Abstract: We combine the standard Campbell and Shiller (1988) present-value model with the classical user cost of housing model to decompose the rental yield into three components: expected future rent growth, cost of capital and risk premium of owning relative to renting. We then apply a quarterly dataset of four major cities (Beijing, Shanghai, Guangzhou and Shenzhen) to explore the question of what forces have driven the movement of China’s housing market. Specifically, using the variance decomposition approach to examine quantitatively how much the variation in rental yield comes from the above-mentioned three components. Our results show that cost of capital is playing a vital role in all the four major cities, while the future rent growth is not a driving force as significant as the cost of capital in the fluctuation of the rental yield. Moreover, we find that another factor -- the risk of owning relative to renting a house -- is accounting for a large part of housing market movement in China. It is also worth noting that the risk of renting relative to owning a house seems to be rising rapidly in China over the recent years.

Key Words: Rental Yield; Dynamic Gordon Growth model; User Cost of Housing Model; Variance Decomposition; China

JEL Classification: G12, R31
1. Introduction

The housing market in China’s major cities has surged for almost 10 years since 2003 until early 2011, with some signs of moderation recently. What economic forces drive the large swings in the China’s housing market? Does it prelude further declines or good prospective returns in the future? Or does it simply reflect a gloomy outlook about future rent that can be generated by housing service? Asset pricing theory tries to answer these questions by relating the price to entire future uncertain cash flow, usually in the form of present-value statement. The rental yield, the equivalent of the dividend-price ratio in the housing market, is of particular importance in assessing the housing market based on this present-value framework, because it reveals agent’s expectations about future returns and rent growth in housing market. In other words, the changes in rental yield must capture the time variation in expected returns and/or expected rent growth rates.

In this work, we would like to start by the standard present-value model of rental yield pioneered by Campbell and Shiller (1988) that decomposes the movement of rental yield mainly into two components: changes in expected future returns and future rent growth. Campbell and Shiller (1988) originally use this framework to explore the dynamics of aggregate stock market returns. Since then, this framework has been applied by researchers to many other areas in finance, such as individual stock returns (Vuolteenaho, 2002), fixed income securities (Shiller and Beltratti, 1992; Campbell and Ammer, 1993), international financial adjustments (Gourinchas and Rey, 2007), and real estate market (Campbell, Davis, Gallin and Martin, 2009; Plazzi, Torous and Valkanov, 2010). For example, Campbell, Davis, Gallin and Martin (2009) and Hiebert and Sydow (2011) use the same framework to study the fluctuations in the real estate markets for the U.S. and EU, respectively. To our best knowledge, this is the first research to examine the driving forces of mainland Chinese housing market within the present-value model of rental yield.

More importantly, we would go beyond the standard present-value model of rental yield to incorporate features in the housing markets through the user cost of housing model (Hendershott and Slemrod, 1983; Jorgenson, 1963; Poterba, 1984) to gain further economic insights into the present-value model of rental yield. In other words, we would be able to gain further economic insights into the present-value model of rental yield, if additional structure is imposed on the dynamics of returns and/or rent growth rates. We would take an approach similar to Binsbergen and Kojien (2010) and Plazzi, Torous and Valkanov (2010), who impose additional structure on the specification of expected returns and expected dividend (rent) growth process guided by the empirical properties of stock and real estate’s data. However, unlike Binsbergen and Kojien (2010) and Plazzi, Torous and Valkanov (2010), who specify exogenously a time-series statistical model, we would like to impose structure within a present-value model of rental yield base on an economic model of user cost of housing in order to investigate in more detail the economic properties of the housing market. In this sense,
our work is more related to Campbell, Giglio and Polk (2010), who impose the cross-sectional restrictions of the inter-temporal capital asset pricing model (ICAPM) on asset returns.

In short, we are looking at the question of what forces have driven the movement of China’s housing market, by combining the standard present-value model with the classical user cost of housing model, to decompose the rental yield into three components: the expected future **rents**, **costs of capital**, and **risk premium of owning relative to renting**. We would like to identify which forces have played the most significant part in the movement of the China’s housing market. After using the vector autoregressive methodology to construct empirical proxies for the relevant expectations in our present-value model, we can employ the variance decomposition approach to examine quantitatively how much the variation in rental yield comes from the above-mentioned three components.

Specifically, we would first build a theoretical model by combining the standard Campbell and Shiller (1988) present-value model with the classical user cost of housing model to decompose the rental yield into three components: expected future rent growth, cost of capital, and risk premium of owning relative to renting. And then, based on our theoretical model, we would like to exploit a dataset compiled by the Chinese Mainland DTZ, a global real estate adviser, for the four Chinese first-tier cities (Beijing, Shanghai, Guangzhou and Shenzhen) to explore the question of what forces have driven the movement of China’s housing market.

Our results show that cost of capital is playing an important role in all the four major cities, while the future rent growth is not a driving force as significant as the cost of capital in the fluctuation of the rental yield. Moreover, we find that another factor -- the risk of owning relative to renting a house -- is accounting for a large part of housing market movement in China. It is also worth noting that the risk of renting relative to owning a house seems to be rising rapidly in China over the recent years.

The rest of our work is organized as follows. The next section outlines the log-linearized present-value model of rental yields that combines the standard Campbell and Shiller (1988) present-value model with the classical user cost of housing model. Section 3 presents our implementation of the present-value model of rental yields, including data description and empirical methodology. Section 4 reports the empirical results of variance decomposition showing how each component of the model in driving housing market movements of the four major cities in China. The final section concludes.
2. The Model

The present-value model of rental yield

Following Campbell and Shiller (1988), we start with the definition of one-period holding returns in housing markets to derive a present-value model of rental yield (also called a dynamic Gordon growth model that is a dynamic generalization of the Gordon growth model for housing prices with constant expected returns and rent growth). This present-value model of rental yield provides a useful organizing principle for empirical work to divide the underlying driving forces in housing markets mainly into two parts: one is changes in expected cash flow; the other is changes in expected returns or discount rates. In particular, we define the one-period holding return in housing markets as follows:

\[
R_{i,t+1} = \frac{P_{i,t+1} + L_{i,t+1}}{P_i},
\]

where \( P_{i,t} \) is the price of a house in city \( i \) at the end of time \( t \), \( L_{i,t+1} \) is the rent paid to the corresponding housing holder in city \( i \) over the period from the end of \( t \) to the end of period \( t+1 \), \( R_{i,t+1} \) is the realized gross return held in city \( i \) from the end of \( t \) to the end of period \( t+1 \).

After taking logs of both sides of the above defined one-period holding return, we can derive an approximated log-linearized identity as follows using first-order Taylor expansion:

\[
lp_{i,t} = -\kappa + r_{i,t+1} - \Delta l_{i,t+1} + \rho \cdot lp_{i,t+1},
\]

where \( \Delta l \) indicates the first difference of log rent, \( lp \) denotes the log of rental yield, \( r \) is the log of one-period holding return, \( \rho \) is a parameter that equals \( 1/(1+\exp(E[lp])) \), \( \kappa \) is a constant term in the log-linear approximation.

We can iterate the Eq. (2) \( h \) periods ahead to express rental yield as a discounted sum of future holding returns, rent growth and rental yield as follows:
\[ lp_{i,t} = -\frac{\kappa (1-\rho^h)}{1-\rho} + \sum_{j=1}^{h} \rho^{j-1} r_{i,t+j} - \sum_{j=1}^{h} \rho^{j-1} \Delta l_{i,t+j} + \rho^h lp_{i,t+h}. \] (3)

If we impose the condition that rental dividend yield is stationary, the last term of Eq. (3) would disappear as we iterate forward to the infinite-horizon limit:

\[ lp_{i,t} = -\frac{\kappa}{1-\rho} + \sum_{j=1}^{\infty} \rho^{j-1} r_{i,t+j} - \sum_{j=1}^{\infty} \rho^{j-1} \Delta l_{i,t+j}. \] (4)

Eq. (4) holds ex post, but it also holds ex ante as well since it is an approximated identity. Thus, after taking expectations of both sides of Eq. (4) and noting that, we can express rental yield as a present-value model of infinitely discounted sum of future rent growth and holding returns in housing markets:

\[ lp_{i,t} = -\frac{\kappa}{1-\rho} + \sum_{j=1}^{\infty} \rho^{j-1} E_i \left( r_{i,t+j} \right) - \sum_{j=1}^{\infty} \rho^{j-1} E_i \left( \Delta l_{i,t+j} \right). \] (5)

where the expectation operator E can refer to any information set that includes rental yield.

It deserves noting that Eq. (5) shows rental yield reveals agent’s expectation about expected future returns and expected future rent growth in housing markets. If rental yield varies at all, it must mechanically come from the changing expected future returns or rent growth or both, given that rental yield is stationary. On the one hand, investors would bid up house prices relative to current rent, if they expect future rent will be higher than they are today. Then, today’s low rental yield forecasts the subsequent rise in rents. On the other hand, house prices can also be high if expected returns are low. That is, the same rents in the future are discounted at a lower rate. Then, today’s low rental yield forecasts low returns in the future.

In addition, we can follow the approach of Campbell and Shiller (1988) to use the dynamic accounting identity derived in Eq. (5), to decompose the variance of the rental yield into the sum of variance and covariance terms as follows by taking into account the possible correlation among various components:

\[ \text{var}(lp_{i,t}) = \text{var} \left( E_i \sum_{j=1}^{\infty} \rho^{j-1} r_{i,t+j} \right) + \text{var} \left( E_i \sum_{j=1}^{\infty} \rho^{j-1} \Delta l_{i,t+j} \right) + \text{cov} \left( E_i \sum_{j=1}^{\infty} \rho^{j-1} r_{i,t+j}, E_i \sum_{j=1}^{\infty} \rho^{j-1} \Delta l_{i,t+j} \right). \] (6)

Specifically, we need first to employ appropriate method to construct empirical proxies for corresponding terms in the right hand side of Eq. (5). And then, we can
compute the variance or standard deviation of each term to examine quantitatively how much the variation in rental yield comes from changes in expected returns, and how much is due to changes in expected rent growth. The relative contribution of different components to the movement of the current rental yield could then be measured by the variance of that component, calculated as the percentage share of the variance of the current rental yield.

It is also worth noting that the present-value model of rental yield is a dynamic accounting identity with minimum assumptions such as stationarity. In other words, we are only using dynamic identities together with and the variance decomposition approach to derive our empirical results. Therefore, our results are robust on inferring relative importance of future expected returns and rent growth in driving the variation in rental yield.

**Imposing the housing user cost model as a restriction condition**

However, the strength is also the weakness. Although the present model enables us to uncover the proximate causes of changes in rental yield, it does not clarify why the expected returns and profitability change so much, and so never really provides an economic explanation of fundamental factors driving the variation in housing markets. Moreover, there is a large literature documenting that almost all asset price movements, either in stocks or real estate, are due to changing expected returns rather than to changing expectations of future cash flow. It also holds in China’s housing market, as we will show later in this work. It thus implies that we have to attribute a large portion of housing market movement to time-varying discount rates that is harder for people to capture, rather than easier-to-understand rent growth. In order to open the black-box like discount rates, we may need to go beyond the standard the present-value model of rental yield to incorporate features in the housing markets. In other words, we would be able to gain further economic insights into the present-value model of rental yield, on if additional structure is imposed on the dynamics of returns and/or rent growth rates.

In what follows, we would take an approach similar to Binsbergen and Kojien (2010) and Plazzi, Torous and Valkanov (2010), who impose addition structure on the specification of expected returns and expected dividend (rent) growth process guided by the empirical properties of stock and real estate’s data. However, unlike Binsbergen and Kojien (2010) and Plazzi, Torous and Valkanov (2010), who specify exogenously a time-series statistical model, we would like to impose structure within a present-value model of rental yield based on an economic model of housing user’s cost in order to investigate in more detail the economic properties of the housing market. In this sense, our work is more related to Campbell, Giglio and Polk (2010), who impose the cross-sectional restrictions of the intertemporal capital asset pricing model (ICAPM) on asset returns.
In real estate economics literature (e.g., Jorgenson, 1963; Hendershott and Slemrod, 1983; Poterba, 1984), the classical user cost of housing model assumes that the housing market is an efficiency market without friction. There is a no arbitrage condition meaning that the marginal benefit which is the rental price, must be equal to the marginal cost, namely, the user cost of housing.

\[ L_{i,t+1} = UC_{i,t+1} \]  \hspace{1cm} (7)

where \( L_{i,t+1} \) is the rent paid to the homeowner in city \( i \) over the period from the end of \( t \) to the end of period \( t+1 \), \( UC_{i,t+1} \) is the cost of owning a house of corresponding homeowner in city \( i \) over the period from the end of \( t \) to the end of period \( t+1 \), which is known as user cost or imputed rent.

As defined by literature, the user cost is the sum of several components, usually can be divided into three categories. The first element is the cost of capital. People can use a leverage to buy a house, thus, the homeowner has to pay a mortgage and/or lose a return on an alternative investment. We consider the capital cost as the sum of interest payment \( (P_i, (1-LTV_{i,t})r_{i,t+1}^{fr}) \) and the opportunity cost of the installment payment \( (P_i, (1-LTV_{i,t})r_{i,t+1}^{fr}) \). Thus the capital cost \( P_i C_{i,t+1} \) is the weighted average of risk-free deposit rates \( (r_{i,t+1}^{fr}) \) and mortgage rates \( (r_{i,t+1}^{m}) \), with loan-to-value ratio \( (LTV \in [0,1]) \) as the weight: \( P_i C_{i,t+1} = P_i \left[ (1-LTV_{i,t})r_{i,t+1}^{fr} + LTV_{i,t} r_{i,t+1}^{m} \right] \).

The second element of user’s cost of owning a house includes depreciation, maintenance costs, and risk premium. Following the literature, we assume that both the depreciation and maintenance costs are invariant over time as a fraction of current housing prices, i.e., \( (P_i \delta_i + P_i \theta_i) \). On the other hand, according to Sinai and Souleles (2005), the risk premium is not only time-varying, but can also be positive or negative. Thus, we follow the literature to assume the risk premium of owning relative to renting as a changing fraction of current housing prices \( (P_i \gamma_{i,t+1}) \). In sum, the cost of retaining a house can be denoted as \( P_i M_{i,t+1} = P_i \left( \gamma_{i,t+1} + \theta_i + \delta_i \right) \).

Third, since the homeowner have the option to resell the house in the future, a potential capital gain or loss should also be taken into account: \( E_t \left( P_{i,t+1} \right) - P_{i,t} \).
In some other countries, owning a house can be entitled to some tax benefits that should be deducted, such as the deductibility of mortgage interest from income tax. Meanwhile, the homeowner can also be obliged to paying property tax. Fortunately, our sample is immune from those tax considerations. Therefore, the housing user cost model applied to our study can be written as followings:

\[
L_{t,j+1} = P_{t,j}C_{t,j+1} + P_{t,j}M_{t,j+1} - \left[ E_t \left( P_{t,j+1} \right) - P_{t,j} \right].
\]

(8)

If we rewrite the above Eq. (8), we can obtain:

\[
\frac{L_{t,j+1} + E_t \left( P_{t,j+1} \right)}{P_{t,j}} = 1 + C_{t,j+1} + M_{t,j+1}.
\]

(9)

Provided that the rents is determined or paid in advance that is typical in the rental market, the rental price for the next period would be included in the information set at time \( t \), so that we have \( L_{t,j+1} = E_t \left( L_{t,j+1} \right) \). Since the information set at time \( t \) also includes the housing price \( P_{t,j} \), the left side of the Eq. (9) can be rewritten as

\[
E_t \left[ \frac{L_{t,j+1} + P_{t,j+1}}{P_{t,j}} \right].
\]

Then, we can have:

\[
E_t \left( R_{t,j+1} \right) = 1 + C_{t,j+1} + M_{t,j+1}.
\]

(10)

Taking logs of both sides, we can obtain\(^1\):

\[
E_t \left( r_{t,j+1} \right) \approx c_{t,j+1} + m_{t,j+1},
\]

(11)

where \( r_{t,j+1} = \log \left( R_{t,j+1} \right) \) is the log of one-period returns, \( c_{t,j+1} = \log \left( 1 + C_{t,j+1} \right) \) denotes the log of capital cost, \( m_{t,j+1} = \log \left( 1 + C_{t,j+1} + M_{t,j+1} \right) - c_{t,j+1} \) is the cost of retaining a house mainly reflecting the changing risk premium.

\(^1\) Of course, \( E(R_{t+1}) \neq \exp \left( E(r_{t+1}) \right) \), because \( E \left[ f \left( x \right) \right] \neq f \left[ E \left( x \right) \right] \). But, we can derive \( \log \left( E_t \left( R_{t+1} \right) \right) \approx E_t \left( r_{t+1} \right) \) approximately. For example, if the housing return \( R \) follows log-normal distribution, we have \( E(R) = \exp \left( E(r) + \sigma^2 (r) / 2 \right) \). Since \( r - E(r) \) is small, the higher order terms, such as \( \sigma^2 (r) / 2 = E \left[ \left( r - E(r) \right)^2 \right] / 2 \), would be small enough to be ignored. As a result, the equality \( E(R) \approx \exp \left( E(r) \right) \) holds approximately.
Having obtained the housing user cost model in the form of Eq. (11), we can then nest it within a present-value model of rental yield, in order to further decompose the discount rate into two components: the cost of capital and the risk premium of owning relative to renting. In other words, we can impose the above Eq. (11) as a restriction condition into Eq. (5) to acquire:

\[ lp_{t,j} = -\frac{\kappa}{1-\rho} + \sum_{j=1}^{\infty} \rho^{j-1} E_t \left( c_{t+j} + m_{t+j} - \Delta l_{t+j} \right). \]  

Eq. (12) shows that we can decompose the rental yield into three components: the expected future rents, costs of capital, and risk premium of owning relative to renting. Similar to Eq. (6), we can examine quantitatively how much the variation in rental yield comes from the above-mentioned three components, by decomposing the variance of the rental yield into the sum of variance the three components together with the covariance terms among them.

\[ \text{var}(lp_{t,i}) = \text{var} \left( E_t \sum_{j=1}^{\infty} \rho^{j-1} c_{t+j} \right) + \text{var} \left( E_t \sum_{j=1}^{\infty} \rho^{j-1} m_{t+j} \right) + \text{var} \left( E_t \sum_{j=1}^{\infty} \rho^{j-1} \Delta l_{t+j} \right) + \text{covariance terms} \]  

(13)

Below, we would apply the present-value model of rental yield in Eq. (12) to a quarterly dataset of four major cities in China, in order to explore the question of what forces have driven the movement of China’s housing market. Specifically, by employing the variance decomposition approach, we can examine quantitatively the relative importance of different forces in driving the variation in rental yield over time.

3. Empirical Implementation

Data

We apply a vector autoregression (VAR) system to construct time-series estimates of expected housing returns, cost of capital and rent growth by using four empirical proxy variables2: (1) rental yield, (2) housing return, (3) cost of capital and (4) rent growth rate.

House prices, rents and rental yield

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2 For the variable of risk premium of renting relative to buying, we use a similar method which applied in Campbell and Shiller (1988) about taking dividend as the residual term of model, and through the model equation (13) to construct it. However, we should bear in mind that this method is easy to overestimate the impact of risk premium; because residual term includes the linear approximation error and other not estimated factors. We will discuss these problems later in this section and find that these effects are not worthy of too much worry.
The residence data set we use in our study is house prices \(P_{i,t}\) and rents index \(L_{i,t}\) of four major cities (namely Beijing, Shanghai, Guangzhou, Shenzhen)\(^3\) and is provided by DTZ\(^4\). The residential prices and rents index in each city are corresponding transactions data of secondhand high-end residence in a given quarter.\(^5\) The index data is on a quarterly basis, and the available time period of Shanghai, Guangzhou and Shenzhen is beginning in the first quarter of 1991(1991:Q1) and ending in the first quarter of 2011(2011:Q1), while the time span of Beijing's price index is from 1993:Q2 to 2011:Q1 and rent index also covers the sample period 1991:Q1 to 2011Q:1. All index series are converted in 1993:Q3 as the base period. To the best of our knowledge, the DTZ index is the only kind of housing market index that can capture one housing price cycle in China, especially at a city-level, and this novel advantage is essential for our analysis.

Given the advantage of DTZ index, we are the first to construct city-level time series data of rental yield in China. To obtain a series in levels for the rental yield, we then use data of a survey from China International Capital Corporation Limited (CICC) to benchmark the level of the rental yield in 2006:Q1. And we work with log rental yield:

\[
lp_{i,t}=\log\left(\frac{L_{i,t}}{P_{i,t}}\right).
\]

**Housing returns**

Based on four cities' house price indexes from DTZ and rental yield which we construct above, the log housing returns are calculated as:

\[
R_{i,t} = \log \left[ \frac{(lp_{i,t}+1)P_{i,t}}{P_{i,t-1}} \right].
\]

**Rent growth rates**

The log rent growth rates are computed as:

\[
\Delta l_{i,t} = \log L_{i,t} - \log L_{i,t-1}.
\]

**Cost of Capital**

As we defined earlier in this paper, the unit cost of capital \(C_{i,t}\) is

\[
\left[ (1-LTV_{i,t-1})r_{i,t} + LTV_{i,t-1}r_{i,t}^{m} \right].
\]

We use 1-year deposit interest rate and 5-year above loan interest rate respectively as the proxy variables of risk free interest rate and mortgage

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\(^3\) The practitioners often refer to these four cities as first-tier cities in China. Real estate development of these four cities is apparently ahead of other cities in China.

\(^4\) DTZ is a global real estate adviser founded in 18\(^{th}\) century UK and entered Chinese mainland market in 1993.

\(^5\) DTZ will not announce details about how they construct their data series. To the best of our available information, the sample of DTZ's index is continuous and comparable across cities and over time.
loan interest rate. The interest rate data is from the People's Bank of China (PBoC). For convenience of analysis, we assume the down payment ratio is 20%, and corresponding LTV ratio is $80\%$.

Table (1) presents the descriptive statistics on the above four variables, prior to log and demean. We report time series averages, standard deviations, maximum and minimum. From Table 1 we can see that the averages of rental yield of four cities ranging from 0.047(Shanghai) to 0.085(Beijing), with the standard deviations varying from 0.025(Shanghai) to 0.048(Beijing); which means that the valuation level of Shanghai’s housing market is the highest and Beijing is the lowest on average, while the volatility of housing market in Beijing is higher than other cities and Shanghai is the lowest. The volatility of housing returns of four cities is very close, but Shanghai’s return is relative lower than the other three cities. Both means and standard deviations of rent growth rate of four cities are close plus means are negative, indicating that these cities' rental growth trends are generally declining in the sample period. It is worth to mention that the volatility of cost of capital and rental yield of these cities is similar.

Table 1 Descriptive statistics for variables included in VAR system

<table>
<thead>
<tr>
<th>Variables</th>
<th>Statistics</th>
<th>Beijing</th>
<th>Shanghai</th>
<th>Guangzhou</th>
<th>Shenzhen</th>
</tr>
</thead>
<tbody>
<tr>
<td>$l_{p_{i,t}}$</td>
<td>Max</td>
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<td>0.098</td>
<td>0.183</td>
<td>0.188</td>
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<tr>
<td></td>
<td>Min</td>
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<td>0.023</td>
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<tr>
<td></td>
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<td>0.048</td>
<td>0.081</td>
<td>0.082</td>
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<tr>
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<td>Std.dev.</td>
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<td>0.025</td>
<td>0.037</td>
<td>0.036</td>
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<td>Observation</td>
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<td>81</td>
<td>81</td>
<td>81</td>
</tr>
<tr>
<td>$r_{i,t}$</td>
<td>Max</td>
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<td>0.320</td>
<td>0.343</td>
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<tr>
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<td>Min</td>
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<td>-0.098</td>
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<td>80</td>
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<td>$\Delta l_{i,t}$</td>
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<tr>
<td>$c_{i,t}$</td>
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<tr>
<td></td>
<td>Std.dev.</td>
<td>0.032</td>
<td>0.032</td>
<td>0.032</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>Observation</td>
<td>81</td>
<td>81</td>
<td>81</td>
<td>81</td>
</tr>
</tbody>
</table>

Notes: This table reports summary statistics for rental yield ($l_p$), returns ($r$), rent growth ($\Delta l$) and cost of capital ($c$) of four cities. The table lists the max, the min, the mean, the std.dev and the observation. The sample is quarterly observations of four cities from 1991:Q1 to 2011:Q1, except

$^6$ Zhu(2006) also considers the upper value of mortgage rate in China is 80%.
that Beijing’s house price index is from 1993:Q2 to 2011:Q1.

**Methodology**

Since the expectations variables in Eq. (5) and (12) are unobservable, we need to construct empirical proxies for the expectations to implement the decomposition of rental yields. We adopt the VAR methodology, proposed by Campbell (1991) and Campbell and Ammer (1993), and then applied in housing markets by Campbell et al (2009) and Hiebert and Sydow (2011), to create proxies for relevant expectations. We follow Campbell et al (2009) to specify a first-order VAR for the sake of parsimony:

\[ Z_{t+1} = A \cdot Z_t + \varepsilon_{t+1}, \]  

(14)

where \( Z_t = [\Delta l, r, c, lp] \) is a 4-dimensional vector of state variables including rent growth (\( \Delta l \)), returns (\( r \)), costs of capital (\( c \)), and rental yields (\( lp \)); \( A \) is the coefficient matrix; \( \varepsilon_{t+1} \) is the forecasting error. Note that all the variables in this VAR model are demeaned so that we specify the VAR model without constant terms. In other words, we focus only on the variation of variables under question in the form of deviations from their equilibrium values. The constants in the log-linearized present-value model are also ignored.

Having obtained the proxies for expectations variables in hand, we could use the dynamic accounting identity defined in Eq. (5) to decompose the rental yield into the discounted sum of expected future rent growth and returns, or we can use the dynamic user cost of housing model derived in Eq. (12) to decompose the rental yield into three components: the expected future rents, costs of capital, and risk premium of owing relative to renting. Then, the relative contribution of different components to the movement of the rental yield in China’s four major cities could then be measured by the variance of that component, calculated as the percentage share of the variance of the current rental yield.

Given the VAR model we just specified, we can obtain the future forecasts of state variables at any time horizon as follows:

\[ E_t[Z_{t+h}] = A^hZ_t, \]  

(15)

---

7 Although the BIC criterion would select 2 lags for the cases of Shanghai and Shenzhen, we confirm that adding more lags would not change our results qualitatively. Not only will it be unable to improve the forecasting ability of our VAR model, but also has little impact on the empirical results of variance decomposition.
where \( h \) is the length of forecasting horizon.

Then, we have the Eq. (5) written as

\[
l p_t = \sum_{j=1}^h \rho^{|j-1|} E_t (r_{t+j}) - \sum_{j=1}^h \rho^{|j-1|} E_t (\Delta l_{t+j}) = \epsilon_t \sum_{j=1}^h \rho^{|j-1|} A^{i} Z_t - \epsilon_{A}^t \sum_{j=1}^h \rho^{|j-1|} A^{i} Z_t
\]

\[
= \epsilon_t A (1 - \rho A)^{-1} Z_t - \epsilon_{A}^t A (1 - \rho A)^{-1} Z_t = lp_t^t + l p_{A}^t,
\]

where \( \epsilon_t \) is a unit vector that selects the corresponding variable of 4-dimentional vector \( Z_t \). For example, given that rent growth is the first element of the VAR system, the selection vector in the case of first-order VAR is just the forth column of a 4x4 identity matrix, denoted \( e_{A} \). Similarly, \( e_t, e_c \) and \( e_{lp} \) denote the selection vector of returns, costs of capital and rental yields, respectively.

4. Empirical Results

VAR estimates

Table (2) reports the estimation results of the forecasting equations of the rent growth, return, cost of capital, and rental yield in our VAR model for all the four major cities in China. Table (2) consists of four panels with each summarizing the results for a city of Beijing, Shanghai, Guangzhou, and Shenzhen. In addition to the coefficient estimates and their associated standard errors, each panel also reports the \( p \) values of Wald tests that none of the forecasting variables are significant together with adjusted \( R \), in order to gauge the forecastability of endogenous variables in our VAR model. The Wald tests for the joint significance of the forecasting coefficients appear to indicate that all the endogenous variables in our forecasting VAR are predictable. However, the adjusted \( R \) statistics seem to suggest that the extent to which variables are predictable would vary a lot from one variable to another.

<table>
<thead>
<tr>
<th>City</th>
<th>Dep</th>
<th>( \Delta l_t )</th>
<th>( r_t )</th>
<th>( c_t )</th>
<th>( lp_t )</th>
<th>City</th>
<th>Dep</th>
<th>( \Delta l_t )</th>
<th>( r_t )</th>
<th>( c_t )</th>
<th>( lp_t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>BJ</td>
<td></td>
<td>0.331 (0.107)</td>
<td>0.115</td>
<td>0.029</td>
<td>0.262</td>
<td>SH</td>
<td></td>
<td>0.232 (0.092)</td>
<td>0.069</td>
<td>0.038</td>
<td>0.197</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.141 (0.129)</td>
<td>0.193</td>
<td>0.013</td>
<td>0.001</td>
<td></td>
<td></td>
<td>0.318 (0.107)</td>
<td>0.119</td>
<td>0.004</td>
<td>0.225</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: VAR Estimation Results
\[
\begin{array}{cccccc}
<table>
<thead>
<tr>
<th>\text{Variable}</th>
<th>\text{Beijing}</th>
<th>\text{Shanghai}</th>
<th>\text{Guangzhou}</th>
<th>\text{Shenzhen}</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{(c_{t-1})}</td>
<td>0.385 &amp; 0.737 &amp; 0.928 &amp; -0.033</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(0.367)} &amp; (0.423) &amp; (0.049) &amp; (0.425)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(lp_{t-1})}</td>
<td>-0.032 &amp; 0.019 &amp; 0.000 &amp; 1.004</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(0.015)} &amp; (0.019) &amp; (0.001) &amp; (0.021)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{Wald}</td>
<td>0.000 &amp; 0.000 &amp; 0.000 &amp; 0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\text{\(Adj.R^2\)} \quad 0.251 \quad 0.477 \quad 0.975 \quad 0.992

\text{\(\Delta l_{t-1}\)}

<table>
<thead>
<tr>
<th>\text{Beijing}</th>
<th>\text{Shanghai}</th>
<th>\text{Guangzhou}</th>
<th>\text{Shenzhen}</th>
</tr>
</thead>
<tbody>
<tr>
<td>\text{(\Delta l_{t-1})}</td>
<td>0.003 &amp; 0.031 &amp; 0.021 &amp; -0.005</td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(0.145)} &amp; (0.111) &amp; (0.014) &amp; (0.144)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(r_{t-1})}</td>
<td>0.320 &amp; 0.328 &amp; 0.019 &amp; 0.069</td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(0.098)} &amp; (0.098) &amp; (0.010) &amp; (0.124)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(lp_{t-1})}</td>
<td>-0.018 &amp; 0.031 &amp; 0.000 &amp; 1.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{(0.012)} &amp; (0.017) &amp; (0.001) &amp; (0.018)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\text{Wald}</td>
<td>0.000 &amp; 0.000 &amp; 0.000 &amp; 0.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\text{\(Adj.R^2\)} \quad 0.903 \quad 0.210 \quad 0.966 \quad 0.980

Note: The sample is quarterly observations of four cities from 1991:Q1 to 2011:Q1, except that Beijing's house price index is from 1993:Q2 to 2011:Q1. The Wald tests report the associated p values. In parentheses are heteroskedasticity-autocorrelation consistent standard errors.

On the one hand, we find that only a small portion of the variability can be accounted for by our forecasting VAR for both the rent growth and return. While the rent growth appears to be mainly forecast by its own lag in Beijing and Shanghai, its predictability is mainly due to other forecasting variables than its own lag in Guangzhou and Shenzhen. Contrary to rent growth, the holding returns show some degree of persistence in Guangzhou and Shenzhen markets but not in Beijing and Shanghai.

On the other hand, our results show that a substantially large amount of fluctuations in rental yield and cost of capital can be captured by the VAR model. In particular, both the rental yield and cost of capital seem to follow a highly persistent AR(1) process in either cases with a coefficient of more than 0.9. Consistent with the theoretical model, higher rental yield would not only forecast economically and statistically significant higher future holding returns, but also tend to be associated with lower rent growth in the future.

**Actual and estimated rental yield**

Before using the one-period VAR estimates to conduct the variance decomposition analysis, we would like to examine how well the present-value model of rental yield together with the one-period VAR forecasting results can be fitted into our sample of four Chinese major cities. Despite the solid justification for the dynamic accounting
identity in Eq. (5), the estimated rental yield (sum of the expected future rent growth and returns) can differ from the actual rental yield at least for the following two reasons. First, our log-linearized model of Eq. (5) is an approximated accounting identity, so that it has the chance to involve significant approximation errors, and the errors can even pile up at longer horizons as we iterate the approximated one-period identity forward to express the rental yield as a present-value model of discounted sum of future rent growth and holding returns. Second, it is also possible that the one-period forecasting VAR model may not be adequate in capturing the long-horizon dynamics of rent growth and returns. For example, our estimates of rental yield may not equal to the actual rental yield if investors do not form forecasts of expectation variables according to the one period VAR model specified in Eq. (14).

![Figure 1: Actual and estimated rental yield](image)

Given the estimates of VAR coefficients matrix \((A)\), we can compute the estimated rental yield by adding up the two terms at the right hand side of Eq. (5). We then compare the estimated rental yield with the actual rental yield in Figure (1). Our result seems to suggest that the estimated rental yield based on one-period VAR can capture the movements of actual rental yield pretty well throughout our sample period for all for major cities, in the sense that the two terms at the right hand side of Eq.(5) almost add up to the actual rental yield. For the sake of clarity, we also plot the difference between actual and estimated rental yield. It appears that the difference is not only small in scale, but also highly stable. In sum, the evidence indicates that errors in approximation process and one-period VAR-based estimates of expectation variables seems not to be the main driver of movements in rental yield for China’s housing markets. Therefore, we can conclude that the present-value model of rental yield together with the one-period VAR estimates can perform quite well empirically in tracking the movement of rental yield for all the four major cities in China.

**Variance decomposition of rental yields**

Table (3) reports the results of variance decomposition of log rental yields based on
the dynamic Gordon growth model of Eq. (5). The variance of rental yields is decomposed into the sum of two variance components related to expected present value of rent growth and returns, together with the covariance between them. The first row of each city panel reports the total contribution, while the second row shows the contribution as a percentage of the variance of rental yields. In general, it is evident from the table that expected returns played the most significant role in the movement of rental yields in all the four major cities. The rent growth, of course, also have contributed to the variation in rental yields, but not as important as expected returns. In other words, our results about the information content of the variation in rental yields through time in China’s four major cities, are more similar to those of the U.S. as reported by Campbell et al. (2009) rather than the Euro area countries (e.g. Hiebert and Sydow, 2011).

Table 3: Variance decomposition of rental yield based on the dynamic Gordon growth model

<table>
<thead>
<tr>
<th>City</th>
<th>$\Delta l_t$</th>
<th>$r_t$</th>
<th>$lp_t$</th>
<th>City</th>
<th>$\Delta l_t$</th>
<th>$r_t$</th>
<th>$lp_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>BJ</td>
<td>0.066</td>
<td>0.166</td>
<td>0.332</td>
<td>VAR</td>
<td>0.032</td>
<td>0.448</td>
<td>0.325</td>
</tr>
<tr>
<td></td>
<td>(Frac) 0.197</td>
<td>(0.499)</td>
<td>(1.000)</td>
<td>(Frac) 0.098</td>
<td>(1.379)</td>
<td>(1.000)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STD 0.256</td>
<td>0.407</td>
<td>0.576</td>
<td>STD 0.179</td>
<td>0.669</td>
<td>0.570</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(Frac) 0.444</td>
<td>(0.706)</td>
<td>(1.000)</td>
<td>(Frac) 0.311</td>
<td>(1.175)</td>
<td>(1.000)</td>
<td></td>
</tr>
<tr>
<td>SH</td>
<td></td>
<td></td>
<td></td>
<td>Corr Matrix:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\Delta l_t$ 1.000</td>
<td>-0.363</td>
<td>-0.814</td>
<td>$\Delta l_t$ 1.000</td>
<td>0.740</td>
<td>0.637</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r_t$ -0.363</td>
<td>1.000</td>
<td>0.836</td>
<td>$r_t$ 0.740</td>
<td>1.000</td>
<td>0.989</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$lp_t$ -0.814</td>
<td>0.836</td>
<td>1.000</td>
<td>$lp_t$ 0.637</td>
<td>0.989</td>
<td>1.000</td>
<td></td>
</tr>
<tr>
<td>GZ</td>
<td>0.009</td>
<td>0.121</td>
<td>0.211</td>
<td>VAR</td>
<td>0.028</td>
<td>0.085</td>
<td>0.149</td>
</tr>
<tr>
<td></td>
<td>(Frac) 0.044</td>
<td>(0.575)</td>
<td>(1.000)</td>
<td>(Frac) 0.189</td>
<td>(0.572)</td>
<td>(1.000)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>STD 0.096</td>
<td>0.348</td>
<td>0.459</td>
<td>STD 0.168</td>
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<td>0.386</td>
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</tr>
<tr>
<td></td>
<td>(Frac) 0.210</td>
<td>(0.758)</td>
<td>(1.000)</td>
<td>(Frac) 0.435</td>
<td>(0.756)</td>
<td>(1.000)</td>
<td></td>
</tr>
<tr>
<td>SZ</td>
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<td></td>
<td>Corr Matrix:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\Delta l_t$ 1.000</td>
<td>-0.752</td>
<td>-0.834</td>
<td>$\Delta l_t$ 1.000</td>
<td>-0.532</td>
<td>-0.813</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$r_t$ -0.752</td>
<td>1.000</td>
<td>0.990</td>
<td>$r_t$ -0.532</td>
<td>1.000</td>
<td>0.926</td>
<td></td>
</tr>
<tr>
<td></td>
<td>$lp_t$ -0.834</td>
<td>0.990</td>
<td>1.000</td>
<td>$lp_t$ -0.813</td>
<td>0.926</td>
<td>1.000</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table reports the variance decomposition of the rental yield ($lp$) into the sum of two variance components related to expected present value of rent growth ($\Delta l$) and returns ($r$) together with the covariance between them, based on the dynamic Gordon growth model of Eq. (5). A four-variable first-order quarterly VAR is employed to construct the empirical proxies for the relevant expectations in our present-value model. The rows of “VAR” (“STD”) report the variance (standard deviations), while the rows of “Frac” show the contribution as a percentage of the variance of the rental yield.
Although rent growth played only a moderate role in the variation of rental yields, comparing to the expected returns that accounted for the greatest part of housing market movement, the relative importance of rent growth and expected returns can vary among cities. For example, in Beijing, while the variation in expected return is the dominant force with explaining 50 percent of the time varying movement of rental yields, changes in expected rent growth can still account for about 20 percent of the variation in rental yields. However, in Shanghai, the expected return explains almost all variation in rental yields, with little remaining that could be attributed to rent growth.

Table (4) reports the results of variance decomposition of log rental yields for the four major cities over the 1991-2011 period based on the dynamic user cost model of Eq. (12), which is derived by imposing housing user cost model as a restriction into the dynamic Gordon growth model. In other words, we further decompose the black-box like discount rate into two components: the cost of capital and the risk premium of owning relative to renting. Therefore, employing the same variance decomposition approach, the variance of rental yields could be decomposed into the sum of three variance components related to expected present value of rent growths, costs of capital and the risk premia of owning relative to renting, together with the covariance between them. We report the results using the same layout as Table (1). In addition, we also plot in Figure (2) the movement actual rental yields over the 1991-2011 period, together with its three components related to expected rent growth, cost of capital, and risk premium of owning of renting, respectively.

Table 4: Variance decomposition of rental yield based on the dynamic user cost model

<table>
<thead>
<tr>
<th>City</th>
<th>$\Delta l_t$</th>
<th>$c_t$</th>
<th>$\gamma_t$</th>
<th>$lp_t$</th>
<th>City</th>
<th>$\Delta l_t$</th>
<th>$c_t$</th>
<th>$\gamma_t$</th>
<th>$lp_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>BJ</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>SH</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>VAR</td>
<td>0.066</td>
<td>0.068</td>
<td>0.040</td>
<td>0.332</td>
<td>VAR</td>
<td>0.032</td>
<td>0.433</td>
<td>0.054</td>
</tr>
<tr>
<td></td>
<td>(Frac)</td>
<td>(0.197)</td>
<td>(0.203)</td>
<td>(0.121)</td>
<td>(1.000)</td>
<td>(Frac)</td>
<td>(0.098)</td>
<td>(1.334)</td>
<td>(0.166)</td>
</tr>
<tr>
<td></td>
<td>STD</td>
<td>0.256</td>
<td>0.260</td>
<td>0.200</td>
<td>0.576</td>
<td>STD</td>
<td>0.179</td>
<td>0.658</td>
<td>0.232</td>
</tr>
<tr>
<td></td>
<td>(Frac)</td>
<td>(0.444)</td>
<td>(0.451)</td>
<td>(0.347)</td>
<td>(1.000)</td>
<td>(Frac)</td>
<td>(0.313)</td>
<td>(1.155)</td>
<td>(0.408)</td>
</tr>
<tr>
<td></td>
<td>Corr Matrix:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Corr Matrix:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>$\Delta l_t$</td>
<td>1.000</td>
<td>-0.114</td>
<td>-0.917</td>
<td>-0.814</td>
<td>$\Delta l_t$</td>
<td>1.000</td>
<td>0.533</td>
<td>0.820</td>
</tr>
<tr>
<td></td>
<td>$c_t$</td>
<td>-0.114</td>
<td>1.000</td>
<td>0.479</td>
<td>0.668</td>
<td>$c_t$</td>
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<td>1.000</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>$\gamma_t$</td>
<td>-0.917</td>
<td>0.479</td>
<td>1.000</td>
<td>0.971</td>
<td>$\gamma_t$</td>
<td>0.820</td>
<td>-0.003</td>
<td>1.000</td>
</tr>
<tr>
<td></td>
<td>$lp_t$</td>
<td>-0.814</td>
<td>0.668</td>
<td>0.971</td>
<td>1.000</td>
<td>$lp_t$</td>
<td>0.637</td>
<td>0.987</td>
<td>0.147</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td></td>
<td>VAR</td>
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<td>0.118</td>
<td>0.095</td>
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<td>VAR</td>
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<td>0.0105</td>
<td>0.095</td>
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<td>(0.560)</td>
<td>(0.451)</td>
<td>(1.000)</td>
<td>(Frac)</td>
<td>(0.189)</td>
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<td></td>
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<td>0.343</td>
<td>0.308</td>
<td>0.459</td>
<td>STD</td>
<td>0.168</td>
<td>0.323</td>
<td>0.307</td>
</tr>
<tr>
<td></td>
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<td>(0.748)</td>
<td>(0.672)</td>
<td>(1.000)</td>
<td>(Frac)</td>
<td>(0.435)</td>
<td>(0.839)</td>
<td>(0.797)</td>
</tr>
</tbody>
</table>
Corr Matrix:

\[
\begin{array}{cccc}
\Delta l & 1.000 & -0.933 & 0.111 & -0.834 \\
c & -0.933 & 1.000 & -0.316 & 0.732 \\
\gamma & 0.111 & -0.316 & 1.000 & 0.412 \\
l_p & -0.834 & 0.732 & 0.412 & 1.000 \\
\end{array}
\]

Corr Matrix:

\[
\begin{array}{cccc}
\Delta l & 1.000 & -0.975 & 0.552 & -0.813 \\
c & -0.975 & 1.000 & -0.641 & 0.752 \\
\gamma & 0.552 & -0.641 & 1.000 & 0.020 \\
l_p & -0.813 & 0.752 & 0.020 & 1.000 \\
\end{array}
\]

Note: This table reports the variance decomposition of the rental yield \((lp)\) into the sum of two variance components related to expected present value of rent growth \((\Delta l)\), capital cost \((c)\), and risk premium of owning relative to renting \((\gamma)\), together with the covariance between them, based on the dynamic user cost model of Eq. (12). A four-variable first-order quarterly VAR is employed to construct the empirical proxies for the relevant expectations in our present-value model. The rows of “VAR” (“STD”) report the variance (standard deviations), while the rows of “Frac” show the contribution as a percentage of the variance of the rental yield.

Figure 2: Decomposition of rental yield based on dynamic user cost model

We have three main findings from the decomposition of rental yields based on the dynamic user cost model. First, we can find that the term of cost of capital is the primary source of variability in rental yields across all the four major local housing markets. Remember that the cost of capital reflects a combination of mortgage rates and deposit rates, which are determined mainly by the People's bank of China. Therefore, our results suggest that monetary policy in China can exert great influence over the housing market movement.

Second, we find that there seems to be some heterogeneity in the relative importance of cost of capital to other factors across four major cities in China. Of the four major local housing markets, changes in expected costs of capital played a much more important role in Shanghai, followed by Shenzhen, Guangzhou and Beijing. Changes in expected costs of capital are a much more relevant driving force in Shanghai markets than other two factors three. Measured either in variance or standard deviation, the variability of costs of capital is several times higher than the
volatility of expected rent growth. It can be observed even more clearly from Figure (3) that the movement of the cost of capital term is almost identical to that of rental yields. On the other hand, the relative contribution of expected rent growth shows as almost equivalent importance as the role of costs of capital in Beijing.

Finally, we find that the variation of risk premia of owning relative to renting is also an important source of variation in rental yields. Owning to the dynamic housing user cost model, we are capable of measuring the influence of changing risk premia, although the risk premium of owning relative to renting is not directly observable. Specifically, taking a similar approach of Campbell and Shiller (1988) who treat the expected future dividend growth as a residual, the term of risk premia of owning relative to renting can be obtained as a residual using Eq. (12). Consistent with to the earlier findings of Sinai and Souleles (2005), our results show clearly that the risk premium of owning relative to renting in China’s four major cities is not time-varying, but also an important determinant of housing market variability. There are pros and cons of our measure of risk premia of owning relative to renting. On the one hand, contrary to Sinai and Souleles (2005) who use an ad-hoc proxy of the risk premium, we derive a measure of risk premia of owning relative to renting based on an economic model. On the other hand, it is also worth of noting that we tend to overstate the variability of risk premium if the VAR understates the predictability of other relevant variables or there exists some errors in log-linear approximation, since our approach treats the risk premium component as a residual of the estimation.

**Risk premium of owning relative to renting**

In order to examine the dynamics profile of risk premia of owning relative to renting, we plot in Figure (3) the changes of risk premia computed from Eq. (12) for all the four major cities over the past two decades. We can find two main results from the Figure. First, there seems to be some heterogeneity across the four housing markets. While Shanghai, Guangzhou and Shenzhen markets show much larger up and downs in the fluctuations of risk premia of owning relative to renting, the risk premium of owning relative to renting in Beijing appears to be trending down over the last two decades with only moderate spikes, suggesting the housing price risk bear by residents in Beijing relative the rent risk have declined consistently.

Second, all the four major housing markets in China exhibit key similarities in the movement patterns of risk premia of owning relative to renting that suggest the changes of investor’s preference in housing markets are closely related to macro factors. Specifically, the risk premia of owning relative to renting declined early 1990s, followed by a period of bounce back in the late 1990s. Around 2000, the risk premia of owning relative to renting started declining again in all the four major housing markets. From late 2008 to early 2009, probably because of the increased risk aversion of housing market investors due to global financial crisis and/or the rising macroeconomic risks due to the surging of house prices in several past years, the risk
premium of owning relative to renting has ever reversed its declining trend. But soon it once again tend to decline since 2010, suggesting that the rent risk faced by residents in Beijing relative the housing price risk have been back to the rising trend.

**Figure 3: Risk premium of owning relative to renting**

5. Conclusions

There are mainly two approaches in the literature concerning the variation in rental yield in the housing market. The first one is from the perspective of asset pricing. Usually, this string of researches would employ a present-value model to examine the information content of the variation through time in rental yields, without taking into account the characteristics of housing markets. The other one is, on the other hand, based on the static user’s cost model of real estate economics that is derived from the no-arbitrage condition between the renting and purchasing a house. However, this approach would suffer from not only the inability of capturing the time-varying aspect of rental yield, but also the quantitative examination of relative importance of different forces in driving the variation in rental yield. In this paper, we combine the standard Campbell and Shiller (1988) present-value model with the classical user cost of housing model to decompose the rental yield into three components: expected future rent growth, cost of capital and risk premium of owning relative to renting.

We then apply the present-value model of rental yield to a quarterly dataset of four major cities in China to explore the question of what forces have driven the movement of China’s housing market. Our results are three-fold: First, we find that the present-value model of rental yield performs quite well in our sample period for the four major cities. The approximation errors seem not to be the main driver in the variation of rental yields. Second, using the variance decomposition approach, we find that the expected return in the future can explain a large portion of variation in the rental yield, while the role of expected rent growth is limited. Third, when further imposing the housing user cost model as a restriction condition into the present-value
model, our results show that cost of capital is playing a vital role in all the four major cities, followed by the risk of owning relative to renting a house that is also accounting for a large part of housing market movement in China. Forth, similar to the previous literature using ad-hoc measures, our model-based measure of risk premium of renting relative to owning a house in four major cities of China is also time-varying. It is also worth noting that the risk of renting relative to owning a house seems to be rising rapidly in China over the recent years.

Our results therefore have two important implications for the Chinese housing market. First, the monetary policy or credit policy can exert its leverage over the housing market, since the capital cost is the most important factor in determining the time-varying changes in the housing market. Therefore, the monetary policy instead of administrative measures may be a more appropriate tool in containing the heating housing market in China. Second, although the rent growth can only have limited impact on the housing market directly, it can influence the variation in rental yield indirectly through the changes in risk premia of renting relative to owning a house. Therefore, the development and improvement of the renting market, such as the effects to establish a public housing system to provide decent, safe and stable rental housing for eligible families, could be a stabilizing factor for the Chinese housing market.

Reference:


