

THE REPEAT RENT INDEX

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Abstract—We employ a weighted repeat rent estimator to construct quarterly indexes that expand the profession's ability to make cross-sectional comparisons of housing markets. Our analysis shows that there is considerable heterogeneity in the behavior of rents across cities over the 2000–2010 decade, but the number of cities and years for which nominal rents fell is substantial; rents fell in many cities following the onset of the housing crisis in 2007; and the repeat rent and Bureau of Labor Statistics indexes differ due to sampling and construction methods.

I. Introduction

STUDIES of real estate markets have long been hampered by the lack of reliable information on the flow price of housing. In contrast to the voluminous information on constant-quality real estate sale prices (from, e.g., the Federal Housing Finance Administration), comparable indexes for rents have not been available. The only widely available data come from the Bureau of Labor Statistics (BLS), which compiles household survey data to construct rental indexes. The BLS constructs rent indexes from these surveys for the nation, the Census regions, and a limited number of metropolitan areas.

The BLS rent series is practically the only data source for information on the flow price of housing services. As a result, it often appears in various housing studies. For example, Dougherty and Order (1982) and Bajari, Benkard, and Krainer (2005) use rental indexes as proxies for the price of housing service flows in common user-costs models. In another example, Sinai and Souleles (2005) rely on rent indexes to demonstrate that home ownership is an effective hedge for anticipated housing rent increases. Furthermore, rent indexes lie at the heart of the growing literature examining house price bubbles (McCarthy & Peach, 2004; Himmelberg, Mayer, & Sinai, 2005; Campbell & Shiller, 1988, 2005; Brunnermeier & Julliard, 2008; and Campbell et al., 2009; and many others.) Thus, to the extent that the BLS rent index fails to adequately capture changes in housing service flow prices, new data that track residential rents could have important impacts in a number of areas.

This research rectifies that data lacuna in three ways. First, we eschew surveys of existing renters in favor of using only newly signed lease contracts. Such contracts are, by that fact, more reflective of current market conditions than are surveys of renters in the middle of leases; moreover, we use

only leases that are signed by new tenants in order to avoid possible tenure biases. Second, we employ a weighted repeat rent estimator that replicates for the rental market, as closely as possible, the weighted repeat sales estimator of Calhoun (1996), following Case and Shiller (1989) and Bailey, Muth, and Nourse (1963).¹ This method of estimating house price indexes has become standard, primarily because of its use by the Federal Housing Finance Agency (FHFA) in constructing the widely used repeat sales indexes for housing for every MSA in the United States; constructing a similar estimator for rents would seem a fitting addition. Third, we are able to construct quarterly indexes for a larger number of cities than are available for the BLS, thus expanding the profession's ability to make cross-sectional comparisons of housing markets, particularly in conjunction with FHA data.

In the next section, we describe our raw data, which consist of observations on rent contracts collected by Experian RentBureau, as well as detail the conversion of these data into repeat rent observations. In section III, we review the standard regression models that facilitate the creation of repeat sales (and now rent) indexes and compare this to the methods that the BLS uses.

In section IV, we present our findings. First, we present the rent indexes for a large number of cities and describe in general terms their behavior over the past decade. Second, we provide explicit comparisons between our repeat rent index and the BLS index for eleven large metropolitan areas and compare the behavior of our repeat rent index to the BLS index. Our first general conclusion is that there is considerable heterogeneity in the behavior of rents across cities over the 2000–2010 decade, but the number of cities and years for which nominal rents fell is substantial. Second, rents fell more, or rose more slowly, over the decade than would be inferred from the BLS data. In particular we find that rents fell in many cities following the onset of the housing crisis in 2007. This is not usually observed in the BLS. Third, repeat rent indexes (RRI) are more volatile than the BLS indexes. And finally, the BLS lags the repeat rent index by two to four quarters. Granger causality tests on that account indicate that RRI Granger-causes the BLS index. The last two conclusions follow directly from the differences in sampling methods and index construction. These differences are attributable to the differences in sampling methodology; we contrast our methodology, which uses only new contracts with new tenants, as raw material for the index construction, with the BLS, which surveys households about their current rent and thus is not reflective of current market conditions.

In section V, we perform two robustness checks. The first simulates the BLS methodology using our data; we find that

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¹ Eichholtz, Straetmans, and Theebe (2012) employ a similar repeat rent estimation method to construct an Amsterdam rental index for the period from 1550 to 1850.

the indexes produced by this simulation are much closer to BLS indexes than our own. The second controls for temporal changes in the Experian RentBureau sample and confirms that our results do not suffer from changes in unit quality over time due to the introduction of new properties to the data set. These results provide evidence that the differences in the two indexes are not the result of the different sample collected by Experian RentBureau but due to the BLS reliance on surveys. Section VI concludes.

II. Data

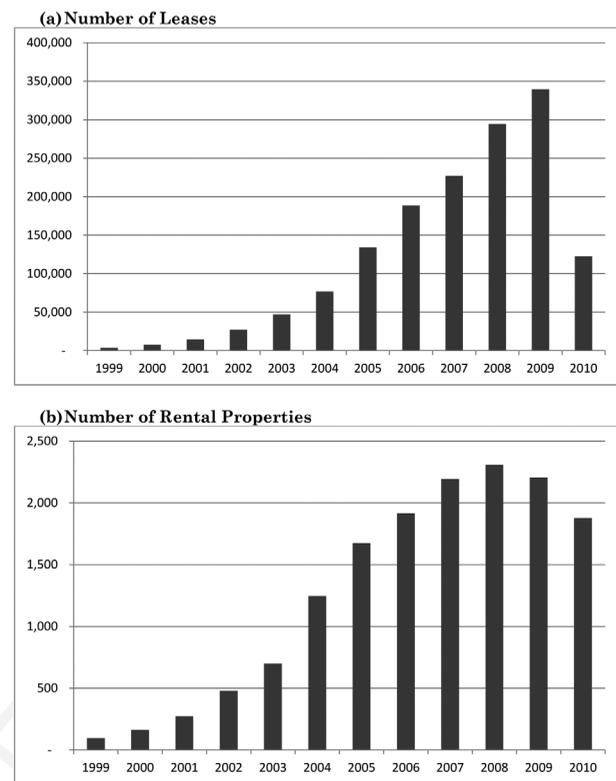
We use the residential rent transaction data compiled by Experian RentBureau for the period from January 1998 to December 2010. RentBureau maintains a national database on tenant rental payment performance collected from property management companies. The database contains lease characteristics (lease start date, lease termination date, renter move-in date, renter move-out date, last transaction date) and property location (city, state, and postal-code). To maintain privacy, limited information is disclosed on specific property locations and individual renters. The company updates lease records every month, noting whether rent was paid on time, the type of payment delinquency, and if applicable, the accrued number of late payments, along with any write-off on rental or nonrental payments due. Over time, RentBureau expanded its geographic coverage, adding new properties and locations to the database.²

Rent payments for each lease, whether active or closed, are recorded in a 24-digit vector representing the renter's payment performance over the previous 24 months from the month of reporting or the month the lease ended. Each position in the payment vector contains one of six codes indicating the status of that month's payment: on time, late, bounced check, outstanding balance, write-off of rent, and write-off of nonrent. Since RentBureau maintains only a 24-month payment record for each lease, lease payment records are left censored. The rental data were last updated in November 2010, the last month of reporting. We restrict our analysis to lease observations with rent payments greater than \$100 per month.

In addition to the 24-month vector of rental payment performance, each lease observation also reports the monthly rent for that lease. This rent value is the monthly rent at the start of the individual tenant's tenancy in that unit. Since RentBureau maintains a unique identification number for each rental unit in each property, we are able to create a time series of monthly rents on the same apartment units by linking observations by the unit identification number and using information about the lease start and end dates as well as the tenant's move-in and move-out dates. Since the majority of residential leases are twelve-month contracts, the ability to link apartment units using the unique unit identification

² See Ambrose and Diop (2014), who are the first to use the RentBureau data in a study of tenant rental defaults, for a more complete description of the RentBureau data.

FIGURE 1.—DISTRIBUTION OF LEASES AND RENTAL PROPERTIES BY YEAR



number allows us to create a rent series holding unit quality constant.

Our final data filter is to eliminate leases where the same tenant is renewing a lease. This is to avoid the sitting or tenure discount (or perhaps premium) that is available to renewing tenants (Genesove, 2003; Goodman & Kawai, 1985; Guasch & Marshall, 1987; Hubert, 1995; Kanemoto, 1990; Raess & von Ungern-Sternberg, 2002). We do this by comparing the move-in date and the date of the first rental payment. For new tenants, this first payment is normally at the time of the signing of the rental contract and before the tenant physically takes possession of the unit, whereas for renewed leases, the tenant has (except under quite unusual circumstances) already moved in; this comparison discriminates between new and renewed leases, so we eliminate the latter from the sample.

After applying the above filters and removing observations with missing or incorrectly coded data (e.g., rents less than \$100 per month, move-in dates after 2010, or incorrectly coded unit ID numbers), the data set contains information on over 1.4 million individual lease contracts originated for 551,126 individual residential units in 2,934 multifamily properties (or complexes). On average, the database contains 2.7 lease contracts per individual apartment unit. Figure 1 shows the frequency distribution of the leases and rental properties per year. The yearly frequency count of leases in panel a reveals how RentBureau significantly expanded its lease tracking activity during the previous decade. For

TABLE 1.—DISTRIBUTION OF LEASES ACROSS STATES

State	Lease Contracts		Individual Units		Apartment Complexes		Average	
	Number	Percent of Total	Number	Percent of Total	Number	Percent of Total	Lease per Unit	Unit per Complex
Alabama	8,639	0.6%	4,191	0.8%	22	0.7%	2.1	191
Arkansas	4,820	0.3%	1,166	0.2%	6	0.2%	4.1	194
Arizona	151,710	10.2%	63,502	11.5%	336	11.5%	2.4	189
California	173,135	11.7%	61,886	11.2%	454	15.5%	2.8	136
Colorado	48,916	3.3%	18,107	3.3%	78	2.7%	2.7	232
Connecticut	1,706	0.1%	681	0.1%	8	0.3%	2.5	85
District of Columbia	2,940	0.2%	928	0.2%	4	0.1%	3.2	232
Florida	215,510	14.5%	72,694	13.2%	338	11.5%	3.0	215
Georgia	217,440	14.7%	82,293	14.9%	406	13.8%	2.6	203
Iowa	4,885	0.3%	1,749	0.3%	14	0.5%	2.8	125
Idaho	2,214	0.1%	771	0.1%	4	0.1%	2.9	193
Illinois	11,240	0.8%	4,669	0.8%	25	0.9%	2.4	187
Indiana	9,386	0.6%	3,592	0.7%	17	0.6%	2.6	211
Kansas	5,210	0.4%	1,266	0.2%	6	0.2%	4.1	211
Kentucky	6,876	0.5%	2,230	0.4%	10	0.3%	3.1	223
Louisiana	4,437	0.3%	1,824	0.3%	9	0.3%	2.4	203
Massachusetts	8,313	0.6%	3,272	0.6%	20	0.7%	2.5	164
Maryland	7,655	0.5%	3,032	0.6%	24	0.8%	2.5	126
Maine	197	0.0%	85	0.0%	1	0.0%	2.3	85
Michigan	21,958	1.5%	6,980	1.3%	47	1.6%	3.1	149
Minnesota	3,577	0.2%	1,100	0.2%	8	0.3%	3.3	138
Missouri	2,005	0.1%	550	0.1%	7	0.2%	3.6	79
Mississippi	3,812	0.3%	1,629	0.3%	12	0.4%	2.3	136
North Carolina	58,614	4.0%	22,372	4.1%	108	3.7%	2.6	207
Nebraska	3,770	0.3%	1,233	0.2%	10	0.3%	3.1	123
New Hampshire	1,478	0.1%	495	0.1%	2	0.1%	3.0	248
New Jersey	85	0.0%	62	0.0%	1	0.0%	1.4	62
Nevada	22,446	1.5%	7,795	1.4%	40	1.4%	2.9	195
New York	6,466	0.4%	2,754	0.5%	20	0.7%	2.3	138
Ohio	19,179	1.3%	5,442	1.0%	30	1.0%	3.5	181
Oklahoma	17,166	1.2%	5,237	1.0%	27	0.9%	3.3	194
Oregon	14,710	1.0%	4,604	0.8%	22	0.7%	3.2	209
Pennsylvania	76	0.0%	66	0.0%	5	0.2%	1.2	13
South Carolina	31,174	2.1%	11,730	2.1%	83	2.8%	2.7	141
Tennessee	38,325	2.6%	14,072	2.6%	66	2.2%	2.7	213
Texas	255,685	17.2%	103,166	18.7%	491	16.7%	2.5	210
Utah	6,019	0.4%	2,852	0.5%	13	0.4%	2.1	219
Virginia	42,701	2.9%	13,650	2.5%	58	2.0%	3.1	235
Washington	47,714	3.2%	17,175	3.1%	100	3.4%	2.8	172
Wisconsin	901	0.1%	224	0.0%	2	0.1%	4.0	112
Total	1,483,090	100.0%	551,126	100.0%	2,934	100.0%	2.7	169

example, RentBureau reported payment transaction data on 7,586 leases in 2000 and had expanded to 339,443 leases by 2009. Panel b reports the number of individual rental properties underlying the lease records. Again, we see a dramatic increase over time in the number of properties reporting to RentBureau. Table 1 reports the distribution of leases across states. The top five states represented in the data are Texas (17%), Georgia (15%), Florida (15%), California (12%), and Arizona (10%). Together, these five states account for approximately 69% of all the leases in the data set.

In the analysis that follows, we compare our repeat rent index to the BLS rental index for eleven large metropolitan areas. Thus, table 2 reports the distribution of lease contracts across the MSAs that match with the markets covered by the BLS. We note that the RentBureau data contain information on 518,381 leases in the BLS markets, which represents approximately 35% of the national data set. Not surprising, since RentBureau began operations in the South, Atlanta has

the largest representation in the database. Over the period from 2000 to 2010, RentBureau contains information on 170,046 lease contracts on 66,945 apartment units in Atlanta. This represents approximately 2.5 lease contracts per unit over the sample period. Furthermore, the 66,945 units are located in 326 different apartment complexes across the city. Other major markets with over 10,000 leases in the database are Dallas, Houston, Los Angeles, Miami, San Francisco, Seattle, and Washington, DC. Interestingly, San Francisco has the highest average number of leases per unit (3.1), with 18,225 leases on 5,803 units in 48 complexes. Of the BLS markets, Detroit has the fewest number of leases (4,967), with an average of 2.2 leases per unit.

III. Methods

The repeat rent index is a quality-constant measure of rent changes in a particular market over time. In constructing this

TABLE 2.—DISTRIBUTION OF LEASES ACROSS THE MAJOR MSAs

MSA	Lease Contracts		Individual Units		Apartment Complexes		Average	
	Number	Percent of Total	Number	Percent of Total	Number	Percent of Total	Lease per Unit	Unit per Complex
Atlanta	170,046	32.8%	66,945	32.5%	326	29.4%	2.5	205
Boston	6,624	1.3%	2,579	1.3%	16	1.4%	2.6	161
Dallas	94,400	18.2%	39,786	19.3%	190	17.2%	2.4	209
Detroit	4,967	1.0%	2,237	1.1%	19	1.7%	2.2	118
Houston	91,928	17.7%	39,683	19.3%	186	16.8%	2.3	213
Los Angeles	33,296	6.4%	13,055	6.3%	145	13.1%	2.6	90
Miami	20,361	3.9%	7,096	3.4%	27	2.4%	2.9	263
New York	6,330	1.2%	2,675	1.3%	19	1.7%	2.4	141
San Francisco	18,225	3.5%	5,803	2.8%	48	4.3%	3.1	121
Seattle	43,488	8.4%	15,634	7.6%	89	8.0%	2.8	176
Washington	28,716	5.5%	10,561	5.1%	42	3.8%	2.7	251
Total	518,381	100.0%	206,054	100.0%	1,107	100.0%	2.5	177

index, we look to methods established for similar quality-constant indexes in the residential sales market. The obvious problem in both markets is that simple averages of transaction prices in each time period do not account for the changing (presumably rising) quality of the transacted units, and so will presumably overstate the rate of price increase. One could use these transacted units in the construction of an index if the quality of the units, as embodied by the characteristics of these units, was controlled for. The most common method of doing this is through hedonic regressions. With a database of transactions, their dates, and their characteristics, consider a regression of the form

$$\log P_{it} = \beta_0 + X_i\beta + \gamma_2 T_2 + \cdots + \gamma_N T_N + \varepsilon_{it} \quad (1)$$

where P_{it} is the price of the i th housing unit at time t , X_i is a row vector of housing characteristics for the i th unit, and β is a column vector of regression coefficient and characteristic weights. $T_j, j = 1, \dots, N$ are binary variables that equal 1 if the transaction took place during time period j , and γ_j are the associated coefficients.³ The error term ε_{it} is assumed to be a random walk plus noise (Case & Shiller, 1989). By virtue of including X in the regression, the γ_j terms represent the incremental value of transactions taking place in period j , holding quality constant.⁴

A major difficulty is that not all of the quality measures may be recorded in the data because some of the X s are unobserved. This can cause difficulties since the bias that arises in regression models when there are omitted variables can be severe. However, as Bailey et al. (1963), pointed out, one can net out the effects of those omitted variables when differences (rates of change, to be precise) are considered. So taking the difference in the predicted transaction prices from time periods s and t results in

$$\log P_{it} - \log P_{is} = \gamma_t T_t - \gamma_s T_s + \varepsilon_{it} - \varepsilon_{is}. \quad (2)$$

Thus, the rate of change (over $t - s$ periods) is a function only of the time periods involved (and the change in the “noise”) and not due to any quality variable (whether observed or unobserved). So, by constructing a data set comprising of sales (or rents) of properties for which there are at least two observations, we can reformulate the model into the repeat sales regression (Bailey et al., 1963):

$$\log P_{it} - \log P_{is} = \gamma_2 D_2 + \cdots + \gamma_N D_N + \varepsilon_{it} - \varepsilon_{is} \quad (3)$$

where

$D_t = 1$ if the second sale in the pair took place
at time period t ,

$D_t = -1$ if the first sale in the pair took place
at time period t .

By using log prices on the right-hand side, the parameters represent percentage differences in prices from the base year. Note that the index for that base year is 0 (since all $D_i = 0$).

Case and Shiller (1989) popularized this method of estimating house price indexes; however, they noted that the error term in equation (3) is very likely heteroskedastic due to differences in the gap between transactions. Calhoun (1996) suggests the following three-stage procedure: first, estimate equation (3) using OLS; second, regress the squared residuals from that equation on $(t - s)$ and $(t - s)^2$ and collect the fitted values; and third, use the inverse of the square roots of those fitted values as weights in a weighted least squares regression of equation (3). The resulting γ s form the weighted repeat sales index. We directly apply these methods. Instead of prices, we use contract rents evaluated at the time of lease signing to construct (weighted) repeat rent indexes.

Some authors have objected to the use of repeat sales on the general grounds that changes in the X or β vector are not accounted for (Case & Quigley, 1991; McMillen & Thorsnes, 2006). Such changes are not accounted for in the FHFA indexes, and we do not do so here; the RentBureau

³For convenience, we include an intercept term and omit one of the T variables from the equation. Without loss of generality, we choose T_1 for that role.

⁴One can interpret the intercept as representing the price of housing in the first period and the sequence γ_2 through γ_N as a constant-quality price index for housing for respective time periods.

database does not contain structural characteristics in any case. A more serious and specific objection to repeat sales indexes is that properties that appear more than once in a transactions database are by that fact systematically different from the database as a whole. In a hot market, a property with multiple transactions might be the result of rapid renovation and quick sale, that is, “flipping” (Meese & Wallace, 1997). This sort of objection has far less force in the rental market. Most obvious, renters cannot flip. A related point is that rents, unlike sales, are observed at regular intervals, so that sample selection per se is not an issue. However, a major difference between our data and the BLS survey is that we specifically identify new lessees and use only new contract rents as the raw material for our indexes. We argue that this is an important difference and that we are explicitly using a selected sample, but that this is precisely the reason that our index construction, for many purposes, is to be preferred over that of the BLS.

The BLS rent index is, as noted, constructed using surveys of renting households. Actually, BLS publishes both a rent index and an owners’ equivalent-rent index. The latter measures rental rates of owner-occupied housing units and so is not particularly germane to our inquiry here. Verbrugge and Poole (2010) discuss the differences between the two and their recent divergence. The BLS compiles six panels of households, each of which is surveyed every six months on a rotating basis (e.g., panel 1 is surveyed in January and July, panel 2 in February and August).⁵ To simplify for the moment, assume just one such panel exists. An index for this panel alone is constructed from the percentage change of the aggregate rents of the panel. That is, the rent index at time t is

$$\delta_t = \delta_{t-6} \left[\frac{\sum_i \omega_i R_{it}}{\sum_i \omega_i R_{it-6}} \right]^{\frac{1}{6}}, \quad (4)$$

where ω_i is the weight attached to the i th unit to allow the sample of units to be representative of the population. Thus, given some base value for the first time period (just as in the repeat sales method), the rate of price increase is calculated as the rate of increase in the weighted sum of rents for the entire panel.

As noted above, there are six panels, so, monthly data are available, and the updating each month is based on the previous month’s index (albeit from a different panel):

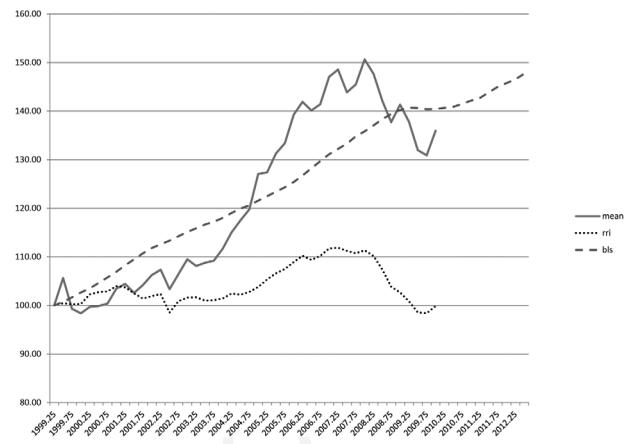
$$\delta_t = \delta_{t-1} \left[\frac{\sum_i \omega_i R_{it}}{\sum_i \omega_i R_{it-6}} \right]^{\frac{1}{6}}. \quad (5)$$

Thus, the BLS method also uses repeated observations on the same units to construct its index, and both BLS and our RRI take advantage of the fact that rents are more regularly observed than are prices.⁶ However, the sampling meth-

⁵ See U.S. Bureau of Labor Statistics (2007) for details on the BLS method.

⁶ Thus while the form of the BLS index is similar to that of a chain index, the regularity of its sampling makes it more immune to the criticism of chain indexes in Bailey et al. (1963).

FIGURE 2.—NATIONAL REPEAT RENT AND BLS INDEXES



ods that BLS use indicate two differences between the two indexes.

First and most important, our method reflects current market conditions. If all leases are annual, only 1/12th of the BLS sample will reflect market conditions and some rents will reflect market conditions that are (nearly) a year old. Our use of rents from leases at the beginning of the rental contract ensures that the data used in the construction of our indexes will reflect the contemporaneous market conditions and suggests further that in times of market change, the RRI will lead the BLS index, since the BLS reflects only the conditions at time t at some future time period (depending on the distribution of renewal months.)

Second, the BLS method smooths over the rental index. Verbrugge (2008) discusses this in the context of the discrepancy in volatility between the estimated user cost of housing and the BLS index. As he explains, there is implicit and explicit smoothing in the BLS index due to temporal aggregations. The implicit smoothing occurs because the index is an average of all leases, newly renewed leases and previously renewed ones. The explicit smoothing occurs because the BLS index is constructed from overlapping semiannual growth rates and is often calculated from the same units under the same rental contract in a previous survey. As a result, the volatility of the BLS index underrepresents the actual volatility of rental prices.⁷

IV. Results

Figure 2 shows the aggregate national repeat rent index and the national BLS rent index. In addition, for comparison, it also shows the mean rent prevailing on leases in our data set. The BLS index indicates that national rents increased throughout the sample period with a brief pause in

⁷ Two other distinctions are worth noting. First, the BLS constructs an arithmetic index, as opposed to a multiplicative one (Shiller, 1991). This difference is somewhat artificial, as one can be converted to the other with appropriate reweighting. Second, the BLS is a real-time index, whereas the RRI is regression based; as new data are added and the regression reestimated, the entire index could be slightly changed.

2009. According to the BLS index, national housing costs (as approximated by aggregate rents) increased on average 3.1% per year between 1999 and 2010. In contrast, the national repeat rent index (RRI) indicates that rents were mostly constant during the first half of the sample period (1999–2004), increasing 2.8% in total or 0.48% per year, and actually ended 0.1% lower in 2010 than in 1999.

A simple analysis of correlations between the respective indexes confirms that the RRI and BLS do not move together. For example, over the full sample period (1999–2010), the simple correlation coefficient between the quarterly change in the BLS and RRI indexes is 13%. However, over the period prior to the financial crisis, the simple correlation coefficient was –4%. We confirmed the simple correlations by estimating the following regression of the change in indexes,

$$\begin{aligned} \Delta RRI_t = & \alpha + \beta_1 \Delta BLS_t + \beta_2 Crisis + \beta_3 Crisis \\ & \times \Delta BLS_t + \varepsilon_t, \end{aligned} \quad (6)$$

where ΔRRI_t and ΔBLS_t represent the quarterly change in the RRI and BLS indexes, respectively, and *Crisis* is a dummy variable equal to 1 during the period of the financial crisis (2007–2010) and 0 otherwise. The estimated coefficients are statistically insignificant, confirming our visual analysis that the RRI and BLS series do not track each other.

Figure 3 compares the repeat rent index (RRI) with the BLS rent index and the sample average rent for the eleven comparison MSAs. All of the indexes are normalized to 100 for the first time period for which the RRI can be constructed for that MSA. The eleven panels are presented in ascending order of the average standard errors of the RRI index. A few observations are immediately evident.

First, and somewhat surprising, the mean rent does not always rise at a higher rate than the indexes. The point of controlling for quality (through whatever method one chooses) is that unobserved quality improvements over time will cause the mean rent index to rise even when there is no change in the constant quality rental rates. In this sample, it is often the case that mean rent increases are less than index changes. While in some sense this blunts the need for quality-controlling indexes, it is also reassuring that our repeat sales indexes are perhaps not subject to the critique of Clapp and Giaccotto (1998), Case and Quigley (1991), and McMillen and Thorsnes (2006) in that unobserved renovation biases repeat sales indexes upward. Second, unlike the BLS, the RRI exhibits a sharp decline after 2007 in most cities. This is of interest because it contradicts, at least partially, one story about the financial crisis, which is that rent price ratios after 2007 were climbing, thus making owner occupation a better financial decision (Yglesias, 2012). Third, and related to the previous two points, the average growth rate of the RRI is lower than that of the BLS index. Fourth, the RRI is, on visual inspection, more volatile than the BLS index. Fifth, the RRI tends to lead the BLS index roughly by one year. We provide statistical evidence on these last three points shortly.

As an example, in Dallas (figure 3a), the RRI shows small twin peaks in the first quarters of 2001 and 2002, and the BLS index exhibits twin peaks in the second quarters of 2002 and 2003. The RRI hit the bottom in the first quarter of 2004, and the BLS index hit the bottom in the second quarter of 2005. After four years of an upward trend, the RRI started to decrease in the second quarter of 2008, and the BLS index started to decrease in the fourth quarter of 2009. The recent decline is sharper in the RRI than in the BLS.

Similarly, in Seattle (figure 3b), the RRI marked a peak in the first quarter of 2008 after five years of steady appreciation, and the BLS index marked a peak in the first quarter of 2009. The RRI fell sharply until reaching a bottom in the third quarter of 2009. The BLS slightly decreased until reaching a bottom in the third quarter of 2010.

In Atlanta (figure 3c), the RRI reached a peak in the second quarter of 2001, and the BLS index reached a peak in the second quarter of 2002. The RRI bottomed in the fourth quarter of 2003, and the BLS index bottomed in the first quarter of 2005. The rent appreciation in the RRI continued for three years but ended around the second quarter of 2007. The appreciation in the BLS index ended around the first quarter of 2008. Both indexes exhibit declines thereafter.

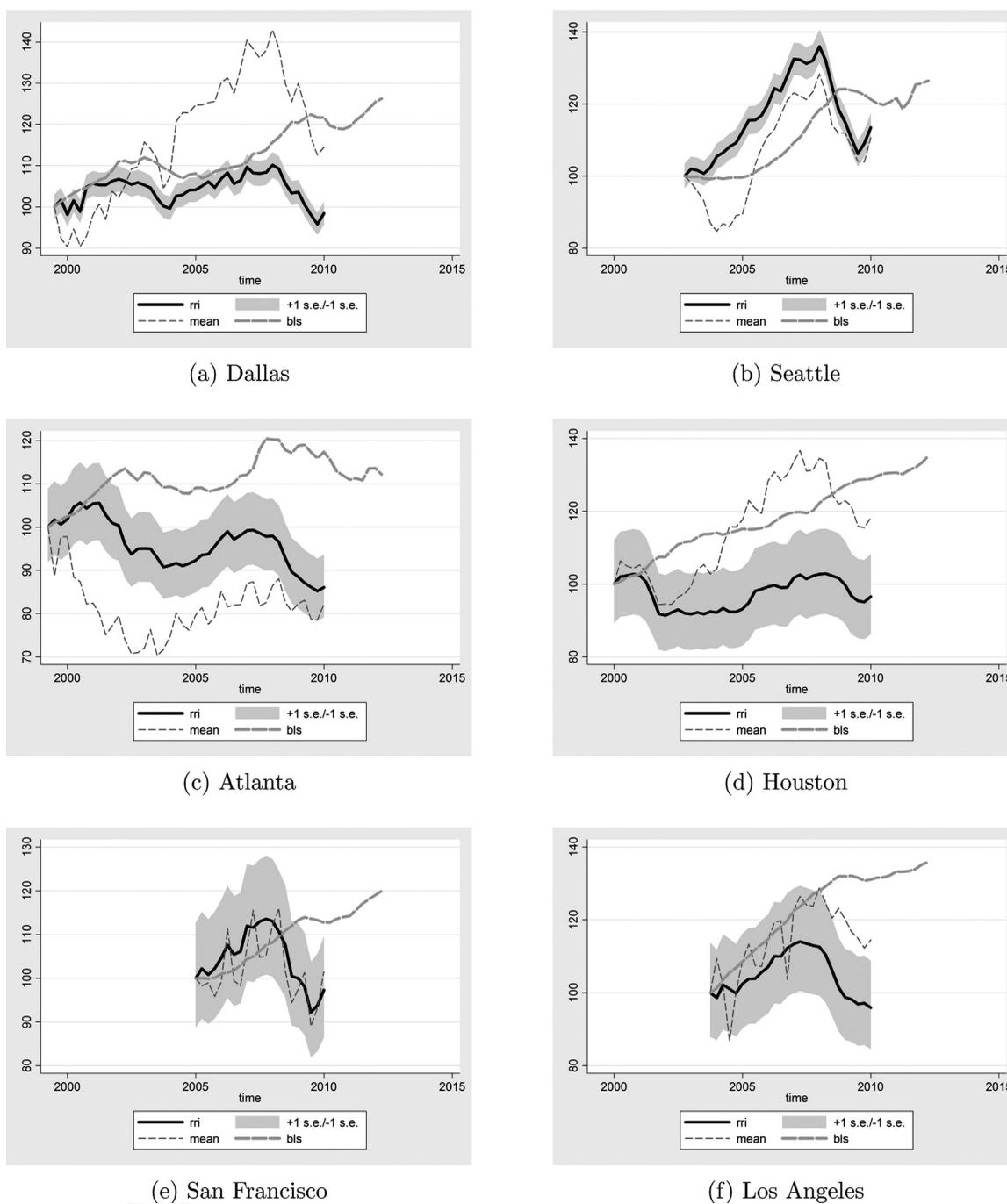
Table 3 presents the annualized quarterly growth rates of the RRI and the BLS index for the eleven MSAs and the results of the *t*-test for equal mean growth rates between the two indexes.⁸ The RRI exhibits a lower mean growth rate than the BLS index for all MSAs. The simple average of the mean growth rates for eleven MSAs is –1.0% per annum for the RRI and 2.8% per annum for the BLS index.⁹ The difference is largest for Miami (–3.3% for the RRI and 3.9% for the BLS index) and smallest for Houston (0.7% for the RRI and 2.3% for the BLS index). The statistical significance of the difference between the indexes varies across MSAs. For example, in Dallas, Los Angeles, and Miami, we reject the null hypothesis of an equal mean at a 5% significance level against an alternative hypothesis that the mean growth rate of the RRI is lower than that of the BLS. For other MSAs, the difference is not statistically significant, possibly due to relatively short time series.

The table also presents the results of the *F*-test for equal variance of quarterly growth rates between the RRI and BLS.

⁸ The standard errors are HAC corrected and thus robust to heteroskedacity and serial correlation.

⁹ This difference partly arises because the BLS constructs its rent index by inflating the survey-based rent changes for aging adjustments. The aging adjustment factors are $1/(1-d)$, where *d* is the rate of physical depreciation (U.S. Bureau of Labor Statistics, 2007). However, the annual rates of aging adjustment for major MSAs are very small (Lane, Randolph, & Berenson, 1988); for example, the aging adjustments for our sample cities are Houston (0.11%), Dallas (0.14%), Miami (0.16%), Atlanta and Washington (0.17%), Los Angeles (0.22%), San Francisco (0.23%), Detroit (0.24%), Seattle (0.25%), and Boston and New York (0.36%). Thus, aging corrections do not alter our conclusions. Furthermore, Gallin and Verbrugge (2007) note that there is considerable uncertainty about the proper correction. They note that newer units may have higher depreciation rates. Even so, their suggested depreciation adjustments do not account for the differences between the two series.

FIGURE 3.—COMPARISON OF INDEXES FOR ELEVEN MSAs



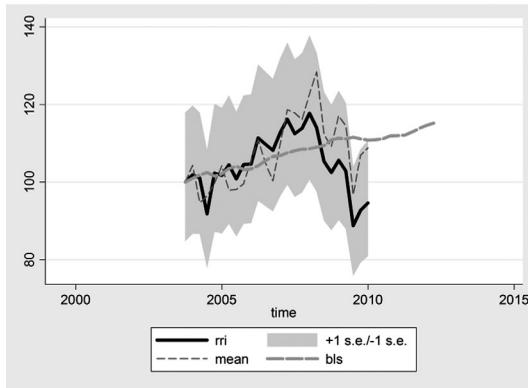
The RRI exhibits a larger variance in growth rates than the BLS index for all comparison MSAs. For example, in Dallas, the HAC variance of RRI is 6.7 times larger than that of the BLS index. Except for Atlanta, we reject the null hypothesis of equal variance at a 1% level of significance against an alternative that the variance of RRI is lower than that of the BLS, which is congruent with our expectations, given the discussion of Verbrugge (2008).

Since we do not have BLS sample sizes for each city, one might conclude that the difference in volatility may be

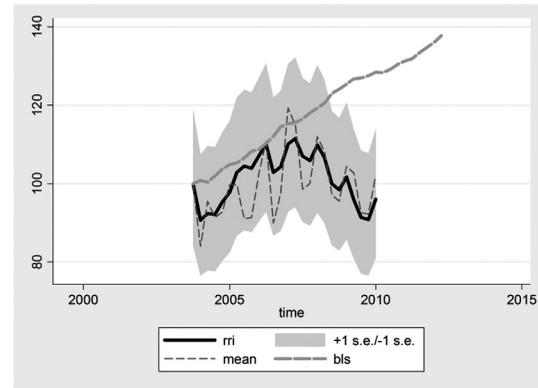
due to the RRI using smaller samples than BLS. In order to investigate this topic, we used the estimated coefficients from the RRI regression and the associated covariance matrix to construct a synthetic distribution of RRIs. We then calculate volatilities of these indexes and find that they are, on average, no greater than those displayed in table 3.¹⁰ Thus, the volatility of our series is not due to the imprecision of the estimated coefficients in the repeat rent regression.

¹⁰ Tabulated results are available on request.

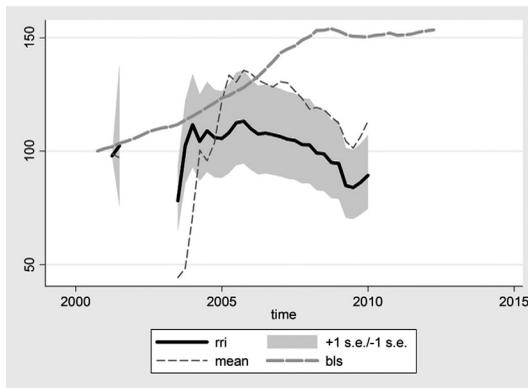
FIGURE 3.—(CONTINUED)



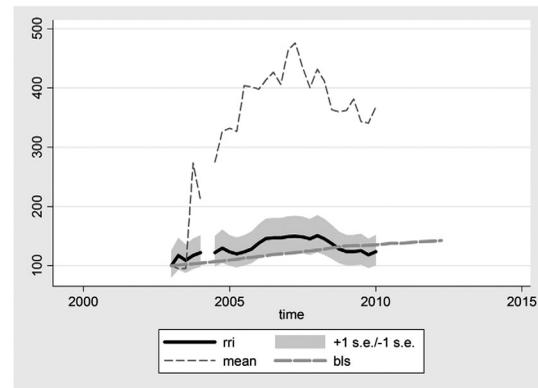
(g) Boston



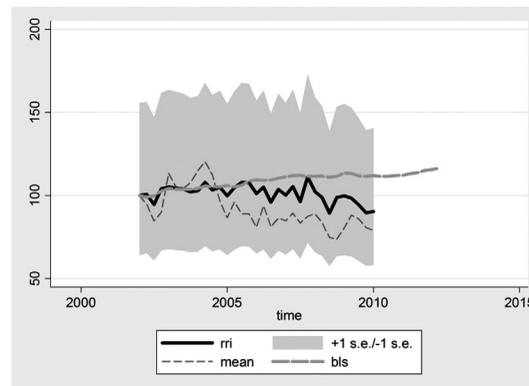
(h) Washington, DC



(i) Miami



(j) New York



(k) Detroit

We now present evidence on the time series properties of these rental indexes. The first question is whether the new rental indexes share the same stationarity properties as the BLS. To that end, we present in columns 1 and 2 of table 4 the probability values of Phillips-Perron tests for unit roots for each of the individual RRIs and BLS indexes respectively. Recall that the null hypothesis in the Phillips-Perron test is that the series has a unit root. With only a few exceptions, the probability values are greater (usually much greater) than 0.05, and so by the usual criteria, we do not reject the null

hypothesis that these series are nonstationary. There are, to be sure, exceptions, so the conclusion is not universal. On that account we use a panel unit root test. The Im, Pesaran, and Shin (2003) test constructs critical values for the average Dickey-Fuller test statistic under the null that the panel data have a unit root. The probability value for this test is 0.46 for the RRI and 0.95 for the BLS panel, indicating a failure to reject that null.

Given these results, we next determine whether the two indexes, for any given MSA, are cointegrated. It is natural

TABLE 3.—GROWTH RATES

MSA	Mean log Δ RRI	HAC SE of log Δ RRI	Mean log Δ BLS	HAC SE of log Δ RRI	Mean Difference	p -Value of Equal Mean (one-side)	Variance Ratio V(RRI)/V(BLS)	p -Value of Equal Variance (one-side)
Atlanta	-0.014	0.019	0.015	0.014	0.029	0.114	1.80	0.105
Boston	-0.014	0.042	0.016	0.006	0.031	0.238	55.03	0.000
Dallas	-0.011	0.018	0.024	0.007	0.035	0.043	6.69	0.000
Detroit	-0.020	0.042	0.011	0.009	0.031	0.239	23.10	0.000
Houston	0.007	0.016	0.023	0.006	0.015	0.192	8.62	0.000
Los Angeles	-0.013	0.022	0.038	0.009	0.051	0.019	6.70	0.000
Miami	-0.033	0.031	0.039	0.013	0.073	0.018	5.68	0.000
New York	0.001	0.042	0.042	0.005	0.041	0.164	69.83	0.000
San Francisco	-0.005	0.030	0.024	0.007	0.029	0.172	19.85	0.000
Seattle	0.002	0.035	0.039	0.012	0.037	0.163	9.10	0.000
Washington	-0.004	0.037	0.040	0.005	0.044	0.123	47.58	0.000

This table compares the annualized value of mean quarterly log change in the RRI and the BLS index for eleven MSAs during a common time period between 2005 and 2010. The Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors with one-quarter lags are also reported. The p -value of equal mean is based on the one-sided t -test between RRI and BLS. The HAC variance ratio is used for the F -test for an equal variance of log changes between the RRI and the BLS index (the p -value is reported).

TABLE 4.—CAUSALITY TESTS

	Phillips-Perron		Johansen	Granger Causality	
	RRI	BLS		RRI→BLS	BLS→RRI
Atlanta	0.87	0.40	17.7*	0.13	0.14
Boston	0.53	0.61	6.60	0.22	0.02
Dallas	0.33	0.87	10.00	0.05	0.45
Detroit	0.01	0.41	11.90	0.18	0.37
Houston	0.49	0.80	8.50	0.00	0.02
Los Angeles	0.81	0.04	32.00*	0.00	0.76
Miami	0.05	0.77	21.10*	0.86	0.04
New York	0.16	0.82	11.70	0.35	0.96
San Francisco	0.71	0.89	19.90*	0.00	0.09
Seattle	0.51	0.95	38.5*	0.00	0.00
Washington, DC	0.52	0.96	8.40	0.66	0.10

The first two columns' entries are probability values for the null hypothesis that the given index contains a unit root. The third column is the test statistic for the null hypothesis that the pair of indexes for a give MSA are cointegrated. Asterisks indicate rejection at the 5% level. The last two columns are probability values for the null hypothesis that the first-named series does not Granger-cause the second-named series.

to suspect that they would be, since the unit root in both series could result from common stochastic trends resulting from permanent shocks to the MSA's housing market, and so would be reflected in both series, as opposed to permanent shocks in, say, the particular sampling pattern of either of the two indexes. We employ the standard Johansen-Juselius test, which uses the rank of the matrix of level coefficients in a vector error-correction model to assess cointegration. If the rank is 1, then cointegration exists, and if 0, then the two series are not cointegrated. In Table 4 we present the trace test for the null that the rank is 0. Rejection (i.e., in favor of the alternative that the rank is 1) indicates cointegration exists. The results are split down the middle, with test statistics for five of the eleven MSAs indicating cointegration exists. Therefore we again have a need for recourse to panel methods and employ the test of Westerlund (2007). There are multiple versions of the test, depending on the nature of the alternative hypothesis, but all of them have probability values greater than 0.90 and so the conclusion we draw is that the series are (jointly considered) not cointegrated.¹¹

¹¹ See Persyn and Westerlund (2008) for a description of the tests' implementation in Stata.

We next turn to the Granger-causal relationship between the two series. Again, we consider this first on a city-by-city basis. Given the results on integration and cointegration, it is appropriate to conduct the Granger tests using first differences. The tests thus regress the change in RRI on lagged changes on both RRI and BLS. A rejection of the F -test that the BLS coefficients are jointly 0 indicates that BLS causes RRI. The roles of BLS and RRI are then reversed. We expect from these latter regressions a rejection, given our initial belief that RRI reflects current market conditions, but BLS does so only with a lag. We use four lags of each in these regressions, and the probability values are displayed in the last two columns of table 4. In those columns, using a 5% critical value, we find that in five cases, RRI causes BLS but not the reverse; in two cases, BLS causes RRI but not the reverse; and in three, cases neither Granger-causes the other (although in two of those, the probability value for RRI causing BLS is the lower of the two). Finally there is one case where there is mutual causality.

In summary, the evidence is weighted, as we expected, toward the RRI index being causally prior to BLS. But once again we appeal to panel regressions to settle the question. We run a simple panel version of the above regressions and include MSA dummies to capture fixed effects. The probability value for the test of BLS causing RRI is 0.22, while for the reverse, the probability value is .03. Thus, jointly considered, our conclusion is unambiguously that RRI is causally prior to BLS, not the reverse.

V. Robustness Checks

A. Simulation of BLS Indexes

A concern in comparing our RRI to the BLS index is that our samples may not be similar. For example, it is possible that the units tracked by RentBureau have greater turnover than units sampled by the BLS and such differences might result in rent discounts applied to properties in the BLS sample. Alternatively, the RentBureau sample comprises primarily larger apartment complexes that are professionally

managed, while the BLS sample includes a wider variety of property sizes. Thus, in order to confirm that our primary results are not a reflection of the differences in sample but truly reflect the differences in index construction method, we attempt to simulate, to the extent possible, the BLS methodology, but using the RentBureau sample. We cannot reproduce the BLS methods exactly; even with our largest city samples (e.g., Atlanta), it is infeasible to divide that sample into six subsamples and repeatedly construct rotating indexes for each of these subsamples. In addition, it is impossible to conduct the BLS's geographical stratified sampling procedure. Instead, we capture the main features of the BLS method using the following procedure.¹² For any given month, we select any property that has a recorded rent in that month and also six months prior. We then construct aggregate growth rates across those two months similar to equation (4). We repeat this for every month in the city sample and construct a month-to-month sample similar to equation (5).¹³ We thereby replicate three important features of the BLS index: (a) rents are collected from arbitrary points in the lease duration; (b) multiple rents may be collected in the same lease, thus overstating the smoothness of the index; and (c) we select from both new and existing leases.

The results for Atlanta are contained in figure 4a and for Dallas in figure 4b, where the actual BLS, our simulated BLS, and the RRI are displayed (along with two other series to be discussed shortly).¹⁴ All of these series are renormalized to 100 at the first quarter of 2006 for convenience in discussing the postcrisis period. Remarkably, our simulated BLS index tracks the actual BLS quite well. In particular, it does not decline during the 2006–2010 period. In other words, if the BLS had used the RentBureau sampling methods, its indexes would look much the same as before. The fact that RentBureau oversamples larger complexes (or any other sampling difference) does not appear to be the explanation for the differences in the two sets of indices.

Systematic evidence on this is contained in table 5. The table entries contain for the three series (and the two others discussed below) the correlation coefficients from each pair of series, derived from the goodness-of-fit measure panel regressions of each series on the other with city fixed effects included in the bivariate model. As can be seen there, the RRI is basically uncorrelated with the BLS series, yet our simulated BLS is highly correlated with the actual BLS.

B. Temporal Changes in Sample Composition

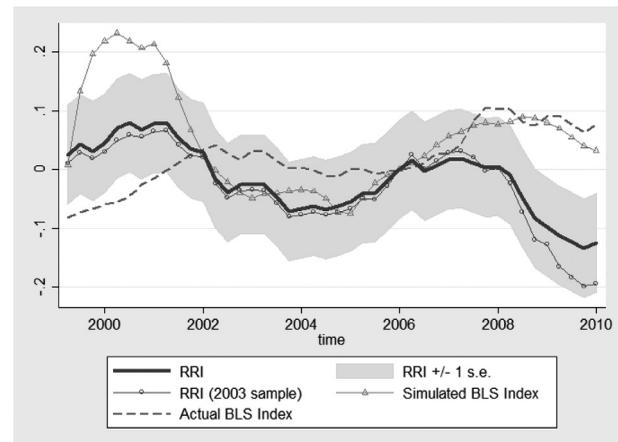
A second related concern is that the RentBureau sample is changing over time in ways that are different than

¹² McCarthy and Peach (2010) also attempt to replicate the BLS methodology using American Housing Survey Data. The AHS samples units only every two years; nevertheless, its estimates are broadly consistent with the BLS.

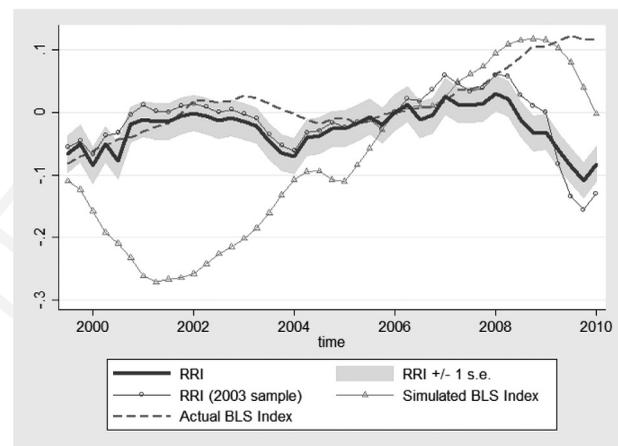
¹³ However, unlike in equations (4) and (5), we do not weight these observations.

¹⁴ We highlight Atlanta and Dallas since these cities have the longest histories and largest samples. A complete set of results for all MSAs is available on request.

FIGURE 4.—COMPARISON OF REPEAT RENT INDEX AND BLS INDEX FOR ATLANTA AND DALLAS



(a) Atlanta



(b) Dallas

the BLS sample. As we noted in section II, RentBureau expanded operations throughout the 1990s and 2000s, and during this period, new apartment complexes were added to the database as property management firms contributed information.¹⁵ Although the expansion in the RentBureau data should not systematically bias the RRI since the repeat rent method explicitly controls for the introduction of new units by requiring two rental contacts on the same unit, the introduction of new units could bias the index if units that enter the sample in later periods were systematically different in quality from the units that were included in the data earlier. We construct samples that used only properties that were observed in 2003 and constructed a repeat rent index and a simulated BLS index (as described above) using those observations (through 2010).

The results for Atlanta and Dallas are also displayed in figure 4. The figures reveal that over the period from 2000 to 2008, the full RRI and the 2003 restricted sample RRI are highly correlated. Only toward the end of the sample period

¹⁵ As noted above, figure 1 clearly shows the temporal expansion in number of properties and leases.

TABLE 5.—AVERAGE CORRELATIONS

	BLS_Actual	BLS_S	BLS_S2003	Mean	Mean_2003	RRI	RRI_2003
Simple Average							
BLS_Actual	1.00						
BLS_S	0.56	1.00					
BLS_S2003	0.55	0.90	1.00				
Mean	0.29	0.58	0.49	1.00			
Mean_2003	0.35	0.64	0.60	0.81	1.00		
RRI	-0.08	0.26	0.14	0.60	0.52	1.00	
RRI_2003	0.22	0.51	0.39	0.63	0.67	0.82	1.00
Panel regression method							
BLS_Actual	1.00						
BLS_S	0.68	1.00					
BLS_S2003	0.71	0.93	1.00				
Mean	0.39	0.62	0.52	1.00			
Mean_2003	0.55	0.78	0.74	0.85	1.00		
RRI	-0.04	0.19	0.06	0.52	0.39	1.00	
RRI_2003	0.32	0.55	0.46	0.64	0.69	0.77	1.00

This table reports pairwise correlations between different indexes. The upper panel reports the simple average of correlation coefficients for ten major MSAs. The lower panel reports the square root of the R^2 from panel regressions of each series on the other with MSA fixed effects. The listed indexes are, from left to right (and from top to bottom), the actual BLS index, a simulated BLS index using the RentBureau sample (the full sample and the 2003 sample), the mean rent indexes (the full sample and the 2003 sample), and repeat rent indexes (the full sample and the 2003 sample).

(2009–2010) does the 2003 restricted sample tend to deviate from the full RRI. The simple correlation statistic reveals that the full RRI and 2003 sample RRI are correlated at 98% and 93% for Atlanta and Dallas, respectively. Table 5 shows the simple average of the correlation statistics for the eleven cities in our study. We note that the simple average of the correlations is 82%, while the regression-based correlation coefficient indicates that the two series are correlated at 77%. Based on this evidence, we conclude that our full RRI does not suffer from changes in unit quality over time due to the introduction of new properties to the data set.

The results of these two robustness checks indicate that differences in the two samples and any changes in the samples over time are not the cause of the observed differences between the RRI and the BLS rental index. Rather, the difference lies in the fact that we use only new contracts with new tenants; in the cold housing market immediately following the 2007 crash, new tenants received substantial discounts. This was the reality of housing market conditions during that period, something that was missed in the BLS series.¹⁶

VI. Conclusion

We have constructed repeat rent indexes for a large number of cities, thus filling a hole in the currently available data. We find that these series behave rather differently from BLS rent data. Our general conclusions are that the number of cities and years for which nominal rents fell is substantial, and by more than would be indicated by the BLS data, particularly after the onset of the housing crisis in 2007. Repeat rent indexes (RRI) are more volatile than the BLS indexes, which is attributable to the smoothed nature of BLS sampling. Finally, the

¹⁶ Although the pool of new tenants might contain more “lemons” than the pool of sitting tenants, it is unlikely that this is the source of the bias. It is doubtful that lower-quality tenants would be rewarded with lower starting rents. Furthermore, Ambrose and Diop (2014) provide evidence that the pool of new tenants following the 2007 housing crash was actually of higher quality.

BLS lags the repeat rent index, which is consistent with the idea that the BLS index is not indicative of current market conditions.

These differences are consistent with the differences in sampling methods. Most important, the BLS’s use of surveys implies that its indexes do not reflect contemporaneous market conditions, particularly after the 2007 housing market crash. The BLS indexes may be appropriate for measuring of cost-of-living indexes, because they may represent rents of the typical household, which on average does not, in fact, face current market conditions, but for studies of the housing market, the Repeat Rent Index may do a better job.

The differences in the paths of these rental indexes are striking and provide grounds for new research on rental markets. In particular, this will provide new perspectives the contribution of rent to cost-of-living indexes, the relative volatility of rent and housing prices, and the path of rent-price ratios and real estate capitalization, especially in the wake of the 2007 crash in prices. All of these are the object of current research.

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