations

Here, we provide supplementary information about the pricing equations for both land and equipment, following the setup of firms in Section 4.1 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:

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

$$1 = \int\int M_{t,t+1} R^K_{i,t+1} p_{z_i}(z_{i,t+1}|z_{it}) p_a(a_{t+1}|a_t) d_{z_i} d_a \tag{C.2}$$

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

$$R^S_{i,t+1} = \frac{F_{S_{i,t+1}} + q^s_{i,t+1} + \frac{1}{2}\eta_s \left(\frac{S_{i,t+1} - S_{it}}{S_{it}}\right)^2}{q^s_{it}} \tag{C.3}$$

$$R^K_{i,t+1} = \frac{F_{K_{i,t+1}} + (1-\delta) q^k_{i,t+1} + \frac{1}{2}\eta_k \left(\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2 - \delta^2\right)}{q^k_{it}} \tag{C.4}$$

and where

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

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

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

$$q_{it}^s = P_t + \eta_s \left(\frac{S_{i,t+1} - S_{it}}{S_{it}} \right) \quad \text{(C.5)}$$

$$q_{it}^k = 1 + \eta_k \left(\frac{I_{it}}{K_{it}} - \delta \right). \quad \text{(C.6)}$$

The pricing equations (equations C.1-C.2) 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 C.3 and C.4, 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.

C.2 Model Solution

Here, we supplement Section 4.4 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 of local firms $\overline{K}_{m,t} = \sum_j \int K_{ijm,t} di$.[15] Since $\overline{K}_{m,t}$ is determined endogenously and requires aggregation of local firms' capital holdings, we also guess a parameterized functional form for $\overline{K}_{m,t}$.

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

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 input for the firms' optimization problem (Equation C.1 and C.2). 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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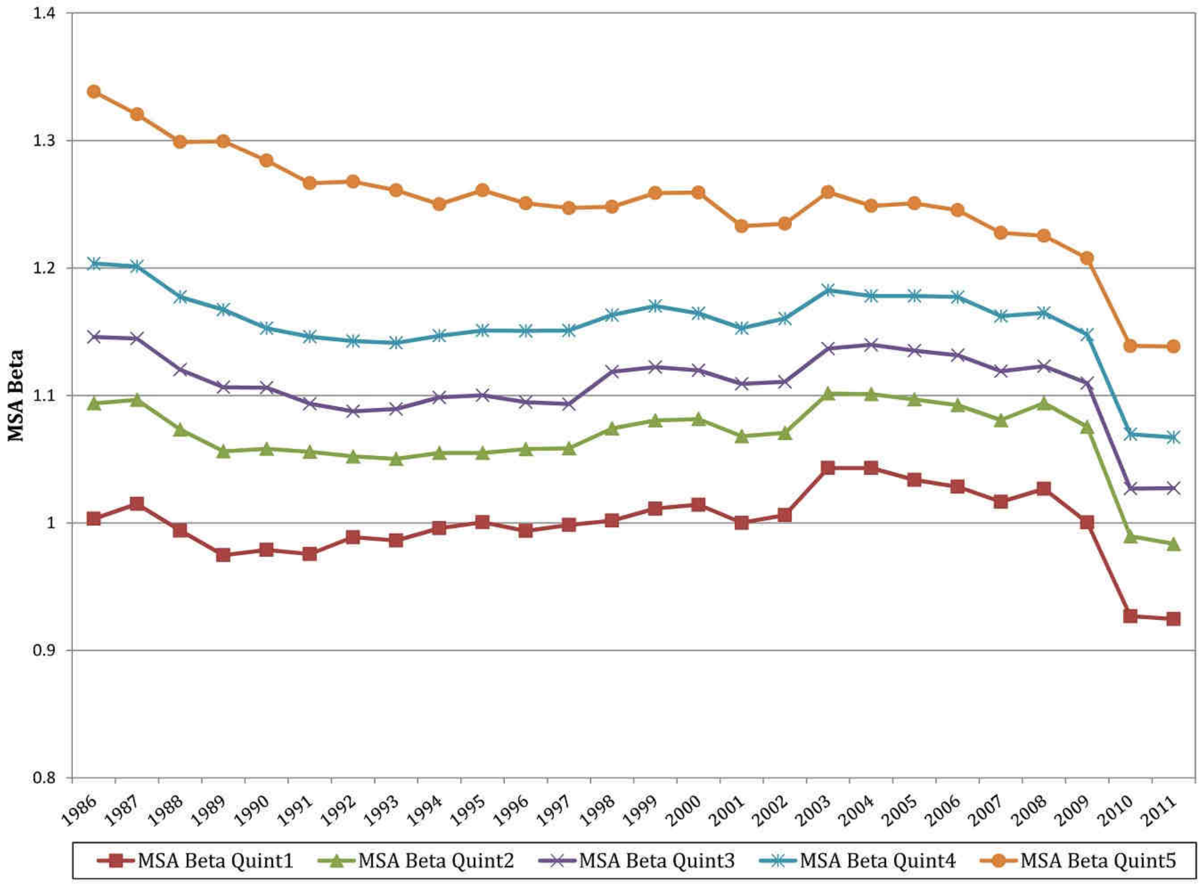

Figure IA.1. Time Series of MSA Betas. The figure illustrates the median local beta for the MSAs sorted into five beta quintiles over the 1986-2011 period. Portfolios are rebalanced every year.

Table IA.1
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 in consecutive years. Local betas, β_m^{local} are calculated as the average of the industry betas operating in that area, weighted by the employment share of 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.2
Factor Price Sensitivity and Local Beta

The table reports the 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). Calculation of β_m^{local} is described in Table 2, annual wage growth for industries is explained in Table 3, and real estate returns are described in Table 4. First-stage regressions

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

for wages are estimated over 1990-2011, housing are estimated over 1986-2011, commercial real estate and rent are estimated using available data from 2001-2011 period. 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 effect, and commercial real estate regression includes property type fixed effect (Office, Industrial, Retail, Apartment, Hotel). Robust standard errors are reported in parantheses. *, **, and *** represent significance level of 10%, 5%, and 1%, 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.3
Alternative Measures of Local Beta

Panel A reports the effect of aggregate shocks on the 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. 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 × 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 5. 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 (%). In Panel A, columns 1-3 and 5-7 have industry × 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 1990-2011 in columns 1-3 of Panel A, 1986-2011 in column 4 of Panel A and columns 1-4 of Panel B, and 2001-2011 in columns 5-8 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 level of 10%, 5%, and 1%, 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 × β_{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.×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.×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.4
Panel Regression of Equity Returns and Local Beta over the Expanded Sample Period

The table reports the relationship between the future returns of the firms located in an MSA and the local beta, β_m^{local} over an expanded sample period, 1970-2011. Calculation of β_m^{local} is described in Table 2. We assign 1986 β_m^{local} to all years prior to that. In Panel A, we regress future monthly return 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 the 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 3-6 use firm level RER, columns 7-10 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 level of 10%, 5%, and 1%, 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.5
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 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 6 and Table 7, 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 2. *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 the 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 3-6 use firm level RER, columns 7-10 use industry level RER, computed as the average RER of firms in each industry. Regression sample period is 1986-2011. Standard errors are clustered by firms and are presented in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, 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.6
Panel Regression of Local Industry Portfolios

The table reports the relationship between future returns of portfolios of firms located in an MSA and the local beta, β_m^{local}. We form equal-weighted industry-MSA portfolios, and run panel regressions with industry $\times$ month fixed effects. Calculation of β_m^{local} is described in Table 2. Regression sample period is 1986-2011. Standard errors are clustered by industries and are presented in parentheses. *, **, and *** represent significance level of 10%, 5%, and 1%, 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