Municipal Risk and the Cross-Section of Housing Returns

Anthony W. Orlando
California State Polytechnic University, Pomona

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Abstract

In this paper, I test whether standard asset pricing models explain the cross-sectional variation in housing returns across municipalities within a large urban county. I construct diversified housing portfolios at the municipal level, isolating risk factors within each city's borders. I calculate time-series betas between these portfolios and a variety of market portfolios, including equity markets, housing markets, and regional markets. I conduct a cross-sectional analysis to compute risk premia for these betas, as well as other potential state variables that economic theory suggests: income, momentum, regulation, size, and value. I find the most significant results for momentum and value. From these results, I build a new factor model that illustrates the unique risks faced by investors in the housing market.

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1 Introduction

Why do investors earn different rates of return on housing assets in different geographies? To date, the finance literature has made little progress in answering this question, despite a long literature explaining the cross-sectional variation in return on equities and bonds. This paper brings rich new datasets to bear on this question—and in so doing, it proposes a new multifactor model to quantify and understand the risks faced by investors trying to allocate the housing portion of their portfolio within a metropolitan area.

In this paper, I construct a multifactor model building on the classic insight of Ross (1976). First, I construct diversified housing portfolios at the municipal level, isolating risk factors within each city's borders. Second, I calculate time-series betas between these portfolios and a variety of market portfolios, including equity markets, housing markets, and regional markets. Third, I conduct a cross-sectional analysis to compute risk premia for these betas using the standard Fama and MacBeth (1973) methodology. I also compute risk premia for other potential state variables that economic theory suggests: income, momentum, regulation, size, and value. Finally, I combine the most significant of these factors into a parisimonious model to explain the cross-section of housing returns at both annual and monthly frequencies.

To my knowledge, Case, Cotter, and Gabriel (2011) is the only paper to apply a similar model to the housing market, but their unit of analysis is the metropolitan area and they only use properties with repeated sales. They find an average beta of 0.8 with the national housing market, but they do not find a significant beta with equity market returns. They also test multifactor models that mimic the classic asset pricing factors found in the literature to be significant in equity markets. They do not find that the "small-minus-big" and momentum factors are large or significant in most metropolitan areas. Finally, they measure idiosyncratic risk as the standard deviation of squared residuals, given that housing portfolios tend to be less diversified than equity portfolios, and they find significance in less than one-fifth of the markets. Overall, their multifactor model explains approximately 30% of the cross-sectional variation of returns across metropolitan areas.

Is the metropolitan area the most informative level of variation? Given the high transaction costs and information problems associated with moving across the country, it seems unlikely that the choice of metropolitan area is a first-order consideration for most homeowners. Instead, most investors are more likely to choose their metropolitan area based on path dependence (a.k.a. "home bias") or labor market choices, making the municipality or neighborhood more important for their housing optimization function. As a result, my first innovation is to replicate Case, Cotter, and Gabriel (2011) at the municipality level using a rich dataset of median home values per square foot from Zillow from 1996 to 2016.

Significant heterogeneity will remain after controlling for the size and momentum factors, however, largely due to different institutional environments, which a large literature has shown to matter for economic growth (North 1990, Acemoglu, Johnson, and Robinson 2002). At the municipality level where housing investments are made, the institutions that matter most are land-use regulations. My second innovation, therefore, is to estimate risk premia for land-use regulations, using the Wharton Residential Land-Use Index, a common survey-based variable. My third innovation is to include income, as well as income and size growth, to capture unique features of urban economics that may influence risks and returns. My final innovation is to include a new measure of value, using Zillow's relatively new price-to-rent ratio, to capture predictability documented by Campbell and Shiller (1988) and Fama and French (1992) in the equity market.

My multifactor model explains approximately 50% of the cross-sectional variation, a significant improvement over Case, Cotter, and Gabriel (2011), as well as the traditional CAPM and Fama-French models.[1] It loads most significantly on income growth, momentum, and value, particularly at the monthly frequency where there are more time periods to ensure statistical power. It does not find significant loadings, however, on income, regulation, or size, calling into question several theoretical predictions from the urban economics literature. These findings are original and important for understanding housing markets, from the perspective of investors as well as policymakers.

The remainder of the paper is organized as follows. Section II presents several asset pricing models that can be applied to the housing market. Section III discusses priced state variables that can be tested with these models. Section IV describes the data and methodology for calculating housing returns and conducting these tests. Section V estimates these methods to tests the models across a large cross-section of municipalities. Section VI reviews my conclusions and suggests directions for future research.

2 Asset Pricing Models for Housing

Assets produce uncertain returns.[2] This is their nature. They transform capital into a distribution of possible payoffs over time. We can formalize this statement with the general equation,

$$p_t = E\big(m_{t+1}, x_{t+1}\big) \ , \tag{1}$$

where p_t is the asset price, x_{t+1} is its future payoff, and m_{t+1} is a stochastic discount factor, also referred to as the pricing kernel, the state-price density, or the marginal rate of substitution. All these names are different ways of saying that m_{t+1} tells us how much the asset's future payoffs are worth to the investor today. It will be useful for us to think of this equation in terms of gross returns, defined as

$$R_{t+1} = \frac{x_{t+1}}{p_t} \ . \tag{2}$$

Combining these equations, we arrive at

$$1 = E(mR) \ , \tag{3}$$

[1]See, for example, an adjusted R^2 of 0.10 and 0.16, respectively, in (Adrian, Etula, and Muir 2014).

[2]"Uncertain" here refers to von Neumann and Morgenstern's (1944) decision-making with respect to a distribution of risky outcomes, not the immeasurability definition in Knight (1921).

which says that one dollar today will generate a return of R tomorrow. In the case of the risk-free rate R^f, the expectation is not a random variable. It is certain because it is risk-free by definition. Therefore, we can separate the two components,

$$1 = E(m)R^f \ , \tag{4}$$

$$\text{or } R^f = 1/E(m) \ . \tag{5}$$

For uncertain returns, we have to use the covariance decomposition[3] to arrive at

$$p = E(m)E(x) + cov(m, x) \ , \tag{6}$$

$$\text{or } p = \frac{E(x)}{R^f} + cov(m, x) \ . \tag{7}$$

The price of the asset is therefore a combination of its risk-neutral price and the covariance of its payoff with the discount factor. We can restate this equation in terms of the returns of asset i ,

$$1 = \frac{E(R^i)}{R^f} + cov(m, R^i) \ , \tag{8}$$

$$\text{or } E(R^i) - R^f = -R^f cov(m, R^i) \ . \tag{9}$$

Thus, the asset's excess return is proportional to its covariance with its discount factor (Cochrane 2005). All major asset pricing theories boil down to this finding: The investor is being paid in excess of the risk-free rate in the amount of a risk premium, which is how exposed the asset's return is to some source of risk (Ross 1976). What makes each theory different is what they identify as the source of risk, i.e. the definition of the discount factor m.

2.1 The Capital Asset Pricing Model (CAPM)

The first asset pricing theory to take this form was the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964), Lintner (1965), and Black (1972). It identified the sole source of priced risk as the risk of the entire market.[4] Thus, it stated excess returns in the familiar equation now taught in business schools around the world:

$$E(R^i) - R^f = \beta_{i,R^M} \left[E(R^M) - R^f \right] \ , \tag{10}$$

[3] $cov(m, x) = E(mx) - E(m)E(x)$

[4] It is important to note that this is not the only source of risk *per se*, only that it is the only type of risk that matters for asset pricing. Sharpe and Lintner built on the finding of Markowitz (1952) that an investor can diversify away *idiosyncratic* risk, the risk of an individual asset apart from its exposure to the market, leaving the market risk as the only *non-diversifiable* risk that affects an investor looking to minimize variance for a particular return.

which is simply a restatement of our earlier, more general excess return equation, with the discount factor being a linear transformation of the market return:[5]

$$m_{t+1} = a + bR^M_{t+1} \ . \tag{11}$$

The most attractive feature of the CAPM, from a research standpoint, is the ease of testing it with the available data. It does not require financial data on each individual stock other than their returns over time, and it does not require any macroeconomic or microeconomic data other than the returns of the market. Douglas (1968), Black, Jensen, and Scholes (1972), Miller and Scholes (1972), Blume and Friend (1973), and Fama and MacBeth (1973) conducted early tests with these returns. They found, consistent with the model, that high-beta portfolios tend to have higher excess returns than low-beta portfolios, but the relationship is weaker than the theory predicts. According to the above equation, portfolios of stocks should fit a "Securities Market Line" with the risk-free rate as the y-intercept and the excess return of the market as the slope. Instead, studies consistently find such a line to be too steep to fit the data. One by one, researchers began finding "anomalies" that did not fit this line.

2.2 The Intertemporal Capital Asset Pricing Model (ICAPM)

As Cochrane (2005) points out, the CAPM is the same as saying that investors only care about wealth, as the market return is nothing more than the return on total wealth in society:

$$E(R^i) - R^f = \beta_{i,R^W}\left[E(R^W) - R^f\right] \ , \tag{12}$$

and therefore, investors price assets based on their payoffs' exposure to the change in wealth. Since the empirical evidence seemed to show otherwise, Ross (1976) proposed an addendum. Yes, investors care about these payoffs, but they also care about what they can *do* with the payoffs. Thus, for example, they may not like a high pay off as much if it comes at the same time that the price of consumption goods goes up, making them less able to spend and enjoy it, or they might like it more when their labor income goes down, allowing them to smooth their consumption in bad states of the world. This expanded version, which came to be known as the "Intertemporal Capital Asset Pricing Model" (ICAPM), was the first theory to predict that the discount factor might include multiple risk factors that covary with the asset's payoffs. Rather than simply trying to achieve the highest return for the lowest variance, known as the "mean efficient" portfolio in CAPM parlance, the optimal portfolio should be "multifactor efficient."

While not as simple as the CAPM, the ICAPM allows for much richer empirical tests. Researchers are no longer restricted to estimating betas on market returns alone. Now, they can estimate betas for as many risk factors as they can think of.[6] The most influential of these new

[5] See Cochrane (2005) for a full derivation.

[6] Of course, this can be a dangerous license. Parsimony is still a prized feature of any clean, elegant model.

"multifactor models" has been the three-factor model proposed by Fama and French (1973):

$$E(R^i) - R^f = \beta_{i,R^M}\left[E(R^M) - R^f\right] + \beta_{i,s}E(SMB) + \beta_{i,h}E(HML) \ , \tag{13}$$

where SMB is the difference between portfolios of small stocks and big stocks, and HML is the difference between portfolios of high book-to-market stocks and low book-to-market stocks. This model consistently performs better in explaining stock returns. Sometimes, a momentum factor (Jegadeesh and Titman 1993) and a liquidity factor (Pástor and Stambaugh 2003) are added as well.

2.3 The Role of Housing

Housing has not played a large explicit role in the asset pricing literature. Implicitly, the above-mentioned theories assume that it is just another asset, generating payoffs that are discounted in the same way as stocks and bonds, and that it generates a consumption stream of housing services that blend into the investors utility function with other types of consumption.

Putting aside the theoretical implications, this assumption might be reasonable for empirical tests of the models if the researchers actually include housing in this way. The CAPM, for example, does not refer to R^M as the *stock* market return. It is supposed to represent the market for *all* assets. Recall that Cochrane (2005) referred to it as R^W, the return of overall wealth in the economy. Dating back to its origination with Markowitz (1952), the theory shows that investors can only diversify away all idiosyncratic risk and obtain the mean-efficient portfolio if they can trade a basket of all assets. More broadly, the proofs underlying all these models rely on the assumption of complete markets, meaning investors have access to state claims that span the payoff space (Fama and Miller 1972). While this assumption is clearly unrealistic in the absolute, it may serve as a first-order approximation if the model at least includes *most* of the payoff space. Running empirical tests on the stock and bond markets alone fails this test. Housing comprises two-thirds of the average household's portfolio (Goetzmann 1993, Brueckner 1997, Bayer, Ellickson, and Ellickson 2010). It is clearly not negligible.

The reason for this exclusion is obvious and justifiable: Until recently, researchers have not had access to good data on housing returns. Stocks and bonds trade many times a day in a liquid market with low transaction costs. Most homes do not sell for several years at a time, and when they do, it can take months to find a buyer and complete a transaction, typically at a much higher cost as a percentage of both the asset and the portfolios of the two parties. Trying to measure the beta of any one asset requires repeated sales, and studies have shown that these betas are not constant. They vary over time (Cochrane 1999). By the time the first repeat sale occurs, the beta might have changed, and so might the house itself.

In this paper, I overcome these challenges by using a comprehensive housing price index that estimates the value of all houses at a given point in time, as explained below. This index adjusts as the house itself changes, and it standardizes the products across geography and time on a per-square-foot basis. I further address the challenge of testing the CAPM by explicitly incorporating housing into the market portfolio. To my knowledge, this is the first paper to advance the literature in these ways.

3 Priced State Variables in Housing

Now that we can build an asset pricing model for housing, what state variables should we include? A priced state variable should have a significant effect on investors' welfare. It should be costly, if not impossible, for investors to diversify away their exposure to this risk. As a result, they should expect higher returns for holding assets that are more exposed to fluctuations in this state variable.

The most obvious risk factor is the national market. Assuming a closed economy, investors are necessarily exposed to the vagaries of the all-encompassing market portfolio and should demand higher returns from assets that expose them even more.[7] This is the intuition behind the CAPM. The same logic can apply to lower levels of geography if it is costly for investors to diversify away their exposure to regional shocks as well. Theory and empirical evidence suggest that this is the case for metropolitan areas, where households are exposed to nondiversifiable income shocks related to their jobs (Ortalo-Magné and Rady 2006, Bayer, Ellickson, and Ellickson 2010, Ortalo-Magné and Prat 2016). As a result, a full test of the CAPM at the municipality level should include factors representing both national and regional market portfolios.

Previous literature suggests other dimensions of risk that might affect local housing returns. In this section, I discuss five classic predictions from both theory and empirical evidence that can be tested with available data.

3.1 Income

Several urban theories predict that income shocks should be capitalized into housing prices. Higher median incomes should therefore be associated with higher housing prices—and prices should grow faster when incomes grow faster (Ortalo-Magné and Rady 2006, Bayer, Ellickson, and Ellickson 2010, Ortalo-Magné and Prat 2016). These theories have not been tested, however, using local housing data. If income shocks are somewhat diversifiable, they may not be significantly priced into returns after all.

It is even less clear how income levels should be associated with housing price growth—that is, how stocks relate to flows. Historically, there has been convergence in incomes between rich and poor metropolitan areas, consistent with the prediction of standard growth models (Solow 1956). In recent decades, however, this convergence has reversed, with rich regions becoming comparatively richer and poor regions falling behind—and, correspondingly, housing prices have risen faster in richer regions (Ganong and Shoag 2017). This divergence may explain a significant portion of the rise in wealth inequality across the country (Furman 2015). In fact, recent empirical work suggests

[7] Even in a large open economy, it is very costly to diversify away national risk, especially in a financially integrated world where nations' market exhibit significant comovement.

that the rise in housing wealth explains almost all of the rise in the capital-output ratio during this period (Rognlie 2015). The literature is silent, however, on whether this dynamic is occurring within metropolitan areas—and if so, whether it is sufficient to explain the cross-section of returns across municipalities.

3.2 Momentum

Jegadeesh and Titman (1993) famously show that asset returns tend to follow previous trends. Specifically, high performers in previous months tend to outperform the market in future months—and vice versa. Grundy and Martin (2001) confirm that this anomaly holds even after controlling for other risk factors, such as the classic Fama and French (1973) three-factor model. It appears that most of this "momentum" can be explained at the industry level, rather than the individual firm level, and therefore it may be difficult to diversify away. Exploiting a momentum strategy would require high-risk exposure to multiple correlated firms within the same industry (Moskowitz and Grinblatt 1999).

One can imagine the same problem facing real estate investors. Chasing recent "winners" and "losers" in the housing market might require exposure to multiple correlated houses within the same city. Early work by Case and Shiller (1989) showed momentum at the MSA level, but the literature has not investigated this question at the municipality level. Is there enough correlation within municipalities that it represents a risk factor distinct from MSA-level momentum?

3.3 Regulation

Land-use regulations restrict housing supply in a municipality. They reduce construction, and according to the basic laws of supply and demand, they make housing units more expensive. This correlation is strong and demonstrated throughout the literature, typically by comparing metropolitan areas.[8] We have very little evidence on whether this relationship holds between municipalities within a metro area.

We have even less evidence on whether regulation is a state variable that matters for diversified investors. The leading view in the urban economics literature argues that inelasticity of land supply played an important, some say the *most* important, role in the boom-and-bust cycle (Glaeser, Gyourko, and Saiz 2008). This theory has not been tested at the municipal level where regulations are actually adopted, however, nor has it been tested in conjunction with classic risk factors in the asset pricing literature. Theoretically, regulatory risk could go in either direction. Land-use regulations reduce homeowner risk, and therefore could yield lower returns. Alternatively, land-use regulations increase developer risk, and therefore could yield higher returns.[9] Ultimately, we want to know which risk matters more. Who is the marginal investor: the homeowner or the developer?

[8] See, for example, Green, Malpezzi, and Mayo (2005), Quigley and Raphael (2005), Glaeser, Gyourko, and Saks (2005), Schuetz (2009), Saiz (2010), and Gyourko, Mayer, and Sinai (2013).

[9] When developers invest in a municipality, there is uncertainty about how long the regulatory process will take to approve the building—if they approve it at all. They risk losing money in this process if they do not get approval, and they risk holding onto the land so long that they get stuck in a market downturn.

3.4 Size

Size has been the most persistent and studied anomaly is asset pricing. Fama and French (1992) famously show that small stocks earn a much higher return than would be predicted by any extant models. The literature continues to debate the reason for this robust result. It is likely a combination of the informational disadvantage that investors face in assessing small stocks and the illiquidity that makes them riskier if investors are financially constrained (Pástor and Stambaugh 2003). It is easy to see how both of these explanations could apply to small cities as well, raising the question of whether size is a state variable that matters for housing returns.

Urban theory gives another reason to consider size: agglomeration effects. A long literature has demonstrated the ways in which large concentrations of people and firms are advantageous, attracting more people and firms as positive spillovers create a virtuous cycle (Duranton and Puga 2004, Rosenthal and Strange 2004). It is not clear, however, whether this growth affects housing returns—that is, whether it represents a priced risk for which investors demand a commensurate return.

3.5 Value

"Value investing" has been made famous to current generations by Warren Buffett, but its origin dates back to Buffett's mentor, Benjamin Graham, who taught that the surest path to long-term success was selecting firms with high earnings relative to their stock price. Good fundamentals, he reasoned, would eventually be rewarded by the market if the investor was patient enough to wait for the reward, whereas the opposite—a high stock price signaling expectations of future earnings growth—was unlikely to payoff with a higher future price since investors had already bid up the price with their expectations (Graham 1949). Inherent in this explanation are two potentially nondiversifiable risk factors: the illiquidity of waiting for prices to rise and the exposure to a firm whose price signals that the market does not have enough information to expect prices to rise.

Fama and French (1992) gave a similar explanation when they demonstrated that this E/P ratio does indeed correlate strongly with the cross-section of returns. It is also consistent with Campbell and Shiller's (1988) finding that current earnings predict future dividends, the cash flows which prices are supposed to value in expectation. If the same is true of housing—that current rents predict future cash flows and it is risky to bet on those rents to grow faster when prices are lower—then we should expect that "value investing" works in real estate as well. The price-to-rent ratio may therefore serve as a priced state variable to explain the cross-section of housing returns.

4 Data and Empirical Approach

This section presents a standard methodology from the asset pricing literature and applies it to housing at the municipality level. I follow this classic approach to allow clean interpretation and easy comparison with equity and bond applications. In the conclusion, I discuss alternate methodologies that will be used for robustness checks in a future draft.

4.1 Housing Returns: Definition and Construction

Before testing any asset pricing model, the researcher must make two decisions: how to calculate returns of a given asset over time and how to form diversified portfolios from these assets. Until recently, these decisions have seemed nearly insurmountable in the housing market.

The first calculation requires a reliable measure of all housing values in a given geography. Case and Shiller (1989) formed a repeated-sale index based on multiple transactions of the same property. While this approach made the return a true measure of price growth in a given asset over time, it did not control for changes in the asset itself, such as modifications to or depreciation of the house. Even more concerning, it limited the sample size to the unrepresentative subset of properties that transacted multiple times. Other researchers created hedonic indices that expanded the sample to all properties that transacted at least once, controlling for observable building characteristics. The sample still was not representative of all the properties that an investor could purchase; it only gave the value of those that did transact, a decision that clearly involved selection bias (Englund, Quigley, and Redfearn 1999). Moreover, controlling for the observable characteristics alone was probably inferior to actually comparing the same house over time.

The second calculation requires a long enough time period to draw statistically significant conclusions at a given geographic level. While the literature has been able to make statements about metropolitan areas, they rarely drill down to the municipality level where they have lacked sufficient observations. It is only now that we have at least a decade worth of high-quality transaction data to form portfolios at every city within a large urban county such as Los Angeles.

Zillow owns the most comprehensive dataset of housing values in the United States. Not only do they have all publicly recorded transactions over time, but they can combine these transactions with listing values and other non-transaction data that they collect on their website, which is now the predominant site for buyers and sellers in today's housing market.[10]

Zillow uses these data to calculate a median home value index (ZHVI) in five steps: First, they calculate raw median sale prices for all properties, whether they transacted or not, with $r_{i,j}(t)$ representing the raw median price for market segment i in geographic region j at time t.[11] Second, they adjust for any residual systematic error in region j at time t,

$$b_j(t) = \text{Median} \frac{z_j(t-1) - s_j(t)}{s_j(t)} \ , \tag{14}$$

where $s_j(t)$ is a vector of the actual sales prices transacted and $z_j(t-1)$ is Zillow's estimate of those properties' value in the period before they transacted. The adjusted median $u_{i,j}(t)$ will correct for this error in Zillow's estimates by incorporating the new sales data about those properties into the raw median price:

$$u_{i,j}(t) = \frac{r_{i,j}(t)}{1 + b_j(t)} \ . \tag{15}$$

[10]This predominance has become particularly strong since Zillow's merger with its largest competitor, Trulia, in 2015 (Kusisto and Light 2015).

[11]The market segment is the type of building—single family, condo, etc.

Third, they apply a five-term Henderson (1916) moving average filter to reduce noise. Fourth, they adjust for seasonality with a decomposition proposed by Cleveland, Cleveland, McRae, and Terpenning (1990), where the time series is broken down into seasonal, trend, and remainder components:

$$U(t) = S(t) + T(t) + RE(t) \ , \tag{16}$$

and then the seasonal component $S(t)$ is subtracted. Finally, Zillow deletes all time series that have too few observations, too much volatility, or too many outliers, gaps, or jumps to meet their standard of quality control.[12]

The resulting data are available in a variety of forms, from time series of particular building types to different quantiles. I employ the median home value per square foot index, which captures all residential buildings and standardizes prices as a function of size for the best comparability. I download these indices at the municipality level, which indicates the average return across all homes in the city—in other words, as diversified as an investor can be within that city.[13] Since the municipality is my unit of observation, it is fitting for each portfolio to represent a different municipality, just as the asset pricing literature tends to form equity portfolios based on the factors they intend to study.[14]

At a national level, these portfolios will tend to cluster by region. Cities in the Los Angeles metropolitan area will correlate more closely with each other than they will with cities in the Houston metropolitan area. As a result, a national analysis runs the risk of conflating state variables that matter at the regional level with those that matter at the municipality level. Since this paper is focused on municipal risk, I narrow my focus to one major urban county, the lowest level of government within which municipalities operate. At this level, any variation in the cross-section of municipal portfolios must represent differences in the municipalities themselves, not in counties or metropolitan areas or other larger geographies.[15] I focus on Los Angeles County for its size and its variety of different geographies, topographies, and neighborhood characters. It is one of the most ideal laboratories within which to study cross-sectional variation in municipalities.

Within Los Angeles County, Zillow publishes median home value per square foot for over 80 municipalities from 1996 to 2016. These data are available at a monthly frequency. I estimate my asset pricing models at this frequency, and I also aggregate up to the annual frequency by averaging over the twelve monthly observations for each city in a given year.

[12] For more details, see `https://www.zillow.com/research/zhvi-methodology-6032/`.

[13] To download these and other data from Zillow, go to `https://www.zillow.com/research/data/`.

[14] The most commonly used data for equity research comes from Kenneth French's website, `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`. To study the size factor, for example, he has different portfolios sorted on the size of the firms. Correspondingly, I have housing portfolios sorted on the size of the cities.

[15] Landvoigt, Piazzesi, and Schneider (2015) take a similar approach to the housing market(s) of San Diego.

4.2 Empirical Strategy

My empirical strategy proceeds in two stages. First, I conduct a time series analysis to estimate betas on the market portfolio,

$$R^e_{i,t} = c_i + \beta_{i,R^M}\left[E(R^M) - R^f\right] + \epsilon_{i,t} \ , \tag{17}$$

where excess returns are defined as $R^e_{i,t} = E(R^i) - R^f$ for city i at time t. Unlike previous literature, however, I include housing returns in several specifications of the market portfolio. I begin with the traditional equity market portfolio, downloaded from Kenneth French's website, where he defines it as "all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11." For the riskless return r_f, I use French's "one-month Treasury bill rate (from Ibbotson Associates)." I compare this estimate to a housing market portfolio, using the national Case-Shiller Index, as well as the regional Los Angeles index from Case-Shiller. The most direct test of the CAPM, however, comes when I create an original "composite" market portfolio, weighted 70% on the equity return and 30% on the housing return to mimick the ratio of the size of each market overall in the U.S. economy.

Second, I conduct a cross-sectional analysis to test the risk factors predicted by theory. This is the classic approach pioneered by Fama and MacBeth (1973). To test the CAPM, for example, I estimate a cross-sectional regression across municipalities in each time period on the betas derived from my time-series analysis,

$$R^e_{i,t} = \alpha + \lambda_{t,R^M}\beta_{i,R^M} + \xi_i \ , \tag{18}$$

where λ_{R^M} is the risk premium that investors demand for increased exposure to fluctuations in the overall market. I report the average risk premium across all time periods,

$$\hat{\lambda}_{R^M} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_{t,R^M} \ , \tag{19}$$

along with t-statistics computed using the Fama-MacBeth standard errors:

$$\hat{\sigma}^2(\hat{\lambda}) = \frac{\frac{1}{T}\sum_{t=1}^{T}(\hat{\lambda}_t - \hat{\lambda})^2}{T} = \frac{1}{T^2}\Big[\sum_{t=1}^{T}(\hat{\lambda}_t - \hat{\lambda})^2\Big] \ . \tag{20}$$

Similarly, I estimate risk premia on proxies for income, momentum, regulation, size, and value. Because these proxies are not constantly traded or easily mimicked by portfolios, I employ the Fama and French (1992) approach of regressing excess returns in each period on the state variables themselves, rather than estimating betas on portfolios as I have done to test the CAPM. For income, a combination of Census decadal estimates and mid-decade American Community Survey estimates, with linear interpolation to fill in the gaps. For momentum, I use lags of the excess housing returns themselves. For regulation, I use the Wharton Residential Land Use Regulatory Index developed by Gyourko, Saiz, and Summers (2008), which has become the standard measure in the literature.[16] For size, I use annual population estimates from the Los Angeles County website. For value, I use the price-to-rent ratio published by Zillow for each city monthly from 2010 to 2016.[17] Finally, I calculate growth rates in income and size as well, since the literature suggests that they might have an effect on housing returns too.

Finally, I use the results from the first two stages to build the first multifactor model to explain the cross-section of returns across municipalities.

5 Main Empirical Results

5.1 Time-Series Analysis

I begin by estimating equation 17 on the U.S. equity market portfolio. This is the classic test of the CAPM. The annual betas are shown in Table 1, listed from the highest to the lowest. The cities at the top of the list tend to be suburban communities on the fringe of Los Angeles County, where construction activity was excessive during the latest "bubble" period (Orlando and Redfearn 2018). It is not surprising, therefore, that their returns are most sensitive to fluctuations in the national market. At the bottom of the list are several high-income communities, where it is difficult to build. It appears that they are most insulated from national shocks. Overall, the average beta is 0.149, a very low correlation, suggesting that most homes in these cities can help investors diversify their portfolios from year to year, even if they do not act as a direct hedge (which would require a negative beta). From month to month, Table 2 shows that the beta is even lower, 0.027 on average, indicating that monthly housing returns have almost no relation to monthly equity returns. The short-term behavior of these cities is independent of the performance of firms in the equity market.

Unsurprisingly, the cities' median returns are much more sensitive to the national housing market. Table 3 shows an average beta of 1.568, indicating that most cities in Los Angeles County overshoot the national market, exceeding its gains and losses in each direction. This is a more volatile metropolitan area than most, but again, the high-end communities like Beverly Hills and Malibu are the least volatile. The monthly betas in Table 4 are lower. Short-term returns are likely driven less by national trends and more by city-specific differences. Still, there is a high average beta of 0.773, indicating that most cities follow the same general path in most months.

My "composite" portfolio should be the closest to the opportunity set facing investors. Given the size of the stock market relative to the housing market, this portfolio tends to follow equities more closely, resulting in a low average annual beta of 0.289 in Table 5 and a very low average monthly beta of 0.037 in Table 6. Based solely on the CAPM, investors should not expect very high returns in Los Angeles County housing, as these returns do not add much risk exposure to a diversified portfolio.

[16] Orlando and Redfearn (2018) critique this measure on a variety of grounds. The flaws they identify may be one reason why the index fails to correlate with housing returns in this paper's findings.

[17] Unfortunately, this allows very few observations at an annual frequency, which will make it difficult for my analysis to find statistically significant results.

For homeowners who cannot diversify much outside of the county, however, the regional beta matters as well. Tables 7 and 8 indicate that these investors have more reason to demand high returns, with average betas of 0.829 and 0.602, respectively. Again, however, investors in high-end communities like Beverly Hills and Malibu should not be expecting high returns based on their betas, which are less than half of the region's average. If anything, it appears that the suburban communities are the ones who should demand high returns to justify volatile exposure to the markets.

5.2 Cross-Sectional Analysis

Do these betas matter? Do investors treat them as true risk factors and price houses accordingly? I find very little evidence that this behavior is occurring. On the contrary, it appears that high-beta cities are earning lower housing returns—and vice versa.

Tables 9 and 10 present these results by estimating cross-sectional equation 18 for each time period and averaging to obtain a different risk premium for each type of market portfolio. According to Table 9, for instance, investors do not demand a statistically significant risk premium for a city that is more exposed to annual fluctuations in equity, housing, or even regional markets. In fact, the sign is negative, ranging from -0.16 for the national housing market to -0.52 for the regional housing market to -4.50 for the national equity market. The F-statistics are very low, suggesting that the equation does not explain the cross-section of annual returns at all, and the intercept is high and statistically significant, indicating that the betas do not explain a significant portion of the variation in returns. The story is similar for monthly returns, even though the higher number of observations lowers the F-statistic. In fact, the average R^2 is even lower, as month-to-month variation has essentially nothing to do with sensitivity to national or regional shocks.

The conclusion is clear: When the marginal investors choose to allocate the housing portion of their portfolio in Los Angeles County, they are not concerned with national or regional shocks. Other risk factors are paramount. The rest of my cross-sectional analysis illuminates these potential risks.

According to Table 11, none of the annual risk factors are statistically significant. This is not surprising, given the low number of time periods. Given this constraint, I look for the factors that are closest to significance. These are income growth and value. Consistent with the "value investing" philosophy, higher price-to-rent ratios are associated with lower housing returns. Contrary to several recent theories, however, cities with faster income growth actually experience lower housing returns. If anything, lower income growth appears to be the risk factor for which investors demand compensation.

Equally important is what Table 11 does *not* show. It does not show that a city's median income, regulatory stringency, size, or size growth is related to its housing returns. Richer cities are not experiencing higher housing returns, on average, nor are poorer cities converging by this metric. The risk premium for income is zero. More regulated cities are not experiencing higher housing returns, contrary to the Glaeser and Gyourko hypothesis. On the contrary, they are experiencing lower housing returns, though the risk premium is not significant. Bigger cities are not experiencing higher housing returns, nor are faster growing cities. Several important predictions from the urban literature do not find support in these asset pricing tests.

Table 12 confirms these findings with greater significance. Again, income, regulation, size, and size growth do not command risk premia, while income growth and value are now statistically significant, indicating that lower income growth and lower price-to-rent ratios are compensated with higher monthly housing returns.

The most significant risk factor, however, appears to be momentum. Table 13 shows that the preceding year's returns positively predict the current year's returns with high significance. This effect fades beyond one year. For monthly returns, however, Table 14 eight previous periods all positively predict the current year's returns, though it is difficult to assess the strength of the more delayed predictions without an autoregressive model.

These findings are original and interesting, especially as they allow us to build the first multifactor model to begin explaining the cross-section of returns across municipalities within a metropolitan area.

5.3 A New Multifactor Model

At the annual frequency, I test one three-factor model and two two-factor models that include the most significant risk factors from my cross-sectional analysis: value, income growth, and momentum from the preceding year. Table 15 reports the results. The three-factor model does not perform well. It has a low F-statistic, and it only explains 18% of the cross-section in housing returns. The value and momentum factors perform marginally better by themselves, but it is the two-factor model with income growth and momentum that perform the best. They are clearly significant risk factors, though we still cannot explain almost three-quarters of the cross-section of returns. I return to this problem in the conclusion with suggestions for future research.

At the monthly frequency, I include the same three factors, as well as the market beta and three more preceding periods of momentum. The first column of Table 16 reports the results from this four-factor model.[18] The model is clearly successful, explaining half of the cross-sectional variation with a high F-statistic. It is not as parsimonious as it should be, however, with the first period of momentum being the only statistically significant factor on its own. The second column removes the other periods of momentum, making the value factor significant but still not improving the fit of the model. The third model is my preferred specification, focusing only on value and momentum, both of which are highly significant. The F-statistic more than doubles with this improvement. It is clear than the price-to-rent ratio and the previous month's momentum are two significant risk factors, representing state variables that are priced into monthly housing returns at the municipality level.

[18] I treat momentum as one factor, regardless of how many lags are included.

6 Conclusion

For too long, the asset pricing literature has been unable to make robust statements about the housing market due to the lack of high-quality, high-frequency data. This paper shows that those days are over. It tests classic asset pricing models in the context of the housing market in Los Angeles County, with a different portfolio for each municipality, and it shows that there are indeed significant risk factors that explain substantial variation in the cross-section of returns. Specifically, it finds that income growth, momentum, and value all contribute to the difference in returns that investors expect to compensate them for various risks. It creates a new multifactor model that helps us understand the housing market—and it points in an exciting new direction for researchers to apply the theory of Ross (1976).

In future drafts of this paper, I intend to test more factors based on economic theory. Just as Pástor and Stambaugh (2003) test a liquidity factor in the equity market, I can use the number of transactions in each city from public records data provided by DataQuick to measure betas with liquidity in the housing market. Just as Adrian, Etula, and Muir (2014) test a leverage factor in the equity market, I can use the dollar volume of new mortgages, as well as the average loan-to-value ratio, from the HMDA database to measure betas with leverage in the housing market.[19] The multifactor model in this draft, in other words, is just the beginning of an exciting research agenda.

In fact, the housing market offers some advantages that the equity market does not. For example, the spatial distribution of housing assets allows for a regression discontinuity design along city borders, enhancing our ability to draw causal inference from these asset pricing tests. My DataQuick transactions allow me to conduct such inference, as they are geocoded, and the initial results confirm some of the findings in this paper.

For now, this paper takes a first step toward a new understanding of the stochastic discount factor that prices housing assets—and the risk premia that investors are paid in excess of the risk-free rate. It connects classic lessons from Ross (1976) to a market that affects the majority of Americans, possibly even more strongly than the equity market. It suggests that the two markets are similar in several important ways. Momentum and value represent common risk factors, extending the ICAPM across asset classes. It also raises new questions about the way that these asset classes might differ, with implications for the future of the economy and the models we use to understand it.

[19] HMDA is the Home Mortgage Disclosure Act, and it requires financial institutions to publicly disclose mortgage data.

Table 1: Annual Betas on U.S. Equity Market Portfolio

City	Beta	City	Beta
Signal Hill	0.468	Hacienda Heights	0.115
Lancaster	0.459	Rancho Palos Verdes	0.115
Arcadia	0.429	Temple City	0.114
Palmdale	0.423	Pomona	0.114
Littlerock	0.411	Commerce	0.113
Maywood	0.378	South Pasadena	0.111
Valinda	0.377	La Puente	0.111
Lomita	0.370	Alhambra	0.111
La Habra Heights	0.351	El Monte	0.111
Huntington Park	0.339	Willowbrook	0.111
Bell	0.338	West Whittier-Los Nietos	0.111
West Covina	0.330	Covina	0.110
Ladera Heights	0.322	Duarte	0.110
Hawthorne	0.317	Hermosa Beach	0.110
Westmont	0.256	View Park-Windsor Hills	0.110
Cudahy	0.247	Rolling Hills Estates	0.109
Santa Clarita	0.178	San Dimas	0.109
Acton	0.172	Alondra Park	0.108
Lake Hughes	0.162	Pasadena	0.107
Hawaiian Gardens	0.154	Downey	0.106
Agoura Hills	0.152	Pico Rivera	0.106
Lakewood	0.151	La Verne	0.106
La Mirada	0.150	San Marino	0.106
Compton	0.150	Whittier	0.105
Calabasas	0.150	Gardena	0.105
Castaic	0.141	Lawndale	0.105
Palos Verdes Peninsula	0.140	South Gate	0.104
La Crescenta-Montrose	0.139	Bellflower	0.101
Diamond Bar	0.137	Inglewood	0.100
Artesia	0.132	Manhattan Beach	0.099
Walnut	0.132	Santa Monica	0.097
Los Angeles	0.130	Monrovia	0.097
Bell Gardens	0.129	Redondo Beach	0.097
La Canada Flintridge	0.128	Claremont	0.096
San Fernando	0.126	Azusa	0.095
Santa Fe Springs	0.125	Palos Verdes Estates	0.094
Rowland Heights	0.125	South San Jose Hills	0.094
South El Monte	0.125	Montebello	0.093
East La Mirada	0.125	Paramount	0.092
West Athens	0.125	Avocado Heights	0.092
Baldwin Park	0.124	Glendora	0.091
Burbank	0.124	Altadena	0.091
Monterey Park	0.123	Lynwood	0.091
Culver City	0.122	Sierra Madre	0.090
Cerritos	0.121	Rosemead	0.090
East Los Angeles	0.121	Hidden Hills	0.089
Glendale	0.121	San Gabriel	0.088
West Puente Valley	0.120	West Hollywood	0.086
Norwalk	0.119	Florence-Graham	0.085
South Whittier	0.119	Avalon	0.084
West Carson	0.119	Beverly Hills	0.077
Long Beach	0.118	El Segundo	0.076
Topanga	0.118	Rolling Hills	0.037
Carson	0.116	Malibu	0.023
Torrance	0.116	**Average**	**0.149**

Table 2: Monthly Betas on U.S. Equity Market Portfolio

City	Beta	City	Beta
Acton	0.074	San Dimas	0.017
San Fernando	0.051	La Verne	0.017
South Gate	0.041	Avocado Heights	0.016
South San Jose Hills	0.041	Whittier	0.016
La Puente	0.039	Inglewood	0.016
Willowbrook	0.039	View Park-Windsor Hills	0.015
West Athens	0.038	Glendora	0.014
Commerce	0.038	Montebello	0.014
Hawaiian Gardens	0.038	La Canada Flintridge	0.014
Palmdale	0.038	Alondra Park	0.014
East La Mirada	0.037	Altadena	0.013
West Puente Valley	0.034	Culver City	0.012
Santa Clarita	0.032	Pasadena	0.012
Artesia	0.031	Pico Rivera	0.012
West Carson	0.031	Rancho Palos Verdes	0.012
La Mirada	0.029	Calabasas	0.011
Gardena	0.028	Lakewood	0.011
Duarte	0.027	Claremont	0.011
West Covina	0.027	Manhattan Beach	0.011
Azusa	0.026	Walnut	0.011
El Monte	0.025	Malibu	0.011
South Whittier	0.025	Palos Verdes Estates	0.010
East Los Angeles	0.025	Arcadia	0.010
Downey	0.025	Lake Hughes	0.009
Baldwin Park	0.025	Florence-Graham	0.009
South El Monte	0.024	Hermosa Beach	0.009
Bellflower	0.024	Rolling Hills Estates	0.009
Bell Gardens	0.024	South Pasadena	0.009
Monterey Park	0.023	Torrance	0.009
Pomona	0.023	Lancaster	0.009
Beverly Hills	0.023	Santa Monica	0.008
Paramount	0.023	Redondo Beach	0.008
Monrovia	0.023	Sierra Madre	0.007
Castaic	0.022	West Hollywood	0.006
San Marino	0.022	Palos Verdes Peninsula	0.006
Hacienda Heights	0.021	Lomita	0.006
Santa Fe Springs	0.021	Compton	0.005
Los Angeles	0.021	San Gabriel	0.005
Long Beach	0.021	Burbank	0.002
Glendale	0.020	Temple City	0.002
Carson	0.020	Hawthorne	0.001
Lawndale	0.020	La Habra Heights	0.000
El Segundo	0.020	Topanga	-0.001
Covina	0.020	Rolling Hills	-0.002
Hidden Hills	0.020	Littlerock	-0.004
Norwalk	0.019	Avalon	-0.006
Lynwood	0.019	Valinda	-0.007
Rosemead	0.019	Westmont	-0.008
Agoura Hills	0.018	Maywood	-0.010
Cerritos	0.018	Signal Hill	-0.012
Rowland Heights	0.018	Huntington Park	-0.013
Alhambra	0.018	Bell	-0.023
Diamond Bar	0.017	Cudahy	-0.027
West Whittier-Los Nietos	0.017	Ladera Heights	-0.032
La Crescenta-Montrose	0.017	**Average**	**0.027**

Table 3: Annual Betas on U.S. Housing Market Portfolio

City	Beta	City	Beta
San Fernando	2.289	Bell	1.481
Hawaiian Gardens	2.223	Altadena	1.477
Paramount	2.211	Maywood	1.472
Florence-Graham	2.196	Glendora	1.470
Signal Hill	2.165	San Dimas	1.468
Pomona	2.143	Huntington Park	1.465
South San Jose Hills	2.133	Agoura Hills	1.462
Littlerock	2.104	Monrovia	1.458
Lynwood	2.060	Diamond Bar	1.457
Lake Hughes	2.054	Cudahy	1.442
South Gate	2.041	Rowland Heights	1.435
Commerce	2.020	West Covina	1.428
Palmdale	2.015	Lomita	1.426
La Puente	2.013	Monterey Park	1.414
West Puente Valley	2.010	Hawthorne	1.412
Willowbrook	2.007	Pasadena	1.407
East Los Angeles	2.006	Burbank	1.407
West Athens	2.000	La Verne	1.403
Baldwin Park	1.965	Claremont	1.400
Lawndale	1.962	Alhambra	1.391
Norwalk	1.955	Glendale	1.368
Inglewood	1.952	Culver City	1.346
Bell Gardens	1.947	Cerritos	1.334
Pico Rivera	1.928	Acton	1.324
Azusa	1.903	Walnut	1.301
Artesia	1.896	Avalon	1.298
West Carson	1.896	Arcadia	1.287
Lancaster	1.880	Torrance	1.275
West Whittier-Los Nietos	1.859	Santa Monica	1.270
South Whittier	1.846	Calabasas	1.260
Carson	1.840	La Crescenta-Montrose	1.247
Downey	1.831	Compton	1.241
Gardena	1.831	Temple City	1.235
Santa Fe Springs	1.811	Westmont	1.231
South El Monte	1.811	Hermosa Beach	1.221
Bellflower	1.804	Redondo Beach	1.207
Los Angeles	1.798	San Gabriel	1.202
El Monte	1.778	Palos Verdes Peninsula	1.193
Avocado Heights	1.751	Sierra Madre	1.175
Santa Clarita	1.726	El Segundo	1.166
East La Mirada	1.702	La Habra Heights	1.152
Long Beach	1.694	Manhattan Beach	1.134
Duarte	1.690	Rancho Palos Verdes	1.106
Lakewood	1.685	La Canada Flintridge	1.096
Castaic	1.683	Rolling Hills Estates	1.066
La Mirada	1.654	South Pasadena	1.061
View Park-Windsor Hills	1.654	Topanga	1.055
Montebello	1.650	Ladera Heights	1.046
Covina	1.647	Palos Verdes Estates	1.000
Valinda	1.593	San Marino	0.991
Whittier	1.580	Malibu	0.952
Alondra Park	1.563	Beverly Hills	0.931
Rosemead	1.557	Hidden Hills	0.719
West Hollywood	1.520	Rolling Hills	0.614
Hacienda Heights	1.514	**Average**	**1.568**

Table 4: Monthly Betas on U.S. Housing Market Portfolio

City	Beta	City	Beta
San Fernando	1.209	San Dimas	0.772
Paramount	1.142	Burbank	0.770
Hawaiian Gardens	1.142	Agoura Hills	0.769
Lake Hughes	1.127	Monterey Park	0.767
Florence-Graham	1.105	West Hollywood	0.757
Pomona	1.104	Rowland Heights	0.749
South San Jose Hills	1.093	Pasadena	0.747
South Gate	1.066	Alhambra	0.740
Lynwood	1.061	Claremont	0.739
La Puente	1.054	Cerritos	0.738
Commerce	1.053	La Verne	0.736
West Athens	1.049	Glendale	0.730
West Puente Valley	1.033	Culver City	0.701
East Los Angeles	1.025	Temple City	0.698
Baldwin Park	1.020	Walnut	0.692
Norwalk	1.012	Torrance	0.675
Lawndale	1.009	Sierra Madre	0.667
Willowbrook	0.999	La Crescenta-Montrose	0.666
Pico Rivera	0.997	El Segundo	0.665
Azusa	0.990	Calabasas	0.650
Inglewood	0.989	Lancaster	0.647
Bell Gardens	0.987	Hermosa Beach	0.644
Artesia	0.977	Palos Verdes Peninsula	0.644
Gardena	0.969	San Gabriel	0.636
Carson	0.954	Redondo Beach	0.636
West Carson	0.952	Avalon	0.633
South Whittier	0.949	Santa Monica	0.629
Downey	0.945	Littlerock	0.585
Los Angeles	0.933	La Canada Flintridge	0.570
Bellflower	0.932	Manhattan Beach	0.569
West Whittier-Los Nietos	0.927	Palmdale	0.566
South El Monte	0.924	Rancho Palos Verdes	0.553
Santa Clarita	0.923	Rolling Hills Estates	0.551
El Monte	0.911	Huntington Park	0.541
Santa Fe Springs	0.898	Malibu	0.540
Duarte	0.889	Palos Verdes Estates	0.538
Lakewood	0.887	Maywood	0.525
Long Beach	0.883	Bell	0.522
Avocado Heights	0.875	South Pasadena	0.522
East La Mirada	0.872	San Marino	0.516
View Park-Windsor Hills	0.867	Hawthorne	0.510
Ladera Heights	0.862	La Habra Heights	0.500
Castaic	0.857	Westmont	0.471
La Mirada	0.852	Lomita	0.470
Montebello	0.852	Topanga	0.470
Covina	0.845	Beverly Hills	0.470
Alondra Park	0.841	Cudahy	0.462
Signal Hill	0.817	Acton	0.427
Whittier	0.806	Valinda	0.422
Hacienda Heights	0.805	West Covina	0.418
Rosemead	0.795	Compton	0.393
Altadena	0.794	Arcadia	0.360
Diamond Bar	0.785	Rolling Hills	0.329
Monrovia	0.785	Hidden Hills	0.303
Glendora	0.776	**Average**	**0.773**

Table 5: Annual Betas on U.S. "Composite" Market Portfolio

City	Beta	City	Beta
Signal Hill	0.682	Walnut	0.258
Lancaster	0.652	Downey	0.257
Palmdale	0.620	Rowland Heights	0.257
Littlerock	0.611	Inglewood	0.256
Arcadia	0.580	Gardena	0.255
Valinda	0.539	Burbank	0.255
Maywood	0.532	Compton	0.254
Lomita	0.521	Monterey Park	0.253
Bell	0.487	Duarte	0.253
Huntington Park	0.487	Florence-Graham	0.252
La Habra Heights	0.481	Covina	0.251
West Covina	0.474	Lynwood	0.251
Hawthorne	0.459	View Park-Windsor Hills	0.251
Ladera Heights	0.440	Bellflower	0.249
Cudahy	0.379	Glendale	0.248
Westmont	0.376	Hacienda Heights	0.248
Lake Hughes	0.346	Azusa	0.247
Santa Clarita	0.346	Culver City	0.247
Hawaiian Gardens	0.345	Cerritos	0.245
San Fernando	0.313	Alondra Park	0.242
Lakewood	0.307	La Canada Flintridge	0.240
La Mirada	0.304	Whittier	0.239
Artesia	0.295	San Dimas	0.238
Agoura Hills	0.294	Alhambra	0.236
Castaic	0.294	Torrance	0.235
Bell Gardens	0.294	Avocado Heights	0.233
West Athens	0.292	Pasadena	0.231
Baldwin Park	0.29	Temple City	0.230
East Los Angeles	0.288	La Verne	0.229
Pomona	0.288	Montebello	0.228
Los Angeles	0.286	Hermosa Beach	0.224
West Puente Valley	0.286	Topanga	0.224
Acton	0.284	Rancho Palos Verdes	0.223
Norwalk	0.282	Monrovia	0.221
Santa Fe Springs	0.281	Rosemead	0.218
South El Monte	0.281	Claremont	0.216
Calabasas	0.28	Glendora	0.214
West Carson	0.279	South Pasadena	0.214
Commerce	0.278	Altadena	0.214
La Puente	0.275	Rolling Hills Estates	0.212
Willowbrook	0.275	West Hollywood	0.210
Diamond Bar	0.274	Santa Monica	0.209
East La Mirada	0.274	Redondo Beach	0.205
South Whittier	0.274	San Marino	0.204
Carson	0.271	Manhattan Beach	0.203
South Gate	0.267	Avalon	0.194
West Whittier-Los Nietos	0.265	Sierra Madre	0.194
Lawndale	0.264	San Gabriel	0.193
Long Beach	0.264	Palos Verdes Estates	0.188
Pico Rivera	0.263	El Segundo	0.175
La Crescenta-Montrose	0.263	Hidden Hills	0.164
Paramount	0.262	Beverly Hills	0.161
Palos Verdes Peninsula	0.262	Malibu	0.090
El Monte	0.261	Rolling Hills	0.089
South San Jose Hills	0.259	**Average**	**0.289**

Table 6: Monthly Betas on U.S. "Composite" Market Portfolio

City	Beta	City	Beta
Acton	0.123	San Dimas	0.036
San Fernando	0.092	La Verne	0.036
South San Jose Hills	0.077	Whittier	0.036
South Gate	0.076	View Park-Windsor Hills	0.035
Palmdale	0.076	Lancaster	0.035
Hawaiian Gardens	0.073	La Crescenta-Montrose	0.035
La Puente	0.073	Montebello	0.034
West Athens	0.072	Pico Rivera	0.034
Commerce	0.072	Alondra Park	0.033
Willowbrook	0.072	Glendora	0.033
East La Mirada	0.067	Hidden Hills	0.033
West Puente Valley	0.065	Lake Hughes	0.032
Artesia	0.061	Altadena	0.032
Santa Clarita	0.061	Florence-Graham	0.031
West Carson	0.059	Lakewood	0.031
La Mirada	0.056	Pasadena	0.030
Gardena	0.056	La Canada Flintridge	0.029
West Covina	0.054	Culver City	0.029
Duarte	0.054	Claremont	0.028
Azusa	0.053	Arcadia	0.028
East Los Angeles	0.053	Walnut	0.028
Baldwin Park	0.052	Calabasas	0.027
South Whittier	0.051	Rancho Palos Verdes	0.026
Downey	0.051	Manhattan Beach	0.026
El Monte	0.051	Lomita	0.025
Pomona	0.051	Malibu	0.024
Paramount	0.051	Palos Verdes Estates	0.024
Bell Gardens	0.050	Torrance	0.024
South El Monte	0.050	Hermosa Beach	0.024
Bellflower	0.049	West Hollywood	0.022
Castaic	0.046	Redondo Beach	0.022
Monterey Park	0.046	Santa Monica	0.022
Lawndale	0.045	Rolling Hills Estates	0.022
Monrovia	0.045	Compton	0.021
Lynwood	0.045	South Pasadena	0.021
Los Angeles	0.045	Sierra Madre	0.021
Carson	0.045	Palos Verdes Peninsula	0.019
Santa Fe Springs	0.044	Hawthorne	0.019
Norwalk	0.044	San Gabriel	0.018
Hacienda Heights	0.044	La Habra Heights	0.017
Long Beach	0.044	Burbank	0.016
Covina	0.043	Littlerock	0.015
Glendale	0.041	Temple City	0.015
Beverly Hills	0.040	Signal Hill	0.011
West Whittier-Los Nietos	0.040	Topanga	0.006
San Marino	0.040	Westmont	0.005
El Segundo	0.040	Valinda	0.005
Rosemead	0.040	Maywood	0.004
Agoura Hills	0.039	Rolling Hills	0.002
Inglewood	0.039	Avalon	0.002
Cerritos	0.038	Huntington Park	0.000
Rowland Heights	0.038	Bell	-0.016
Diamond Bar	0.038	Ladera Heights	-0.016
Alhambra	0.038	Cudahy	-0.023
Avocado Heights	0.037	**Average**	**0.037**

Table 7: Annual Betas on Los Angeles Housing Market Portfolio

City	Beta	City	Beta
Signal Hill	1.238	View Park-Windsor Hills	0.842
San Fernando	1.196	Huntington Park	0.834
Palmdale	1.147	Whittier	0.827
Littlerock	1.146	Hacienda Heights	0.821
Hawaiian Gardens	1.139	Rosemead	0.816
South San Jose Hills	1.106	Hawthorne	0.804
Pomona	1.101	Cudahy	0.800
Paramount	1.094	Alondra Park	0.800
Florence-Graham	1.082	Agoura Hills	0.798
Lancaster	1.068	Diamond Bar	0.788
La Puente	1.058	Rowland Heights	0.771
Lynwood	1.055	Altadena	0.764
South Gate	1.055	San Dimas	0.763
West Puente Valley	1.043	West Hollywood	0.758
Commerce	1.026	Glendora	0.752
Norwalk	1.022	Monrovia	0.749
West Athens	1.012	Burbank	0.743
East Los Angeles	1.008	Claremont	0.742
Lake Hughes	1.008	La Verne	0.740
Baldwin Park	1.007	Monterey Park	0.739
Bell Gardens	1.001	Alhambra	0.739
Willowbrook	0.997	Cerritos	0.732
Lawndale	0.994	Ladera Heights	0.731
Artesia	0.987	Pasadena	0.727
West Carson	0.987	Acton	0.714
Pico Rivera	0.977	Glendale	0.713
Inglewood	0.977	Walnut	0.708
South Whittier	0.974	Culver City	0.697
Azusa	0.972	Torrance	0.689
West Whittier-Los Nietos	0.957	Avalon	0.687
Downey	0.951	Calabasas	0.686
South El Monte	0.951	Temple City	0.660
Gardena	0.945	La Crescenta-Montrose	0.660
Carson	0.942	Compton	0.639
Santa Fe Springs	0.941	Palos Verdes Peninsula	0.635
Bellflower	0.937	Westmont	0.632
Los Angeles	0.933	Redondo Beach	0.631
El Monte	0.928	San Gabriel	0.630
Santa Clarita	0.912	Santa Monica	0.629
Maywood	0.911	Hermosa Beach	0.629
Valinda	0.907	Sierra Madre	0.602
Lakewood	0.895	El Segundo	0.602
Arcadia	0.895	Rancho Palos Verdes	0.596
Avocado Heights	0.894	South Pasadena	0.568
East La Mirada	0.893	Topanga	0.568
Long Beach	0.892	Rolling Hills Estates	0.565
Castaic	0.877	La Canada Flintridge	0.564
La Mirada	0.876	Manhattan Beach	0.561
Covina	0.869	Palos Verdes Estates	0.516
Bell	0.866	San Marino	0.507
Duarte	0.859	Malibu	0.476
Montebello	0.859	Beverly Hills	0.443
West Covina	0.847	Hidden Hills	0.374
Lomita	0.844	Rolling Hills	0.323
La Habra Heights	0.843	**Average**	**0.829**

Table 8: Monthly Betas on Los Angeles Housing Market Portfolio

City	Beta	City	Beta
Signal Hill	0.919	Rosemead	0.600
San Fernando	0.900	Whittier	0.600
Ladera Heights	0.829	Lomita	0.588
Hawaiian Gardens	0.816	La Habra Heights	0.587
Paramount	0.788	Bell	0.581
Pomona	0.783	Burbank	0.580
Lancaster	0.771	Hawthorne	0.578
South Gate	0.764	Valinda	0.572
West Puente Valley	0.762	Rowland Heights	0.571
South San Jose Hills	0.760	Alhambra	0.571
Lynwood	0.759	San Dimas	0.564
Littlerock	0.754	Monterey Park	0.563
La Puente	0.750	Cerritos	0.560
Norwalk	0.747	Altadena	0.560
West Athens	0.742	Pasadena	0.557
Florence-Graham	0.741	Huntington Park	0.554
Commerce	0.728	Claremont	0.553
East Los Angeles	0.727	West Hollywood	0.553
Palmdale	0.723	Glendora	0.551
Bell Gardens	0.722	Avalon	0.545
Lake Hughes	0.722	La Verne	0.542
Baldwin Park	0.721	Culver City	0.539
Artesia	0.717	Walnut	0.539
Lawndale	0.713	West Covina	0.535
South Whittier	0.709	Glendale	0.534
Pico Rivera	0.708	Monrovia	0.531
Azusa	0.700	Arcadia	0.529
West Carson	0.696	Temple City	0.526
Downey	0.689	Acton	0.521
Gardena	0.686	Cudahy	0.519
Santa Clarita	0.686	Calabasas	0.516
South El Monte	0.685	Torrance	0.514
Carson	0.683	La Crescenta-Montrose	0.495
Los Angeles	0.683	Palos Verdes Peninsula	0.488
Bellflower	0.682	Redondo Beach	0.481
West Whittier-Los Nietos	0.679	El Segundo	0.480
Inglewood	0.679	Hermosa Beach	0.479
Willowbrook	0.675	Sierra Madre	0.470
El Monte	0.674	Santa Monica	0.461
Long Beach	0.664	Westmont	0.456
Santa Fe Springs	0.663	San Gabriel	0.454
Lakewood	0.663	Rancho Palos Verdes	0.445
East La Mirada	0.653	Rolling Hills Estates	0.430
La Mirada	0.648	La Canada Flintridge	0.424
Castaic	0.633	Compton	0.420
Montebello	0.630	Manhattan Beach	0.393
Duarte	0.630	Topanga	0.392
Avocado Heights	0.628	South Pasadena	0.390
Covina	0.626	Palos Verdes Estates	0.387
Agoura Hills	0.625	Malibu	0.374
Hacienda Heights	0.619	San Marino	0.372
Alondra Park	0.613	Beverly Hills	0.310
View Park-Windsor Hills	0.605	Hidden Hills	0.240
Maywood	0.602	Rolling Hills	0.227
Diamond Bar	0.602	**Average**	**0.602**

Table 9: Cross-Sectional Analysis of Annual CAPM Betas

	U.S. Equity	U.S. Housing	U.S. "Composite"	L.A. Housing
Intercept	5.03**	4.79**	5.60***	4.93**
t-FM	(3.06)	(3.39)	(4.88)	(3.52)
Risk Premium	−4.50	−0.16	−4.36	−0.52
t-FM	(0.55)	(0.09)	(0.43)	(0.15)
avg. R^2	0.06	0.33	0.18	0.33
F-stat	0.30	0.01	0.18	0.02
p-value	59.1%	92.8%	67.5%	88.4%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Cross-Sectional Analysis of Monthly CAPM Betas

	U.S. Equity	U.S. Housing	U.S. "Composite"	L.A. Housing
Intercept	0.36***	0.45***	0.38***	0.45***
t-FM	(7.43)	(8.64)	(8.47)	(8.10)
Risk Premium	−2.39	−0.16	−1.59	−0.22
t-FM	(1.83)	(1.70)	(1.77)	(1.52)
avg. R^2	0.08	0.14	0.09	0.14
F-stat	3.36	2.89	3.13	2.32
p-value	6.8%	9.1%	9.3%	12.9%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Cross-Sectional Analysis of Annual Risk Factors

	Income	Income Growth	Regulation	Size	Size Growth	Value
Intercept	5.50	5.59	4.61	5.14	5.40	7.33
t-FM	(1.54)	(2.09)	(2.02)	(1.97)	(1.92)	(1.76)
Risk Premium	0.00	−0.24	−0.10	0.00	−0.05	−0.12
t-FM	(0.66)	(1.43)	(0.72)	(0.84)	(0.47)	(1.02)
avg. R^2	0.23	0.02	0.02	0.01	0.03	0.12
F-stat	0.43	2.04	0.52	0.70	0.01	1.05
p-value	52.1%	17.4%	48.1%	41.4%	91.4%	34.6%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Cross-Sectional Analysis of Monthly Risk Factors

	Income	Income Growth	Regulation	Size	Size Growth	Value
Intercept	0.39***	0.41***	0.33***	0.37***	0.40***	0.83***
t-FM	(3.99)	(5.82)	(5.35)	(5.23)	(5.23)	(5.69)
Risk Premium	0.00	−0.02**	−0.01	0.00	−0.03	−0.02**
t-FM	(1.46)	(3.60)	(1.16)	(1.38)	(1.56)	(2.63)
avg. R^2	0.11	0.02	0.02	0.01	0.02	0.05
F-stat	2.12	12.97	1.35	1.89	2.43	6.94
p-value	14.7%	2.4%	24.7%	17.0%	12.1%	1.0%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Cross-Sectional Analysis of Annual Momentum Factors

	$t-1$	$t-2$
Intercept	2.22	2.33
t-FM	(1.38)	(0.97)
Risk Premium	0.48***	0.10
t-FM	(5.60)	(0.85)
avg. R^2	0.26	0.12
F-stat	31.41	0.72
p-value	0.0%	41.0%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Cross-Sectional Analysis of Monthly Momentum Factors

	$t-1$	$t-2$	$t-3$	$t-4$	$t-5$	$t-6$	$t-7$	$t-8$	$t-9$
Intercept	0.16***	0.30***	0.39***	0.40***	0.38***	0.35***	0.34***	0.38***	0.41***
t-FM	(7.34)	(7.30)	(7.30)	(7.04)	(6.43)	(5.59)	(4.83)	(4.33)	(3.45)
Risk Premium	0.59***	0.33***	0.17***	0.16***	0.15***	0.15***	0.15***	0.13***	0.10*
t-FM	(38.03)	(16.90)	(7.27)	(6.60)	(5.82)	(5.16)	(4.90)	(3.98)	(2.45)
avg. R^2	0.39	0.17	0.10	0.09	0.08	0.08	0.07	0.05	0.04
F-stat	1446.51	285.72	52.83	43.57	33.92	26.61	24.00	15.83	6.00
p-value	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.9%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Multifactor Models for Annual Housing Returns

	(1)	(2)	(3)
Intercept	4.05	4.02	2.58
t-FM	(1.01)	(0.83)	(1.63)
Value	−0.01	−0.02	
t-FM	(0.13)	(0.90)	
Income Growth	−0.02		−0.19
t-FM	(0.13)		(1.93)
Momentum(1)	0.16	0.16	0.45***
t-FM	(0.13)	(0.11)	(4.83)
avg. R^2	0.18	0.19	0.27
F-stat	0.88	1.37	11.72
p-value	51.1%	32.3%	0.0%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 16: Multifactor Models for Monthly Housing Returns

	(1)	(2)	(3)
Intercept	0.25^{*}	0.35^{***}	0.45^{***}
t-FM	(2.45)	(4.25)	(4.96)
Market Beta	0.40	-0.36	
t-FM	(0.60)	(0.73)	
Income Growth	0.00	0.00	
t-FM	(0.85)	(0.07)	
Value	0.00	-0.01^{*}	-0.01^{**}
t-FM	(0.78)	(2.20)	(2.82)
Momentum(1)	0.67^{***}	0.56^{***}	0.69^{***}
t-FM	(24.48)	(19.80)	(21.20)
Momentum(2)	-0.18		-0.20
t-FM	(5.04)		(5.92)
Momentum(3)	0.00		
t-FM	(0.13)		
Momentum(4)	0.06^{*}		
t-FM	(2.30)		
avg. R^2	0.48	0.40	0.46
F-stat	107.51	102.76	261.52
p-value	0.0%	0.0%	0.0%

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Municipalities and social housing managing risk and maximising development. Overview â€“ whatâ€™s IT all about? The provision of social rental housing requires a strong co-operative arrangement between the Municipality and SHI(s) operating in a particular municipal area.Â One critical programme is facilitating and ensuring the delivery of housing to previously disadvantaged within the context of integrated communities. The Municipality must therefore assess needs and demand; help in securing the resources to respond to these; and structure partnership arrangements with key stakeholders to ensure delivery. Perceptions of risk and the institutional arrangements that have developed in response closely mirror philosophical advances in soci-etyâ€™s stance on the sanctity of the persons of individuals. Risk is com-monly understood to exist and require management at the level of the individual rather than the group. The market economy is the ultimate expression of this freedom to transact, preservation of which requires the existence of regulations such as Solvency II to protect individualsâ€™ rights. We investigate the cross-sectional determinants of corporate bond returns and find that downside risk is the strongest predictor of future bond returns. We also introduce common risk factors based on the prevalent risk characteristics of corporate bonds -- downside risk, credit risk, and liquidity risk -- and find that these novel bond factors have economically and statistically significant risk premia that cannot be explained by long-established stock and bond market factors. We show that the newly proposed risk factors outperform all other models considered in the literature in explaining th in the cross-section of hedge fund returns. In the process, we bring an important innovation to the. hedge fund literature by constructing model-free and forward-looking measures of higher-moment.Â Section 3 provides evidence on sensitivity of hedge fundsâ€™ returns to higher moment risks, and estimates the prices of higher moments of equity market returns. Section 4 conducts various specication analyses. Section 5 investigates the dispersion in alphas of mutual funds sorted on their exposures to higher-moment equity risks. Section 6 concludes. 2 Fund Samples and Risk Factors.