Replication Project Final Report

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The paper I have replicated for this project is "Monetary policy, housing rents, and inflation dynamics" by Dias and Duarte (2019). This paper studies the effects of monetary policy shocks on housing rents. To do so, the authors construct a proxy SVAR model to study the response of several housing variables, where the key finding is that rents increase in response to a contractionary monetary policy shock. This paper was chosen because I wanted to learn more about running SVAR models. The authors provide a cleaned dataset and code in MATLAB, so I have chosen to use Python. The replication was done in two parts: firstly, replicating Figures 1 and 2 of this paper which uses US data and secondly, applying this same analysis to Australian data.

1 The Replication with US Data

The first part of the replication involved showing how the housing variables respond to a 25bps contractionary monetary policy shock using the scripts , where the results are shown below in Figures 1 and 2.

The core explanatory variables included in all the variations of the SVAR model solved are Industrial Production, CPI, 1-year Treasury rate and the excess bond premium, which the authors chose because they have standard and well-known IRFs. In Figure 1, the model is solved with housing rents where a cleaned monthly dataset was provided, running from January 1983 to December 2017. In Figure 2, the model is solved separately for each of the following housing variables includedin the model: housing prices, housing rents, the housing stock for the renting vacancy rate and the homeownership rate. A cleaned quarterly dataset was provided, owing to the data availability of some series, running from 1981:Q1 to 2017:Q4. These series are all obtained from FRED.

To generate Figures 1 and 2, there were six key processes to replicate: reading in the data, specifying and estimating the SVAR, narrative identification of the structural shocks, calculating the impulse response functions, running the bootstrapping inference and generating the output plots. Both figures use the same procedures but applied to different datasets. While my code is comprehensively commented, I'll describe the key steps involved in translating the model into code and any challenges.

Since the data was already cleaned, the only transformations required were taking logs of the variables reported as index numbers and levels to turn them into rates. Then, the SVAR is given by,

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + H\epsilon_t, \tag{1}$$

where Y_t is an $n \times 1$ vector of core variables plus the housing variable of interest, A_i for $i = 1, \ldots, p$ and H are $n \times n$ matrices and ϵ_t is vector of n structural shocks. p is the lag order chosen to be 12 for the monthly data and 4 fo the quarterly data, as per common practice. Since H is the matrix that gives the contemporaneous effect of a change in a structural shock j on each variable Y_t, the authors assume the first column of H is the monetary policy shock and denotes it H_1. The impulse response function of Y_t with respect to a monetary policy shock is then given by

$$\frac{\partial Y_t}{\partial \epsilon_{1t}} = A(L)^{-1} H_1, \tag{2}$$

where $A(L) = I_n = A_1L - \ldots - A_pL^p$. The parameters $A(L)^{-1}$ can be identified directly from Equation 1 with $H\epsilon_t = \eta_t$ innovations, which were estimated using ordinary least squares.

To identify the monetary policy shocks H_1, the authors use an approach that combines the external instrument for identifying structural shocks with the high-frequency event studies around monetary policy announcements. Consequently, the authors use changes in the 3-month-ahead monthly federal funds futures around a monetary policy announcement as a valid instrument, where the data is obtained from Gertler and Karadi (Gertler & Karadi, 2015). This is a suitable instrument because the difference before and after a policy announcement represents the change in expectations of financial market participants due to an unanticipated monetary policy action. These steps are done in the function `doProxySVAR` in my Python code, where the IRFs are calculated in the `doIRFs` function. These functions were fairly straight-forward to replicate, although some steps that MATLAB has native functions for, like creating lag matrices, had to be explicitly created in my code.

To estimate the distribution of impulse responses, the authors use a moving block bootstrap (MBB) which I have implemented in my function `doProxySVARci`. While the specific steps implemented are outlined in the code, in summary the MBB method divides the data into overlapping blocks and resamples these blocks to create pseudo-samples to resolve the SVAR model with. This process was repeated 5000 times to get the distribution of the impulse responses so that the 68% confidence bands and the median impulse functions could be plotted. This function was more challenging to replicate because of all the matrix functions and how Python indexes differently, and also along the opposite axes, when using the equivalent `numpy` functions to the MATLAB steps. The provided code also had five other resampling methods implemented that the user could specify which option to choose from, and could also solve the model with more than one shock. Since the goal was to replicate the results shown in Figure 1 and 2, I simplified my code to only use the MBB and reduced all the matrices down a dimension to only solve the SVAR model with a monetary policy shock.

The final plotted IRFs are shown in Figure 1 and 2 and match those shown in Dias and Duarte (Dias & Duarte, 2019).

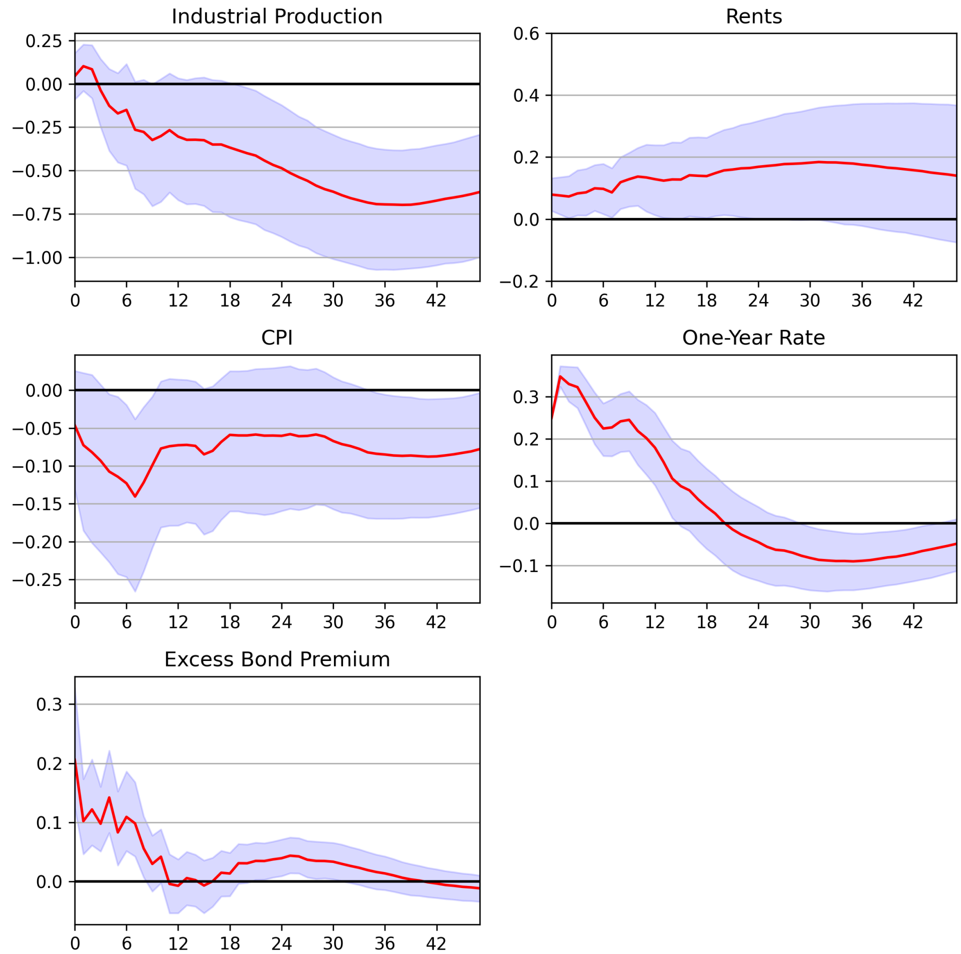

Figure 1: Baseline results produced using my code `replicate_fig1.py` which matches the results of Figure 1 from Dias and Duarte (2019): Percentage responses of the four core variables and housing rents to a 25 bps monetary policy shock. The red lines correspond to the median response and the shaded areas are the 68% confidence bands, generated using a moving block bootstrap method.

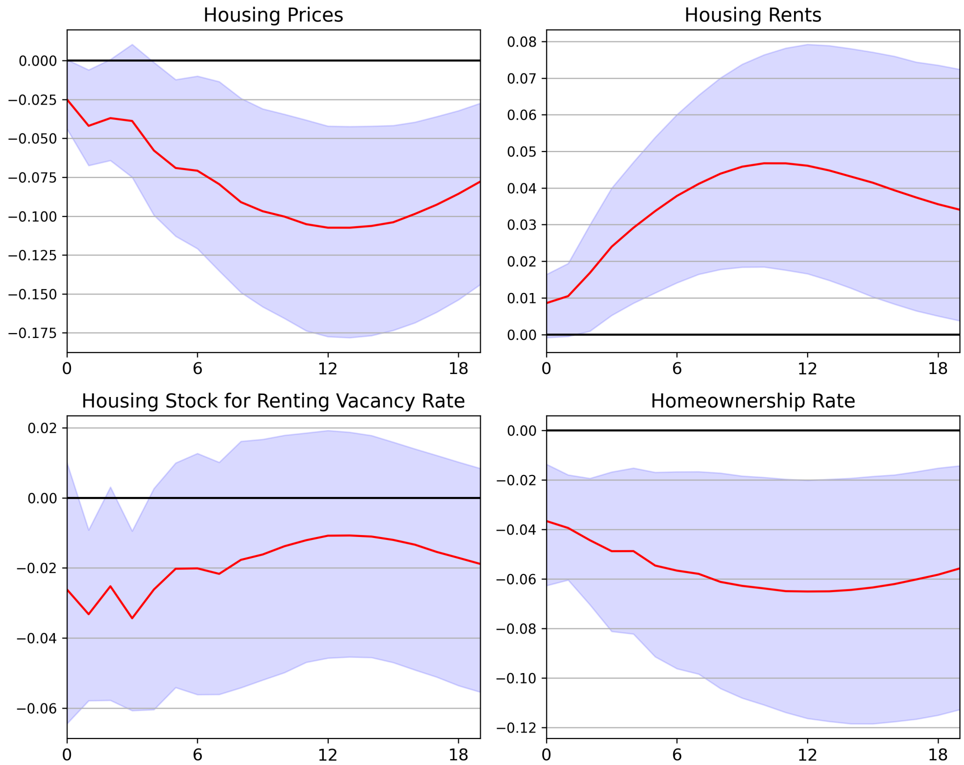

Figure 2: Percentage responses of variables relating to housing tenure decisions (own vs rent) to a contractionary monetary policy shock. These impulse responses were generated using my code `replicate_fig2.py` and matches Figure 2 from Dias and Duarte (2019). The red lines correspond to the median response and the shaded areas are the 68% confidence bands, generated using a moving block bootstrap method.

Figure 1 confirms the paper's result that in contrast to the prices of goods or other services, nominal housing rents increase in response to a contractionary monetary policy shock. Consequently, this is a result of interest because it is expected that nominal prices should decline after a contractionary monetary policy shock whereas we observe the opposite with rents. The authors suggest the explanation that monetary policy affects housing tenure decisions (i.e. own versus rent). Figure 2 tests this explanation by using the same SVAR model to show that that house prices, the home ownership rate and the housing stock available for rent all decline. As homeownership costs increase with increasing interest rates, then the demand for rental housing also increases, reducing the housing stock. Consequently, housing rents rise. The authors then use these results, in addition to further analysis of the other price components of CPI which I have not replicated, to argue that the movement of housing rents accounts for a large proportion of the price puzzle observed.

2 The Replication with Australian Data

The second part of the replication involves applying the codes written in the first part to Australian data. I have created a cleaned dataset from the sources outlined in Table A1 in the notebook `data_cleaning.ipynb`. There are several differences in the dataset I have created compared to the US dataset used by Dias and Duarte (2019) owing to data availability and suitability. For the core variables, I used the Domestic Final Demand (DFD) index instead of the Industrial Production index. DFD is a more localised measure of production while mining makes up a large portion of Industrial Production, which is exported. Since there is no Australian source for the excess bond premium, I have calculated a credit spread by taking the difference in the 3-year yields of Corporate and Government bonds as a measure of risk in the credit market. I have also used the yield on two-year Australian Government bonds in place of the One-Year Rate used since the RBA does not release a one-year maturity series. The data for these bond yield series is monthly, but have been aggregated up to quarterly for this analysis. For Figure 2, the current plan is to omit the Vacancy Rate series unless I am able to obtain the data. The Homeownership Rate is provided at a two-year frequency, but I have interpolated to obtain quarterly values, since I expect this series to remain fairly static over a two-year period. Sine the RBA has only release corporate bond data from 2005, I used quarterly data spanning 2005:Q1 to 2020:Q3. Given this limited dataset, I reduced the number of lags to 2.

For the identification of the monetary policy shocks, I used the monetary policy surprises calculated by He (2021). This series is calculated using the data from the OIS market, which captures expectations of the cash rate. Specifically, it uses the OIS rate measured 30 minutes before and 90 minutes after a monetary policy announcement, which captures the surprises and hence is a proxy to a monetary policy shock.

The scripts used to replicate Figures 1 and 2 using Australian data are `replicate_fig1_AUS.py` and `replicate_fig2_AUS.py`, which use the same procedures as described in Section 1. The results are shown in Figures 3 and 4.

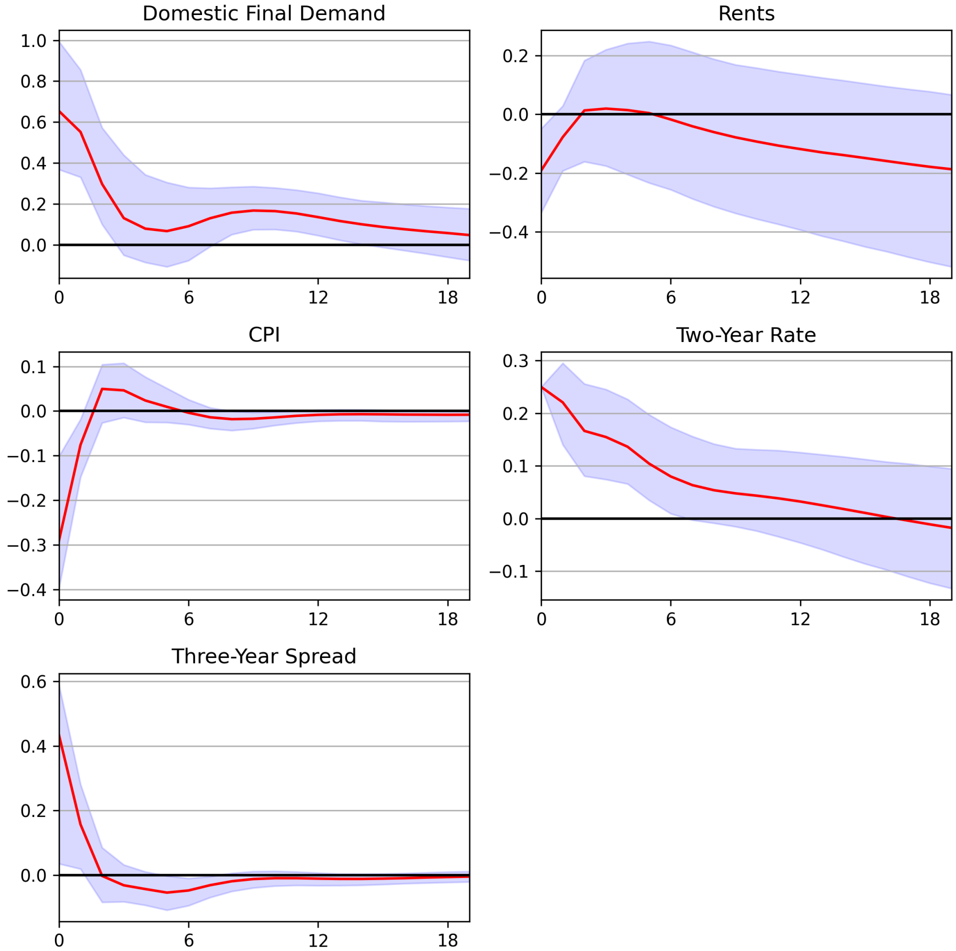

Figure 3: Baseline results produced using my code `replicate_fig1_AUS.py`: Percentage responses of the four core variables and housing rents to a 25 bps monetary policy shock. The red lines correspond to the median response and the shaded areas are the 68% confidence bands, generated using a moving block bootstrap method.

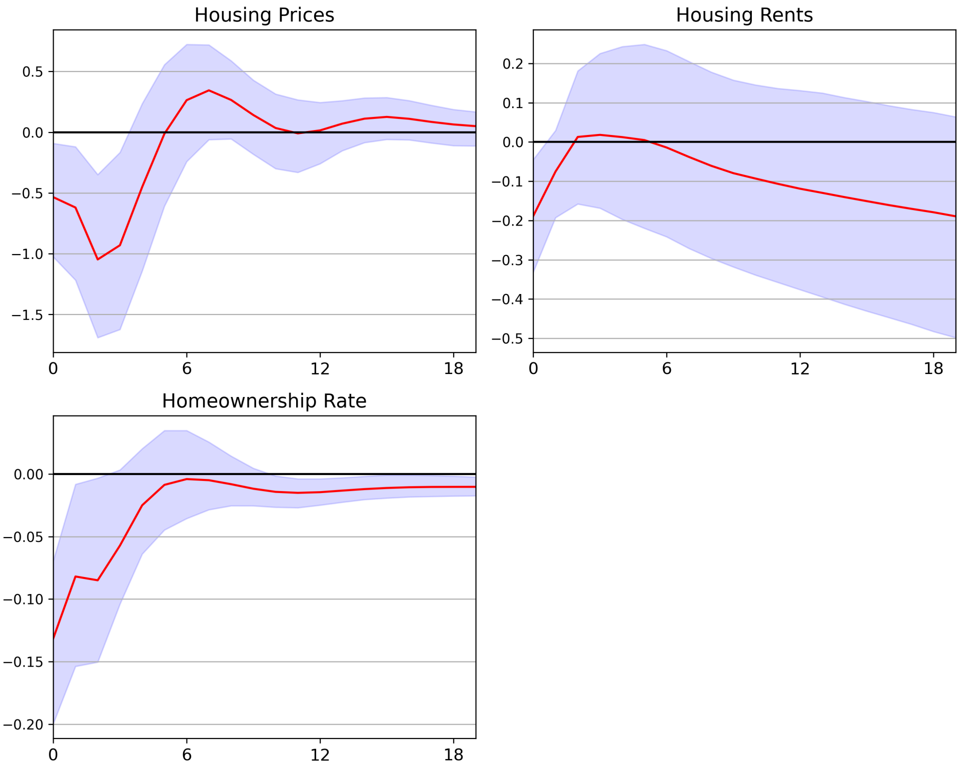

Figure 4: Percentage responses of variables relating to housing tenure decisions (own vs rent) to a contractionary monetary policy shock. These impulse responses were generated using my code `replicate_fig2_AUS.py`. The red lines correspond to the median response and the shaded areas are the 68% confidence bands, generated using a moving block bootstrap method.

In Figure 3, we can see that in contrast to Dias and Duarte's (Dias & Duarte, 2019) results, there is no price puzzle in the CPI impulse responses to a contractionary monetary policy shock. Furthermore, rents decrease while the responses for housing prices and homeownership are more consistent with the US data responses. However, the results for rents are statistically insignificant. Decreasing rents with contractionary monetary policy could be explained by the fact that as interest rates increase on mortgages, more people could lose their homes and increase the rental vacancy rate to drive down rents. Another limitation of the dataset is that rental vacancy data is not publicly available for Australia so I did not include it in the model. However, this should not have affected impulse responses calculated since only one housing variable is used at a time.

However, the behaviours observed are more likely to a result of the model's limitations. Firstly, the model was estimated using a limited range of data which would reduce the accuracy. Moreover, the Australian SVAR model could be misspecified. While I have used the same variables as the US SVAR model, there could be other variables that could influence how housing variables move but aren't included, e.g. unemployment. Given Australia is a small open economy, the effects of monetary policy shocks may not also show as clearly, or are statistically insignificant. There could also be other shocks that explain more of the movements of rents, such housing market shocks. Another limitation could be that the monetary policy shock is not well identified. Consequently, this replication ultimately shows that SVAR models can be more difficult to run with Australian data and that the model presented by Dias and Duarte (Dias & Duarte, 2019) is more well-suited to its US application. If creating an SVAR model for Australia, different equities markets variables could be chosen that have greater data availability.

References

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Gertler, M., & Karadi, P. (2015, January). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics*, *7*(1), 44–76. Retrieved from `http://dx.doi.org/10.1257/mac.20130329` doi: 10.1257/mac.20130329

He, C. (2021). Monetary policy, equity markets and the information effect. *RBA Research Discussion Papers*(5). doi: 10.47688/rdp2021-04

Appendix A

Table A1: Description of Australian Data Series

Series	Source	Series Description	Sample
Domestic Final Demand (A2303859F)	ABS, 5206.0 Australian National Accounts (Table 4)	Total industrial industries, Index Numbers, Seasonally Adjusted	2005:Q1 – 2020:Q3
Two-year Government Bond Yield (FCMYGBAG2)	RBA, Statistical Table F02	Yields on Australian government bonds, interpolated, 2 years maturity	2005:M1 – 2020:M12
Three-year Government Bond Yield (FCMYGBAG3)	RBA, Statistical Table F02	Yields on Australian government bonds, interpolated, 3 years maturity	2005:M1 – 2020:M12
Three-year Corporate Bond Yield (FNFYA3M)	RBA, Statistical Table F02	Non-financial corporate A-rated bonds – Yield – 3 year target tenor	2005:M1 – 2020:M12
CPI (A2325846C)	ABS, 6401.0 Consumer Price Index, Australia (Tables 1 and 2)	Index Numbers, All groups CPI, Australia	2005:Q1 – 2020:Q3
Housing Rents (A3604689J)	ABS, 6401.0 Consumer Price Index, Australia (Table 13)	Index Numbers, Rents, Australia, Seasonally Adjusted	2005:Q1 – 2020:Q3
House Prices (QAUR628BIS)	FRED	Real Residential Property Prices for Australia, Index Numbers, Not Seasonally Adjusted	2005:Q1 – 2020:Q3
Homeownership Rate	ABS, Housing Occupancy and Costs (Table 1.3)	Estimates of the proportion of households with owners	2005-2006 – 2019-20