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

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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)

**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%, in contrast to the 0.8 and 0.3% default rate of Fannie Mae and Freddie Mac multifamily loans, respectively (An and Sanders 2010). 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% but it reached as high as 70% during 2009. In 2011, Fannie Mae provided $24.4 billion in financing for nearly 423,000 multifamily housing units, most of which are “workforce housing”. 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

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1. Here default is defined as 60+ day delinquency.
2. “An overview of Fannie Mae’s multifamily mortgage business.” Fannie Mae, May 1, 2012.
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. 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 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 et al. 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

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.
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. 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 limited (Wheaton et al. 1997; Eichholtz et al. 2012; An et al. 2014; and Ambrose et al. 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 "Methodology" section, we explain our choice of index methodologies; in "Results and Findings" section, we report our findings; we present "Conclusions and Discussions" in a final section.

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.

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 see from Table 1, there are 120,659 records for

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4 See, e.g., Bailey et al. 1963; Kain and Quigley 1970; Rosen 1974; Case and Shiller 1987; Shiller 1991; Geltner 1989; Geltner 1991; Fisher et al. 1994; Quigley 1995; Calhoun 1996; England et al. 1999; Geltner and Goetzmann 2000; Fisher et al. 2003; Cannaday et al. 2005; Fisher et al. 2007; Geltner and Pollakowski 2007; Hwang and Quigley 2010; Deng et al. 2012; Chegut et al. 2013; and many others.

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.
### Table 1  Descriptive statistics of the raw data

|                    | 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  |         |         |          |      |          |        |           |       |

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 16, 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.
106,175 loans and 119,615 properties. 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 16). Therefore, we only construct cash flow indices at yearly frequency.

We match the operating statement data and the loan characteristics data by loan ID. 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 Fig. 8 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 17). 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.

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 too low compared to the neighboring year (e.g., plus or minus 50 % 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 "Methodology" section, 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

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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.
Table 2  Distributions of the starting and ending year of the NOI pairs in the clean sample

| Beg. year | Freq. | Percent | Cum. Freq. | Cum. Percent |
|-----------|-------|---------|------------|-------------|
| 1993      | 77    | 0.1     | 77         | 0.1         |
| 1994      | 208   | 0.26    | 285        | 0.36        |
| 1995      | 326   | 0.41    | 611        | 0.77        |
| 1996      | 440   | 0.55    | 1051       | 1.32        |
| 1997      | 599   | 0.75    | 1650       | 2.07        |
| 1998      | 733   | 0.92    | 2383       | 2.99        |
| 1999      | 733   | 0.92    | 3116       | 3.91        |
| 2000      | 1494  | 1.88    | 4610       | 5.79        |
| 2001      | 2830  | 3.55    | 7440       | 9.34        |
| 2002      | 4397  | 5.52    | 11837      | 14.86       |
| 2003      | 5795  | 7.28    | 17632      | 22.14       |
| 2004      | 7283  | 9.15    | 24915      | 31.29       |
| 2005      | 7253  | 9.15    | 31268      | 40.4        |
| 2006      | 8304  | 10.43   | 40472      | 50.82       |
| 2007      | 10799 | 13.56   | 51271      | 64.38       |
| 2008      | 12598 | 15.82   | 63869      | 80.2        |
| 2009      | 10985 | 13.79   | 74854      | 94          |
| 2010      | 4779  | 6       | 79633      | 100         |
| 2011      | 5039  | 6.33    | 79633      | 100         |

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.

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...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. 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

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 depreciation in commercial properties, not just in multi-family properties (Bokhari and Geltner 2014).
Methodology

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 et al. (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 the hedonic price regression to produce an index of asking rent (Wheaton et al. 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 20 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 et al. 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 and 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 et al. (2012) apply the repeated sales methodology to the Amsterdam rental housing market, and Ambrose et al. (2013) apply the same methodology to U.S. rental rates. A drawback of the repeated sales

| 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                |

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.
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 et al. 1999; Cannaday et al. 2005; Hwang and Quigley 2010; Deng et al. 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.\(^\text{11}\) 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 et al. (2014) 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 et al. (2014) 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

\(^\text{11}\) 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 et al. (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.

### 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           |

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.

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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.

**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 \( r_{i,t,s} \), \( t, s \) as the total growth in NOI of property \( i \) during periods \( (t-s, t] \), then

\[
 r_{i,t,s} = \ln\left(\frac{NOI_{i,t}^{sqft}}{NOI_{i,t-s}^{sqft}}\right), \quad i = 1, \ldots, N; t = s, \ldots, T.
\]  

The repeated measure regression model is specified as

\[
 r_{i,t,s} = \sum_{j=1}^{T} \beta_j x_{i,j} + \varepsilon_{i,t,s}.
\]  

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 \( \sigma^2 \). The RMR NOI index is

\[
 I_t = \exp(\beta_t), \quad I_0 = 1, \quad t = 1, \ldots, T.
\]

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.

**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 Eq. (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 Eq. (2) to vary in this application. More concretely, we specify a diffusion process for the variance such that

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

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 Eq. (2) by OLS. In the second stage, we estimate the diffusion process of the variance specified by Eq. (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 Eq. (2) using a weighted least square (WLS) approach where the weights are the reciprocals of the expected variance obtained from the second stage estimation, $\frac{1}{\sigma^2_{i,t,s}}$. The intuition of this weighting scheme in the three-stage RMR is that lower weights should be assigned to observations that are less reliable.

**Results and Findings**

**Estimates of the RMR and Other Indices**

We present our estimated annual NOI indices in Fig. 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.

\(^{12}\) Here we use the term “noise” for the dispersion of idiosyncratic NOI growth.
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 "Methodology" section, 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 Fig. 2. The five indices shown on the left hand side are the same indices in Fig. 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 Fig. 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 (Fig. 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 "Repeated Measures Regression (RMR)" section, 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, 7 and 8.

| 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 | 8352  | 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     |

Fig. 2 NOI indices of Fannie Mae multifamily properties – impact of outliers
Comparing the RMR index with the three-stage RMR index (the dark dash-dot line and the blue heavy solid line in Fig. 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 (Fig. 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

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          |                |

*p<0.1; **p<0.05; ***p<0.01. Based on the full sample documented in Table 4

Comparing the RMR index with the three-stage RMR index (the dark dash-dot line and the blue heavy solid line in Fig. 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 (Fig. 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

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             |                |
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 Fig. 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

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          |               |

*p<0.1; **p<0.5; ***p<0.01. This is the GLS results. Weight, which is the predicted value from the second stage regression shown in Table 7, is used in the GLS.

Fig. 3 NOI growth RMR point estimate and confidence band
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.

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 Fig. 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 Fig. 9 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 Figs. 9 and 10, 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 Fig. 11 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

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

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{Index} & \text{Simple average} & \text{Weighted average} & \text{Paired average} & \text{RMR} & \text{3-stage RMR} \\
\hline
\text{Log growth mean} & 1.1 \% & 1.3 \% & 0.8 \% & 0.7 \% & 0.8 \% \\
\text{Simple growth mean} & 2.5 \% & 3.0 \% & 1.8 \% & 1.7 \% & 1.8 \% \\
\text{Standard deviation} & 2.6 \% & 2.4 \% & 1.3 \% & 1.5 \% & 1.3 \% \\
\text{(of log growth)} & & & & & \\
\hline
\end{array}
\]
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. In Fig. 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 %, in contrast to the 40 % 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 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 Fig. 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 2010 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).

\[13\] 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.
Finally, we notice that the EGI and PGI growths estimated here conform to the rental growth rate estimated in recent studies by An et al. (2014) and Ambrose et al. (2013) for other market segments.

**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 Fig. 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. 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 Fig. 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 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 et al. 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 areas.
and non-supply constrained markets. We use the regulation index developed in Malpezzi et al. (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 Fig. 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

**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    |                |

*p<0.1; **p<0.5; *** for p<0.01
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% of area median income.\textsuperscript{15,16} “Affordable” means that the family will not spend over 30% of their income on rent. In order to identify 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% of Fannie Mae properties are workforce housing, 56% are low-income housing and only fewer than 3% 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 Fig. 7, we plot the three-stage RMR NOI indices for Fannie Mae workforce housing and low-income housing separately.\textsuperscript{17} We see that starting from early 2000s, workforce housing

\textsuperscript{15} Workforce housing could be housing for ownership but we are only dealing with rental housing in this study.

\textsuperscript{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.

\textsuperscript{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.
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”.\textsuperscript{18}

We notice that workforce housing has a high concentration in supply-constrained areas (Table 13 (panel B and C). 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 14 shows the per-sqft NOI regression results, while Table 15 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 Fig. 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 Fig. 7, low value properties have significant NOI growth during the 1990s and relatively stable NOI during the recent recession.

\textsuperscript{18} Results are robust to different cut-off points in the definition of workforce housing.
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 Fig. 7

| 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                |

Table 12 Categorization of Fannie Mae properties

Table 13 Cross-tabulation of Fannie Mae properties

| Workforce housing | Supply-constrained | Total |
|-------------------|--------------------|-------|
| 0                 | 4560               | 15297 |
|                   | 10737              |       |
|                    | 47.75              |       |
| 0                  | 14.24              | 47.75 |
|                   | 33.52              |       |
|                    | 29.81              | 70.19 |
|                    | 77.72              |       |
| 1                  | 1307               | 16736 |
|                   | 15429              |       |
|                    | 77.72              |       |
| 1                  | 4.08               | 52.25 |
|                   | 48.17              |       |
|                    | 7.81               | 92.19 |
|                    | 92.19              |       |
|                    | 22.28              | 58.97 |
|                    | 58.97              |       |
| Total              | 5867               | 32033 |
|                   | 26166              |       |
|                   | 100                |       |

| Unit<30 | Supply-constrained | Total |
|---------|--------------------|-------|
| 0       | 5484               | 23113 |
|         | 17629              |       |
|         | 72.15              |       |
| 0       | 17.12              | 72.15 |
|         | 55.03              |       |
|         | 23.73              | 67.37 |
|         | 76.27              |       |
| 1       | 93.47              |       |
|         | 67.37              |       |
| 1       | 383                | 8920  |
|         | 8537               |       |
| 1       | 1.2                | 27.85 |
|         | 26.65              |       |
|         | 4.29               | 95.71 |
|         | 95.71              |       |
|         | 6.53               | 32.63 |
|         | 32.63              |       |
| Total   | 5867               | 32033 |
|         | 26166              |       |
|         | 100                |       |

Frequency, percentage, row percentage and column percentage are shown here
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.\footnote{Results are robust to different cutoffs for defining “large” and “small” properties.}

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\,14 and
15. 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 control-
ling for locational differences and differences in other property characteristics,
we find both small properties and extra-large properties have smaller NOI
growth.\footnote{Property value and number of units are highly correlated, so we only include size in number of units in the
regressions.}

\textbf{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

\begin{table}
\centering
\caption{NOI level regression. Dependent variable: per square footage NOI}
\begin{tabular}{lcc}
\hline
Variable & Parameter & Standard error \\
\hline
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 & \\
\hline
\end{tabular}
\end{table}

*p<0.1; **p<0.5; *** for p<0.01
Fannie Mae properties using a unique dataset of building operating statements from Fannie Mae.

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 cyclicity 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

Table 15  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    |                |

*p<0.1; **p<0.5; ***p<0.01
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).

Appendix

Fig. 8 Geographic distribution of Fannie Mae properties

Fig. 9 US Commercial real estate and apartment price indices. Source: Real capital analytics
Fig. 10  NCREIF commercial real estate rental index and NPI. Source: An et al. (2014)

Fig. 11  US multifamily cap rate. Source: Fannie Mae
Table 16  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        |
Table 16 (continued)

| Year and month | Freq. | Percent | Cum. percent |
|----------------|-------|---------|--------------|
| 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          |

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

Table 17 Types of operating statements in the raw data

| Types of operating statements | 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     |
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