High Frequency, High Fidelity: Constructing Daily Housing Price Indexes

Abstract

Housing price indexes (HPIs) have become an increasingly important part of the suite of macroeconomic indicators. The global financial crisis (GFC) of the late-2000s emphasized just how important are trends in housing prices for financial stability. In recent years there have been global efforts to improve the quality and timeliness of such data (IMF 2009, Eurostat 2013, IMF 2019). However, calculating HPIs is challenging because homes sell infrequently and are functionally unique. These two facts make it difficult to compare like-with-like across time and isolate pure housing price change from changes in the composition of homes sold across time. Given the challenges in constructing housing price indexes it is unsurprising that they are often reported at low frequency—monthly or quarterly—compared with price indexes for other asset classes such as shares or bonds. Moreover, Daily indexes are of increasing interest to researchers and practitioners in real estate markets. The advent of housing futures, which have been actively traded since 2006, has meant that there is a demand for timely information on housing price movements (Shiller 2015). This demand is not currently being met by monthly or quarterly HPIs. There is also the broader need for high frequency information on house prices for a range of applications in practice. Housing prices can move rapidly within quarters or months. High frequency indexes also limit temporal aggregation bias. Low frequency indexes will tend to smooth out the peaks and troughs in house prices that will occur within periods (Calhoun et al. 1995, Geltner 2015). Therefore, our primary focus in this paper is on developing and implementing robust and accurate methods for constructing HPIs at high frequency using repeat sales approach. This is particularly challenging because at high frequency the difficulties of few transactions and heterogeneity in homes become particularly acute. We develop a Flexible Regularized Repeat Sales (FRRS) method that makes the best possible use of the available data. The FRRS method addresses one of the major gaps in existing approaches to HPI construction which

is their focus on low frequency price movements.

Earlier work has tried to address the challenge of obtaining higher frequency housing price information. Bokhari and Geltner (2012) and Bourassa and Hoesli (2017) advocated the use of frequency conversion procedures. They employed a two-step procedure to convert an estimated annual HPI into a quarterly HPI. Though this approach has not been used to construct daily indexes from lower frequency HPIs. A drawback of the frequency conversion procedure is that it is unlikely to make optimal use of the data and cannot solve the temporal aggregation problem. A related and innovative contribution was that of McMillen and Dombrow (2001). Their focus was on addressing the challenge of constructing a HPI in the sparse data environment. In their context, this related to small geographic areas with few transactions. The context is similar to ours, though our data sparseness arises because of the focus on a high temporal frequency. McMillen and Dombrow (2001) suggested parameterizing the price index using a low-rank Fourier series approximation. The idea is to flexibly represent the path of house prices by a semi-parametric function. In cases where there are few sales 'nearby' data can be used to interpolate price movements. This approach was applied in a series of papers (McMillen 2003a,b). In more recent work, Bollerslev et al. (2016) outline a two-step approach to estimating a daily house price index. This uses a repeat sales approach. Here price changes for the same property over time are modelled. They first estimate a daily repeat sales index. This naturally embodies a great deal of noise because on some days there will be few sales. In the second step, they employ a Kalman filter-based state-space approach to extract the estimated index's latent house price movements. It is also worth noting the approach in the commercial real estate (CRE) sphere to constructing high frequency indexes. The share prices of many Real Estate Investment Trusts (REITs) are traded on public exchanges. The share price movements of REITs can be used to infer the value of the underlying CRE they hold (Geltner 2015). Unfortunately, such an approach is not possible for residential real estate as REITs generally only hold CRE.

We propose a novel repeat sales approach to constructing high frequency indexes in the presence of sparse data. First, as in McMillen and Dombrow (2001), we propose to parameterize the housing price index by a semi-parametric functional form. While this can

take the Fourier form, as in McMillen and Dombrow (2001), we also investigate a range of other forms including using B-spline and wavelet bases. The advantage of both of these bases over the Fourier is that they are more localized. The Fourier approximation is global in the sense that changing a coefficient potentially impacts on the price index across its entire time domain. This is not the case, at least to the same extent, for either the B-spline or wavelet bases. Here certain coefficients will have localized effects meaning they can be chosen to reflect house price movements over certain time ranges. We will also consider very large bases which mean that the price trends which the index can represent are complex. This is an advantage over existing methods. Second, our estimation approach extends current approaches. Estimation proceeds in a single step. We use the elastic net model of Zou and Hastie (2005), which encompasses lasso and ridge regression, to estimate the parameters of the basis function. Our focus is to approximate as accurately as possible the observed movements in housing prices. Thus our key estimation focus is to parsimoniously predict the observed price changes. This is in contrast with Bollerslev et al. (2016) who smooth the 'raw' repeat sales index rather than the observed price changes. Cross validation methods are used to tune the model to provide optimal predictive accuracy. We call our approach the Flexible Regularized Repeat Sales (FRRS) method.

We apply our methods to a large dataset of around 30 years of property transactions from 1991 to 2021 for Sydney, the largest city in Australia. Given the long time span of the data, it encompasses more than ten thousand days. At a daily frequency, we begin by estimating a standard repeat sales index. This is compared with indexes calculated using the Fourier, B-spline and wavelet basis functions. In each case we use the elastic net estimation approach. The results using the wavelet basis were particularly impressive. It reproduced the low frequency annual price movements with low variance while also picking up many of the high frequency price changes. The wavelet model had the best out-of-sample prediction performance of all the models. The incorporation of wavelet basis in the FRRS method introduces a novel perspective of using wavelets since economists have been focusing on the application of scale decomposition and multiresolution analysis of wavelets (Crowley 2007).

The FRRS approach represents an important advance in methods to construct HPIs. It

has the potential to be useful not only in measuring high frequency housing prices but also in other scarce data environments. This may occur for disaggregated regions or during times in the economic cycle when there are few sales. In this regard, the approach is likely to be useful for modeling high-frequency price movements of infrequently traded commodity, such as fine wines and art pieces.

Using the HPIs we constructed for Sydney, we investigate the monetary policy implication on the Sydney real estate market in comparison to the stock market. Real estate properties as one special type of assets might behave differently compared to the equity market. Existing evidence indicates that monetary policy surprises, which is measured by high frequency identification using cash rate futures, have statistically significant impact on the stock market prices, in both the US and Australia. We aim to compare how the real estate market and the stock market are reacting to the monetary policy surprises, especially during two special time periods, the GFC and the COVID-19 periods. Additional analysis are performed by using different region and different types of real estate assets, for example, Sydney area and non-metropolitan area of New South Wales state; residential and commercial properties. We also explore different measurement of the monetary policy shock other than the HFI, for example, the Economists' survey, and the change of monetary policy rates. Our preliminary results suggest that the monetary policy surprises or changes has no statistically significant impact on the real estate market in Sydney, but the impact is significant on the stock market. This is reasonable as the real estate properties are more sticky than the stocks where the transaction decision and process is also more complicated for real estate market. This provides interesting insights on the monetary policy surprises implication on real estate market.

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