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Cash Flow Performance of Fannie Mae Multifamily Real Estate: Evidence from Repeated NOI and EGI Indices*

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Abstract

Using a unique dataset of building operating statements from Fannie Mae, we develop repeated measures regression (RMR) indices for NOI, EGI and PGI to track the cash flow performance of Fannie Mae-financed multifamily real estate. Our three-stage RMR estimate shows an average NOI growth of about 1.8% during 1993-2011, which is lower than inflation rate and significantly lower than what is usually perceived by investors. Based on the RMR estimates, we find that the whole portfolio of Fannie Mae multifamily properties outperforms NCREIF multifamily properties in NOI growth, especially during the 2000-2001 recession and the Great Recession, which helps explain the superior performance of Fannie Mae multifamily mortgage loans during the recent crisis. In the cross section, multifamily properties in supply-constrained areas have substantially larger NOI growth. Workforce housing performs better than low-income housing even after we control for locational differences and property features. We do not find a size effect in NOI growth once we control for supply constraints. We also find EGI growth to be much less volatile than NOI growth, which implies that changes in operating expenses are the main driving factor of the cyclicality of NOI. Operating expenses also tend to be pro-cyclical – they grow faster during recessions. EGI growth (decline) leads PGI growth (decline), which supports the stock-flow model of rental adjustment where vacancy changes before rent. From a methodological perspective, we find that the conventional methods such as simple average and weighted average over-estimate multifamily NOI growth, likely due to significant sample selection bias and outlier influence. In contrast, the RMR indices control for changes in property quality and are much more robust in the presence of data errors and outliers.

Keywords: Repeated NOI index, repeated EGI index, cash flow performance, multifamily, Fannie Mae, repeated measures regression (RMR)

1. Introduction

The outstanding performance of Fannie Mae's and Freddie Mac's multifamily mortgage portfolio is in sharp contrast to that of private-label CMBS loans during the recent financial crisis. For example, in the second quarter of 2010 the default rate of private-label CMBS loans was 6.3 percent, in contrast to the 0.8 and 0.3 percent default rate of Fannie Mae and Freddie Mac multifamily loans, respectively (An and Sanders, 2010).[1] Given that cash flow (net operating income, NOI) generated by the underlying real estate is the source of income to service the loan and that insolvency is one of the two critical drivers of commercial mortgage default (see, e.g., Goldberg and Capone, 2002; An, et al, 2013), a reasonable hypothesis is that cash flow of multifamily properties that have mortgage loans guaranteed by Fannie Mae and Freddie Mac (hereinafter Fannie Mae properties and Freddie Mac properties) was superior. This intrigues us to study the cash flow performance of Fannie Mae and Freddie Mac properties.

In a broader context, tracking the cash flow performance of commercial properties is important for at least two other reasons: first, operating cash flow and its growth potential are primary determinants of commercial real estate value and long term investment return; second, cash flow risk (uncertainty) and return risk are interrelated, and a good measurement of observable cash flow risk helps us better understand return risk (Geltner, 1990). This paper provides the first systematic and methodological analysis of the cash flow performance of Fannie Mae properties using a unique dataset of building operating statements from Fannie Mae.

Fannie Mae, together with Freddie Mac provides a significant share of the debt financing for millions of multifamily housing units. Historically, the market share of the two companies was about 40 percent but it reached as high as 70 percent during 2009. In 2011, Fannie Mae provided

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[1] Here default is defined as 60+ day delinquency.

$24.4 billion in financing for nearly 423,000 multifamily housing units, most of which are "workforce housing".[2] In this study, we utilize more than 20 years of operating statements of over 100,000 Fannie Mae multifamily properties.

Certainly, to track the performance of real estate we have to deal with some methodological complications. For example, the portfolio of properties appears in our sample can change significantly from time to time. To address this issue, we develop repeated measures regression (RMR) indices for NOI, EGI (effective gross income) and PGI (potential gross income). Our RMR index methodology builds upon the vast literature on repeated sales index (see, e.g., Case and Shiller, 1987; Geltner and Goetzmann, 2000; among many others). It essentially utilizes repeated income records of the same building to measure growth so that omitted variable bias is mitigated. We demonstrate that, comparing to indices constructed with the conventional methods such as simple average and weighted average, the RMR indices control for changes in building quality and are much more robust in the presence of data errors and outliers.

Based on the RMR index, we then compare the cash flow performance of Fannie Mae multifamily properties with that of NCREIF multifamily properties.[3] We first compare the overall performance of the two portfolios of properties, ignoring the difference in the characteristics of the two groups of properties. We then conduct regression analysis to examine whether the observed cash flow difference can be explained by observable building characteristics. The first comparison is meaningful from the perspective of portfolio management, and the second comparison provides us insights about whether there are unobservable

[2] "An overview of Fannie Mae's multifamily mortgage business." Fannie Mae, May 1, 2012.

[3] While most of the Fannie Mae dataset is "workforce" housing, a statistically usable sub-sample may be classified as "low income." The NCREIF apartment sample, on the other hand, would largely represent the more upscale and "luxury" rental housing segment. Nevertheless, we would expect both to be affected by general economic trends but not necessarily to the same degree.

underwriting differences between the Fannie Mae portfolio and other segments of the market. In addition to the comparison between Fannie Mae and NCREIF portfolios, we also conduct cross sectional comparisons within the Fannie Mae portfolio, e.g., that between supply-constrained and non-supply constrained areas, that between workforce housing and low-income housing, and that between large and small properties.

We find that the average NOI growth estimated by our RMR method is lower than those calculated by the conventional method, which is consistent with findings in An, et al (2014) that conventional methods could significantly over-estimate rental growth. Not surprisingly, we find NOI growth to be cyclical. Based on the RMR estimates, the volatility of multifamily NOI is calculated but is shown to be moderate compared to the volatility of asset prices.

During the 1990s, the whole portfolio of NCREIF multifamily properties outperformed Fannie Mae multifamily properties. However, in the 2000s, Fannie Mae properties had significantly higher NOI growth (or less decline) during the two recessions (2000-2001 and 2007-2009), which we believe helps explain the superior performance of Fannie Mae multifamily loans before and during the recent crisis. A property-level regression analysis shows that there is no significant difference in NOI growth between Fannie Mae and NCREIF properties once we control for location, time, and property features.

A number of papers have found that supply-constraints lead to higher level and growth of house price, as well as elevated house price volatility (see, e.g., Glaeser, Gyourko and Saks, 2005; Paciorek, 2011). We find that multifamily NOI growth, but not its volatility, is significantly stronger in supply-constrained areas than in non-supply constrained areas. Workforce housing, the type of housing for “essential workers” such as teachers, police officers, firemen and nurses, had performed similarly to low-income housing in the mid- to late-1990s but has significantly stronger performance since early 2000s. We note that workforce housing does concentrate in supply-constrained areas, but the superior performance of workforce housing persists even after we control for locational differences. On the other hand, small properties (e.g., those with less than 30 units) are shown to have higher than average NOI growth, but that advantage disappears when we take into consideration locational differences.

In contrast to the cyclicality we observe in the NOI index, the EGI index shows a steady upward trend. Therefore, changes in operating expenses must be the main driver of NOI cyclicality. More interestingly, the difference between NOI and EGI growth suggests operating expenses to be pro-cyclical – they grow faster during recessions. This might be explained by property managers' proactive actions (e.g., increased marketing) to reduce the impact of a downturn. Finally, by comparing PGI growth to EGI growth (the difference is the effect of vacancy), we find that EGI growth leads PGI growth. This finding supports the stock-flow model, where vacancy starts to change before rent (Geltner, et al, 2007).

There exists a vast literature on property asset price indices for both commercial and residential real estate.[4] Price indices developed in those studies are widely used for purposes such as risk-return analysis, performance benchmarking, the analysis of market cycles and market efficiency, and mortgage default analysis. Compared to the proliferate literature on asset price indices, research on cash flow indexing, reflecting the space market rather than the asset market, is more

[4] See, e.g., Bailey, Muth, and Nourse, 1963; Kain and Quigley, 1970; Rosen, 1974; Case and Shiller, 1987; Shiller, 1991; Geltner, 1989; Geltner, 1991; Fisher, Geltner, and Webb, 1994; Quigley, 1995; Calhoun, 1996; England, Quigley, Redfearn, 1999; Geltner and Goetzmann, 2000; Fisher, Gatzlaff, Geltner and Haurin, 2003; Cannaday, Munneke and Yang, 2005; Fisher, Geltner and Pollakowski, 2007; Geltner and Pollakowski, 2007; Hwang and Quigley, 2010; Deng, McMillen and Sing, 2012; Chegut, Eichholtz and Rodrigues, 2013; and many others.

limited (Wheaton, Torto, and Southard, 1997; Eichholtz, Straetmans and Theebe, 2012; An, Deng, Fisher and Hu, 2012; and Ambrose, Coulson and Yoshida, 2013 are a few efforts we notice). The present paper is among the first few efforts to construct a repeated measures index of commercial real estate cash flow. Our focus on Fannie Mae properties is of interest in its own right because of the scale and importance of workforce housing in the U.S.. Besides its use to measure and to monitor cash flow performance of commercial properties, an NOI or EGI index will help identify the inter-temporal uncertainty (volatility) of cash flows. We provide such volatility estimates in this paper, which can be critical input parameters for mortgage loan pricing and stress testing.

The rest of this paper is organized as follows: in the next section, we describe our data; in section 3, we explain our choice of index methodologies; in section 4, we report our findings; we present conclusions and discussions in a final section.

2. Data

We use two main datasets from Fannie Mae for this study: the property operating statement data, and the loan characteristics data that include property details.[5]

The loan data file contains variables such as loan ID, loan acquisition date, loan amount, appraisal date and value (of the collateral property), debt-service coverage ratio (DSCR), property location (state, city, zip code, street address), property year built, rentable area (sqft), total number of units, building type, number of stories, senior housing indicator, etc. As we can

[5] The loan characteristics data contain information about all loans that have been acquired by Fannie Mae, no matter whether they are current. So, loans that have been paid off or defaulted are included.

see from Table 1, there are 120,659 records for 106,175 loans and 119,615 properties.[6] As a comparison, the NCREIF data we have contains information for 77,190 multifamily properties.

The operating statement data include yearly or quarterly operating statements for Fannie Mae properties. Variables contained include loan ID, operating statement date and type, occupancy, potential gross income (PGI), effective gross income (EGI), NOI, DSCR, total operating expenses (OE), utility expenses, property tax and many other details on OE. There are 523,990 statements for 77,291 properties (Table 1). During 1986-1999, only yearly statements are available for all properties, and starting from 2000 quarterly statements are available for some but not all properties (Appendix Table 1). Therefore, we only construct cash flow indices at yearly frequency.

We match the operating statement data and the loan characteristics data by loan ID.[7] Due to data coverage gaps between the two datasets, a number of properties are left out. We further exclude properties that are not in Metropolitan Statistical Areas (MSAs). Appendix Figure 1 is a map with the locations of the Fannie Mae properties.

There are several types of operating statements, including “operating/actual”, “underwriting” and “Fannie Mae reviewed” (Appendix Table 2). Since we want to study the actual performance, we focus on “actual” and “operating” statements and leave out “underwriting” or “Fannie Mae reviewed” statements, which are usually projected statements.[8]

[6] Some loans are secured by multiple properties and a few properties carry multiple loans.
[7] Because of the aforementioned problem of non-unique loan-property match, this will create some outliers that will be excluded by our outlier removal procedure discussed later.
[8] Lenders and Fannie Mae usually apply “haircut” to operating income when conducting underwriting.

We further undertake a number of data cleaning efforts. For example, we exclude properties with value less than $10,000 or per unit square footage less than 500. We filter out apparent data errors and outliers such as those with EGI less than zero and those with per unit PGI less than $100/month or greater than $20,000/month. In addition, when we work with the matched sample methodologies to be explained later, we examine the time series of NOIs and EGIs for each property and exclude those NOI and EGI records that are apparently too high or two low compared to the neighboring year (e.g., plus or minus 50 percent change). Those are most likely due to accounting noise. This procedure will create gaps in the longitudinal NOI/EGI data in addition to those that come with the raw data. However, as we will explain later in section 3, the RMR methodology is designed to deal with such a situation.

In our later analysis, we are mostly concerned with the growth rate of NOI and EGI. Therefore, we further identify paired data across time for the same property, for example, NOI pairs (two operating statements for the same property, see Table 2 for the distributions of starting and ending year). Growth calculated from the NOI pair is the type of change in revenue or income actually experienced by investors, as investors purchase and hold over time individual properties, and mortgage loans are collateralized and serviced by the same property over time for which they are initially issued. But the longitudinally paired operating statements are not necessarily in temporally adjacent or consecutive periods of time (see Table 3). Since there are too few observations before 1993, we exclude pairs that have a current year before 1994 and a starting year before 1993.

Our final sample includes 79,633 NOI and EGI pairs for 21,142 properties. Table 4 shows the descriptive statistics of these properties. The median value of the properties is $4.1 million and the average is $8.5 million. Property median number of units is 79 and the median age is 34 years. Median rentable residential area is 66,661 sqft and the average sqft is 106,840. The average per sqft annual NOI is about $6.8 and the average per sqft annual EGI is about $13.00, suggesting that on average property operating expenses absorb almost half the gross revenue.[9] Interestingly, the average annual NOI and EGI growth rate is as low as 1% (measured as continuously compounded rates or log-differences per year). This suggests that in most of the years NOI/EGI growth did not keep up with inflation.[10]

3. Methodology

3.1. A Brief Review of Real Estate Index Methodologies

Major types of real estate index construction methodology include the hedonic regression, the repeated sales regression and simple average or ratio methods such as the arithmetic mean or median per square foot. Hedonic regressions are powerful for the control of heterogeneous property characteristics in order to obtain value changes of "same quality" properties. They are mostly used for residential real estate where a large number of hedonic factors are usually recorded in the data and the properties are relatively homogeneous compared to income properties (see, e.g., Kain and Quigley, 1970; Rosen, 1974). For commercial real estate, Fisher, Geltner & Pollakowski (2007) apply an appraisal-based hedonic regression to NCREIF data to construct asset price, total return, and liquidity-adjusted reservation price indices. For cash flows, Torto-Wheaton Research (now CBRE Econometric Advisors) uses a regression model similar to

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[9] The NOI reported in FNMA data may have been calculated after reserves for capital items. In other industry reports this would be NCF rather than NOI. This might account for the relatively high expense ratio.

[10] Additional analysis of the operating expenses reveals that operating expenses of Fannie Mae properties in the analysis population grew at an average annual rate of 3.6%. One hypothesis is that it is a characteristic typical of physically older properties, and that Fannie Mae properties tend to be old (as noted, the median age is 34 years). This finding, that same-property NOI growth is less than inflation over the long run, would be reflective of real depreciation in the properties, and is supported by other recent empirical evidence about deprecation in commercial properties, not just in multi-family properties (Bokhari and Geltner, 2014).

the hedonic price regression to produce an index of asking rent (Wheaton, Torto, and Southard, 1997). The biggest challenge for hedonic indices of income property is the problem of omitted or poorly measured hedonic variables.

Repeated sales regression has become a more popular index construction methodology in the past twenty years. In a repeated sales regression, no detailed property characteristics are needed. Instead, the regression relies upon repeated observations of sales (sales pairs) of same properties. The repeated sales method is useful in dealing with infrequent, non-synchronized, and non-random housing transactions (Bailey, Muth, and Nourse, 1963; Case and Shiller, 1987; Calhoun, 1996). For residential real estate, the FHFA (originally OFHEO) House Price Index (HPI) and the Case-Shiller Home Price Index based on repeated sales regression have become authoritative. Geltner and Goetzmann (2000) and Geltner & Pollakowski (2007) apply the repeated sales methodology to commercial real estate and the latter provides the basic methodology for the Moody/REAL Commercial Property Price Index (CPPI) and more recently the Moody's/RCA CPPI and RCA metro market indices. Eichholtz, Straetmans and Theebe, (2012) apply the repeated sales methodology to the Amsterdam rental housing market, and Ambrose, Coulson and Yoshida (2013) apply the same methodology to U.S. rental rates. A drawback of the repeated sales methodology is that it leaves out all the transactions that are not paired (properties only sold once) from the analysis.

Given the complementary benefits of the repeated sales regression and the hedonic regression, researchers have developed hybrid indices based on a combination of the repeated sales method and the hedonic method (see, e.g., Quigley, 1995; England, Quigley, Redfearn, 1999; Cannaday, Munneke and Yang, 2005; Hwang and Quigley, 2010; Deng, McMillen and Sing, 2012).

Arithmetic average is an easy-to-apply method to construct a price index and it is widely used for commercial real estate where consecutive appraisal value or income data are available. The most notable application of the arithmetic average method is the NCREIF Property Index (NPI), which is based on value-weighted averages of individual price returns.[11] Apparently, such indices face the primal problem in the construction of longitudinal indices of changes in the composition of assets: they do not control for differences in the properties providing the data from one period to the next. This sample selection problem tends to be more serious for commercial properties than for single-family homes, due to the smaller sample sizes of income-producing properties and the greater heterogeneity of the properties.

Besides the aforementioned three major types of index methodology, there are other index construction methods studied in the literature. For example, Clapp (2004) applies a semi-parametric method to construct house price index based on GIS data. An, Deng, Fisher and Hu (2012) develop a dynamic panel data model for NCREIF rental income and estimate a rental index. It is noteworthy that the Clapp (2004) method relies heavily on GIS data while the An, Deng, Fisher and Hu (2012) relies on panel data with relatively long time series.

Given that most of the properties in our sample have repeated NOIs and that we lack sufficient hedonic information in our current data, the present study adopts the repeated measures regression (RMR) to construct our performance indices. For comparison purposes, we will also present the arithmetic average methods to construct a benchmark NOI index. We discuss our methodologies in more detail in the following.

[11] Given that a large portion of the NCREIF property value information is from appraisals and appraisal values are usually smoothed, Geltner (1989), Geltner (1991), Fisher, Geltner, and Webb (1994) (and many other studies) focus on the bias of price returns calculated from smoothed appraisal data and on how to unsmooth the appraisal data to construct arithmetic average indexes for commercial real estate.

3.2 Repeated Measures Regression (RMR)

A repeated measures index is based only on assets that provide data at least twice over time. The index is based directly and purely on the percentage *change* (or log difference) in the variable of interest (here NOI) between the earlier and later values of the data. The RMR index is thus based entirely on the actual change experiences of the investors in the market. This is arguably the most relevant measure of interest to investors.

The data consists of repeated observations on the NOI of same properties, i.e. NOI pairs. Define $r_{i,t,s}$ as the total growth in NOI of property i during periods $(t-s,t]$, then

$$r_{i,t,s} = \ln\left(NOI_{i,t}^{sqft} / NOI_{i,t-s}^{sqft}\right), i = 1,\cdots,N; t = s,\cdots,T \ . \qquad (1)$$

The repeated measure regression model is specified as

$$r_{i,t,s} = \sum_{j=1}^{T} \beta_j x_{i,j} + \varepsilon_{i,t,s} \ . \qquad (2)$$

Here we have the first NOI measure at $(t-s)$ and the second measure at time t; $x_{i,j}$ is an indicator variable that takes value of -1 if $j = t-s$, and +1 if $j = t$, and 0, otherwise; and $\varepsilon_{i,t,s}$ is disturbance that follows a normal distribution with zero mean and a variance of σ^2. The RMR NOI index is

$$I_t = \exp\left(\beta_t\right), I_0 = 1, t = 1,\cdots,T \ . \qquad (3)$$

Our benchmark indices include simple average index, weighted average index, and paired average index. With the simple average method, we just compute the average NOI/sqft across all the properties that provide current data each period. For the square footage-weighted average NOI index, we aggregate the levels data each period and then compute an index of the average level of the cash flow (per sqft) each period.

A more sophisticated approach that still uses arithmetic averages without applying statistical regression is to disaggregate the analysis and apply it only to the same properties from one period to the next. Here for an NOI pair that have non-adjacent NOI observations, we are calculating the mean NOI growth and use it as the NOI growth for each and every period of a particular property. Then we calculate the average NOI growth of all properties that provide current data each period.

Notice that if we have a constant pool of properties and we observe property cash flow for each property during each study period, then the simple average, the paired average and the RMR will all provide the same results. However, we know this is not the case in our sample (and likely in any sample).

If all repeated observations are adjacent, the RMR approach is equivalent to the paired average approach. Under other circumstances, the two approaches differ in the following way: in the simple average approach, when there is a non-adjacent NOI pair we simply assume that the NOI growth during each period is the same. However, in the RMR approach, we relax this assumption and acknowledge the fact that the NOI growth during each period of the non-adjacent multiple-periods pair may not be equal. The NOI growth during a certain period is estimated by the RMR and the estimated NOI growth is obviously affected by NOI growth of other pairs in our sample that have time intervals overlapping with the current NOI pair.

3.3 Three-stage RMR

While the RMR is superior to the simple average approach when we have non-adjacent observations, it overlooks potential heteroscedasticity when we include both adjacent and non-adjacent observations in the regression. If NOI follows a random walk, then the variance of the disturbance in equation (2) should be an increasing linear function of s, the time interval between the repeated NOI observations (known as the "span"). The intuition is that, in terms of NOI growth, non-adjacent observations should contain higher noise than adjacent observations. The further away the repeated NOI observations are, the higher the noise is.[12]

Therefore, we allow the variance of the NOI disturbance $\varepsilon_{i,t,s}$ in equation (2) to vary in this application. More concretely, we specify a diffusion process for the variance such that

$$\sigma^2_{i,t,s} = \gamma_1 + \gamma_2 s + \gamma_3 s^2 + \gamma_4 \ln\left(MV_{i,t}\right) + \eta_{i,t,s}, \tag{4}$$

where $MV_{i,t}$ is the value of the property measured at t. The inclusion of this second last term in the above equation is to account for heterogeneous variance in error terms for properties with different values. $\eta_{i,t,s}$ is a white noise.

Following Case and Shiller (1987), we adopt a three-stage estimation approach to estimate the RMR NOI index. In the first stage, we estimate equation (2) by OLS. In the second stage, we estimate the diffusion process of the variance specified by equation (4) by regressing the square term of the residuals from the first stage OLS regression to the number of periods between two measures of NOI as well as the log of appraisal value of the property. In the third stage, we re-estimate equation (2) using a weighted least square (WLS) approach where the weights are the

[12] Here we use the term "noise" for the dispersion of idiosyncratic NOI growth.

reciprocals of the expected variance obtained from the second stage estimation, $\frac{1}{\hat{\sigma}^2_{i,t,s}}$. The intuition of this weighting scheme in the three-stage RMR is that lower weights should be assigned to observations that are less reliable.

4. Results and Findings

4.1 Estimates of the RMR and other indices

We present our estimated annual NOI indices in Figure 1. The blue dash-dot-dot, red dot, green dash, dark dash-dot, and the blue heavy solid lines represent the simple average index, the sqft-weighted average index, the paired average index, the RMR index and the three-stage RMR index, respectively. The indices start from 1993, which is given the arbitrary inception value level of 1.

We notice that these five indices fall into two groups, the simple average index and the weighted average index in one group and the paired average index, the RMR index and the three-stage RMR index in the other group, and that there is a wide difference between the two groups. The simple and weighted average indices show substantially higher growth and volatility than the other three indices.

As we discussed in section 3, a critical problem of the simple average and weighted average methods is that they do not control for differences in the properties providing the data from one period to the next. Table 5 shows the full distribution of per square footage NOI by year. We notice that the number of properties included each year evolves considerably, e.g., in 1993 there were only 83 properties that provide NOI in our sample while in 2008 there were 13,513 properties. We also notice that in the tail of the distribution, those later years see some big NOI properties. From 1999 to 2000, the NOI/sqft at the 99 percentile jumped from $15 to almost $22. These are good indications that the quality of sample properties has changed significantly over time and thus the simple average and weighted average indices are impacted by not controlling for these changes.

In addition, we conduct an experiment where we allow more outliers into our sample and re-estimate the five indices. Here an important issue is that in our matched sample methods (the paired average, the RMR and the three-stage RMR), for the needs of input, we calculate NOI/EGI growth of each property during each period and eliminate those NOI/EGI records that are apparently too high or two low compared to the neighboring year. Therefore, the impact of data errors and outliers is smaller in the matched sample methods. We display the indices estimated before and after introducing outliers side by side in Figure 2. The five indices shown on the left hand side are the same indices in Figure 1 except that we rescale them on the Y-axis so that we can compare them with those shown on the right hand side of Figure 2, the five indices estimated with outliers included. We discover that the simple average and weighted average indices change markedly but the paired sample indices are not affected materially, when we include outliers in the estimation sample.

Interestingly, the three paired sample indices (the paired average, the RMR and three-stage RMR) track each other very closely. In fact, they are almost indistinguishable from the chart (Figure 1). The small difference between these three indices is explained by the high percentage of our NOI pairs that are adjacent as shown in Table 3. As we discussed in section 3.2, when all repeated NOIs are adjacent, the RMR methods collapse to the paired average method. In addition to the charts, we present the three-stage RMR estimation results in Tables 6-8.

Comparing the RMR index with the three-stage RMR index (the dark dash-dot line and the blue heavy solid line in Figure 1), we notice that the difference between the RMR index and the three-stage RMR index does not seem to be economically significant even though the three-stage RMR estimates tend to have a narrower confidence band (Figure 3). In other words, the added benefit of the three-stage WLS is marginal here. This is not a surprise, as we have temporally adjacent repeat observations in almost our entire sample, thus, very short spans and very little dispersion in the spans (Table 3).

Finally, we take a close look at the differences between the paired average index and the RMR indices. From figure 1, we notice that the RMR index is probably the most volatile (comparing to the paired average and three-stage RMR indices). This result is confirmed by a comparison of the volatilities of different NOI indices in Table 9. As discussed earlier, when there are non-adjacent NOI observations, by applying equal growth to each period during the multiple time periods, the paired average index method smoothes NOI growth. Therefore, we need the RMR methodology to correct for that. However, we also notice that the NOI growth from non-adjacent observations is less reliable. Therefore, most likely the paired average index smoothes the true growth, but the RMR over adjust the smoothness of a paired average index. Therefore, we believe the most accurate index is the three-stage RMR index.

4.2 NOI, EGI, and PGI Trends and Volatilities

Based on the three-stage RMR index, we now examine the trend and volatility of NOI. As we can see from Figure 1 (the dark line), NOI is cyclical during the 18-year period in our sample (1993-2011). In the 1990s, the index shows steady NOI growth. That is followed by a significant NOI decrease in early 2000s. During 2005-2008, we see another upward trend in NOI. However, in recent years, the index shows significant NOI decrease during the real estate and financial crisis.

These NOI trends are generally consistent with the commercial real estate space market cycles at a broad national scale, although the big rebound in multifamily property values is not seen in NOI (see appendix Figure 2 for changes in multifamily property value during our study period). In terms of volatility, we notice that the NOI is much less variable than the asset prices, at least if we take RCA or NCREIF as the source of indications about how cyclical the asset prices can be. As shown in the Appendix Figures 2 and 3, the amplitude of the asset price cycle is about +80%/-40% for RCA multifamily properties (based on the RCA CPPI) and about +50%/-30% for NCREIF all commercial properties. The NOI cycle we observe here is only about +30% on the upswing and about -10% on the downswing. Since commercial real estate price is determined by NOI and cap rate, there must be significant variations in cap rate over time that cause the much deeper commercial real estate price cycles. Data in Appendix Figure 4 actually support this hypothesis. A moderate decline in NOI but meanwhile a significant increase in cap rate during 2008-2011 caused a free fall in multifamily property values during this period.

We are also interested in the average NOI growth and volatility of the growth as those two parameters are critical inputs for pro forma analysis and stress testing. In a basic pro forma analysis, we need to assume a certain NOI growth and in the scenario (sensitivity) analysis we need to alter that input based on possible variations (the volatility) in NOI growth. In a stress test, we would need the most distressed scenario to reflect the least NOI growth. That NOI growth number should be based on the average NOI growth and its volatility. The average NOI growth and its volatility of the three-stage RMR index, together with those of the other indices, are reported in Table 9. Based on the three-stage RMR estimates, we see that during 1993-2011 the average log growth in NOI is only about 0.8%, which translates into an average simple growth of 1.8%. This is significantly lower than the simple average estimate of 2.6% simple growth, and much lower than the 3% number that is often observed in pro forma analyses. From this perspective, we contend that investors usually over-estimate NOI growth. It is also worth noting that our result suggests that the average NOI growth rate is significantly lower than the inflation rate, so in real terms same-property NOI tends to decline, at least during our study period. This may largely reflect depreciation in the property structures as they age. The volatility of NOI growth during this period is 1.3% in log growth and 3.1% in simple growth.

Next, we apply the same three-stage RMR methodology to EGI and PGI. PGI is essentially the rental rate, while EGI is PGI minus vacancy and collection loss.[13] In figure 4, we plot the EGI index together with the NOI index. Different from NOI, EGI demonstrates far more consistent and less volatile growth during the 1993-2011 periods. From 1993 to 2011, EGI has a cumulative growth of about 55 percent, in contrast to the 40 percent NOI difference between peak and trough. The average log EGI growth is 1% (2.2% in average simple growth) and the volatility is 0.9% (2% in simple growth).

More interestingly, we see that during the early 2000s while EGI was still growing at a moderate rate, NOI declined significantly during 2001 to 2004. Again during the most recent recession (2008-2010), NOI declined significantly while EGI was stable during the 2008-2010 period. The essential difference between EGI and NOI is just the operating expenses (NOI = EGI – Operating Expenses). If NOI is relatively cyclical and overall growing hardly at all, while EGI is much more stable and steadily growing (albeit perhaps slightly less than inflation), it must be

[13] Here we are mixing new leases with existing leases, and we are looking at same-property changes over time (reflecting depreciation), so PGI does not exactly trace the rental market, and our PGI index is not exactly the same thing as a space market rental price index.

that operating expenses are very cyclical. Especially when we look at the two recessions (early 2000s and the most recent), we see significant growth in operating expenses. This is counterintuitive, as we would expect rental income to be cyclical but operating expenses to be stable. This raises questions about property management. A possible explanation is that management of these properties may be proactive about taking measures (e.g., increased marketing) to reduce the impact of a downturn.

In Figure 5, we plot the PGI index together with the EGI index. Interestingly, we see that EGI growth tends to lead PGI growth and is more sensitive to the overall economic environment. For example, during the 2000-2001 recession, EGI declined but PGI kept on growing until 2002. During the recent recession, the growth in EGI slowed down in 2006 and turned to negative in 2007, but changes in PGI lag this trend. More recently, when EGI started to have a recovery in 20010 PGI continued its sharp decline. These results support the stock-flow model of commercial real estate rental adjustment – vacancy (incorporated in EGI but not in PGI) starts to change before rent (Geltner, et al, 2007).

Finally, we notice that the EGI and PGI growths estimated here conform to the rental growth rate estimated in recent studies by An, Deng, Fisher and Hu (2012) and Ambrose, Coulson and Yoshida (2013) for other market segments.

4.3 The Cross Section of Cash Flow Performance

First, we compare the cash flow performance of Fannie Mae properties with that of the NCREIF properties. For that purpose, we obtain NOI data for NCREIF properties and apply the three-stage RMR method to build NCREIF multifamily NOI indices. NCREIF apartment properties tend to be larger and more upscale compared to Fannie Mae properties.

From a portfolio management perspective, we want to compare the whole portfolio of Fannie Mae properties with the whole portfolio of NCREIF multifamily properties. The first chart in Figure 6 provides such a comparison. There is significant difference in NOI growth between Fannie Mae properties and NCREIF properties: during the 1990s, NCREIF properties outperform Fannie Mae properties; but during the 2000-2001 recession, Fannie Mae properties suffer much less and their decline in NOI happened later than that of NCREIF properties; during the 2003-2006 real estate market boom, NCREIF properties again had stronger NOI growth; but again during the recent crisis, Fannie Mae properties had less severe NOI decline; more recently during 2010-2011, NCREIF properties had a sharp rebound in NOI growth but Fannie Mae properties kept their NOI decline. Overall, the volatility of NOI growth of Fannie Mae properties (1.3%) is significantly smaller than that of NCREIF properties (1.9%). It is important to note that during the two recessions, Fannie Mae properties had better cash flow performance, which we believe helps explain the superior performance of Fannie Mae multifamily loans during the recent crisis.

Certainly we recognize that Fannie Mae properties might be located in different areas than the NCREIF properties. And as noted, NCREIF properties are those held by institutional investors and are usually larger properties and typically more upscale.[14] While the median value of Fannie Mae properties is $4.1 million, it is about $26 million for NCREIF apartments. Therefore, we make another comparison in the second chart of Figure 6, where we only include properties that are more than $9 million and located in the 10 large MSAs (New York, Los Angeles, Chicago, Houston, Atlanta, Boston, Dallas, Washington DC, Minneapolis, and Phoenix). The results suggest that Fannie Mae properties in those areas outperform NCREIF properties in terms of

[14] In general most NCREIF apartment properties would probably not be well characterized as “workforce housing” or “low-income” housing.

NOI growth during almost our whole study period. In terms of volatility, they are almost the same.

In addition to location and size, we also notice that Fannie Mae properties tend to be older. Therefore, we conduct a property level regression analysis to see whether there is remaining difference between Fannie Mae and NCREIF properties after controlling for observable differences such as age, size, location, time, and value per unit. Table 10 presents such regression results. After adding those control variables, there is no statistically significant difference in NOI growth between Fannie Mae and NCREIF properties. This result suggests that the cash flow performance differentials between Fannie Mae properties and the NCREIF properties can be explained by observable characteristics. It could be that the market is segmented, or that Fannie Mae has had stricter underwriting.

From a portfolio management perspective, the overall performance of the whole Fannie Mae portfolio of properties is probably the most important. However, from an economic perspective, we are also interested in the cross section of multifamily cash flow performance.

In many areas in the United States, property supply in the space market is constrained by regulations and/or natural geography. A number of academic studies have found that supply constraints lead to higher level and growth of house prices, as well as elevated house price volatility (see, e.g., Glaeser, Gyourko and Saks, 2005; Paciorek, 2011). Therefore, the first cross-sectional aspect we explore is the comparison of cash flow performance of Fannie Mae properties in some typical supply constrained and non-supply constrained markets. We use the regulation index developed in Malpezzi, Chun and Green (1998) to classify supply constrained and non-supply constrained markets.

The supply constrained metro areas we study include New York, Los Angeles, Seattle, Washington DC and Minneapolis. The non-supply constrained metro areas we study include Houston, Chicago, Baltimore, Portland and Atlanta. The first chart in Figure 7 shows the three-stage RMR NOI indices of these two groups. We see a huge difference in NOI growth in these two groups. Supply-constrained markets see significant NOI growth during our study period. Prior to the recent crisis, there was only a short decline in NOI during 2002-2003 in those supply-constrained markets but there was a much deeper and prolonged decline in NOI during 2001-2005 in non-supply constrained areas. The NOIs in 2011 and in 1996 are almost the same in non-supply constrained areas. These results echo findings regarding house price growth with respect to supply constraints. However, we find no evidence that the volatility of NOI growth is significantly higher in supply-constrained areas (Table 11).

Next, we examine a market segment called “workforce housing”. Workforce housing are usually for "essential workers" in a community i.e. police officers, firemen, teachers, nurses, medical personnel. It is usually not a target of affordable housing policies. Workforce housing is a vital component of the economic and social well-being of the country. Improving our knowledge of the investment performance of workforce housing versus other types of income property investment may help investors to make rational capital allocation decisions and help policy makers to craft wise policies.

There is no clear definition of workforce housing. In this paper, we define it as rental properties affordable to families that are earning 60 to 120 percent of area median income.[15, 16] “Affordable” means that the family will not spend over 30 percent of their income on rent. In order to identify

[15] Workforce housing could be housing for ownership but we are only dealing with rental housing in this study.
[16] We experimented with alternative bandwidth of relative income, e.g, 50 to 100 percent of area median income, and found results below to be consistent.

workforce housing, we match MSA median family income into our main data and calculate the qualifying rental rates. We then compare the per-unit PGI (potential gross income) of each property in our sample to the rental rate thresholds to determine whether it is workforce housing.

Table 12 panel A shows that about 41 percent of Fannie Mae properties are workforce housing, 56 percent are low-income housing and only fewer than 3 percent are high-income housing. This result shows that Fannie Mae has been providing major financial support for workforce housing as well as low-income housing. In the second chart of Figure 7, we plot the three-stage RMR NOI indices for Fannie Mae workforce housing and low-income housing separately.[17] We see that starting from early 2000s, workforce housing performed significantly better than low-income housing as well as the Fannie Mae multifamily population at large. In terms of average growth, NOI of workforce housing grew at 1.2% during 1996-2011, compared to 0.7% for the full sample and 0.6% growth for low-income housing. Also, the volatility of workforce housing NOI growth is significantly larger, 2.8% compared to 1.7% for the full sample and 1.3% for low-income housing (Table 11). The comparative results between workforce housing and low-income housing is not a surprise given the governmental support provided to low-income housing. Low-income housing usually has lower rental rates and rental growth is usually limited by public policies such as "rent control".[18]

We notice that workforce housing has a high concentration in supply-constrained areas (Table 12 panel B). Therefore, part of the difference between workforce housing and low-income housing might be due to the effect of supply constraints. In order to tease out the impact of different factors, we conduct a regression analysis at the property level. Table 13 shows the per-sqft NOI

[17] The number of high-income housing is so small in our sample that we are not able to estimate a separate NOI index for high-income housing.
[18] Results are robust to different cut-off points in the definition of workforce housing.

regression results, while Table 14 shows the NOI growth regression results. Here we include MSA-fixed effects, which control for the impact of supply constraints. Other controls include: whether the property is located in the city center, zip code median family income relative to MSA median, property age less than 5, property age higher than 50, property size below 30 units , above 200 units , and year fixed effects (time-dummies). Results show that after controlling for those other variables, workforce housing has both higher per-sqft NOI and NOI growth than low-income housing. But comparing to high-income housing, workforce housing has both lower per sqft NOI and NOI growth.

We also stratify our sample by property value and estimate NOI indices for different subsamples. In the third chart of Figure 7, we plot the NOI indices of the upper quartile of our sample in terms of property value, i.e., those with values higher than $9 million, and the lower quartile of our sample, i.e., those with values within $2 million. We see significant differences. Specifically, low value properties have outperformed high value properties starting from early 2000s. High value properties have NOI trends more similar to that of the population at large, although the decline of NOI during 2008-2010 is more severe for high value properties. As evidenced in Figure 7, low value properties have significant NOI growth during the 1990s and relatively stable NOI during the recent recession.

We separate properties based on the number of units as well. On the one hand, there might be an economy of scale in property management and thus large properties might enjoy an advantage in operating expenses. On the other hand, there may be fewer turnovers in smaller properties. Large properties are probably more concentrated in larger urban centers and filled with younger more transient renters. Smaller properties may be in smaller cities or suburbs and rented by (possibly) older or less transient renters. One would expect turnover rates to be higher in the larger properties. In Figure 7 the last chart, we plot the three-stage RMR NOI indices for properties with no more than 30 units and those with more than 200 units. We see that small properties outperform large properties consistently during the whole study period. In fact, large properties suffered a significant NOI decrease in the 2001 recession and had a slow recovery during 2005-2008 and then suffered another loss in NOI during the recent recession.[19]

However, again we notice that small properties are much more likely to be located in supply-constrained areas. Therefore, we need to control for that in comparing the NOI growth of small and large properties. This is shown in Tables 13 and 14. We see that both small properties (no more than 30 units) and extra-large properties (more than 200 units) have higher NOI/sqft. However, after controlling for locational differences and differences in other property characteristics, we find both small properties and extra-large properties have smaller NOI growth.[20]

5. Conclusions and Discussions

Monitoring the change in property cash flow is important to commercial real estate investors, lenders and mortgage guarantee providers such as Fannie Mae. To develop an index that reveals what the market trend is and the nature of its cyclicality is fundamental to this practice. In this paper, we construct and compare five indices, the simple average index, the weighted average index, the paired average index, the RMR index, and the three-stage WLS index to measure changes in NOI, EGI and PGI of Fannie Mae properties using a unique dataset of building operating statements from Fannie Mae.

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[19] Results are robust to different cutoffs for defining "large" and "small" properties.

[20] Property value and number of units are highly correlated, so we only include size in number of units in the regressions.

We find that the conventional simple average and weighted average indices contain significant sample selection bias and are subject to big influence of data errors and outliers. In contrast, the RMR indices are much more robust in the presence of data errors and outliers, which is common in commercial real estate accounting (non-transaction) data.

Our three-stage RMR estimate shows an average NOI growth of about 1.8% during 1993-2011, which is lower than inflation rate and significantly lower than what is usually perceived by investors. Multifamily NOI is cyclical. It shows significant upward trend in the 1990s but experienced apparent downturn in the early 2000s. However, comparing to the variation of commercial real estate asset prices as tracked by the major indices, the volatility of NOI is moderate. This suggests that changes in cap rate are more important in driving the ups and downs in asset prices. The EGI index shows a steady upward trend and it is much less volatile than the NOI index. Changes in operating expenses are the main driving factor of the cyclicality of NOI and they tend to be pro-cyclical. EGI growth (decline) also leads PGI growth (decline), which supports the stock-flow model of rental adjustment where vacancy changes before rent.

Our indices reveal that the whole portfolio of Fannie Mae multifamily properties outperforms NCREIF multifamily properties in NOI growth, especially during the 2000-2001 recession and the recent crisis. Our indices and regression analysis also reveal that supply-constrained areas have significantly higher average NOI growth but not higher NOI growth volatility. Workforce housing performs better than low-income housing, even controlling for locational differences. We do not find a size effect once we control for supply constraints.

We believe that the current study demonstrates the feasibility of constructing meaningful NOI, EGI and PGI indices using the repeated measures method. For future research, we could explore the possibility of adopting alternative index construction methodologies, e.g., the hedonic method. One could also further our study of cash flow dynamics based on the indices we develop, e.g., to examine the relation between actual NOI growth and the expected NOI growth implied by market price (cap rate).

References

Ambrose, B., E. Coulson and J. Yoshida. 2013. The Repeat Rent Index. Penn State University Working Paper.

An, Xudong, Yongheng Deng, Joseph B. Nichols, Anthony B. Sanders. 2013. Local Traits and Securitized Commercial Mortgage Default. *Journal of Real Estate Finance and Economics* 47: 787-813.

An, X., Y. Deng, J. D. Fisher and M. R. Hu. 2014. Commercial Real Estate Rental Index: A Dynamic Panel Data Model Estimation. *Real Estate Economics*, forthcoming.

An, Xudong and Anthony B. Sanders. 2010. Default of Commercial Mortgage Loans during the Financial Crisis. SSRN working paper.

Bailey, M. J., Muth, R. F., & Nourse, H. O. 1963. A Regression Method for Real Estate Price Index Construction. *Journal of the American Statistical Association* 58: 933–942.

Bokhari, S., and D. Geltner. 2014. Characteristics of Depreciation in Commercial and Multi-Family Property: An Investment Perspective. *Working Paper*, MIT Center for Real Estate.

Calhoun, C. A. 1996. OFHEO House Price Indexes: HPI Technical Description. Working paper, Office of Federal Housing Enterprise Oversight, Washington, D.C.

Cannaday, R., Munneke, H., Yang, T. 2005. A Multivariate Repeat-Sales Model for Estimatiing House Price Indices. *Journal of Urban Economics* 57: 320-342.

Case, K. E. and R. J. Shiller. 1987. Prices of single-family homes since 1970. *New England Economic Review* 1987: 45–56.

Chegut, Andrea M., Piet M. A. Eichholtz and Paulo Rodrigues. 2013. The London Commercial Property Price Index. *Journal of Real Estate Finance and Economics* 47(4): 588-616.

Clapp, J. 2004. A Semiparametric Method for Estimating Local House Price Indices. *Real Estate Economics* 32(1): 127-160.

Deng, Y., D. P. McMillen and T. F. Sing. 2012. Private Residential price Indices in Singapore: A Matching Approach. *Regional Science and Urban Economics* 42 (3): 485-494.

Eichholtz, Piet, Stepan Straetmans and Marcel Theebe. 2012. The Amsterdam Rent Index: The Housing Market and the Economy, 1550-1850. *Journal of Housing Economics* 21(4): 269-282.

England, P., J. M. Quigley, C. L. Redfearn. 1999. The Choice of Methodology for Computing Housing Price Indexes: Comparisons of Temporal Aggregation and Sample Definition. *Journal of Real Estate Finance and Economics* 19(2), 91-112.

Fisher, J., Geltner, D., and H. Pollakowski. 2007 Quarterly Transactions-Based Index (TBI) of Institutional Real Estate Investment Performance and Movements in Supply and Demand. *Journal of Real Estate Finance and Economics* 34: 5-33.

Fisher, J., Geltner, D., and B. Webb. 1994. Value Indices of Commercial Real Estate: A Comparison of Index Construction Methods. *Journal of Real Estate Finance and Economics* 9: 137-164.

Fisher, J., D. Gatzlaff, D. Geltner, D. Haurin. 2003. Controlling for the Impact of Variable Liquidity in Commercial Real Estate Price Indices. *Real Estate Economics* 31(2), 269-303.

Geltner, D. 1989. Bias in Appraisal-Based Returns. *AREUEA Journal* 17(3): 338-352.

Geltner, D. 1990. Return Risk and Cash Flow Risk with Long-term Riskless Leases in Commercial Real Estate. *AREUEA Journal* 18(4): 377-402.

Geltner, D. 1991. Smoothing in Appraisal-Based Returns. *Journal of Real Estate Finance and Economics* 4(3): 327-345.

Geltner, D. and W. Goetzmann. 2000. Two Decades of Commercial Property Returns: A Repeated-Measures Regression-Based Version of the NCREIF Index. *Journal of Real Estate Finance and Economics* 21(1): 5-21.

Geltner, D., N. Miller, J. Clayton and P. Eichholtz. 2007. *Commercial Real Estate Analysis and Investment* (2nd edition). Cengage Learning, Mason, OH.

Geltner, D. and H. Pollakowski. 2007. A Set of Indexes for Trading Commercial Real Estate Based on the Real Capital Analytics Transaction Prices Database. MIT Center for Real Estate Commercial Real Estate Data Laboratory working paper.

Glaeser, Edward L., Joseph Gyourkoand and Raven Saks. 2005. Why is Manhattan So Expensive? Regulation and the Rise in House Prices. *Journal of Law and Economics* 48 (2): 331–370.

Goldberg, L. and C. A. Capone, Jr. 2002. A Dynamic Double-Trigger Model of Multifamily Mortgage Default. *Real Estate Economics* 30(1): 85-113.

Hwang, M. and J. M. Quigley. 2010. House Price Dynamics in Time and Space: Predictability, Liquidity, and Investor Returns. *Journal of Real Estate Finance and Economics* 41: 3-23.

Kain, J. F. and J. M. Quigley. 1970. Measuring the Value of Housing Quality. *Journal of the American Statistical Association* 65(440): 532-548.

Malpezzi, Stephen, Gregory H. Chun and Richard K. Green. 1998. New Place-to-place Housing Price Indexes for U.S. Metropolitan Areas, and Their Determinants. *Real Estate Economics* 26(2): 235-274.

Quigley, J. M. 1995. A Simple Hybrid Model for Estimating Price Indexes. *Journal of Housing Economics* 4(1): 1-12.

Rosen, S. 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy* 82(1): 34-55.

Shiller, R. J. 1991. Arithmetic Repeat Sales Price Estimators. *Journal of Housing Economics* 1: 110-126.

Wheaton, W. C., R. G. Torto, J. A. Southard. 1997. The CB Commercial/Torto Wheaton Database. *Journal of Real Estate Literature* 5: 59-66.

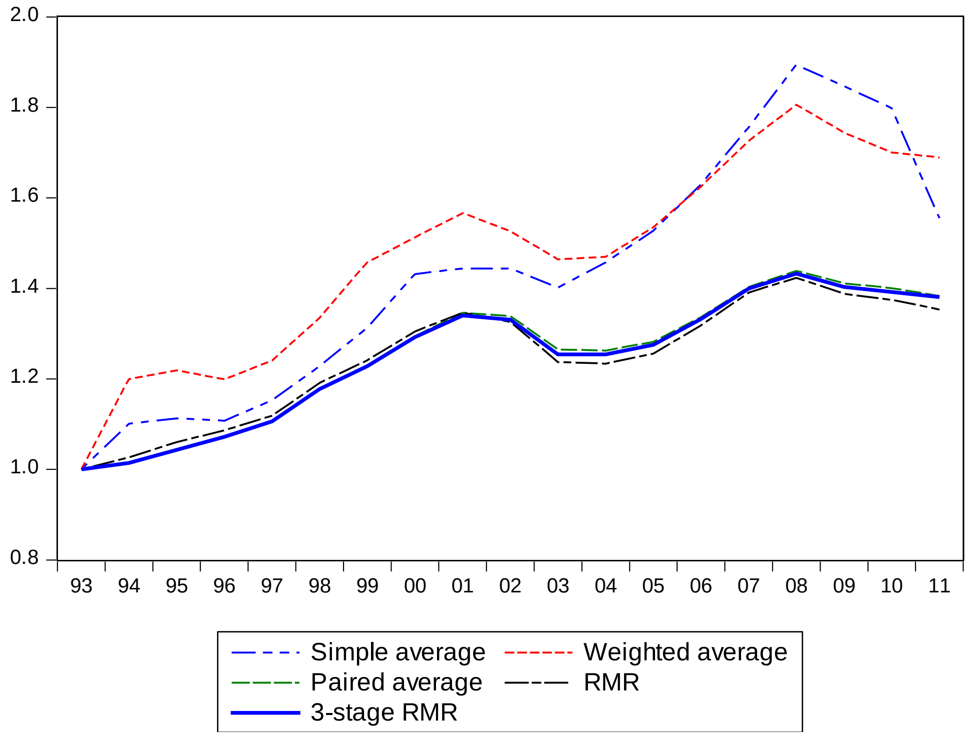


Figure 1 NOI Indices of Fannie Mae Multifamily Properties

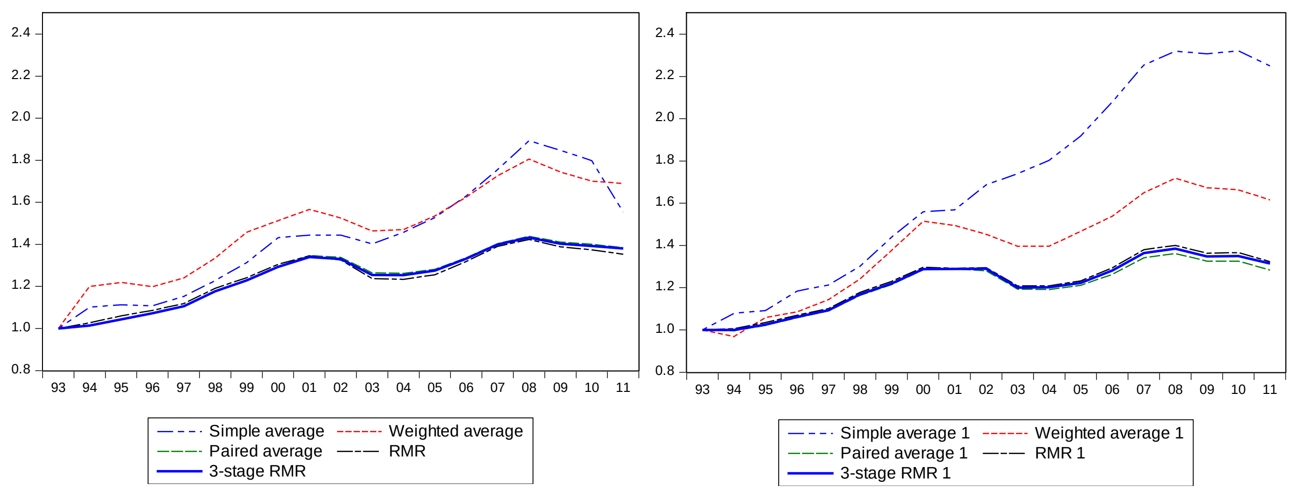


Figure 2 NOI Indices of Fannie Mae Multifamily Properties – Impact of Outliers

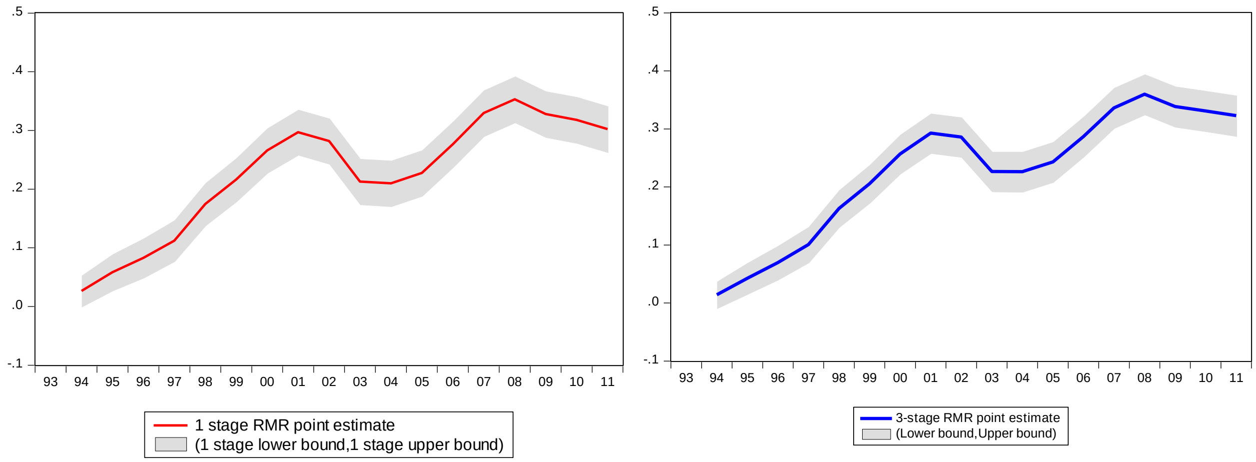


Figure 3 NOI Growth RMR Point Estimate and Confidence Band

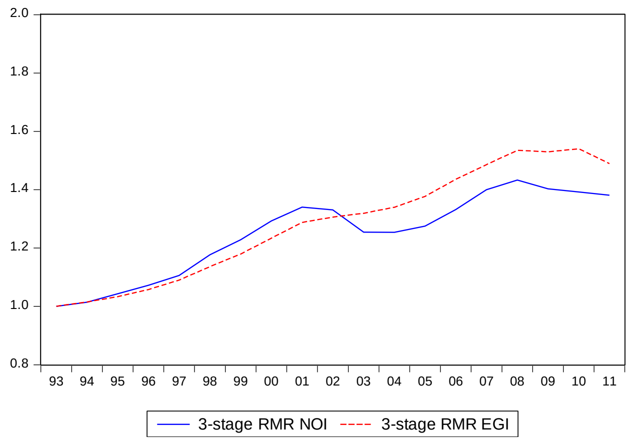


Figure 4 EGI and NOI Indices of Fannie Mae Properties

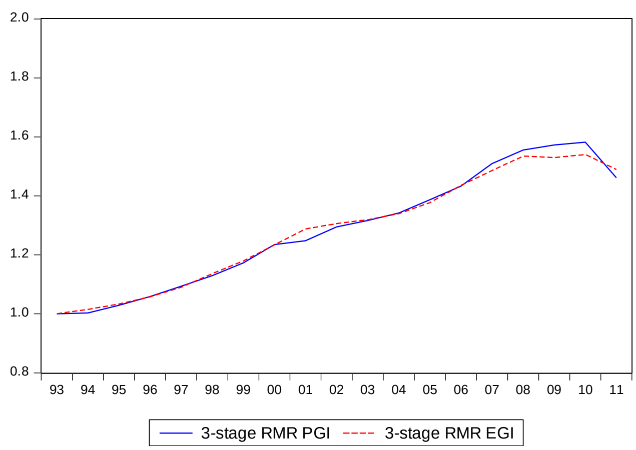


Figure 5 PGI and EGI Indices of Fannie Mae Properties

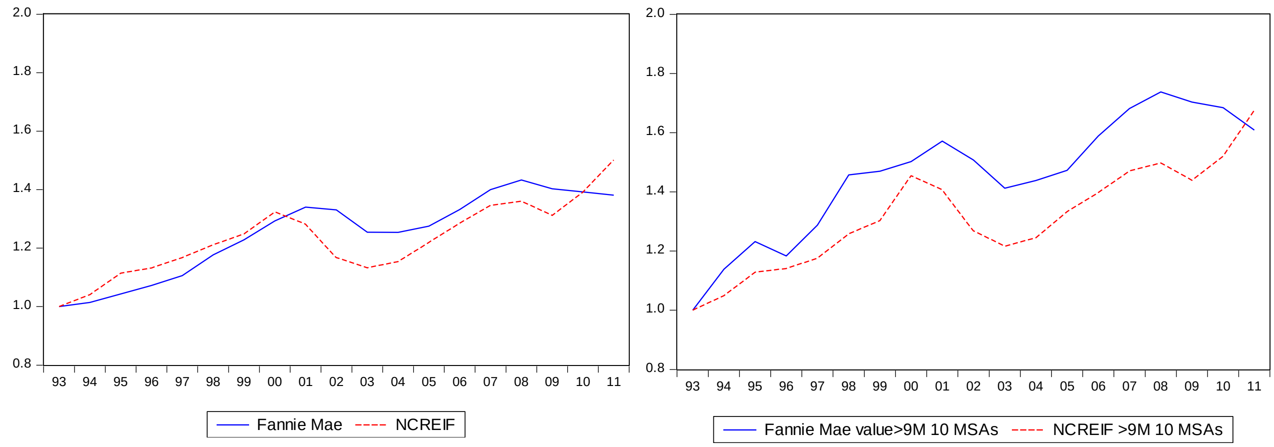


Figure 6 NOI Indices of Fannie Mae and NCREIF Properties

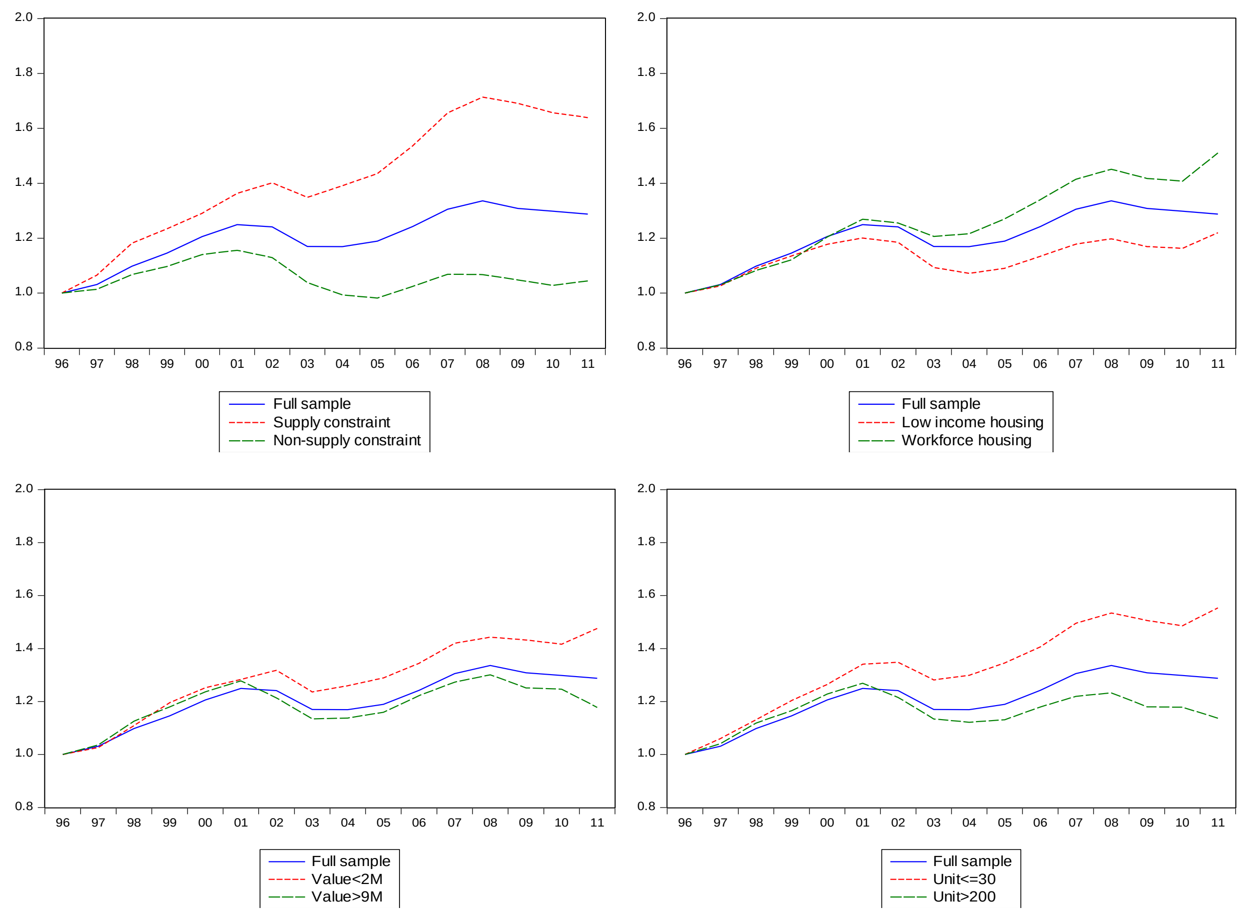
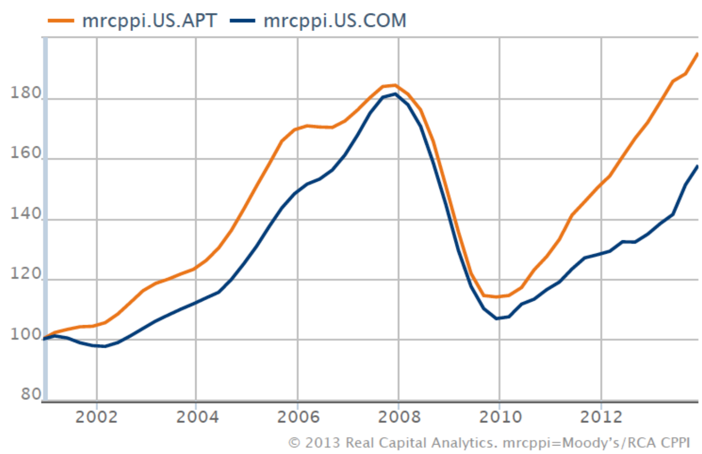


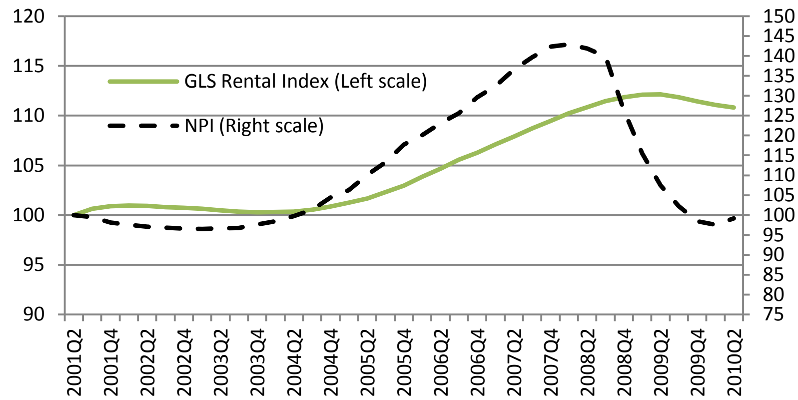
Figure 7 Cross-sectional Comparisons of NOI Index

Note: In the second chart (upper right panel), the full sample includes a third component in addition to low-income housing and workforce housing, which is high-income housing. We don't produce a separate high-income housing NOI index due to the limited number of high-income housing properties in our sample. Supply-constraints are not controlled here or in the bottom two charts.

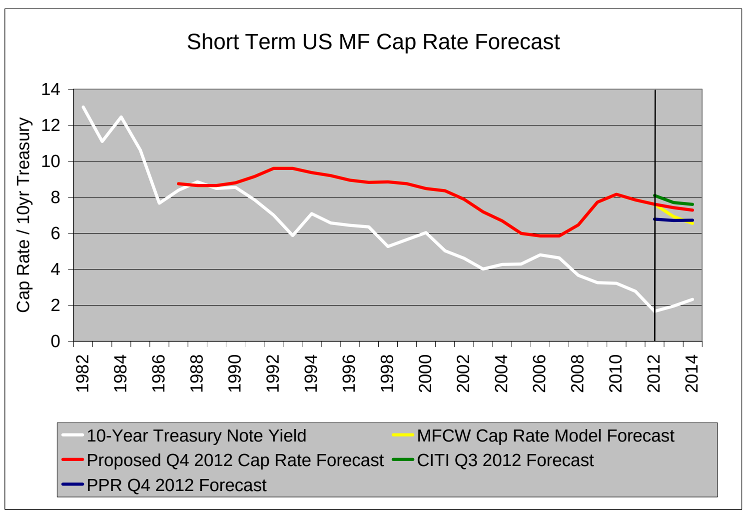
Appendix Figure 1 Geographic Distribution of Fannie Mae Properties



Appendix Figure 2 US Commercial Real Estate and Apartment Price Indices
Source: Real Capital Analytics



Appendix Figure 3 NCREIF Commercial Real Estate Rental Index and NPI
Source: An, Deng, Fisher and Hu (2013)



Appendix Figure 4 US Multifamily Cap Rate
Source: Fannie Mae

Table 1 Descriptive Statistics of the Raw Data

	Variable	N	N Miss	Mean	Std. Dev.	Min	5th Pctl.	Median	95th Pctl.	Max
Property file	**Built year**	98,284	21,331	1,706	664	0	0	1,963	1,999	2,011
	Number of units	116,283	3,332	76	122	1	5	26	300	5,252
	Square footage	72,564	47,051	60,515	131,018	1	3,726	16,337	256,399	9,840,000
	Appraisal amount	75,741	43,874	4,445,149	12,775,125	0	0	1,280,000	17,500,000	1,337,269,838
	N records	120,659								
	N properties	119,615								
	N loans	106,175								
Operating statement file	**EGI**	515,382	8,608	909,074	1,877,086	-387,216	44,730	498,176	2,941,511	659,007,900
	NOI	514,260	9,730	438,555	1,017,030	-3,945,846	2,601	213,910	1,526,032	376,005,700
	N statements	523,990								
	N properties	77,291								

Note: This is from multifamily loans guaranteed by Fannie Mae. The property data and operating statements data come from two separate files. They don't have exactly the same number of properties covered. As shown in Appendix Table 1, the operating statements are available from 1986 to 2012, among which only annual operating statements are available during 1986 and 1999 and the rest are quarterly statements. The purpose of this table is just to show what is available in the raw data. Data cleaning and filtration is conducted before further analysis below.

Table 2 Distributions of the Starting and Ending Year of the NOI Pairs in the Clean Sample

Panel A: First Observation					*Panel B: Second Observation*				
Beg. year	Freq.	Percent	Cum. Freq.	Cum. Percent	End. year	Freq.	Percent	Cum. Freq.	Cum. Percent
1993	77	0.1	77	0.1					
1994	208	0.26	285	0.36	1994	75	0.09	75	0.09
1995	326	0.41	611	0.77	1995	208	0.26	283	0.36
1996	440	0.55	1051	1.32	1996	315	0.4	598	0.75
1997	599	0.75	1650	2.07	1997	434	0.55	1032	1.3
1998	733	0.92	2383	2.99	1998	600	0.75	1632	2.05
1999	733	0.92	3116	3.91	1999	736	0.92	2368	2.97
2000	1494	1.88	4610	5.79	2000	725	0.91	3093	3.88
2001	2830	3.55	7440	9.34	2001	1424	1.79	4517	5.67
2002	4397	5.52	11837	14.86	2002	2719	3.41	7236	9.09
2003	5795	7.28	17632	22.14	2003	4238	5.32	11474	14.41
2004	7283	9.15	24915	31.29	2004	5629	7.07	17103	21.48
2005	7253	9.11	32168	40.4	2005	6921	8.69	24024	30.17
2006	8304	10.43	40472	50.82	2006	7137	8.96	31161	39.13
2007	10799	13.56	51271	64.38	2007	8430	10.59	39591	49.72
2008	12598	15.82	63869	80.2	2008	10505	13.19	50096	62.91
2009	10985	13.79	74854	94	2009	12448	15.63	62544	78.54
2010	4779	6	79633	100	2010	12050	15.13	74594	93.67
2011					2011	5039	6.33	79633	100

Note: After merging the property file and the operating statement file, we have 349,197 operating statements for 70,356 properties. We further exclude non-MSA properties in the analysis, and select only the actual operating statements and exclude underwriting/Fannie Mae reviewed (projected) operating statements. Other filters used include property value greater than $10,000, per unit square footage greater than 500, EGI greater than zero, and per unit PGI greater than $100/month but less than $20,000/month. Also, construction of the NOI pairs requires at least two operating records for each property. There are too few observations before 1993 so we select a starting year of 1993, and those before 1993 are excluded from the analysis.

Table 3 Distribution of the Time Intervals of the NOI Pairs

Time interval (years)	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	74872	94.02	74872	94.02
2	3457	4.34	78329	98.36
3	850	1.07	79179	99.43
4	253	0.32	79432	99.75
5	121	0.15	79553	99.9
6	61	0.08	79614	99.98
7	18	0.02	79632	100
8	1	0	79633	100

Note: The time interval is the span in years between the prior and the next subsequent NOIs for the same property. All data merging, cleaning and filtration noted in Table 2 are applied here.

Table 4 Descriptive Statistics of the NOI Pairs

	Variable	**N**	**Mean**	**Std. Dev.**	**Lower quartile**	**Median**	**Upper quartile**
Properties	Age (years)	20,349	39	27	19	34	49
	Number of units	21,142	123	139	32	79	172
	Square footage	21,142	106,840	125,462	26,670	66,661	146,765
	Appraisal value ($)	21,142	8,452,785	15,787,992	2,032,000	4,136,000	9,000,000
NOI Pairs	Beginning NOI/sqft•year	79,633	6.77	4.99	3.63	5.39	8.60
	Ending NOI/sqft•year	79,633	6.83	5.05	3.64	5.43	8.75
	Log Average Annual NOI Growth	79,633	0.01	0.20	-0.07	0.01	0.09
	Log Average Annual EGI Growth	79,633	0.01	0.11	-0.01	0.02	0.05

Note: This is after all data merging, cleaning and filtration noted in Table 2. The 79,633 NOI pairs are for the 21,142 properties included in the table.

Table 5 Distribution of Per Square Footage NOI by Year

Year	N Obs	Mean	1st Pctl	5th Pctl	Median	95th Pctl	99th Pctl
1993	82	4.12	1.39	1.88	3.78	7.01	11.75
1994	210	4.53	1.74	2.35	4.17	7.71	10.19
1995	328	4.58	1.72	2.36	4.18	8.14	9.58
1996	445	4.56	1.38	2.16	4.09	8.57	11.33
1997	616	4.74	1.49	2.18	4.15	9.46	12.64
1998	778	5.05	1.54	2.25	4.49	10.05	13.11
1999	799	5.41	1.66	2.30	4.67	11.00	15.09
2000	1647	5.89	1.32	2.14	4.90	12.48	21.61
2001	2947	5.94	1.03	2.01	4.89	13.19	22.23
2002	4717	5.94	1.14	1.98	4.97	12.60	18.75
2003	6301	5.77	0.88	1.79	4.78	12.46	19.61
2004	8126	6.00	0.90	1.82	4.92	13.05	21.44
2005	8532	6.29	0.96	1.82	5.10	13.80	23.59
2006	9282	6.71	0.95	1.93	5.45	14.85	25.10
2007	11439	7.23	1.03	1.93	5.74	16.55	28.27
2008	13513	7.79	1.18	2.05	6.26	17.68	29.24
2009	12930	7.60	1.08	2.03	6.13	17.01	27.59
2010	13083	7.40	0.91	1.74	5.90	16.76	27.51
2011	5041	6.40	0.75	1.56	4.90	15.39	29.41

Table 6 OLS Estimates of the RMR Regression

Dependent variable: Log NOI growth

Variable	Parameter Estimate	Standard Error
yyyy1994	0.027	0.027
yyyy1995	0.058*	0.031
yyyy1996	0.083***	0.033
yyyy1997	0.112***	0.035
yyyy1998	0.175***	0.036
yyyy1999	0.216***	0.037
yyyy2000	0.266***	0.038
yyyy2001	0.297***	0.038
yyyy2002	0.282***	0.039
yyyy2003	0.213***	0.039
yyyy2004	0.210***	0.039
yyyy2005	0.228***	0.039
yyyy2006	0.277***	0.039
yyyy2007	0.330***	0.039
yyyy2008	0.353***	0.039
yyyy2009	0.328***	0.039
yyyy2010	0.318***	0.039
yyyy2011	0.302***	0.039
N	79,633	
Adjusted R-Square	0.0233	

Note: * for p<0.1; ** for p<0.5 and *** for p<0.01. Based on the full sample documented in Table 4.

Table 7 The Second Stage Results of the 3-stage RMR Regression

Dependent variable: Square term of the residual from the first stage regression shown in Table 5

Variable	Parameter Estimate	Standard Error
Intercept	-0.508***	0.062
Time interval	0.218***	0.011
Time interval square	-0.006***	0.002
Log property value	0.010***	0.001
Age of the property	0.005***	0.001
N	79,633	
Adjusted R-Square	0.0385	

Table 8 The Third Stage Results of the 3-stage RMR Regression

Dependent variable: Log NOI growth

Variable	Parameter Estimate	Standard Error
yyyy1994	0.014	0.023
yyyy1995	0.042	0.027
yyyy1996	0.070***	0.029
yyyy1997	0.101***	0.031
yyyy1998	0.163***	0.032
yyyy1999	0.206***	0.033
yyyy2000	0.257***	0.034
yyyy2001	0.293***	0.034
yyyy2002	0.286***	0.034
yyyy2003	0.227***	0.034
yyyy2004	0.226***	0.034
yyyy2005	0.243***	0.035
yyyy2006	0.287***	0.035
yyyy2007	0.336***	0.035
yyyy2008	0.360***	0.035
yyyy2009	0.339***	0.035
yyyy2010	0.331***	0.035
yyyy2011	0.323***	0.035
N	79,633	
Adjusted R-Square	0.0220	

Note: * for p<0.1; ** for p<0.5 and *** for p<0.01. This is the GLS results. Weight, which is the predicted error term from the second stage regression shown in Table 7, is used in the GLS.

Table 9 Means and Volatilities of the Five Indices

	Simple average	Weighted average	Paired average	RMR	3-stage RMR
Log growth mean	1.1%	1.3%	0.8%	0.7%	0.8%
Simple growth mean	2.5%	3.0%	1.8%	1.7%	1.8%
Standard deviation (of log growth)	2.6%	2.4%	1.3%	1.5%	1.3%

Note: Log growth is defined as $log\left(\frac{S_t}{S_{t-1}}\right)$, and simple growth is defined as $\frac{S_t}{S_{t-1}} - 1$. The standard deviation (of log growth) shown here is the longitudinal standard deviation, which is the volatility.

Table 10 NOI Growth Regression – Comparing Fannie Mae Properties with NCREIF Properties

Dependent variable: Average log NOI growth (annual)

Variable	Parameter	Standard Error
Fannie Mae property	0.008	0.007
Value per unit	-0.006***	0.002
Property age <5	-0.000	0.007
Property age > 50	0.009**	0.005
Unit<=30	-0.009**	0.004
Unit>200	0.003	0.006
MSA-fixed effect	Yes	
Year-fixed effect	Yes	
N	297,733	
Adjusted R-Square	0.0319	

Note: * for p<0.1; ** for p<0.5 and *** for p<0.01.

Table 11 Means and Volatilities of the Three-stage RMR Index of Different Sub-samples

	Supply-constrained	Non-supply constrained	Workforce housing	Low income housing	Small properties	Large properties
Log growth	1.4%	0.4%	0.9%	0.7%	1.1%	0.7%
Simple growth	3.4%	1.0%	2.1%	1.6%	2.6%	1.6%
Standard deviation (of log growth)	1.9%	1.8%	1.8%	1.5%	1.5%	1.8%

Note: The standard deviation (of log growth) shown here is the longitudinal standard deviation, which is the volatility.

Table 12 Cross-tabulation of Fannie Mae Properties

Panel A Property categorization

Type	Frequency	Percent	Cumulative Frequency	Cumulative Percent
Low-income housing	44757	56.2	44757	56.2
Workforce housing	32580	40.91	77337	97.12
High-income housing	2296	2.88	79633	100

Panel B Cross-tabulation of Fannie Mae Properties

Table of workforce housing by supply-constrained indicator			
Workforce housing	Supply-constrained		
	0	1	Total
0	4560	10737	15297
	14.24	33.52	47.75
	29.81	70.19	
	77.72	41.03	
1	1307	15429	16736
	4.08	48.17	52.25
	7.81	92.19	
	22.28	58.97	
Total	5867	26166	32033
	18.32	81.68	100

Note: Frequency, percentage, row percentage and column percentage are shown here.

Table C Cross-tabulation of Fannie Mae Properties

Table of small property by supply-constrained indicator			
Unit<30	Supply-constrained		
	0	1	Total
0	5484	17629	23113
	17.12	55.03	72.15
	23.73	76.27	
	93.47	67.37	
1	383	8537	8920
	1.2	26.65	27.85
	4.29	95.71	
	6.53	32.63	
Total	5867	26166	32033
	18.32	81.68	100

Note: Frequency, percentage, row percentage and column percentage are shown here.

Table 13 NOI Level Regression

Dependent variable: Per Square Footage NOI

Variable	Parameter	Standard Error
Central city	0.542***	0.023
Zip median income to MSA median	0.734***	0.024
Property age <5	0.172***	0.041
Property age > 50	-0.353***	0.023
Unit<=30	1.029***	0.028
Unit>200	0.119***	0.025
Workforce housing	2.733***	0.024
High income housing	8.761***	0.073
MSA-fixed effect	Yes	
Year-fixed effect	Yes	
N	79,633	
Adjusted R-Square	0.5653	

Note: * for p<0.1; ** for p<0.5 and *** for p<0.01.

Table 14 NOI Growth Regression

Dependent variable: Average log NOI growth (annual)

Variable	Parameter	Standard Error
Central city	-0.004**	0.002
Zip median income to MSA median	-0.010***	0.002
Property age <5	-0.002	0.003
Property age > 50	0.011***	0.002
Unit<=30	-0.007***	0.002
Unit>200	-0.007***	0.002
Workforce housing	0.021***	0.002
High income housing	0.032***	0.005
MSA-fixed effect	Yes	
Year-fixed effect	Yes	
N	79,633	
Adjusted R-Square	0.0373	

Note: * for p<0.1; ** for p<0.5 and *** for p<0.01.

Appendix Table 1 Months When Operating Statements are Available in the Raw Data

Year and month	Freq.	Percent	Cum. Percent
198612	4	0	0
198712	8	0	0
198812	10	0	0
198912	35	0.01	0.01
199012	37	0.01	0.02
199112	31	0.01	0.02
199212	71	0.01	0.04
199312	1032	0.2	0.23
199412	1226	0.23	0.47
199512	1832	0.35	0.82
199612	4200	0.8	1.62
199712	5218	1	2.62
199812	7781	1.48	4.1
199912	9708	1.85	5.95
200003	5	0	5.95
200006	12	0	5.96
200009	18	0	5.96
200012	10769	2.06	8.01
200103	86	0.02	8.03
200106	88	0.02	8.05
200109	102	0.02	8.07
200112	13092	2.5	10.57
200203	127	0.02	10.59
200206	149	0.03	10.62
200209	171	0.03	10.65
200212	17352	3.31	13.96
200303	228	0.04	14.01
200306	241	0.05	14.05
200309	249	0.05	14.1
200312	21721	4.15	18.25
200403	3203	0.61	18.86
200406	4193	0.8	19.66
200409	5853	1.12	20.77
200412	23575	4.5	25.27
200503	5367	1.02	26.3
200506	6488	1.24	27.54
200509	6617	1.26	28.8
200512	24113	4.6	33.4
200603	6395	1.22	34.62

200606	6657	1.27	35.89
200609	7101	1.36	37.25
200612	30800	5.88	43.12
200703	5918	1.13	44.25
200706	6356	1.21	45.47
200709	6304	1.2	46.67
200712	27196	5.19	51.86
200803	6512	1.24	53.1
200806	6866	1.31	54.41
200809	6963	1.33	55.74
200812	33621	6.42	62.16
200903	7066	1.35	63.51
200906	7250	1.38	64.89
200909	14159	2.7	67.59
200912	33839	6.46	74.05
201003	13634	2.6	76.65
201006	15856	3.03	79.68
201009	16166	3.09	82.76
201012	36558	6.98	89.74
201103	15932	3.04	92.78
201106	16427	3.13	95.92
201109	16367	3.12	99.04
201112	4981	0.95	99.99
201212	54	0.01	100

Note: This table includes all operating statement available in the raw data. Non-MSA properties are included in this table.

Appendix Table 2 Types of Operating Statements in the Raw Data

	Frequency	Percent
Underwriting	59,703	17.84
Actual/Operating	274,874	82.15
Fannie Mae reviewed	35	0.01
Other	22	0.01
Total	334,634	100