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Secretary's foreword

By David Martine

The Department of Treasury and Finance (DTF) provides robust and impartial advice to the Victorian Government about the State's economic, commercial, financial, budget and resource management. Our analysis supports decisions on the most effective ways government policy development and funding can be used to make Victoria a better place to live, now and into the future.

Victoria's economy is broadly equivalent to the size of a small Organisation for Economic Cooperation and Development (OECD) nation. Indeed, measured in terms of real gross domestic product (GDP) in 2018, it would be ranked 27^{th} among the 36 OECD member nations, about the size of Hungary and larger than the economies of Iceland, Finland, Luxembourg and New Zealand.[1] There are, however, relatively few economic research publications that focus on economic trends in Victoria.[2] This research volume, *Victoria's Economic Bulletin*, is designed to provide one such contribution.

DTF has invested significantly in the Department's analytical and research capability. This volume provides a snapshot of some of the staff research being undertaken. By publishing it, we hope to contribute to the broader public policy debate on important economic issues in Victoria and Australia, and hope to highlight important trends driving change in the Victorian economy. The articles in this volume are produced by authors to increase awareness about important economic and social trends.

The first article examines the duration and amplitude of Australia's housing cycles and develops a method to predict the end of periods of expansions and contractions. The second estimates Victoria's trend unemployment rate and analyses its historical pattern. The third article explores the relationship between land use regulation and property price growth. The final article investigates involuntary unemployment and post-displacement outcomes in Australia.

I hope the articles provide some insight into the research being undertaken and, perhaps more importantly, start a wider conversation on research into the Victorian economy.

David Martine
Secretary

[1] This is measured in real United States (US) dollars and in constant purchasing-power-parity (PPP) terms.

[2] They reflect the views of the authors and not necessarily those of the Department.

The duration and amplitude of Australia's housing cycles[1]

By James Brugler, Maryam Nasiri and Raymond He

ABSTRACT

This paper provides an empirical study of the amplitude and duration of cycles in Australia's house prices. Using the method developed by Harding and Pagan (2002), we identify peaks and troughs of house prices for six Australian capital cities. We find that, on average, housing expansions last longer and are of greater amplitude than housing contractions. We then estimate a discrete time survival model of house price expansions and contractions. Contractions have positive duration dependence, i.e. the probability that the current contraction will end in the subsequent period increases with the duration of the current cycle. We do not find evidence that expansions have duration dependence. Various macroeconomic indicators are useful predictors of a period of expansion or contraction ending, including the mortgage rate, inflation, wages, stock prices and state final demand.

Overview

Property market cycles can affect the macroeconomy through several channels. Households use real estate wealth to finance consumption (Mian and Sufi, 2011). Property assets, both commercial and residential, can serve as collateral for firms to help relax credit constraints and allow investment (Chaney et al. 2012; Bahaj et al. 2019). Property taxes levied on the nominal value of property are an important source of revenue for many governments. Dynamics in property prices can, therefore, both cause and amplify cyclical movements in consumption, investment and the fiscal position of governments. Understanding the drivers of these cycles can help households, firms and governments better manage the implications of housing cycles.

In this paper, we examine cycles in residential property prices across all Australian state capital cities over a 25-year period from 1993 to 2018. Our contributions are threefold. First, we identify peaks and troughs in each state's housing market using the methodology proposed by Harding and Pagan (2002) and provide a high-level summary of the average amplitude and duration of expansions and contractions. Second, using a survival model developed by Bracke (2013), we examine the dynamics of housing market cycles and test whether various macroeconomic and financial shocks are helpful for predicting turning points in housing markets. Third, we use this survival model combined with DTF macroeconomic forecasts to generate out-of-sample survival predictions for the most recent contraction in the Victorian residential property market.

[1] The author would like to thank the following Department of Treasury and Finance (DTF) staff for their comments and input: Amy Auster, David Hedley and Omid Mousavi. The views expressed are those of the authors and do not necessarily reflect the views of DTF.

Our analysis identifies 41 cycles across the six Australian capital cities. On average, expansion periods are longer than contractions. The average duration of an expansion is in excess of four and a half years, while contractions tend to last less than 18 months. Price increases during periods of expansion are also, on average, significantly larger than subsequent periods where prices decrease. Prices rise by around 71 per cent from trough to peak during a typical expansion but fall by only 7 per cent from peak to trough during a typical contraction. The longest expansion in our sample occurred in Victoria and lasted 145 months from 1996 to 2008, while property prices in South Australia and Tasmania underwent contractions that each lasted 27 months, the longest complete contractions in our sample.

Using a discrete time hazard model, we estimate the existence of duration dependence in the housing market in Australia. For cycles that exhibit duration dependence, the likelihood that the current cycle will end in the next period increases as the cycle progresses. Housing market contractions in Australian capital cities are found to exhibit this property. The length of a contraction is also found to be positively correlated with the length of the previous expansion, a feature referred to as lagged duration dependence. Expansions, in contrast, do not display duration dependence or lagged duration dependence. Similar to Bracke (2013), these results support a 'boom and bust' model of house price phases.[2]

Our final contribution is an investigation of whether contemporaneous values of macroeconomic and financial indicators can help predict the end of expansions and contractions in the subsequent period. We show that interest rates, stock prices, income and population growth can be useful for this purpose. Using Victorian Budget 2019-20 forecasts and ABS data up to December 2018, our models predict that the then on-going contraction in Victorian residential property prices would have ended by the third quarter of 2019 with a probability of more than 98 per cent. Subsequent movements in house prices have since confirmed this out-of-sample prediction.

Our research provides a detailed analysis of how Australian housing cycles have evolved in the past. This research also helps to put into context the relative depth and severity of the recent contraction in Victorian property prices compared to previous cycles and identifies which variables are useful for predicting turning points in cycles.

The rest of this paper proceeds as follows. Section 1 summarises some of the relevant literature. Section 2 describes data and the methodology used to identify turning points. Section 3 describes the characteristics of expansions and contractions. Section 4 tests the duration dependence of housing cycles. Section 5 focuses on the determinants of housing cycles and, finally, Section 6 concludes.

1. Literature review

Although there is a vast body of literature on the determinants of house prices and of durations of economic and financial cycles (e.g. Lunde and Allan, 2004; Lam, 2004), the literature that studies housing cycles is less developed. Bracke (2013) is a notable exception. Bracke (2013) studies a sample of 19 OECD countries (including Australia) over a 40 year period (1970-2010) and finds that, though expansions tend to be longer lived and larger in magnitude than contractions, the discrepancy in average characteristics between different phases is less marked than in Australia. Internationally, periods of expansion tend to last only 1.5 times as long and have amplitudes that are twice as large as periods during which the market experiences a contraction. Bracke (2013) also finds evidence of duration dependence in both expansions and contractions. Cunningham and Kolet (2011) find positive duration dependence for US housing market expansions but show that Canadian house price cycles do not exhibit duration dependence. Agnello and Schuknecht (2011) use a probit model to identify the factors correlated with the occurrence of boom and contraction phases. They find that credit and financial conditions affect the probability of housing booms and contractions taking place.

Analysing housing cycles requires a methodology to identify the beginning and end of a cycle. Harding and Pagan (2002) propose a method based on the algorithm developed by Bry and Boschan (1971) (BB algorithm). The algorithm searches for local maxima and minima in a time series and identifies these as peaks and troughs, subject to the requirement that peaks and troughs alternate and to the conditions for the minimum length of a phase (a detailed description of the algorithm is contained in Section 2). Alternatives to this include Bordo and Jeanne (2002) and Borio and Lowe (2002) who define peaks and troughs in an asset price as periods where the three-year average of the growth rate falls outside a confidence interval defined by the historical first and second moments of the series. Detkens and Smets (2004) and Adalid and Detkin (2007) define asset price booms as a period in which real asset prices are more than 10 per cent above an estimated trend, which is calculated recursively by a Hodrick-Prescott (HP) filter. Ceron and Suarez (2006) use a Markov Switching approach to detect house price cycles.

2 Bracke (2013) argues housing markets are characterised by imperfections and behavioural anomalies which cause prices to periodically overshoot. Then, as expansions get longer, they are increasingly likely to terminate, signalling a progressively unsustainable departure from fundamental price valuations. He states that contractions often act as adjustment periods after long expansions: the longer an expansion, the less likely that the subsequent contraction will be short. According to this argument, he suggests interpreting housing cycles as sequences of booms and busts rather than successions of crashes and recoveries.

2. Data and methodology

We use CoreLogic's Economist Pack dataset that contains monthly data for each of Australia's states and territories. From this data, we obtain monthly hedonic price indices (HPI) for each state capital city from January 1993 to December 2018.[3] The HPI uses a regression framework to estimate the association between property characteristics and transaction prices and then interprets time fixed effects from these regressions as index values. In this sense, the HPI controls for any changes in the composition of properties that transact over time.[4]

We use Harding and Pagan's (2002) BB algorithm to detect turning points in each state's HPI. The algorithm consists of the following three steps:

1. Identification of turning points: for a time series, y_t identifies points that are higher or lower than all other points in a window of surrounding observations where the window is k months on either side of y_t. A local maximum y_t^+ is defined as an observation of the series such that $y_{t-k}, \cdots y_{t-1} < y_t^+ > y_{t+1}, \cdots, y_{t+k}$. A local minimum, y_t, must satisfy: $y_{t-k}, \cdots, y_{t-1} > y_t^- < y_{t+1}, \cdots, y_{t+k}$ by symmetry.
2. Censoring rule: the distance between two turning points must be at least q quarters, where q is chosen to retrieve only significant series movements and avoid noise.
3. Alternating rule: a local maximum must be followed by a local minimum and vice versa. If there are two consecutive maxima (minima), the highest (lowest) y_t is chosen.

The algorithm then labels peaks as '1' and troughs as '-1'. We set k = 12 months and q = 2 quarters.[5] Expansions are periods from a trough to the next peak. Contractions are defined analogously as the periods spanning from a peak to the next trough. The duration of a phase (expansion or contraction) is the number of months between the two turning points, and the amplitude is the percentage change in house prices from the beginning to the end of the phase.[6] Figure 1 plots the HPI for each city where each index is normalised to 100 in December 2009. Blue lines indicate a peak, and red lines indicate a trough. Prices grew significantly across all states from the mid-to-late 1990s to the mid-2000s, before growth slowed substantially around the time of the global financial crisis. House prices diverged after the crisis, with growth in Melbourne and Sydney far exceeding the rest of Australia, and especially Perth, where prices remain below their pre-crisis levels at the end of our sample period.

Table 1 details the end date of all peaks and troughs that we identify across Australia's capital cities. A total of 19 completed expansions and 22 completed contractions can be observed across the six cities over our sample period.

Table 1: Peaks and troughs

	SYDNEY	MELBOURNE	BRISBANE	PERTH	ADELAIDE	HOBART
Peak	Nov–1994	Sep–1994	Oct–1994	Dec–1994	Jul–1994	Oct–1994
Trough	Aug–1995	Jan–1996	Jan–1996	Sep–1995	Oct–1996	Dec–1995
Peak	Jan–2004	Feb–2008	Jan–2004	Dec–2006	Apr–2008	Oct–1996
Trough	Jan–2006	Jan–2009	Dec–2004	Jan–2009	Jan–2009	Dec–1998
Peak	Jan–2008	Aug–2010	Mar–2008	May–2010	Aug–2010	Dec–2007
Trough	Jan–2009	Mar–2012	Jan–2009	Dec–2011	Nov–2012	Feb–2009
Peak	Aug–2010	Nov–2017	Apr–2010	Jun–2014		Jul–2010
Trough	Jan–2012		Jan–2012			Oct–2012
Peak	Jul–2017					Feb–2014
Trough						Dec–2014
Total No. of cycles	9	7	8	7	6	10

Note: The data covers the period from January 1993 to December 2018 inclusive.

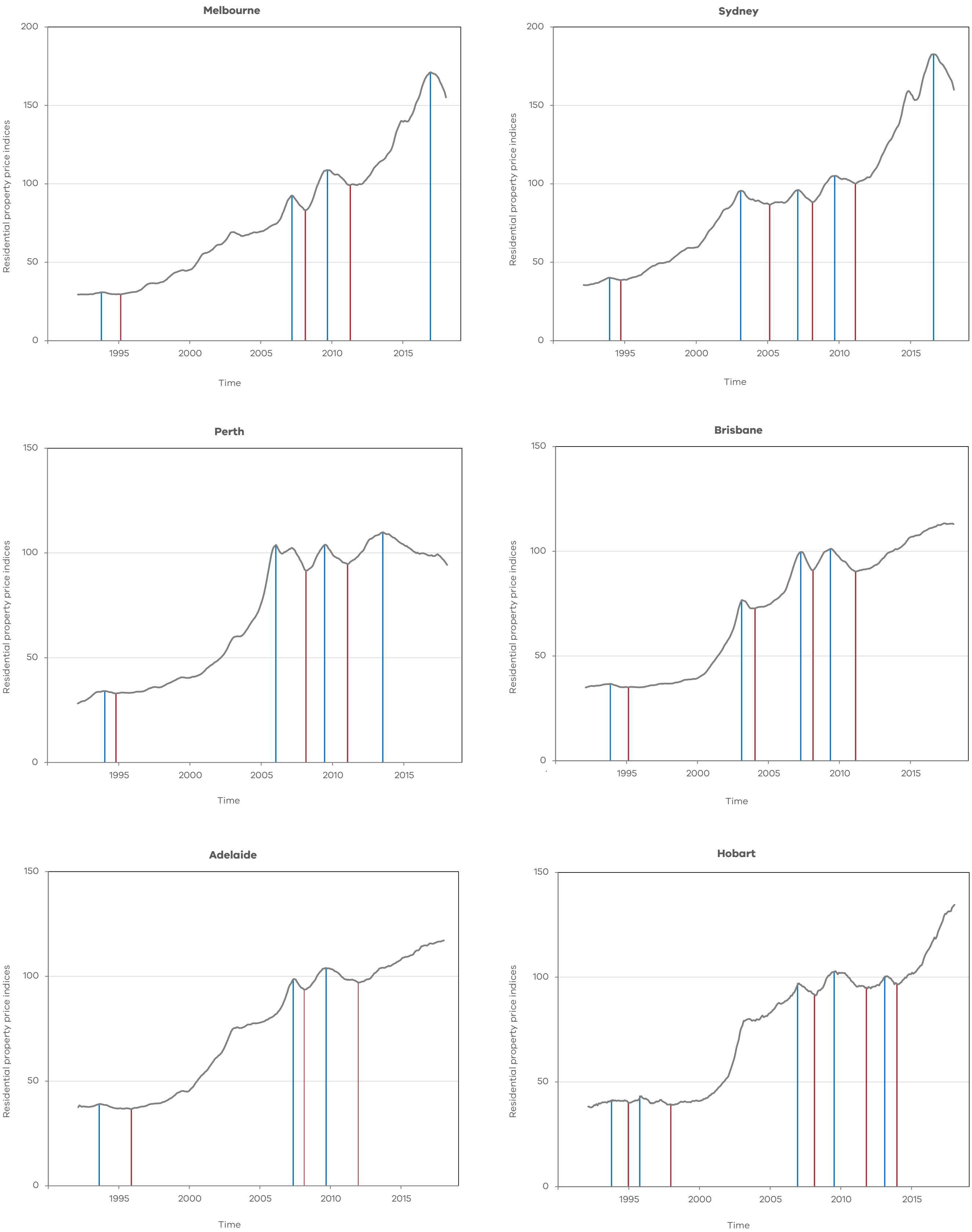
[3] We use the six state capitals because Northern Territory and Australian Capital Territory have different recording conventions, and data from the Northern Territory are only available from 1999.

[4] See CoreLogic. (2018, November 1). CoreLogic Home Value Index - Methodology. Retrieved from CoreLogic Web site: https://www.corelogic.com.au/sites/default/files/2017-09/CL17_CoreLogicIndicesFAQs_Aug.pdf for the methodology that CoreLogic Home Value Index constructed.

[5] Girouard et al. (2006) and Bracke (2013) set k to 6 quarters or 18 months, however, we find that such a high threshold is too restrictive for our dataset, which spans around 26 years. Using these parameters for our data restricts the number of observed peaks and troughs.

[6] By definition, an expansion has a positive amplitude and a contraction has a negative amplitude.

Figure 1: House price cycles in Australian capital cities



Note: Blue lines indicate updturn and red lines denote downturn.

3. Characteristics of expansions and contractions

Table 2 displays the durations associated with these phases. The duration of housing market expansions in our sample ranges from 10 to 145 months. The longest expansions occurred in Melbourne, Adelaide and Perth, lasting from the mid-1990s to the mid-2000s. The longest complete contractions occurred in Hobart and Adelaide and lasted 27 months. The current contraction in Perth, commencing in mid-2014, will likely exceed the existing maximum duration for a contraction when the cycle is completed. Expansions are, on average, significantly longer than contractions (mean of 57 months vs. 17 months, respectively).

Table 2: Duration of phases (months)

	SYDNEY	MELBOURNE	BRISBANE	PERTH	ADELAIDE	HOBART
Contraction	9	16	15	9	27	14
Expansion	101	145	96	135	138	10
Contraction	24	11	11	25	9	26
Expansion	24	19	39	16	19	108
Contraction	12	19	10	19	27	14
Expansion	19	68	15	30		17
Contraction	17		21			27
Expansion	66					16
Contraction						10

Note: Incomplete expansions/contractions are omitted.

Table 3 reports the descriptive statistics (number of expressions or contractions (N), mean, standard deviation (SD), minimum and maximum) for the durations and amplitudes for each price index, split by expansions and contractions. During a typical expansion, house prices grow by approximately 71 per cent compared with the pre-expansion level. House prices contract by approximately 7 per cent during a typical contraction. Using the average durations of the phases, the average monthly price growth rates are 1.24 per cent and -0.41 per cent during expansions and contractions, respectively. In terms of amplitude, the largest single expansions occurred in Perth and Melbourne where prices more than doubled from 1995 to 2006 and from 1996 to 2008, respectively.

Table 4 reports correlation coefficients for house price growth (year-on-year) across the six capital cities. While house price growth is quite correlated within the South and East Coast mainland markets, Western Australia displays less synchronisation with other states.

Table 3: Characteristics of house price cycles in each Australian capital city 1993-2018

	EXPANSIONS							CONTRACTIONS						
	DURATION (MONTHS)			AMPLITUDE (% CHANGE)				DURATION (MONTHS)			AMPLITUDE (% CHANGE)			
	N	MEAN	SD	MEAN	SD	MIN	MAX	N	MEAN	SD	MEAN	SD	MIN	MAX
AUS	19	56.9	48.3	70.8	74.2	6.3	215.6	22	16.9	6.6	-6.9	2.6	-3.1	-11.8
Sydney	4	52.5	38.6	65.0	63.8	10.8	147.8	4	15.5	6.6	-6.5	2.7	-3.9	-9.4
Melbourne	3	77.3	63.5	105.4	95.3	30.7	212.7	3	15.3	4.0	-7.7	3.2	-4.3	-10.1
Brisbane	3	50.0	41.6	55.8	56.2	11.4	119.0	4	14.3	5.0	-7.4	3.0	-4.6	-10.8
Perth	3	60.3	65.0	81.8	115.9	13.5	215.6	3	17.7	8.1	-8.1	4.2	-3.6	-11.8
Adelaide	2	78.5	84.1	90.2	112.1	11.0	169.5	3	21.0	8.5	-6.0	0.7	-5.1	-6.7
Hobart	4	37.8	46.9	44.0	70.0	6.28	148.9	5	18.2	7.8	-6.2	2.8	-3.1	-9.9

Table 4: Correlation of house price growth across capital cities

	SYDNEY	MELBOURNE	BRISBANE	PERTH	ADELAIDE	HOBART
Sydney	1					
Melbourne	0.813	1				
Brisbane	0.555	0.613	1			
Perth	0.112	0.188	0.428	1		
Adelaide	0.565	0.695	0.901	0.357	1	
Hobart	0.311	0.357	0.810	0.412	0.698	1

4. Testing for duration dependence

In this section, we test for duration dependence in property market cycles across Australian capital cities. As discussed in Section 1, house price cycles that exhibit duration dependence are more likely to end the longer they continue. In other words, the probability that a phase ends in period t, conditional on survival until period $t-1$, increases with t. Phases that exhibit lagged duration dependence have durations that are correlated with the duration of the previous phase. We perform separate tests for duration dependence in expansions and contractions.

To test for this phenomena in Australian housing cycles, we follow Bracke (2013) and apply the method suggested by Ohn et al. (2009). Ohn et al. (2009) suggest a straightforward method to check if the upturns and downturns of a series display duration dependence. Similarly to Ohn et al. (2009), we create an indicator variable for each capital city c in our sample that takes the value '0' if city c is experiencing an expansion and '1' otherwise. Then, we keep all observations across capital cities that belong only to expansions plus the first observation that signifies the beginning of the subsequent contraction. We pool this data to form the dependent variable for our tests of duration dependence during expansions.

For contractions, the sub-sample is analogous, but where $S_{c,t} = 0$ denotes that the contraction continues and $S_{c,t} = 1$ denotes the beginning of the next expansion and, therefore, the end of the phase. Using this approach, we represent the continuation of the phase with '0' and the end of the phase with '1' for each type of phase.[7] We then estimate the following Logit regression for expansions and contractions, respectively:

$$Pr\left(S_{c,t} = 1 \middle| S_{c,t-1} = 0\right) = \Lambda(\gamma_c + \ \beta d_{c,t-1}) \qquad (1)$$

where $d_{c,t}$ is the ongoing duration of the current phase at time t, c is city fixed effects, and $\Lambda()$ is the logistic function. We are primarily interested in the sign and significance of β. A significant and positive β in either regression denotes that phase displays duration dependence.

Columns 1 and 3 in panel A of Table 5 report these results for expansions and contractions, respectively. The relevant parameter for expansions is marginally positive but not statistically significant, even at the 10 per cent confidence level. For contractions, we find a larger parameter that is significant at the 1 per cent confidence level. These results indicate that only contractions exhibit duration dependence, which implies that the longer a contraction lasts, the more likely it will end in the following period. Panel B additionally reports the marginal effects for these variables, which have a similar interpretation to the parameter estimates themselves. For example, column (3) shows that if a contraction cycle lasts for one more month, the probability that this cycle will ends increases by 0.41 per cent.

We then test for lagged duration dependence by including the duration of the previous phase in the regression of Equation (1):

$$Pr\left(S_{c,t} = 1 \middle| S_{c,t-1} = 0\right) = \Lambda\left(\gamma_c + \beta d_{c,t-1} + \delta l_{c,t-1}\right) \qquad (2)$$

where all variables are defined as per Equation (1), but we also include the variable $l_{c,t-1}$ which, for expansions, captures the length of the previous contraction, and vice versa. Columns 2 and 4 in panel A of Table 5 report these parameter estimates. Contractions display lagged duration dependence, or in other words, contractions last longer when they follow longer expansions. The reverse is not valid for expansions.

[7] Our set-up differs superficially from that of Bracke (2013) who codes upturns as '1' and downturns as '0' in both sub-samples. We choose to code the continuation of a phase as '0 and the end of a the phase as 1 such that a positive and significant parameter on $d_{i,t-1}$ indicates duration dependence in both cases.

Table 5: Duration dependence test

PANEL A – PARAMETER ESTIMATES	EXPANSIONS		CONTRACTIONS	
	(1)	(2)	(3)	(4)
$d_{c,t-1}$	0.0001	0.0001	0.1029***	0.1309***
	(1.18)	(1.18)	(2.98)	(3.30)
$l_{c,t-1}$		0.0000		0.0142**
		(0.00)		(1.96)
Pseudo R^2	0.0024	0.0024	0.1005	0.1297
State fixed effect	√	√	√	√
N	1 184	1 184	369	369
PANEL B – MARGINAL EFFECTS	**EXPANSIONS**		**CONTRACTIONS**	
$d_{c,t-1}$	0.0001	0.0001	0.0041***	0.0051***
	(1.18)	(1.18)	(2.61)	(2.85)
$l_{c,t-1}$		0.0000		0.0006*
		(0.00)		(1.85)

Note: ***, **, and * denote results are significant at 1 per cent, 5 per cent and 10 per cent, respectively.

5. Determinants of expansions and contractions

In this section, we examine whether contemporaneous macroeconomic or financial variables can predict the end of house price cycles in the next period. We augment Equation (2) with a number of variables that have been commonly used to explain house price dynamics:

- $MORT_t$: Annual difference in lending rates for housing loans to owner-occupiers, or the mortgage rate
- $CPI_{c,t}$: Annual growth in the consumer price index
- $SFD_{c,t}$: Annual growth in the state final demand
- $WAGE_{c,t}$: Quarterly growth rate of the wage price index
- $EMP_{c,t}$: Annual growth in the total number of employed persons

Table 6 provides the descriptive statistics (number of observations (N), mean, standard deviation (SD), minimum and maximum) for the variables that we include in Equation (3). The most volatile variable is SFD, followed by CPI. All these macroeconomic variables are stationary.

The augmented regression equation is:

$$Pr\left(S_{c,t} = 1 \middle| S_{c,t-1} = 0\right) = \Lambda(\gamma_c + \beta d_{c,t-1} + \delta l_{c,t-1} + \rho' X_{c,t-1}) \quad (3)$$

where $X_{c,t-1}$ are the variables listed in Table 6, and all other details are as per Equation (2). Table 7 shows the results from estimating Equation (3) when including these variables. We find that the mortgage rate has explanatory power for both expansions and contractions. An increase in the mortgage rate increases the probability that expansions will end during the next period, while cuts to the mortgage rate predict the end of a contraction. These results suggest that monetary and macroprudential regulation play an important role in determining the length of Australian housing cycles. Relatively loose monetary policy, or the relaxation of credit constraints, can prolong a housing expansion but also help end a contraction.

Table 6: Summary statistics for covariates

VARIABLE	N	MEAN	SD.	MIN	MAX
$MORT_{t-1}$[8]	1 518	-0.106	0.987	-3.800	1.650
$CPI_{c,t-1}$	1 518	7.709	2.645	0.906	13.893
$SFD_{c,t-1}$	1 518	11.130	8.046	-15.171	35.160
$WAGE_{c,t-1}$	1 518	0.266	0.426	0.000	1.944
$EMP_{c,t-1}$	1 518	1.813	1.723	-4.965	7.610

[8] Mortgage rates declined significantly during the 1990s and increased during the 2000s in the lead up to the global financial crisis. Over the past decade, mortgage rates have declined gradually. In this paper, data for mortgage rate ranges from 1993 m1 to 2018 m12. Out of 312 monthly observations, there are 38 incidents of increases and 37 incidents of decreases in mortgage rates. Asymmetry can be observed in mortgage rate changes; the year-on-year mortgage rate change is 0.37 percentage points (pps) during increases, while it is -1.08 pps during decreases. Similarly, the month-on-month mortgage rate changes are 0.25 pps and -0.39 pps for increase and decrease incidents, respectively. The main factor which contributed to changes in mortgage rates is monetary policy.

Table 7: Duration dependence with macroeconomic variables

PANEL A: PARAMETER ESTIMATES	EXPANSIONS	CONTRACTIONS
$d_{c,t-1}$	0.0050	0.1731**
	(0.65)	(2.31)
$l_{c,t-1}$	0.0291	-0.0083
	(0.63)	(-0.76)
$MORT_{t-1}$	1.8123***	-2.5415***
	(4.57)	(-3.54)
$CPI_{c,t-1}$	0.1849*	-0.3346
	(1.86)	(-1.16)
$SFD_{c,t-1}$	-0.0242	0.1437*
	(-0.57)	(1.79)
$WAGE_{c,t-1}$	-0.0401	1.3547**
	(-0.07)	(2.26)
$EMP_{c,t-1}$	-0.3009	0.3041
	(-1.55)	(1.13)
Psuedo R^2	0.1706	0.4480
State FE	√	√
N	1184	369
PANEL B: MARGINAL EFFECTS	**EXPANSIONS**	**CONTRACTIONS**
$d_{c,t-1}$	0.0001	0.0047**
	(0.64)	(2.24)
$l_{c,t-1}$	0.0004	-0.0002***
	(0.62)	(-0.77)
$MORT_{t-1}$	0.0272**	-0.0690***
	(3.48)	(-3.52)
$CPI_{c,t-1}$	0.0028*	-0.0092
	(1.76)	(-1.14)
$SFD_{c,t-1}$	-0.0004	0.0039*
	(-0.56)	(1.75)
$WAGE_{c,t-1}$	-0.0006	0.0368**
	(-0.07)	(2.32)
$EMP_{c,t-1}$	-0.0045	0.0083
	(-1.49)	(1.13)

Notes: Results from estimating $\Pr(S_{c,t} = y_1 | S_{c,t-1} = y_2) = \Lambda(\gamma_c + \beta d_{c,t-1} + \gamma l_{c,t-1} + \rho X_{c,t-1})$, where $(y_1, y_2) = (0,1)$, $\Lambda()$ is the logistic function, and $X_{c,t-1}$ are the macro variables. *, **, *** denote 1 per cent, 5 per cent, and 10 per cent significance, respectively.

There is some evidence that economic activity – as proxied by SFD, wage growth and CPI – are important factors in predicting the end of house price phases. Increases in consumer prices tend to predict the end of the expansion phase, though the relevant parameter is only significant at the 10 per cent level. Assuming that rising inflation leads to more restrictive monetary policy, this finding further corroborates the importance of monetary policy in the housing cycle. Economic growth (SFD) and household income (wage growth) help predict the end of a contraction, though SFD is only significant at the 10 per cent level. We still find evidence of duration dependence during contractions even after incorporating macroeconomic variables, although we no longer find evidence of lagged duration dependence.

5.1 Equity market returns and housing cycles

Table 8 contains regression results that are analogous to Table 7 but also include the monthly return on the ASX 200 index as an explanatory variable. This is motivated primarily by the literature that relates housing and financial assets (e.g. Shiller, 2014; Worzala and Vandell, 1993; Eichholtz and Hartzell, 1996; Algieri, 2013; Cocco et al , 2005; Yao and Zhang, 2005) and because it provides a higher frequency (daily) indicator relative to other included variables.

Table 8 demonstrates that positive stock market returns are negatively correlated with expansions ending, or alternatively, a contraction in equity prices predicts the end of an expansion phase. This finding is consistent with Borio and McGuire (2004) who find that house price peaks tend to be correlated with equity peaks, although it must be noted that monthly equity returns do not necessarily correspond to peaks. We do not find comparable evidence that equity market returns can predict the end of contractions.

Table 8: Duration dependence with macroeconomic variables and a financial market variable

PANEL A: PARAMETER ESTIMATES	EXPANSIONS	CONTRACTIONS
$d_{c,t-1}$	0.0101	0.1545**
	(1.18)	(2.15)
$l_{c,t-1}$	0.0502	-0.0135
	(0.95)	(-1.11)
$MORT_{t-1}$	2.2735***	-3.0160***
	(5.01)	(-3.38)
$CPI_{c,t-1}$	0.1013	-0.0948
	(0.93)	(-0.28)
$SFD_{c,t-1}$	-0.0025	0.0892
	(-0.05)	(1.04)
$WAGE_{c,t-1}$	-0.0932	1.3944**
	(-0.17)	(2.23)
$WPO_{c,t-1}$	-0.2801	0.5400
	(-1.23)	(1.61)
$Stock_t$	-0.0548**	0.0405
	(-2.06)	(1.22)
Psuedo R^2	0.2419	0.4599
State fixed effect	√	√
N	1183	369

Table 8: Duration dependence with macroeconomic variables and a financial market variable (cont.)

PANEL B: MARGINAL EFFECTS	EXPANSIONS	CONTRACTIONS
$d_{c,t-1}$	0.0001	0.0040**
	(1.15)	(3.49)
$l_{c,t-1}$	0.0007	-0.0003
	(0.97)	(-1.13)
$MORT_{t-1}$	0.0312***	-0.0792***
	(3.80)	(-3.33)
$CPI_{c,t-1}$	0.0014	-0.0025
	(0.92)	(-0.27)
$SFD_{c,t-1}$	-0.0000	0.0023
	(-0.05)	(1.02)
$WAGE_{c,t-1}$	-0.0013	0.0366**
	(-0.17)	(2.29)
$WPOP_{c,t-1}$	-0.0038	1.0142
	(-1.21)	(1.62)
$Stock_t$	-0.0008*	0.0011
	(-1.94)	(1.23)

Notes: Results from estimating $Pr(S_{c,t} = y_1 | S_{c,t-1} = y_2) = \Lambda(\alpha + \beta d_{c,t-1} + \gamma l_{c,t-1} + \rho X_{c,t-1} + \gamma_c)$, where $(y_1, y_2) = (0,1)$, $\Lambda()$ is the logistic function, and $X_{c,t-1}$ are the macro variables. *, **, *** denote 1 per cent, 5 per cent, and 10 per cent significance, respectively.

5.2 Predicting the duration of the recent contraction

Having the estimated parameters on hand, we perform an experiment in which we predict the time for the end of the recent downturn in the housing market in Victoria. Our analysis indicates that the most recent peak in Melbourne dwelling prices occurred in November 2017. While recent data suggests that the subsequent contraction has since ended, our results, based on the DTF data, show that the recent downturn in Melbourne finished in the third quarter of 2019. We, therefore, examine whether or not our estimated regressions would have predicted the end of the contraction, based on estimated parameters and DTF macroeconomic forecasts. The probability of ending a given upturn or contraction in the current period is:

$$Pr\left(S_{ct} = 1 \middle| S_{c,t-1} = 0, \hat{X}_{c,t}\right) = \Lambda(\hat{X}_{c,t}{}'\beta) = \frac{e^{\hat{X}_{c,t}{}'\beta}}{1+e^{\hat{X}_{c,t}{}'\beta}} \quad (4)$$

where $\hat{X}_{c,t}$ are DTF forecasts of variables that we include in the logistic regression in Equation (3). We use forecasts from the Victorian Budget (May 2019) and compute the marginal probability of the contraction spanning the months June 2019 to October 2019.

Table 9 shows the predicted cumulative probability that the current contraction phase in Victoria ends in each month. The model predicts that the ongoing contraction experienced in Victoria was very likely to have ended by the last quarter of 2019.[9]

Table 9: Predicted probability of the current ongoing phase ending

ONGOING CONTRACTIONS	PROBABILITY PHASE FINISHES BY...
June 2019	72%
July 2019	86%
August 2019	94%
September 2019	98%
October 2019	100%

6. Conclusion

In this paper, we study 25 years of house price cycles in Australia. We identify peaks and troughs in all capital city housing markets using a rigorous data-driven approach. We describe the features of these cycles, with a focus on duration and amplitude, and test for duration dependence and for whether these macroeconomic and financial variables can be useful predictors of phase ends.

We show that, consistent with international evidence, expansions are, on average, longer-lived than contractions and that contractions (but not expansions) display duration dependence. A number of macroeconomic variables help to predict the end of phases, most notably the mortgage rate, indicating the important role of monetary and macroprudential policy in managing these cycles. The models that we employ can, in the future, be useful tools for estimating the likelihood that ongoing phases will continue into the budget year and beyond.

[9] We updated our analysis based on newly available data up to Nov 2019. CoreLogic data suggest Melbourne house prices troughed in May 2019, and an upturn subsequently started in Jun 2019. Using DTF macroeconomic forecasts up to Jun 2023, our model states that the probability that the Melbourne house prices will continue to increase up to the end of the forecast horizon is 83 per cent.

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Estimating Victoria's trend unemployment rate[1]

By Bonnie Li, Tim Stephen, Nicholas McMeniman and Grace Gao

ABSTRACT

The degree of spare capacity in the labour market is a key consideration in economic forecasting. One common measure of the degree of spare capacity is the gap between the unemployment rate and a modelled estimate of the trend unemployment rate. Building on existing literature, this paper estimates the trend unemployment rate for Victoria using a model of the non-accelerating inflation rate of unemployment. The methodology used in this paper finds that the trend unemployment rate has fallen over the past few years and is currently estimated to be around 4.7 per cent. The current model estimate is close to the current unemployment rate, suggesting there is limited spare capacity in the Victorian economy, although this estimate is subject to some uncertainty.

Overview

The degree of spare capacity in the labour market is a key consideration in forming views on wage and inflationary pressures in the economy. A common measure of spare capacity in the labour market is the unemployment gap, which is the difference between the observed unemployment rate and the trend unemployment rate.

When the observed unemployment rate is above trend, there is spare capacity in the labour market. This means there will be downward pressure on wage growth and inflation, as competition among workers means employers do not need to raise wages to attract suitable employees. Conversely, when observed unemployment is below trend, there is a shortage of workers, resulting in upward pressure on wage growth and inflation as firms bid up wages.

This paper analyses factors that are likely to have contributed to changes in the trend unemployment rate in Victoria in recent years and provides an updated estimate of the trend unemployment rate.

The remainder of this paper is structured as follows. Section 1 discusses developments in the Victorian labour market and drivers of the trend unemployment rate. Section 2 compares two different modelling approaches to estimate the trend unemployment rate. Section 3 outlines a model for Victoria's trend unemployment rate and associated data requirements. Section 4 presents results and model sensitivities. Section 5 provides concluding thoughts.

[1] The authors are grateful for comments from Paul Donegan, Craig Michaels, Anthony Rossiter, Jonathan Dark, Shenglang Yang and Omid Mousavi. The views expressed are those of the authors and do not necessarily reflect the views of DTF.

1. Drivers of the trend unemployment rate

The past few years have seen large and sustained declines in unemployment rates in many advanced economies, suggesting these economies may be approaching capacity constraints. However, many countries continue to experience low wage growth and inflation despite the strength of their labour markets.

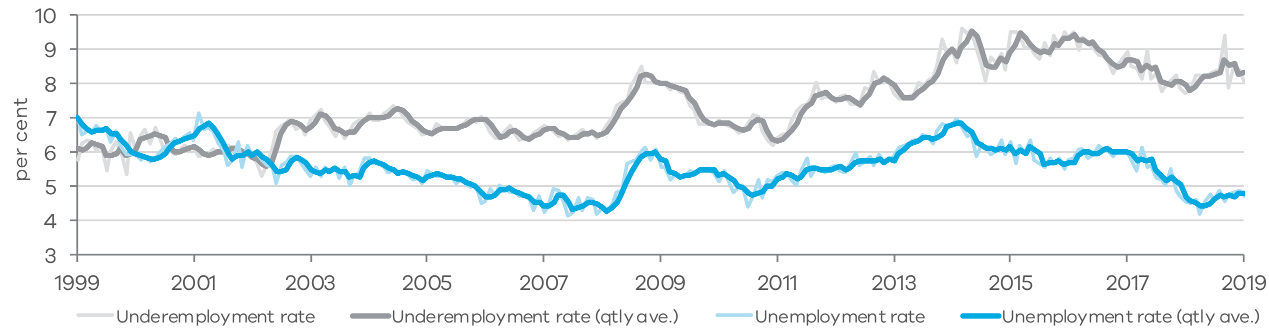
In Victoria, the quarterly average unemployment rate fell by 1.2 percentage points over the two years to September 2019 and is currently below 5 per cent (Figure 1) — around the same level seen prior to the global financial crisis (GFC). The underemployment rate (which measures the proportions of employed persons who would like to work more hours) has also fallen slightly over this period but overall remains elevated.

Historically, extended periods of low unemployment have been associated with high wage growth. While Victorian wage growth has increased since 2016, it remains well below the 4 per cent rate of annual growth seen in late 2008, and well below what the reduction in the unemployment rate would imply (Figure 2). This inconsistency may suggest that the relationship between the unemployment rate and wage growth has changed. It could also reflect that the rate of underemployment in Victoria has increased somewhat over the long term.

A key consideration in explaining this divergence is the flexibility of the labour market, and in particular, the observed increases in labour supply. The female population and older cohorts of both sexes are increasingly participating in the labour market, partly reflecting changes in social attitudes and improved health outcomes, which increases longevity risk in retirement (Brown and Guttman, 2017).[2] This has offset a negative contribution to the participation rate from population ageing. Additional labour supply means there may be more capacity in the labour market than the unemployment (or underemployment) rate may suggest. Any further addition to labour supply will place downward pressure on wage growth, all else constant.

The labour market may also exhibit 'hysteresis' effects, which, in this context, refer to instances where short-run disturbances in the economy affect the long-run trajectory of unemployment. There is evidence of this occurring in Victoria during the early 1990s recession, where the long-term unemployment rate rose sharply and took a long time to abate. But hysteresis effects can also work in the opposite direction. When labour markets tighten, previously long-term unemployed people are more likely to be hired. This helps them build up skills and experience that improve their future employment prospects, thus structurally lowering unemployment (Ellis, 2019).

Figure 1: Unemployment and underemployment 1999-2019, Victoria



Source: ABS

Figure 2: Wage growth and unemployment 1999-2019, Victoria

Source: ABS

[2] This refers to the risk that retirees will not have enough superannuation savings to last the full period of their retirement.

It is notable that unemployment rates for the long-term unemployed (one year or longer) have declined in recent years, particularly within the past year or so (Figure 3). The reduction in the long-term unemployment rate, if sustained, suggests the trend unemployment rate may also have declined somewhat.

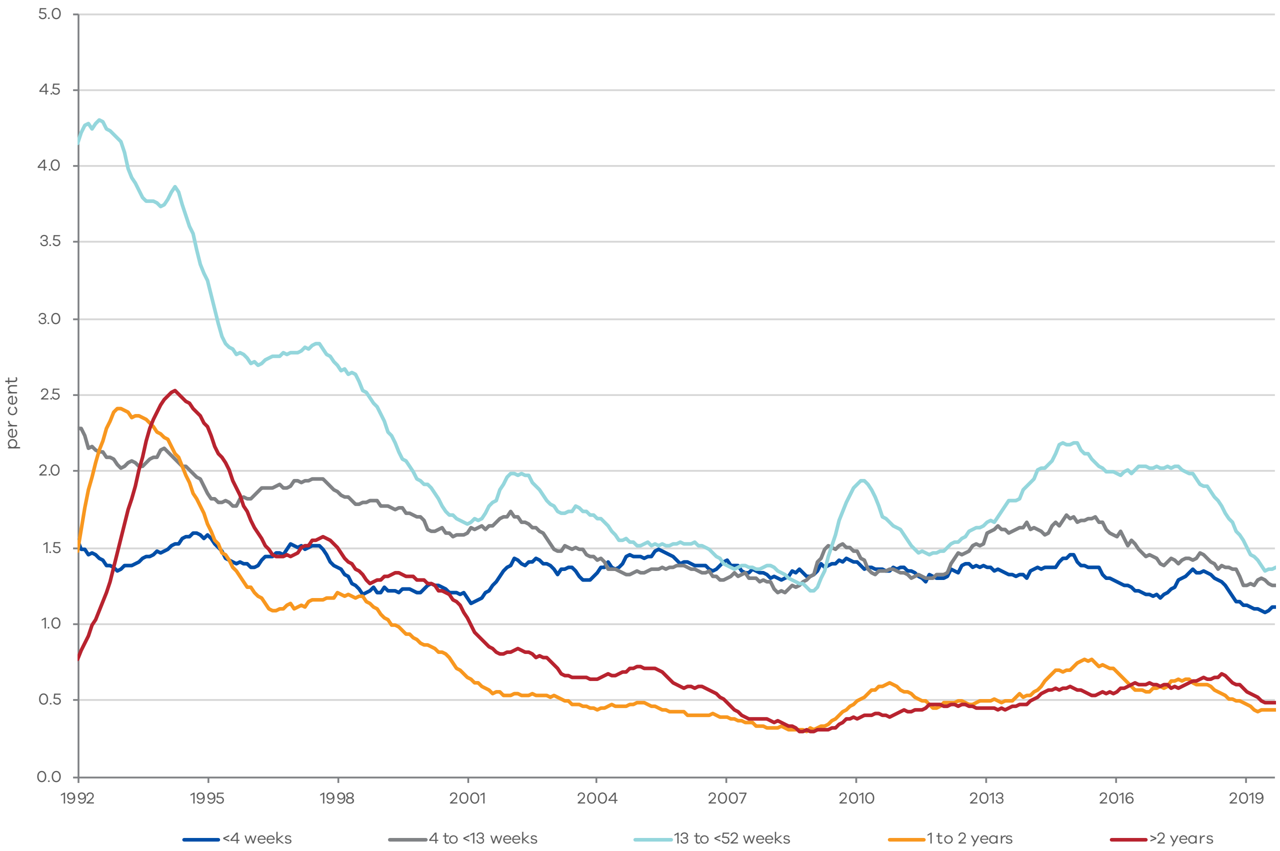
The unemployment rates of those unemployed between four and 52 weeks have also declined significantly over the past two years.[3] While this is likely to reflect the strong cyclical performance of the Victorian economy over this period, it could also reflect better matching of the unemployed to job opportunities given the emergence of online job advertising and app-based job search technologies. Among other things, this would suggest a more efficient labour market (Ellis, 2019).

There are other factors that affect wage growth and inflation besides labour market spare capacity.

- One key factor is that technological advancement, particularly in information and communications technologies, has significantly lowered input costs (capital rental prices) for many firms. It may also mean that some previously non-tradeable services which comprise large inputs for many firms have become tradeable and more cost-effective, such as accounting services.
- Technology has also driven a more integrated global trading system (i.e. greater import penetration in the traded sector), which has exposed many firms to greater competition. Technological developments have, therefore, constrained input cost inflation at the same time as they have limited some firms' ability to lift output prices.
- Labour productivity growth, which is a necessary pre-condition for substantial real wage rises, has been lacklustre in the post GFC period (the drivers of which are manifold and predate the GFC; see Productivity Commission (2017)).

Hence, it is reasonable to expect that the trend unemployment rate will change over time. Ultimately, the trend unemployment rate is unobserved. There is some degree of uncertainty around estimates of time-varying trend unemployment. There are several ways to model it in practice, and each method can provide different results. The following section discusses two broad approaches to estimating the trend rate of unemployment in more detail.

Figure 3: Unemployment rate, Victoria, by unemployment duration



Source: ABS

[3] The unemployment rate of those unemployed up to four weeks, who can broadly be thought of as the frictionally unemployed, has declined only slightly over the past 25 years. This is perhaps unsurprising as there will always be a certain proportion of the labour force between jobs.

2. Phillips Curve and Beveridge Curve approaches

This section provides an overview of two approaches for estimating the trend unemployment rate: those estimating the non-accelerating inflation rate of unemployment (NAIRU) based on the Phillips Curve, and those using the job vacancy rate based on the Beveridge Curve.[4]

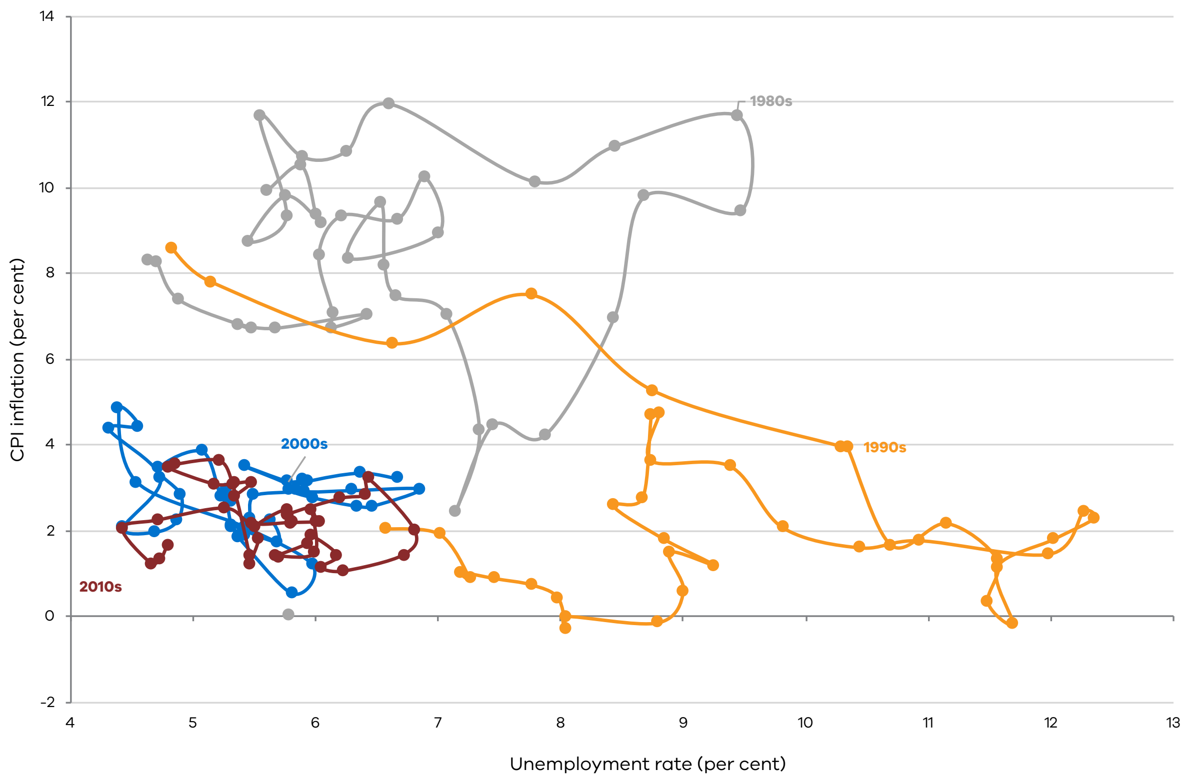
2.1 Phillips Curve models

The classical short-run Phillips Curve depicts an inverse relationship between the unemployment rate and wage growth or inflation (Phillips, 1958). Phillips considered that under sufficient demand conditions, wage growth flowed through to prices as businesses pass on higher costs of production in the form of higher output prices. In doing so, Phillips observed an empirical correlation between unemployment and inflation. The short-run Phillips Curve for Victoria over the past four decades is presented in Figure 4.

Models of the Phillips Curve were later formalised on the assumption that employers and employees have rational expectations about future rates of inflation, are forward looking and fully informed (Friedman, 1968). If employees are aware their nominal wages have not kept pace with inflation, and expect this will persist, they would rationally renegotiate their wages to reflect a higher expected rate of inflation. As nominal wages increase, production costs for employers rise, and they will lift their prices to maintain profits on the expectation that other firms will do so as well.

These models distinguish between a short-run and long-run relationship. While there is a trade-off between inflation and unemployment in the short-run, there is no such trade-off in the long run where inflation is stable. That is, in the long run, there is only one equilibrium unemployment rate that is consistent with stable inflation. Estimates of this trend unemployment rate using the Phillips Curve approach are commonly known as the NAIRU.

Figure 4: Short-run Phillips Curve, 1980-2019, Victoria



Source: ABS
Note: Each dot represents a quarterly observation.

[4] The NAIRU is distinct from the concept of a 'natural' rate, which refers to the rate of unemployment that prevails when an economy is in long-run equilibrium and is not affected by short-run rigidities in labour and product markets. In structural models which impose long-run equilibrium conditions on the economy, the NAIRU and the natural rate converge to the same rate as the unemployment gap and the output gap converge to zero.

As an estimate of the trend unemployment rate, the NAIRU may change over time. This is a key explanation for why inflation and unemployment have simultaneously declined in recent years, and it does not necessarily suggest the short-run inverse relationship has broken down. Indeed, there is empirical evidence that the short-run inverse relationship has not changed too significantly in many countries (including Australia) and remains a valid framework for assessing wage and price pressures in the economy (Arsov and Evans, 2018). From a forecasting perspective, the NAIRU provides a helpful framework, as it provides a link between inflationary and wage pressure and the degree of spare capacity in the labour market.

In the literature, Gruen, Pagan and Thompson (1999) and Cusbert (2017) are two applications of the Phillips Curve approach in Australia. Both use a state-space model approach, with observable wages and inflation equations and an unobserved NAIRU that follows a random walk. There are many studies of the Phillips Curve approach using different specifications. Laubach (2001) uses an observable price equation and a random-walk NAIRU with a drift where the drift also follows a random-walk process, and applies it to seven economies, including Australia. Gianella, Koske, Rusticelli and Chatal (2008) subsequently applied Laubach (2001) to 19 OECD countries.

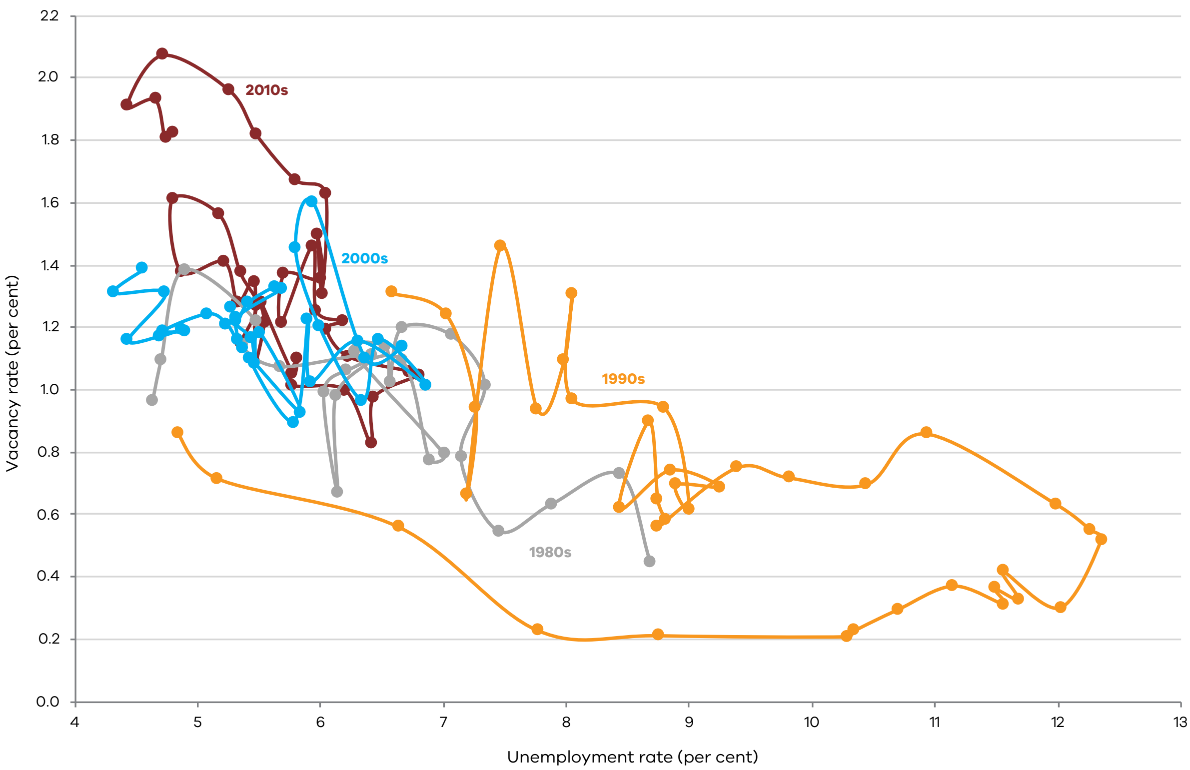
2.2 Beveridge Curve models

An alternative modelling approach uses the Beveridge Curve, which depicts an inverse relationship between the unemployment rate and the job vacancy rate (i.e. the number of unfilled jobs as a proportion of the labour force). The trend unemployment rate is estimated by assuming that when the labour market is in equilibrium, both the vacancy rate and unemployment rate are in equilibrium (Groenewold, 2003).

A benefit of the Beveridge Curve approach is that the inclusion of the vacancy rate in the equation provides insight into the efficiency of the labour market vis-à-vis matching of the unemployed with vacancies. However, a Beveridge Curve approach does not provide any insight into wage and price pressures. Furthermore, the approach requires an estimate of the equilibrium vacancy rate, and methods to estimate it differ greatly in the literature (see, for example, Fahrer and Pease, 1993; Groenewold, 2003; and Kennedy, Luu and Goldbloom, 2008). The estimate of the equilibrium unemployment rate may differ by up to a few percentage points and can only ever be as robust as the estimate of the equilibrium vacancy rate (Kennedy, Luu and Goldbloom, 2008).

The Beveridge Curve for Victoria over the past four decades is presented in Figure 5. A challenge of using a Beveridge Curve approach in the Victorian context is that the Curve has shifted recently, and with the limited number of observations since the shift, it is difficult to be confident in the new Beveridge Curve's estimate of the trend unemployment rate. The Curve's estimation is further limited by the lack of data on vacancies in 2008 and 2009.

Figure 5: Beveridge Curve, Victoria



Source: ABS

Note: Each dot represents a quarterly observation. Vacancy data were not published by the ABS from the September quarter of 2008 to the September quarter of 2009 inclusive.

3. A Victorian trend unemployment rate model

This paper uses the Laubach (2001) Phillips Curve model to estimate Victoria's trend unemployment rate for its apparent robustness and successful general application to a wide range of economies.

The Laubach (2001) model uses a state-space approach, with one observable equation and two unobservable equations with up to three lags. The observable Equation (1) describes the relationship between the variation of inflation from its expectation and the unemployment gap, controlling for the exchange rate and commodity prices. The unemployment gap is measured as the difference between the unemployment rate and the NAIRU. In this model, the NAIRU follows a random walk with drift (Equation (2)), with the drift being another random walk (Equation (3)). The residuals are assumed to be independently distributed.

Formally:

$$
\begin{aligned}
\Delta\pi_t = \;& \beta_1 \cdot \Delta\pi_{t-1} + \beta_2 \cdot \Delta\pi_{t-2} + \beta_3 \cdot \Delta\pi_{t-3} \\
& + \gamma_1(u_{t-1} - u_{t-1}^N) + \gamma_2(u_{t-2} - u_{t-2}^N) + \gamma_3(u_{t-3} - u_{t-3}^N) \\
& + \delta_{1,1}\Delta c_{t-1} + \delta_{1,2}\Delta c_{t-2} + \delta_{2,1}\Delta x_{t-1} + \delta_{2,2}\Delta x_{t-2} + \epsilon_t \qquad with\ \epsilon_t \sim N(0, \sigma^2), \quad (1) \\
& u_t^N = u_{t-1}^N + \mu_{t-1}^N + \varepsilon_t \qquad with\ \varepsilon_t \sim N(0, \sigma_\varepsilon^2), \quad (2) \\
& \mu_t^N = \mu_{t-1}^N + \zeta_t \qquad with\ \zeta_t \sim N(0, \sigma_\zeta^2). \quad (3)
\end{aligned}
$$

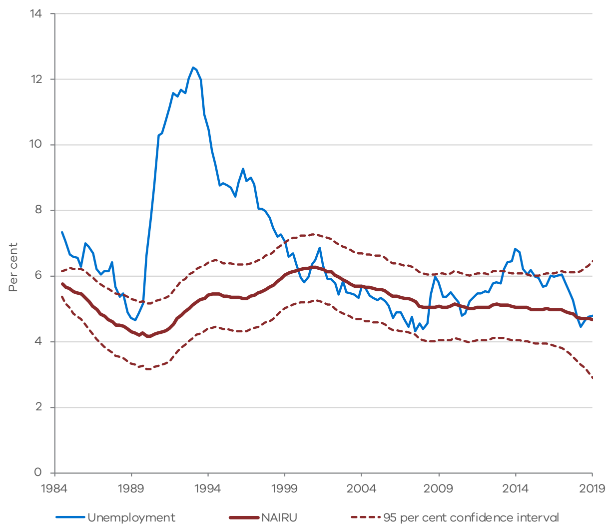
where $\Delta\pi_t = \pi_t - \pi_t^e$ denotes the difference between inflation π_t and inflation expectations π_t^e, u_t is the unemployment rate, u_t^N is the NAIRU, Δc_t and Δx_t are first-order log-differences in commodity prices and the exchange rate, and u_t denotes the stochastic drift applied to the NAIRU equation with the initial value $\mu_0 = 0$. The error terms in Equations (1)–(3) follow a normal distribution with zero mean and variances σ^2, σ_ε^2 and σ_ζ^2.[5]

4. Modelling results and sensitivities

Using data from December quarter 1984 to September quarter 2019 (detailed in Appendix A), the Victorian NAIRU was estimated using the method outlined in Appendix B. The results are presented in Figure 6. The estimated NAIRU fluctuates over the estimation period and has fallen over the past few years to a current estimate of 4.7 per cent with a 95 per cent confidence interval of 2.9-6.4 per cent. The confidence interval has widened in recent periods because there is less data to support the estimation. As more information becomes available, the confidence interval will narrow over time.

The results suggest that while the sharp fall in the unemployment rate over the past two years reduced spare capacity in the labour market, the unemployment rate is currently not materially different from the estimated NAIRU and the fall was not sufficiently large to generate significant inflationary pressure.

Figure 6: NAIRU estimate for Victoria



Note: Confidence interval estimated using Monte Carlo simulation.

The estimated unemployment gap, measured as the difference between the unemployment rate and the NAIRU, displays a strong correlation with the deviation of inflation from long-term expectations, as shown in Figure 7 and Figure 8. However, they do not move in lock step, as there are other factors which affect inflation, such as commodity prices and the exchange rate.

[5] As discussed in Laubach (2001), a problem in the estimation of unobserved-components models like the specifications considered here is the 'pile-up' effect. The maximum likelihood estimates have the undesirable property of point mass at zero even if their true value is greater than 0. To avoid biased estimates of the variances, this paper follows the recommendation in Laubach (2001) and other literatures (Staiger et al 1997, King et al 1995) to fix the parameters $\sigma_\varepsilon = 0.2$ and $\sigma_\zeta = 0.015$.

Figure 7: Estimated unemployment gap and inflation deviation in Victoria

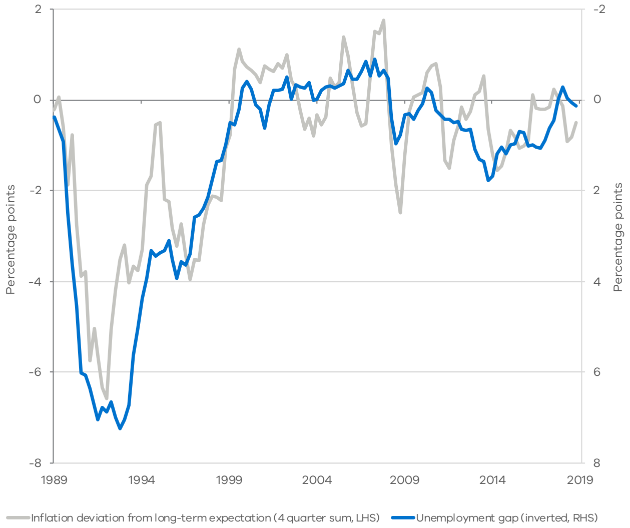
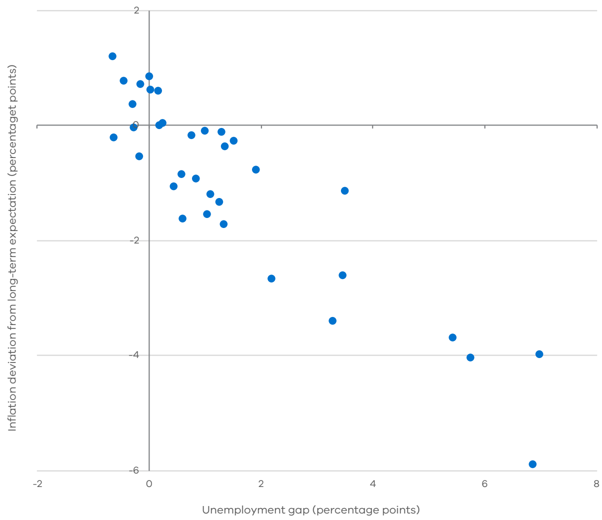


Figure 8: Estimated unemployment gap and inflation deviation in Victoria



Note: Each dot represents a calendar year.

Estimation of the NAIRU involves some degree of uncertainty, particularly when estimated in real time. We obtain the real-time NAIRU estimates by estimating the model period-by-period, using only data up to that period. The end-points of the real-time estimates since March quarter 2000 are shown in Figure 9. Real-time end-point NAIRU estimates are subject to material revisions as new data emerge to help assess the past unemployment gap. Using the data up to September quarter 2018, our model estimated the NAIRU at 5.5 per cent, with the actual quarterly unemployment rate at that time sitting below the estimate at 4.7 per cent. However, using economic data since then, the model now estimates the NAIRU in September quarter 2018 to be around 4.7 per cent.

Figure 9: Real-time end-point NAIRU estimate for Victoria

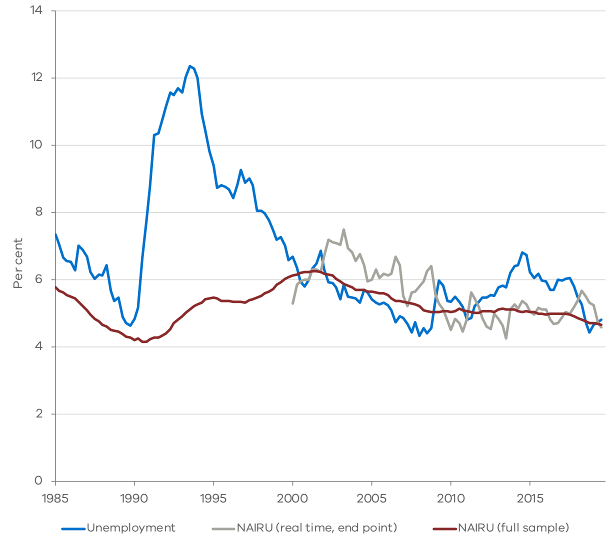
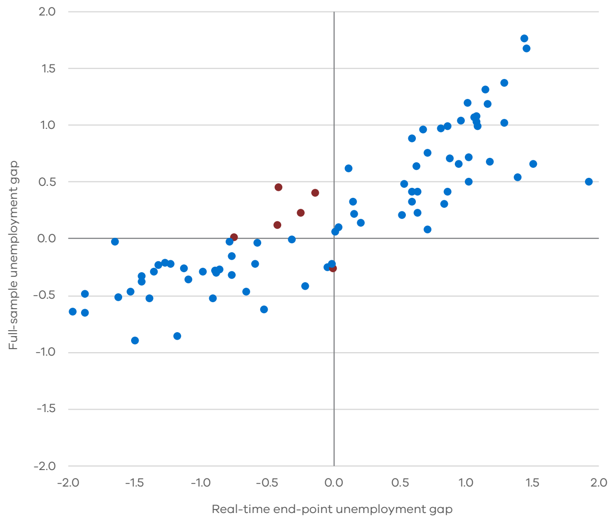


Figure 10: Real-time end-point and full-sample NAIRU estimates since March 2000



Note: Red dots indicate the quarter for which the real-time unemployment gap had the opposite sign to the full-sample unemployment gap.

While real-time end-point estimates may be subject to sizeable revisions, they seldom change the sign of the estimated unemployment gap; that is, the assessment of whether the labour market is under or over capacity often holds over time. Since the March quarter of 2000, the assessment only differed in six quarters, or 8 per cent of the time, as shown in Figure 10.

We further explored the model's robustness by using different measures of inflation expectations, exchange rates, as well as different lags and controls. While the NAIRU estimate changes little with most of these variations, it is very sensitive to changes in the measure of inflation expectations, which is a finding common to several earlier studies (see, for example, Cusbert, 2017). Fluctuations highlight the challenge of estimating the NAIRU and the risk of a misspecification of the model. Users of NAIRU estimates should take these risks and sensitivities into consideration.

5. Conclusion

Estimates of the NAIRU are uncertain and lie within a wide confidence interval. Nonetheless, they are useful for assessing the degree of spare capacity in the labour market and forecasting inflation and wage growth. Using a Phillips Curve approach, and notwithstanding model uncertainty, our estimates suggest that the NAIRU in Victoria may have fallen from 5.5 per cent and is currently estimated to be around 4.7 per cent with a 95 per cent confidence interval of 2.9-6.4 per cent.

This experience has been mirrored in other jurisdictions. New South Wales and Queensland have both recently lowered their estimates of trend unemployment, and the RBA recently lowered its estimate of the NAIRU from 5.25 per cent to 4.5 per cent (Ellis, 2019; Lowe, 2019).

While other modelling approaches, such as using the Beveridge Curve, may yield different estimates of the trend unemployment rate, our estimate for Victoria may help inform judgements about the degree of spare capacity in the labour market as well as the outlook for wages and inflation.

Appendix A: Data

Below are the relevant data and any adjustments made to them in the estimation in section 4.

Inflation

The model uses the quarterly rate of inflation for Melbourne. The data is published by the Australian Bureau of Statistics (ABS) in the catalogue 6401.0 – Consumer Price Index.

Due to the removal of the wholesale tax and the introduction of the goods and services tax (GST) in 2000-01, the inflation series is adjusted using the national estimates of the impact published by the RBA (2019). The adjustments in the quarterly growth rates are +0.1 percentage points in September and December quarters 1998, -0.1 percentage points in March quarter 1999, -0.2 percentage points in December quarter 1999 and March quarter 2000, and -3.0 percentage points in September quarter 2000.

Inflation expectations

NAIRU estimates are sensitive to inflation expectations. Inflation expectations can be inferred through financial market prices, as well as through surveys (for example, of businesses, unions and economists). However, there are no such measures specific to Victoria. In this paper, we use a rolling 10-year historical average of the quarterly rate of inflation in Melbourne as an estimate for inflation expectations.

Unemployment

The model uses the quarterly average of the Victorian seasonally adjusted unemployment rate published by the ABS in catalogue 6202.0 – Labour Force Survey, Australia.

Exchange rate

The exchange rate has a significant impact on inflation in small open economies such as Victoria. In this paper, we use the Australian-US exchange rate. Data for quarterly exchange rates have been derived using the average of monthly data published by the RBA (Table F11).

Commodity prices

Commodity prices also have a strong influence on inflation and are therefore chosen as a control. In this paper, we use the average of the monthly RBA Index of Commodity Prices (ICP, published in Table I2).[6]

[6] Available at https://www.rba.gov.au/statistics/cpi-excluding-tax.html (Accessed on 1 October 2019).

Appendix B: NAIRU estimation

We estimate the NAIRU iteratively in a similar procedure to that described in Shunway and Stoffer (2016, pp. 302-3), as follows:

1. Select an initial parameter for NAIRU, $u_t^{N\,(0)} = u^{N\,(0)}$, where the bracket in the superscript denotes the number of iterations.
2. Estimate the initial values for other parameters using the full sample data in the observable equation:

$$\Delta\pi_t = \beta_1^{(0)}\Delta\pi_{t-1} + \beta_2^{(0)}\Delta\pi_{t-2} + \beta_3^{(0)}\Delta\pi_{t-3} + \gamma_1^{(0)}\left(u_{t-1} - u_t^{N\,(0)}\right) + \gamma_2^{(0)}\left(u_{t-2} - u_t^{N\,(0)}\right) + \gamma_3^{(0)}\left(u_{t-3} - u_t^{N\,(0)}\right) + \delta_{1,1}^{(0)}\Delta c_{t-1} + \delta_{1,2}^{(0)}\Delta c_{t-2} + \delta_{2,1}^{(0)}\Delta x_{t-1} + \delta_{2,2}^{(0)}\Delta x_{t-2} + \epsilon_t$$

$$\text{where } \epsilon \sim N\left(0, {\sigma^{(0)}}^2\right) \quad (4)$$

3. Update the estimate of $y_t^{(0)}$, which is the residual from excluding NAIRU:

$$y_t^{(0)} = \Delta\pi_t - \left(\beta_1^{(0)}\Delta\pi_{t-1} + \beta_2^{(0)}\Delta\pi_{t-2} + \beta_3^{(0)}\Delta\pi_{t-3} + \gamma_1^{(0)}u_{t-1} + \gamma_2^{(0)}u_{t-2} + \gamma_3^{(0)}u_{t-3} + \delta_{1,1}^{(0)}\Delta c_{t-1} + \delta_{1,2}^{(0)}\Delta c_{t-2} + \delta_{2,1}^{(0)}\Delta x_{t-1} + \delta_{2,2}^{(0)}\Delta x_{t-2}\right) \quad (5)$$

4. Update NAIRU estimates with the Kalman filter (Box 1) using the "dlm" package in R with the following specification:

$$y_t^{(0)} = \mathrm{F}^{(0)}\Theta_t^{(0)} + v_t,\ v_t \sim N\left(0, {\sigma^{(0)}}^2\right)$$

where $F^{(0)} = \left(0, -\gamma_1^{(0)}, -\gamma_2^{(0)}, -\gamma_3^{(0)}, 0,0,0,0\right)$,

$\Theta_t^{(0)} = \left(u_t^{N(0)}, u_{t-1}^{N(0)}, u_{t-2}^{N(0)}, u_{t-3}^{N(0)}, \mu_t^{(0)}, \mu_{t-1}^{(0)}, \mu_{t-2}^{(0)}, \mu_{t-3}^{(0)}\right)$

and $\Theta_t^{(0)} = G\Theta_{t-1}^{(0)} + w_t,\ w_t \sim N(0, W)$

where

$$G = \begin{bmatrix} 1&0&0&0&1&0&0&0\\ 1&0&0&0&0&0&0&0\\ 0&1&0&0&0&0&0&0\\ 0&0&1&0&0&0&0&0\\ 0&0&0&0&1&0&0&0\\ 0&0&0&0&1&0&0&0\\ 0&0&0&0&0&1&0&0\\ 0&0&0&0&0&0&1&0 \end{bmatrix} \quad W = \begin{bmatrix} \sigma_\varepsilon^2&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&\sigma_\zeta^2&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0&0 \end{bmatrix}$$

The initial values for $\Theta_t^{(0)}$, $\Theta_0^{(0)}$ are distributed with the mean

$$m_0^{(0)} = \left(u^{N\,(0)}, u^{N\,(0)}, u^{N\,(0)}, u^{N\,(0)}, 0,0,0,0\right)$$

and a diagonal covariance matrix

$$C_0^{(0)} = diag(\sigma_\varepsilon^2, \sigma_\varepsilon^2, \sigma_\varepsilon^2, \sigma_\varepsilon^2, \sigma_\zeta^2, \sigma_\zeta^2, \sigma_\zeta^2, \sigma_\zeta^2).$$

The standard deviation for the unobserved equations are is set at $\sigma_\varepsilon = 0.2$ and $\sigma_\varepsilon = 0.015$.

Update $\Theta_t^{(1)}$, setting it as the smoothed output with the first element being the new estimates of NAIRU, $u_t^{N\,(1)}$, as well as the $\Theta_0^{(1)}$ distribution parameters $m_0^{(1)}$ and $C_0^{(1)}$.

5. Repeat steps 2-4 to refine estimates with additional iterations, until the variations in the parameters become sufficiently small.

BOX 1: KALMAN FILTER

The Kalman filter is an econometric technique that uses a time series of observed variables to estimate unobserved variables by estimating a joint probability over the variables for each period.

The filtering algorithm works in a two-step process: the forecast step where the unobserved variable is predicted one period ahead, and the update step where the observation during a period is used to inform a now-cast of the unobserved variable. The algorithm is run recursively through time from the first period to the last period, adding one observation at a time.

It is common to then use a backward recursive smoothing technique, which works from the last period to the first period. The smoothing algorithm revises the previous periods to reflect the observations as well as the likely distribution of the unobserved variables following that period.

For our estimation, we set the tolerance requirement as the largest change in the parameters from the previous iteration to be less than 10^{-6}. The initial values were set at $u_t^{N\,(0)} = u_1 = 6.42$ and $\mu_t^{(0)} = 0$. We found the modelling results are relatively stable with respect to the selection of $u^{N\,(0)}$ ranging between 0 and 9.

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Melbourne housing market dynamics: Impact of land supply on detached residential prices[1]

By Jason Lejcak, Alicia N. Rambaldi and Madeleine Tan

ABSTRACT

This paper builds on the literature that attempts to establish the relationship between land use regulation and property price growth. Utilising a newly constructed dataset that matches property transactions to planning permit applications at the statistical area 2 (SA2) level in Greater Melbourne, the effect of land supply restrictiveness is estimated directly. This contrasts with the alternative approach used by Kendall and Tulip (2018) in their paper for the Reserve Bank of Australia (RBA). Issues of endogeneity are addressed by using instrumental variables (IVs) to estimate the elasticities of approval rates and greenfield developments within a panel IV model.

Results find that changes in land supply impact property prices differently in the inner-city area relative to the outer regions of Melbourne, likely due to the role of densification. A 10 per cent increase in greenfield development leads to a 5 to 8 per cent reduction in prices, while a 10 per cent increase in approvals in an outer SA2 would lead to a 6.2 per cent reduction in price. Firstly, results suggest that densification has spillover effects, putting upward pressure on the price of remaining residential detached land, within a 21 km radius of the city. From this, the question as to how we understand what constitutes land supply arises. Land supply does not need to refer to the release of plots of land for development only. Especially in the inner-metro areas of the city, an increase in land supply could extend to include a relaxation of building height restrictions as it presents as a potential for development of new dwellings.

Secondly, without allowing for further densification in this inner ring, supply restrictiveness can almost double the price of detached residential land in certain local government areas (LGAs), such as Melbourne City and Yarra City councils. These results indicate that the paper by Kendall and Tulip (2018) may significantly underestimate the impact of supply restrictions on price in some areas.

1. Introduction

Property prices are the observed result of both demand and supply pressures. The empirical literature on the property market has focused primarily on demand-side factors, ranging from macroeconomic drivers such as interest rates and consumer demand to local characteristics such as nearby amenities. Empirical studies on the relationship between supply-side factors and property price growth, however, have been limited for several reasons, such as issues of identification (endogeneity) and the required data being unavailable.

[1] This paper is derived from the Honour's thesis by Jason Lejcak at the University of Queensland in 2018. The work was conducted as part of the ARC Linkage Grant LP160101518, held by the University of Queensland and the Department of Treasury and Finance, Victoria (DTF). The views expressed are those of the authors and do not necessarily reflect the views of DTF. We would like to thank James Hansen at the University of Melbourne for his feedback, and Elena Ryan at the University of Queensland for her assistance with figures and maps..

This work builds on literature that has attempted to establish the relationship between land use regulation and house prices. Specifically, this is done at a disaggregated local government area (LGA) or statistical area 2 (SA2) level, acknowledging the heterogeneous nature of this relationship across a single city. Topological issues constraining the supply of land can be complex to control for, but must be considered in order to analyse regulatory impacts on property prices. While empirical works focussing on other cities have had to contend with this issue, Melbourne presents as an excellent case study as it is largely unaffected by geographic restrictions.

This paper analyses the relationship between land supply restrictions and detached dwelling price growth. The analysis utilises a pioneering dataset that spatially merges settled property transaction data with planning permit data for all types of dwelling applications (e.g. single, multiple, subdivision). Appropriate measures of supply restrictiveness within this dataset are identified as measures of development activity, i.e. approval rates and greenfield development. A panel IV model is used in our modelling approach as it addresses the issue of endogeneity, in line with the approach used by Hilber and Vermeulen (2014).[2]

In our approach, the effect of land supply restrictiveness on property prices is estimated directly. This contrasts with the approach taken by Kendall and Tulip (2018) that relies on their hedonic model's residuals and estimates of the parameter associated with land size (intensive margin). Relying on the residual of a hedonic model to estimate a 'zoning wedge', as the authors define it, assumes that the model specification is correct and that the residuals do not capture anything else that might impact property prices other than land supply restrictions.

Our results find that changes in land supply impact property prices differently in the inner-city areas relative to the outer regions of Melbourne, likely due to the role of densification. Densification appears to have spillover effects in our estimates on detached dwelling prices. It puts upward pressure on the price of remaining detached residential land within a 21 km radius of the city.

As our panel IV model is a log-linear model, reversing the log transformation provides estimates of a multiplicative factor of fundamentals driving property prices at the SA2[3] level. These results show that without allowing for further densification in this inner-ring, supply restrictiveness can almost double the price of detached residential land in certain LGAs, such as Melbourne City and Yarra City councils. As such, these results challenge the results in the paper by Kendall and Tulip (2018), indicating that they may be significantly underestimating the impact of supply restrictions on price, especially in inner-city areas of Melbourne.

The rest of the paper is organised as follows. Section 2 presents key empirical work on land supply restrictions and house price growth. Section 3 describes the constructed dataset. Section 4 summarises the main results from the analysis done in the thesis. Section 5 closes with a discussion and plans for future work.

[2] Tests for endogeneity were conducted in Lejkac's thesis to ensure that this issue was addressed in the panel IV model.

[3] SA2 stands for Statistical Area Level 2. See definition at https://www.abs.gov.au/ausstats/abs@.nsf/Latestproducts/88F6A0EDEB8879C0CA257801000C64D9

2. Land supply restrictions and house price growth

Of the studies on the link between land use regulation and house price growth, e.g. Glaeser, Gyourko and Saks (2005a; 2005b) and Quigley and Aphael (2005), none have yet established a causal link due to the problem of endogeneity. Regulatory constraints and the price sensitivity of dwellings to regulatory changes have often been left unaddressed in the literature. Identifying the direction of causality is problematic since, on the one hand, limited land supply could have contributed to strong property price growth in an area. On the other hand, the rate of land release may increase in areas where it is profitable for developers to enter the local market, i.e. areas where property price growth has been strong. In addition, endogeneity presents as a problem due to omitted variable bias.

The work by Hilber and Vermeulen (2014) presents as the first analysis of its kind attempting to deal with this issue in order to assess the impact of land supply restrictiveness and topological constraints on house prices in England, at the LGA level. As part of their analysis, they utilise a panel IV model. In addition to this contribution to the literature, their study also uses two novel measures of land use restrictiveness: the rate of refusal and the share of developed land. Very few papers in the literature consider land supply restrictiveness in this way. The rest of the literature has relied mainly on survey data or shadow prices, as in Saiz (2010). The work in our paper follows the approach taken by Hilber and Vermeulen (2014) by considering planning permit approval rates and greenfield development as measures of land supply restrictions.

Using spatial data on US properties to analyse the impact of government regulation or geographic restrictions on long-run differences in house price growth, Gyourko, Mayer and Sinai (2013) estimate the elasticity of land size. They find that land zoning and land use restriction policies influence housing supply elasticities and that patterns of spatial dispersion in house prices and income growth are related. This is likely due to the increasing scarcity of land in certain metropolitan areas and towns, coupled with a growing number of high-income families nationally. The increase in high-income individuals and families raises the price and income dispersion across suburbs, which eventually skews the distributions of price growth and income. Gyourko, Mayer and Sinai (2013) refer to these suburbs as 'superstar suburbs'. Similarly, Kendall and Tulip (2018) use this approach to examine and quantify the effect of zoning on housing prices in Australia's four largest cities, with Melbourne being one of them.

We acknowledge that there is a difference between land supply and dwelling supply and that the link between land supply release and the offsetting of price pressures could depend on increasing dwelling supply; i.e. approved land may only be developed into dwellings with a significant lag. There exists a stream in the literature that investigates this idea. Murray (2019) presents a framework on the issue of land supply, land banking and property prices through the lens of an options model. Although the framework is beyond the scope of our current analysis, it presents as an interesting avenue for future work.

3. Data and methodology

The analysis in this paper relies on two data sources: CoreLogic's settled sales and the Victorian Department of Environment, Land, Water and Planning's (DELWP) data from Planning Permit Activity Reporting System (PPARS).

3.1 CoreLogic settled sales

We have transaction-level data from CoreLogic on houses sold between 2006 and 2017 across Victoria. The location and key hedonic characteristics such as land size, number of bedrooms, number of bathrooms and age of the structure are known.

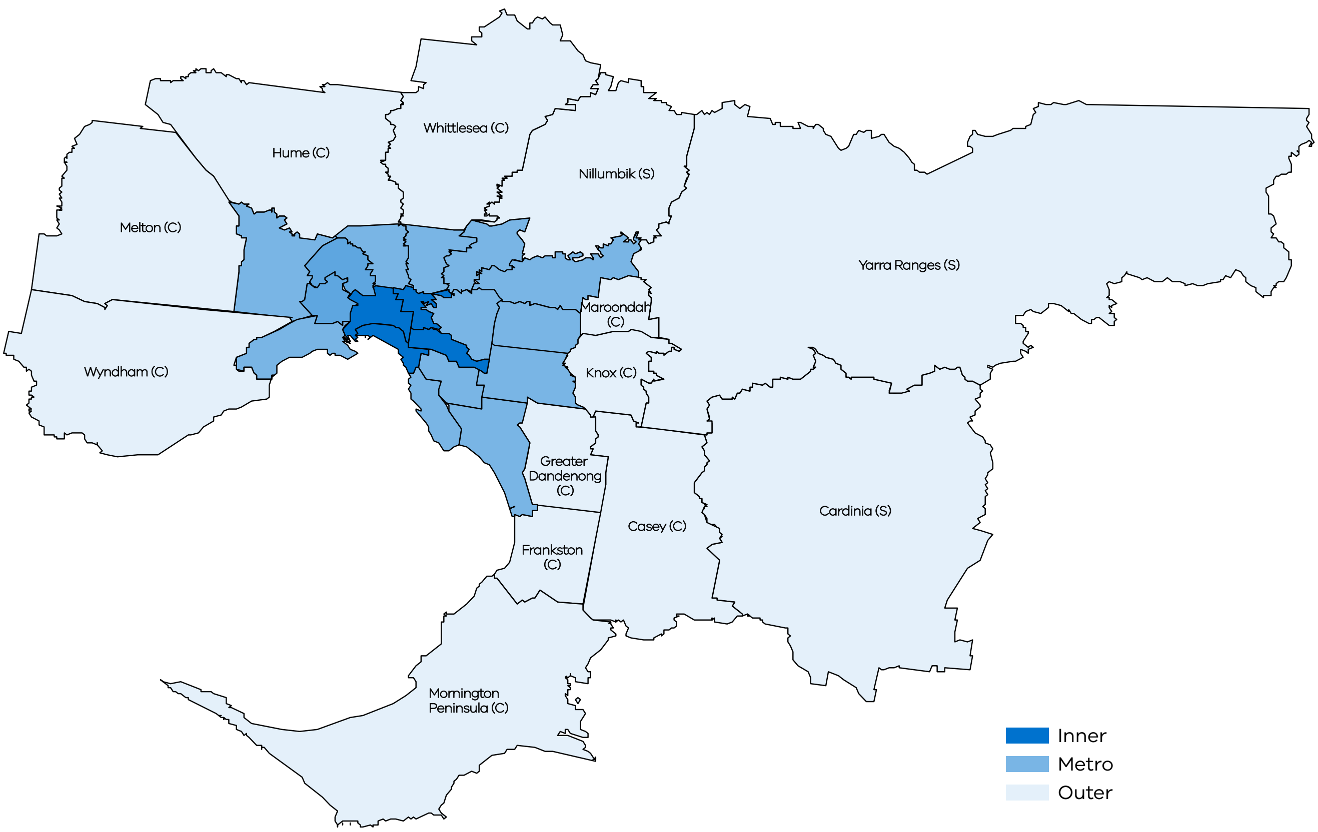
3.2 Planning permit and activity reporting data[4]

The planning data cleaning process focuses on two important filters: restrictions to a residential proposed land use and application categories that relate to an increase in the dwelling stock and densification. We construct the key variables as follows:

1. Average permit approval rate: for a given SA2, constructed by taking the count of all permit approvals for a given year and dividing it by the total number of permits applied.[5]
2. Greenfield development: the proportion of vacant or agricultural lots developed into residential land at an SA2 level. This captures the effect of a change in zoning.

We aggregate and merge both data sets at an SA2 level (as we cannot merge by addresses). These regions of Melbourne are detailed in the map in Figure 1.

Figure 1: Regions of Melbourne



[4] The PPARS data is publicly available, upon request. The PPARS manager has been consulted for permission to use the data for this research as per the terms and condition of its use.

[5] Category 3: Extension to an existing dwelling or structure associated with a dwelling; Category 5: One or more new buildings; Category 6: Single dwelling; Category 16: Subdivision buildings; Category 7, 8, and 25: Multi-dwelling (note: Categories 7 and 8 are old classifications of multi-dwellings).

In Figure 2, we graph the permit approval rate across the major regions in Greater Melbourne. The approval rate was somewhat steady over the time horizon and across all regions, somewhat suggesting there is little change. However, these planning decisions are made at a more local level. If we look at the average annual change in approval rates at an SA2 level, we are better able to see the heterogeneity (see Figure 3, where we notice this wide deviation). Therefore, the analysis will focus on the sensitivity or elasticity of prices arising from changes in approvals.

Figure 2: Permit approval rate by region

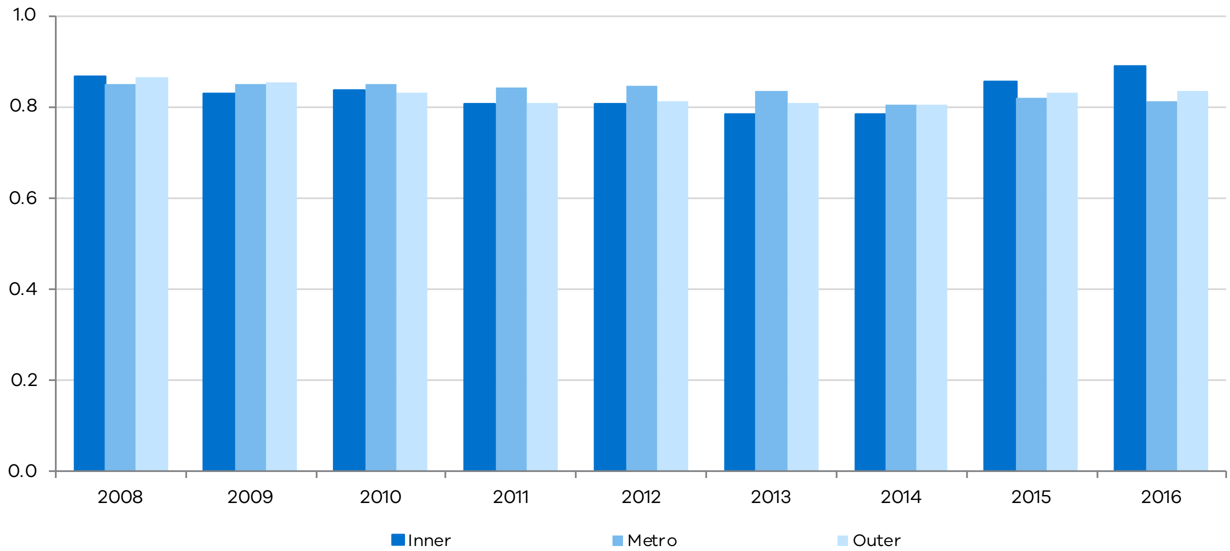


Figure 3: Histogram of SA2s' annual change in approval rate (2008-2016)

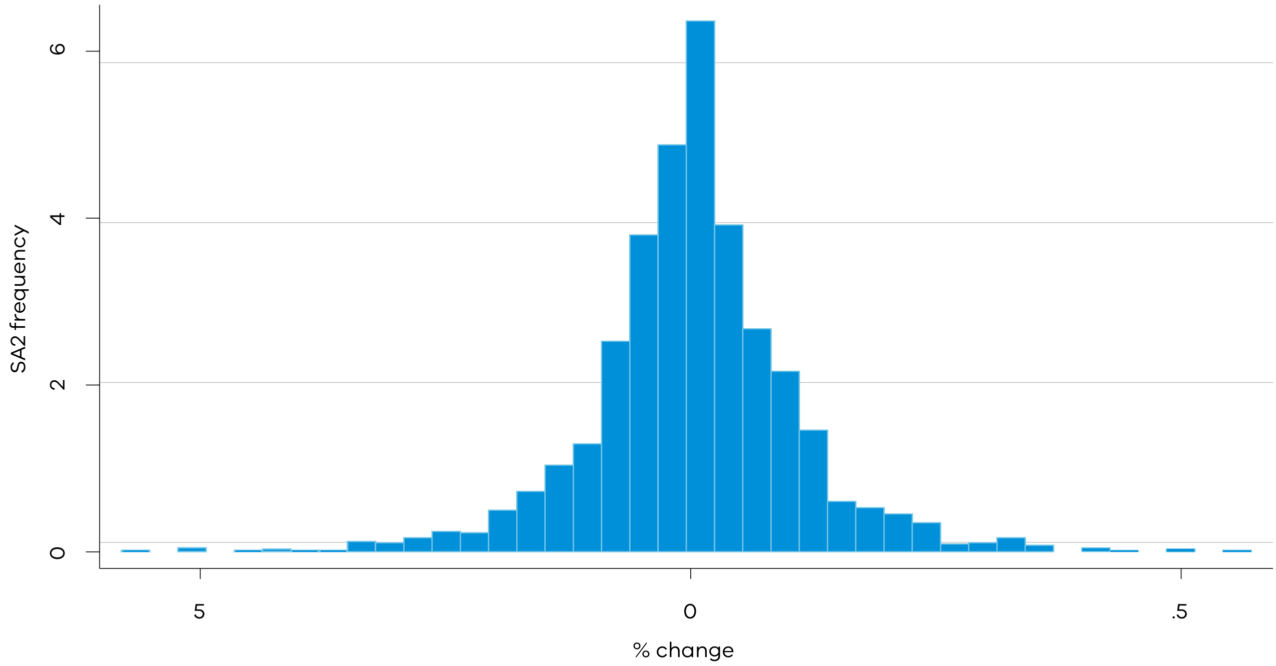
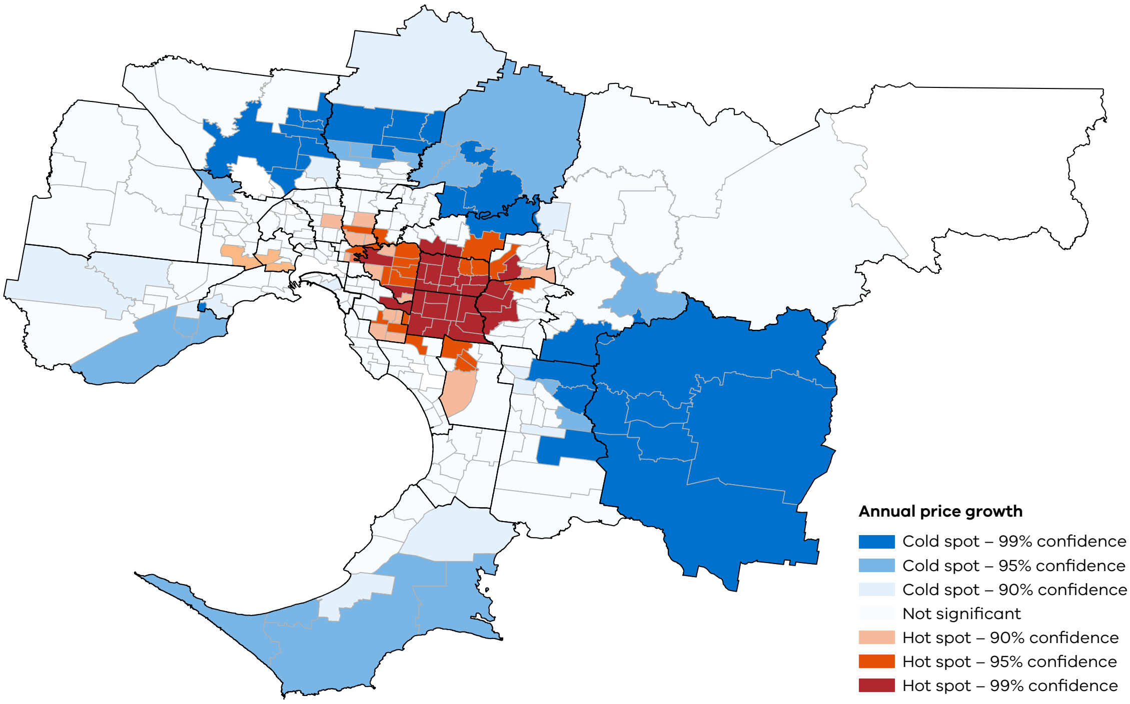
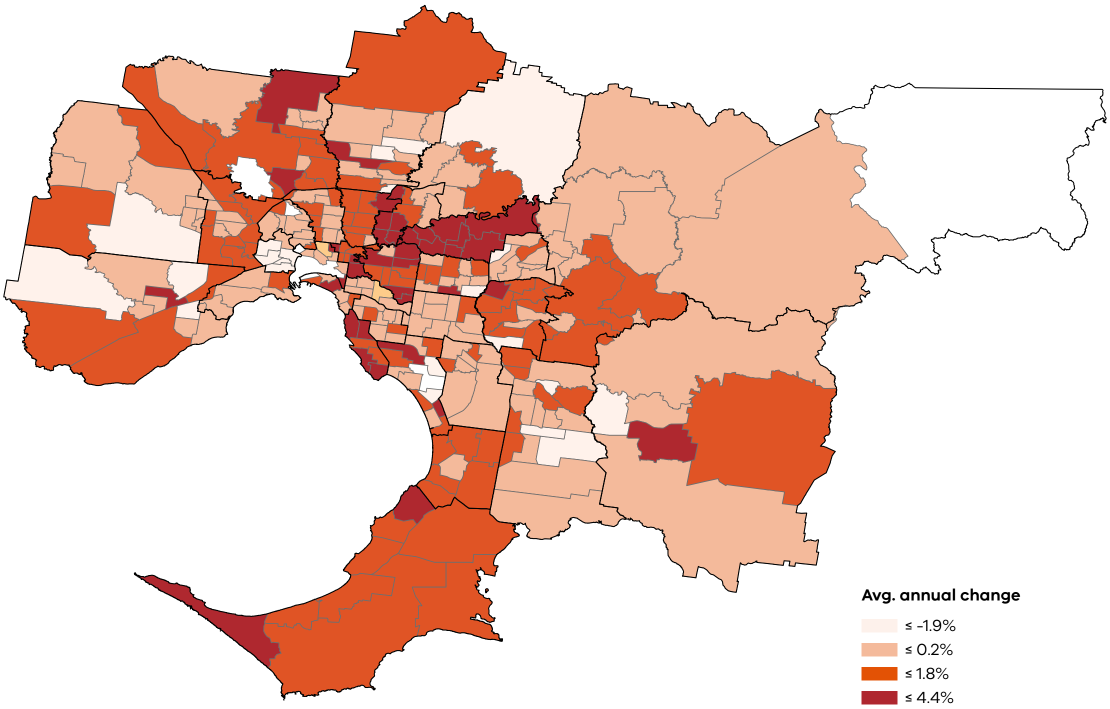


Figure 4 illustrates that the relationship between land supply restrictiveness and strong annual price growth is not clear cut. In this figure, we see that there are areas that are more restrictive (in terms of low permit approval rates) that correspond to strong average annual price growth, in line with expectations. However, there are just as many areas where low permit approval rate changes might also correspond to areas with slow annual price growth. This highlights the endogeneity issue.

The analysis, therefore, relies on the panel IV estimation approach to address the endogeneity in the variables of interest, as described in the next section.

Figure 4: Statistically significant cold and hot SA2s' annual price growth (top); Permit approval rates annual change (bottom). Period: 2008-2016.*





* Based on GI* statistics.

3.3 Panel IV estimation

The log median SA2 property price is a function of development activity, hedonic characteristics (e.g. number of bedrooms, land size), location, time and individual effects. Development activity is defined as the variables that capture supply restrictiveness from the PPARS dataset and are significant explanatory regressors of property prices. The hedonic characteristics are controls for the quality of the housing stock, and thus, they are a quality adjustment of the median sale price.

The estimated panel model is specified as follows:

$$\log(Price_{SA2,t}) = \alpha_{SA2} + \gamma_t + \delta_0 D_{SA2,t} + \delta_1 D_{SA2,t} \times L_{SA2,t} + \beta X_{SA2,t} + \epsilon_{SA2,t} \quad (1)$$

This is a standard two-way effects model that allows the intercept to vary with differing SA2s and over time. $D_{SA2,t}$ is development activity (the approval rate, or the approval rate and the rate of greenfield development), which is also interacted with the location of the land, $L_{SA2,t}$. Two different measures of location were considered, the first being the distance of the SA2 to the CBD in kilometres and the second being based on dividing Greater Melbourne into two regions — the inner-metro and outer regions.[6] The individual SA2 and time effects are captured in α_{SA2} and γ_t, respectively. In order to address issues of endogeneity, three instruments for the endogenous development variables are used. These variables are assessment effort (complex), VCAT appeal (VCAT) and VIC smart application availability (VICsmart). They are available for each permit and are aggregated at the SA2 level.

3.3.1. Instruments used

The instruments used include:

- Complex (assessment effort): 1 indicates complex (more than 5 person days), 0 indicates simple or average (5 or less person days), a measure of council efficiency;
- VCAT appeal: proportion of permits whose outcome was initially appealed by the applicant and ultimately successful, a measure of council preferences and local opposition;
- VIC smart application: 1 indicates there is a streamlining process for straightforward planning permit applications, 0 indicates there is none, a measure of council efficiency.

Table 1: Relationship between instruments and endogenous variables

INSTRUMENT	APPROVAL RATE	GREENFIELD
Complex	Negative	Negative
VCAT appeal	Positive	Positive
VIC smart application	Positive	Negative

The results in Table 1 are summarised from the first stage regressions, and show the correlation between each endogenous variable (approval rate and rate of greenfield development) and the instrumental variables. We found the instruments are strong. Across alternative specifications of the first stage regressions, the correlations are highly significant (using F-tests and under-identification tests) providing support for the strength of the instruments used. In addition, the instruments chosen must be causally independent of prices. We justify this is the case as follows:

Complex effort: Is the LGA permit assessment time a driver of house prices? Do house prices determine the permit assessment time of an LGA? We argue not in both directions. The time it takes to review an application is dependent on a number of key factors, with the most important being the resources of the planning authority and the needs of the community, rather than median house prices.

Even if the permit assessment time of an LGA is short, if almost all of their applications are rejected, a developer would certainly take little comfort in receiving that rejection quickly. The price growth would be driven by the application rejections (i.e. more restrictive) rather than factors relating to the efficiency of the LGA.

VICsmart: Not causally related to prices. Vacant plot redevelopment is a more complex application that cannot be streamlined. Negatively correlated with greenfield development. Positively correlated with approval rates.

Appeals: Correlated with approvals but not with prices.

4. Results

The panel models, presented in Table 2, use the greenfield development variable alongside the approval rate, with various interactions and instruments used for identification.

Across all the models, we obtain significant estimates and supporting evidence of the strength of our IVs, including the F-statistics and under-identification tests. Model 1 has the best fit, although it does not include greenfield developments. Models 3 and 4 only differ by their definitions of location. In Model 3, it is determined by a binary division of the city into outer and inner-metro areas. Model 4 is identical; however, the location is a continuous variable — distance to the CBD. Both models show a negative elasticity with respect to greenfields, indicating a 10 per cent increase in the development of greenfields reduces prices by 5 (Model 3) or 8 (Model 4) per cent. In terms of approvals, the effect is positive in inner Melbourne and negative in outer Melbourne, where a 10 per cent increase in approvals in an outer SA2 would lead to a 6.2 per cent reduction in price. Using Model 4, with a continuous distance to the CBD, we find the marginal effect changes sign at about 21 km from the CBD. This channel is related to increases in the detached housing stock; i.e. a simple rightward shift of the supply curve. This still reveals the vulnerability and sensitivity of detached dwellings in the outer region to increased planning restrictiveness. If approval rates for developments fall and/or slow, prices may rise. This finding may have significant policy implications; the rezoning of existing uses of land and the new release of land in more suburban regions are likely to impact price.

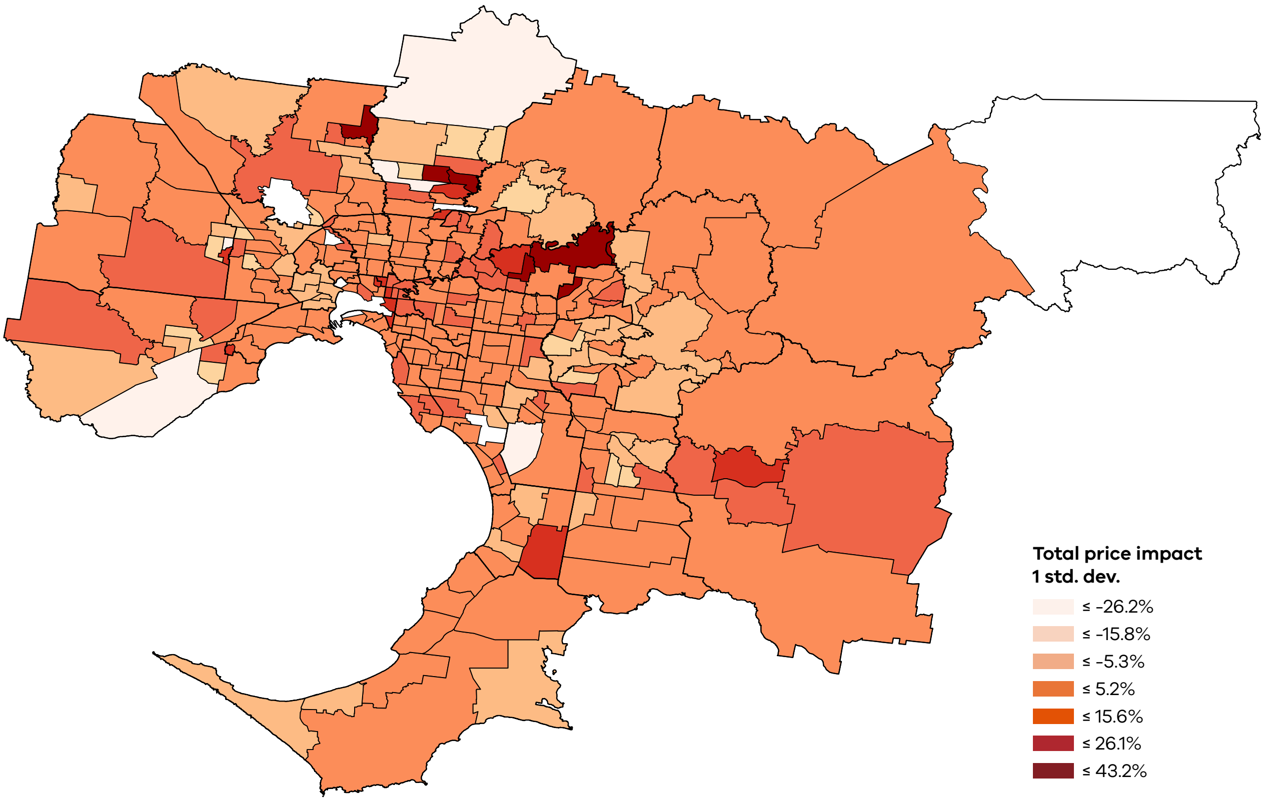
[6] The standalone approval rate term is not included if location is used in terms of the SA2's distance to CBD.

Table 2: SA2 price modelling

DEPENDENT VAR.	(1) LOG PRICE	(2) LOG PRICE	(3) LOG PRICE	(4) LOG PRICE	(5) LOG PRICE	(6) LOG PRICE
Approval rate	-0.00221***		0.00332**	0.00969**		0.00382**
	(2.71)		-2.37	-2.15		-2.34
Dist. To CBD				-0.000581**		
(w/ approval)				(-2.39)		
Outer			-0.00954***			-0.01033***
(w/ approval)			(-3.34)			(-3.29)
Green fields		-0.01128***	-0.00498**	-0.00813**		
		(-2.90)	(-1.98)	(-2.44)		
Dist. To CBD					-0.0503**	-0.0189*
(w/ green fields)					(-2.59)	(-1.82)
Log land size		0.152**	0.189***	0.137**	0.108	0.176***
		-2.38	-3.85	-1.98	-1.52	-3.27
Dist. To CBD	-0.0358***	-0.0135	-0.0366**	-0.0009	-0.0305	-0.0449**
	(-2.72)	(-0.78)	(-2.16)	-0.04	(-1.15)	(-2.53)
N	2616	2616	2616	2616	2616	2616
Clusters	292	292	292	292	292	292
R-squared	0.88	0.53	0.78	0.5	0.3	0.75
Kleibergen-Paap rk LM	17.97	12.54	16.53	16.05	8.4	11.76
p-value	0	0	0	0	0	0
F stat. (exc. Inst.)	27.51	15.16	11.6	11.6	15.16	11.6
p-value	0	0	0	0	0	0
Weak identification		13.01	6.52	5.93	8.55	4.4
Instruments	Complex	VicSmart app	Complex VCAT appeal VicSmart app	Complex VCAT appeal VicSmart app	VicSmart app	Complex VCAT appeal VicSmart app

Note: t statistics in parentheses * p <0.10 , ** p <0.05 , *** p <0.01

Figure 5: Price impact of restrictiveness from 2010–2016



In terms of price elasticity, Figure 5 summarises the results at the SA2 and LGA level (using Model 3). The house prices in Manningham and selected SA2s in Whittlesea were found to experience very high and positive regulatory impacts. The impact of the approval rate of residential development also appears to have a higher price elasticity in the more suburban regions of Melbourne. This is confirmed using the distance to CBD interaction, which shows that as we move further away from the CBD, the elasticity rises. In saying this, the price impact of these restrictiveness measures still appears to be quite high in the inner-metro region.

If we use the interaction of approvals and distance to the CBD, we find a negative elasticity, implying that regions further from the city face a higher elasticity of price to approval rates. A similar negative relationship with distance emerges with greenfields.

Why is the impact in the inner region positive and weaker than the outer (especially for approval rates, see Model 6 in Table 2)? Our model concentrates on the demand for detached dwellings. In the inner-city areas, the model explains the price of land associated with detached dwellings to be redeveloped. That is, increased developer demand for land to construct multi-dwelling complexes implies a higher approval rate, as we constructed the approval rate to include multi-dwelling developments. This leads to greater demand for detached dwellings for redevelopment. This story relates to the densification of the inner-city areas.

Put another way, although higher approval rates should, theoretically, have a negative effect on prices (through the increased stock of dwellings), there is a possibility that the approval rate could also reduce the number of detached dwellings in an LGA due to densification occurring closer to the inner city.

We can confirm that the volume of sales of detached homes has been falling in the metro regions, while the sale of units and apartments has been increasing. However, we cannot confirm the cross price effects between detached and multi-storey dwellings since the analysis focused on detached dwellings only.

Thus, we find that as we move further away from the CBD, the marginal effect becomes increasingly negative to such an extent that in the outer region, increased approval rates lead to greater additions to the dwelling stock and, thus, a lower detached dwelling price.

5. Discussion

This study sought to understand how local land use regulation affects property price growth in Greater Melbourne.

The study uses an alternative estimation approach to that used by Kendall and Tulip (2018). The rate of permit approvals and additional greenfield development are included in a property price model. These measures of supply restrictiveness are endogenous, and thus, a panel IV estimation is used. The impact of land supply release on property prices was found to differ between the inner-metro and outer regions. As land supply increases in the outer region, property price growth is dampened; however, the effect on prices is positive in the inner city due to the scarcity of detached residential land.

To estimate the effect of regulation on the prices of detached dwellings from the panel IV model (see Equation (1)), it is first noted that we must reverse the log transformation:

$$Price_{SA2,t} = e^{(\alpha_{SA2}+\gamma_t+\delta_0 D_{SA2,t}+\delta_1 D_{SA2,t}\times L_{SA2,t}+\beta X_{SA2,t}+\epsilon_{SA2,t})} \quad (2)$$

$$\Rightarrow Price_{SA2,t} = e^{(\delta_0 D_{SA2,t}+\delta_1 D_{SA2,t}\times L_{SA2,t})}e^{(\alpha_{SA2}+\gamma_t+\beta X_{SA2,t}+\epsilon_{SA2,t})} \quad (3)$$

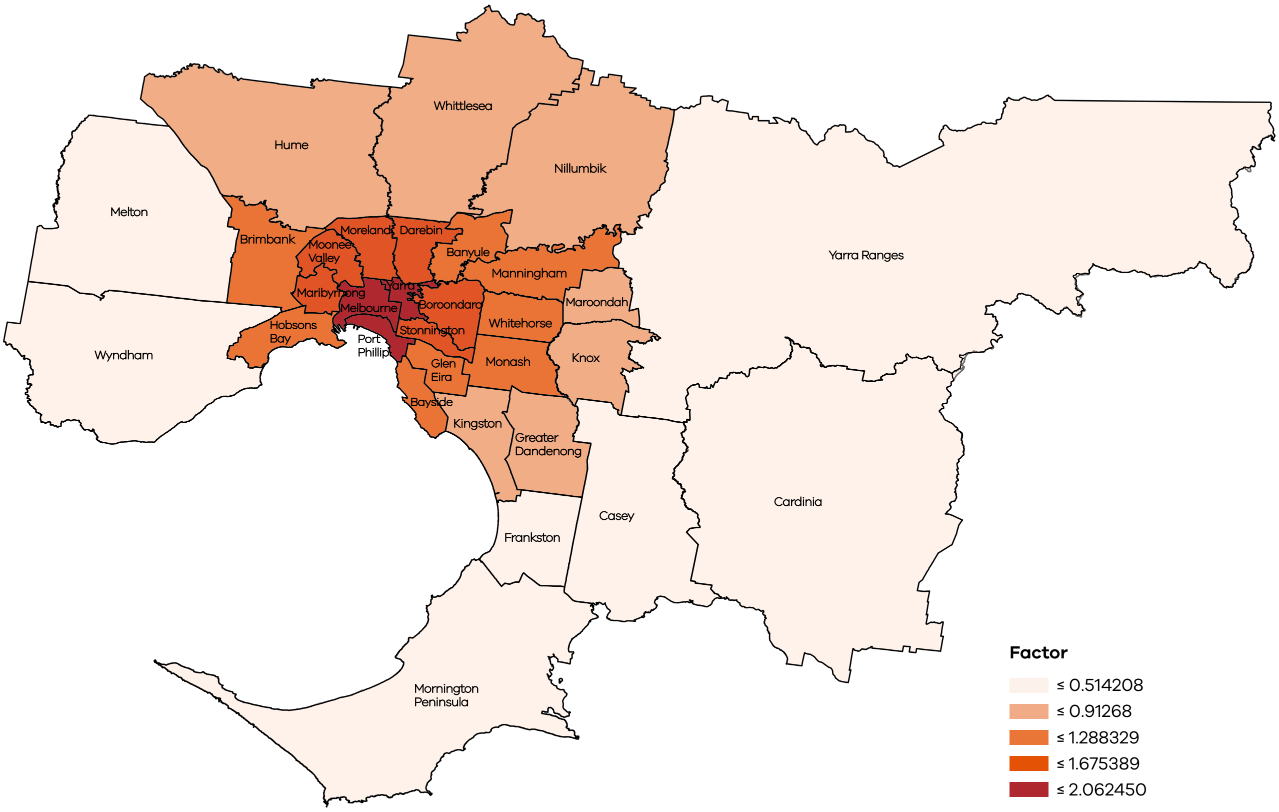
The first element in this product is a multiplying factor that provides an estimate of the impact of land supply release on property prices. Using the model that includes approval rates, greenfield development and interactions, we computed this factor and aggregated it at the LGA level. The results are presented in Figure 6.

An estimated factor below one indicates land supply regulation effects are lowering the price of detached dwellings, while an estimated factor above one indicates land supply regulation effects might be increasing the price of detached residential properties closer to the CBD.

These results suggest that while increased land supply release could alleviate upward price pressure in specific locations, mainly in the outer areas of Melbourne, it increases the per-square-metre value of developable land in the inner-metro region. The latter result is likely due to the role of densification and the price dynamics of units and apartments. The estimates could be conflating the effects of land supply regulation with the impact of densification on detached residential land prices.

Based on the inner-metro result, the question as to how we understand what constitutes land supply arises. Land supply need not be constrained by definition as the release of plots of land for development only. Especially in the inner-metro areas, an increase in land supply could extend to include a relaxation of building height restrictions as it allows for the development of new dwellings. Further work on this topic will be conducted in the future.

Figure 6: Supply restrictiveness factor at the LGA level of aggregation



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Involuntary unemployment in Australia[1]

By Andrew Kemp and Darren Wong

ABSTRACT

This paper uses the Household, Income and Labour Dynamics in Australia (HILDA) panel study to investigate involuntary job loss in Australia. We count a job loss as 'involuntary' when a survey respondent reported leaving the job they had held at the time of the previous survey for reasons unrelated to the voluntary decision of the worker, such as being laid off or because their place of employment/business had closed down.

We find the job loss rate has averaged at a higher level in the survey years following the global financial crisis (GFC) than in the survey years prior, consistent with the unemployment rate. As with other studies, we find that people experiencing involuntary job loss, compared with the overall employed population, are more likely to be male, are younger, less educated, more likely to be casually employed, employed for a shorter tenure, and more likely to be in a 'blue collar' occupation. Most individuals experiencing involuntary unemployment will be re-employed within 12 months, with females more likely than males to leave the labour force altogether following an involuntary job loss. Permanent workers who experienced job loss and found new employment in a casual capacity reported noticeable drops in job satisfaction indicators of their new work.

1. Introduction

The magnitude of labour market flows in Australia is significant. In October 2019, there were an estimated 84 200 unemployed Australians who were employed the previous month, and likewise, 102 700 employed Australians who were unemployed the previous month (ABS, 2019). For most of these workers, unemployment is both voluntary and transitory. There are many reasons why workers may choose to voluntarily leave their job, including lack of job satisfaction or simply wanting a better job, as well as numerous reasons relating to personal circumstances, such as returning to study, starting a family, illness, or retirement.

Why then focus on involuntary unemployment? Losing a job involuntarily is associated with a number of adverse financial, health and employment effects. Previous longitudinal studies suggest involuntary job loss is associated with worsening mental and physical health (Burgard, Brand and House, 2007). Job displacement has been shown to reduce future earnings (OECD, 2013), and studies of older workers point to the particularly pernicious effects of involuntary unemployment, both on their health and their future employment prospects (Chan and Huff Stevens, 2001; Gallo, Bradley, Siegel and Kasl, 2001). There is a stigma to getting 'fired' that has ingrained itself in community expectations and popular culture.

[1] The views expressed are those of the authors and do not necessarily reflect the views of DTF.

It is, therefore, important to understand the incidences of involuntary job loss across the labour market more broadly, including which demographics, occupations or industries make up most involuntary job losses. Media reports of high-profile cases of job displacement, such as the closure of Australia's car manufacturing industry, or ruminations on the threat of automation, often mask the broader patterns of involuntary job loss across Australia.

This paper investigates three aspects of involuntary unemployment in Australia. Firstly, the job loss rate across time, from 2002 to 2016, and how it varies across different demographics and types of work. Secondly, the post-displacement outcomes for individuals who have lost their job, whether they have returned to employment, are unemployed or have left the labour market altogether. Finally, this paper looks at changes in job satisfaction for permanent and casual employees who lost their main job but found new employment in the next wave.

2. Data

This paper uses data from the HILDA survey to investigate the characteristics of involuntary unemployment in Australia. HILDA is a household panel survey that covers the years (as of July 2018) 2001-2016, in 16 waves. It is designed to be a nationally representative longitudinal survey of Australian households. Beginning from wave 2, the survey asks respondents who have changed jobs or who are no longer employed since the last survey to state the main reason they stopped working in that job.

We consider respondents who listed 'got laid off/no work available/retrenched/made redundant/employer went out of business/dismissed, etc.' as the main reason they left their previous job to have experienced involuntary job loss. Additionally, those respondents who were self-employed but whose business closed down for economic reasons ('went broke/liquidated/no work/not enough business') are also considered to have experienced involuntary job loss. This is consistent with the definition provided in Bubonya, Cobb-Clark and Wooden (2017), which includes all instances of involuntary job loss, distinct from the concept of 'job displacement', which refers only to workers affected by mass layoffs or the closure of their employer's business.

For simplicity, we restrict the data of involuntary job loss to those jobs that were held at the time of each HILDA survey. This excludes those instances where a HILDA-survey participant may have been fired from a job obtained in between each interview. We further drop any observations in which a survey participant claims to have been fired from their main job held at the time of the previous survey wave but who was not listed as employed in the previous wave. Pooling the data, we find a total of 4 695 instances of involuntary job loss, or about 3.7 per cent of the employed population.

Table 1 describes some key characteristics of persons who have experienced involuntary unemployment compared with those who left their job voluntarily and with the broader employed population. For this purpose, we have chosen to define a voluntary job-leaver as someone whose main reason for leaving their main job was either 'not being satisfied with the job' or 'wanting to obtain a better job'. These are the two most common reasons given in the HILDA survey for leaving voluntarily, although there are other circumstance-specific reasons for leaving, such as pregnancy/looking after dependents, returning to studying or moving location. Pooling the data, the weighted survey results show that compared with the employed population, people experiencing involuntary job loss are more likely to be male, younger, less educated, casually employed, employed for a shorter duration, and in an occupation requiring routine, manual work.

Table 1: Characteristics of persons experiencing involuntary job loss, voluntary job leavers, and employed persons, 2002–2016

	1. INVOLUNTARY JOB LOSS	2. VOLUNTARY JOB LEAVER	3. EMPLOYED
Age			
Mean	38*	30	40
Previous tenure with employer			
Median	2 years*	1 year	4 years
	%	%	%
Sex			
Male	61.3*	53.42	54.1
Female	38.7*	46.58	45.9
Education			
Bachelor or above	20*	26.8	28.3
Cert III, IV, diploma or advanced diploma	34.4*	29.8	32.5
Year 12 or less	45.5*	43.4	39.1
Previous employment contract (for employees)			
Permanent or ongoing	58*	55.3	68.1
Fixed-term contract	9.2	8.6	9.2
Casual	32.4*	35.8	22.3
Other/don't know	0.4	0.3	0.4
Number employed at previous place of work			
Less than 5	21.6*	14.2	19.8
5 to 19	31.3*	33.3	24.7
20 to 99	26.4	30.3	27.6
100 plus	20.8*	22.1	27.9
Occupation			
Managers	10.8*	9.7	13.1
Professionals	15.1*	18	23
Technicians and trades	17.8*	13.3	13.6
Community and person services	8*	12.5	10.2
Clerical and administrative	14.8	12.7	14.8
Sales workers	9.6	15.8	9.1
Machinery operators	8.9*	6.1	6.3
Labourers	15*	11.9	9.9

* Proportions are statistically different from those of the employed population (column 3), at 1 per cent level of significance.

3. Characteristics of involuntary job loss

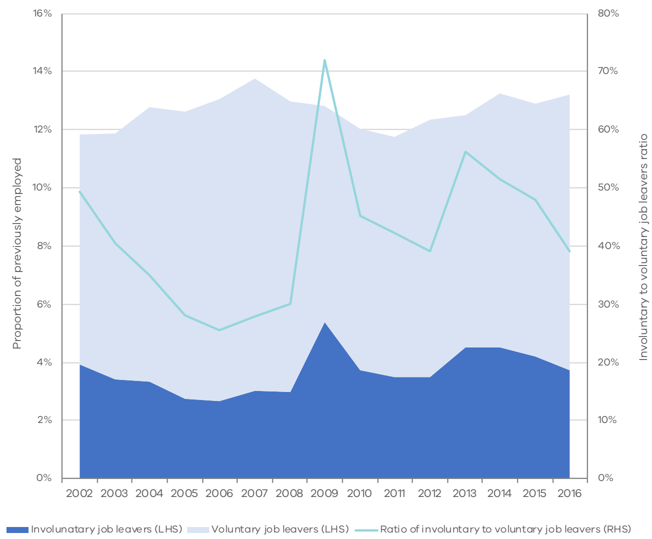
These results are broadly intuitive and consistent with the current literature. For instance, we would expect casual workers to be over-represented in job loss occurrences, given the relative lack of employment protection they receive compared with those employed on a permanent basis. As casual employment is heavily skewed towards younger workers, so too is the age profile of involuntary job loss. The finding that persons experiencing involuntary job loss are more likely to be male is consistent with other studies. Wilkins and Wooden (2013) identified a higher job loss rate for males than females in Australia and showed that much of this pattern can be explained by the types of jobs chosen. Industries that are more sensitive to the business cycle and on average exhibit higher job loss rates are typically characterised by a higher male-to-female ratio.

To investigate the pattern of involuntary job loss across time, we calculate an average involuntary job loss rate using the same method as in Bubonya, Cobb-Clark and Wooden (2017). This is defined as persons who have experienced involuntary job loss in a given year as a proportion of persons employed in the previous year. Figure 1 plots the job loss rate over the HILDA waves for Australia and Victoria, showing similar patterns for each jurisdiction. The peak in 2009 coincides with the global financial crisis (GFC), with a noticeable increase in the average Australian job loss rate following the GFC (2010-2016) of 3.9 per cent compared with 3.1 per cent pre-2009. The difference between the higher average job loss rate post-GFC and the average job loss rate pre-GFC is statistically significant at the 1 per cent level.[2]

Figure 2 plots the ratio of involuntary job leavers to voluntary job leavers, which appears qualitatively similar to the movements of the job loss rate in Figure 1. Additionally, we plot the job loss rate for involuntary and voluntary job leavers. These patterns suggest the involuntary job loss rate is countercyclical, like the unemployment rate.

Figure 1: HILDA survey job loss rate for Australia and Victoria, 2002–2016

Figure 2: Trends in reasons for job-leaving over time



[2] We calculate this using the following equation $Y_t = \beta_0 + \beta_1 T + u_t$, where Y is the annual job loss rate and T is a dummy variable equal to 1 for the post-GFC years (2010–2016). We exclude 2009 from the equation as we are only interested in the years before and after the 2009 spike in the job loss rate, and we perform a t test on the coefficient of the dummy variable.

Figure 3 plots the job loss rate alongside the unemployment rate and a measure of job security to illustrate that all three measures behave similarly in their cyclical movements. Our measure of job security is taken from HILDA, which asks respondents who are employed to give a percentage chance (from 0 to 100) of them losing their job in the next 12 months. Following Foster and Guttman (2018), our job security measure takes the average job security rate in each HILDA wave and subtracts the Figure from 100, making it effectively a rating of job retention perception.

Job loss rates also vary between types of work. Industries that are more sensitive to the business cycle tend to have more volatile job loss rates, as Figure 4 shows. Manufacturing and construction exhibit consistently higher job loss rates than service-based industries. Social services, which are predominantly made up of education and health care related work, exhibit consistently low rates of job loss relative to the other industry categories and are seemingly impervious to business cycle conditions.

Technological advancements and the increasing computerisation of work have led to concerns about job loss through automation. One estimate suggests more than five million jobs in Australia could be lost to automation over a 10-20 year period (CEDA, 2015). Typically, jobs that are vulnerable to automation are most likely to be those where the tasks can be easily defined by rules and processes and so substitutable by some degree of mechanisation or artificial intelligence. These can be manual tasks, such as repetitive assembly, or cognitive tasks, such as record keeping.

Figure 3: Australian job loss rate, unemployment, and job security perception, 2001-2016

Figure 4: Australian job loss rate by industry type, 2002–2016

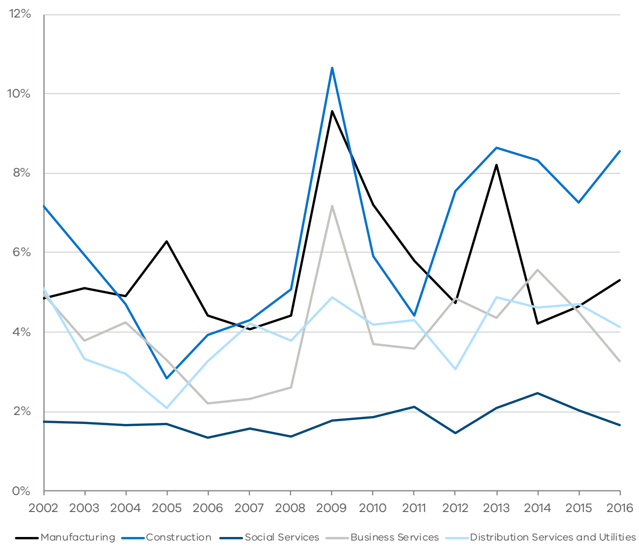


Figure 5: Australian job loss rate by task type, 2002-2016

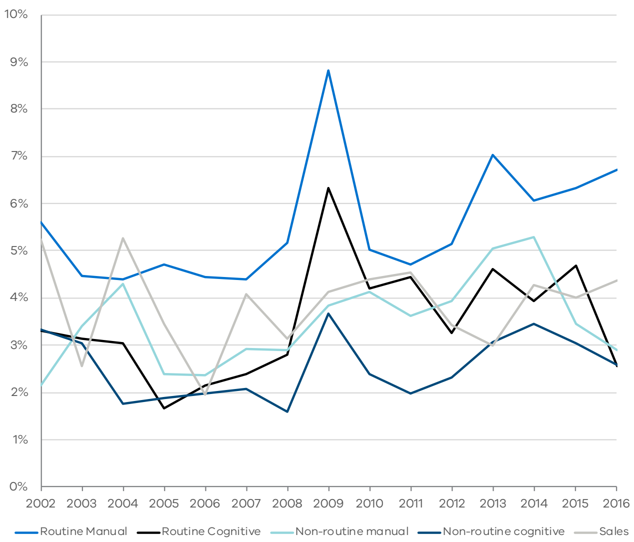


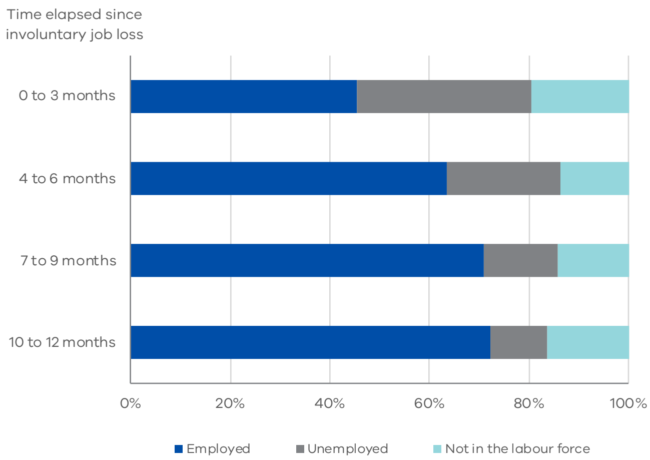
Figure 5 plots the job loss rate according to task type, using the same categorisation method as Borland and Coelli (2017), which assigns a task type according to a worker's occupation using the Australian and New Zealand Standard Classification of Occupations (ANZSCO). Routine manual tasks are consistently characterised by a higher involuntary job loss rate over the HILDA survey period compared with the other four categories, while the job loss rate for non-routine cognitive tasks is typically lower than all five categories across the HILDA survey period. Routine tasks appear to have experienced higher spikes in job loss rates during the GFC than the non-routine categories. While it is difficult to separate the cyclical factors impacting job loss rates from broader structural changes in the labour force, these patterns are consistent with the decline in routine-based employment over the past 30 years (Heath, 2016).

4. Employment outcomes following involuntary job loss

Most people who lose their job involuntarily will find employment again within 12 months. On average, 66.5 per cent of respondents found new employment within the same wave that they reported involuntary job loss. The proportion of respondents who were unemployed or left the labour force altogether averaged around 17 per cent. Consistent with the trend in the job loss rate, re-employment has averaged at a lower level after the GFC than before (significant at the 5 per cent level).

Using an additional variable in HILDA, we can better understand the timing of the job loss. In Figure 6, we combine our indicator for job loss with another survey question, which asks whether the survey participant has been 'fired or made redundant' 0 to 3 months ago, 4 to 6 months ago, 7 to 9 months ago, or 10 to 12 months ago. In total, this gives us 2 239 observations in the sample. That the sample size is reduced by more than 2 000 observations indicates people are answering the two survey questions differently — an interesting fact on its own but one that we do not investigate further.

Figure 6. Employment status over time for people who experienced involuntary job loss



Pooling the data, we find around 45 per cent of respondents who experienced involuntary job loss in the past three months were re-employed, 35 per cent were unemployed, and 20 per cent were not in the labour force. Re-employment status only changes marginally in 10 to 12 months, compared with 7 to 9 months, where around 72 per cent of respondents are employed. Figure 7 charts employment status for men and women, again illustrating the differing labour market characteristics of the two sexes. Around 48 per cent of males were re-employed within the first three months, compared with 42 per cent of females. Compared with men, a greater proportion of females not employed are not in the labour force, a pattern also supported by international evidence (Farber, 2005). Almost 12 per cent of males reported not being in the labour force after losing their job in the previous 10 to 12 months, compared with almost 24 per cent of females.

However, not everyone who is re-employed returns to the same employment contract. Table 2 suggests slightly more than 60 per cent of employees who are employed on a permanent or casual basis can expect to return to the same type of employment contract after experiencing involuntary job loss. As the following section indicates, the nature of the work obtained following job loss is an important factor in the overall welfare impact of involuntary job loss.

Figure 7: Employment status over time for males and females who experienced involuntary job loss

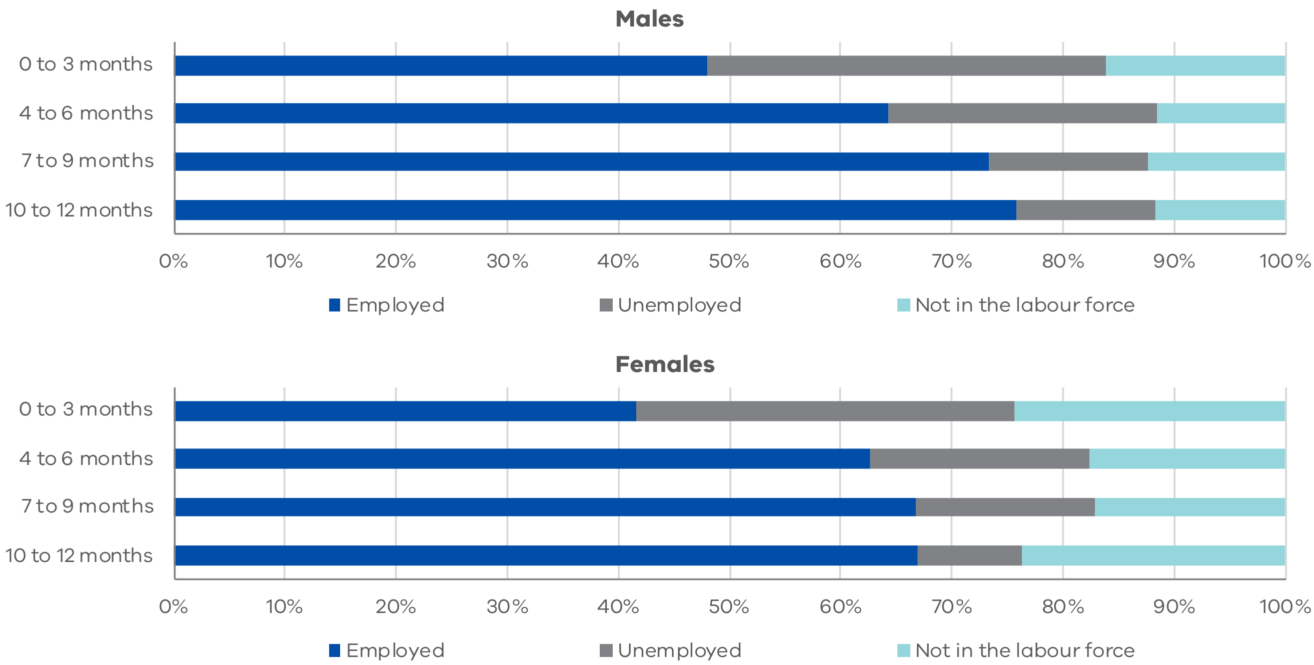


Table 2: Change in employment contract following involuntary job loss

		EMPLOYMENT CONTRACT IN THE PERIOD AFTER JOB LOSS OCCURRED		
		CASUAL	FIXED-TERM	PERMANENT OR ONGOING
Employment contract in the period of job loss	Casual	63%	5%	31%
	Fixed-term	27%	26%	47%
	Permanent or ongoing	26%	12%	61%

5. Job satisfaction in re-employment following jobs loss

The wellbeing effects of job displacement tend to focus on workers in full-time employment who have had multiple years of labour market experience, largely on the basis that the effects of displacement are more pronounced when individuals have 'firm-specific' human capital that cannot be transferred easily to new employment (Kletzer, 1998). The magnitude of these effects will depend on the length of the unemployment spell and the nature of the new work following re-employment.

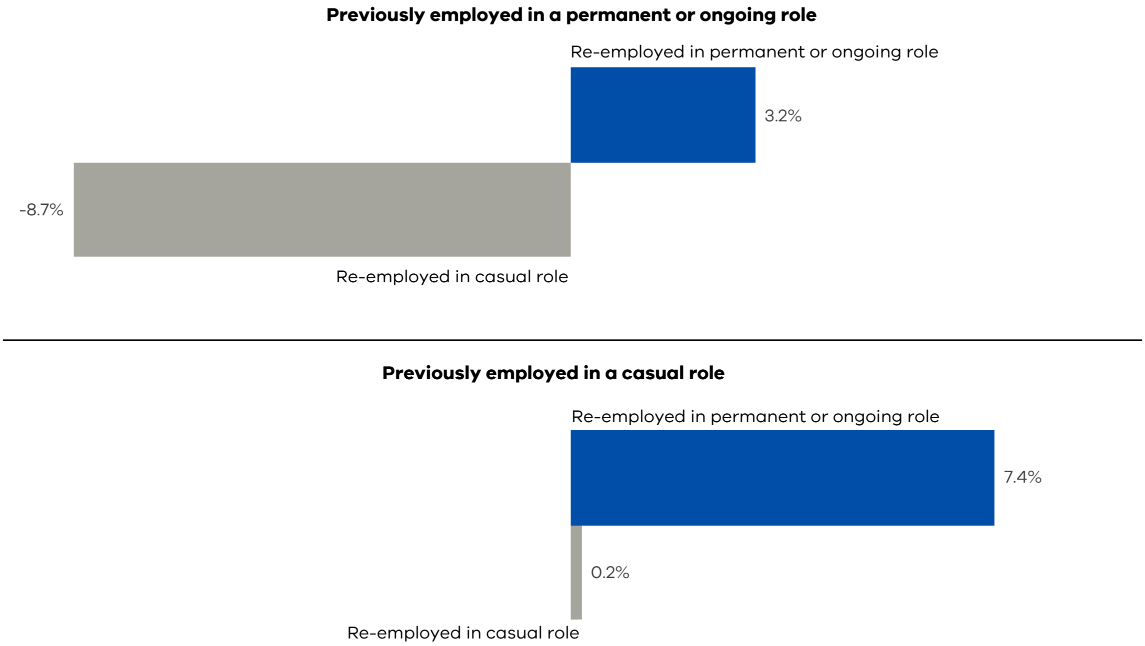
The panel characteristics of HILDA are useful in tracking a range of self-assessed wellbeing indicators for individuals following involuntary job loss. This has the benefit of seeing how different groups of individuals are affected by job loss. In this section, we look at changes in job satisfaction for individuals who have been re-employed by a new employer following involuntary job loss. We compare the changes between those who lost a permanent or ongoing role with those who lost a casual role.

HILDA asks respondents a number of wellbeing questions that require a self-assessed rating from 0 (totally dissatisfied) to 10 (totally satisfied) on job-related questions. These include overall job satisfaction, satisfaction with hours worked, and satisfaction with the work itself. To assess how these change between jobs, we look at the change in the proportion of people who reported high satisfaction in the job they held prior to job loss and the job they held following re-employment. We define high satisfaction as a self-assessed rating of 7 or greater.

Figure 8 compares the changes in the proportion of people with high overall job satisfaction in the job they held before and after the involuntary job loss incident. Individuals who lost a permanent or ongoing role but found new employment in a casual capacity exhibited the most pronounced fall, with the proportion of these individuals reporting high overall job satisfaction falling by 8.7 percentage points. Conversely, those who lost a casual role but found new employment in a permanent capacity exhibited a positive change, with the proportion of individuals reporting high overall job satisfaction increasing by 7.4 percentage points.

These patterns are qualitatively similar for satisfaction in hours worked and satisfaction in the work itself. For these two indicators, the proportion of individuals reporting higher satisfaction fell for workers moving to a casual contract from a permanent contract, while increasing for individuals moving from a casual contract to a permanent contract.

Figure 8: Change in the proportion of people with high job satisfaction in new employment, following involuntary job loss



6. Conclusion

This paper has examined some key characteristics of involuntary job loss in Australia as reported in the HILDA survey from waves 1 to 16. We find that the average job loss rate is higher in the years following the GFC compared to the years prior. The job loss rate varies across industries and is typically more volatile in those industries that are more sensitive to the business cycle, such as manufacturing or construction. Service-based industries exhibit lower job loss rates, particularly social services.

Consistent with findings elsewhere, the composition of individuals experiencing involuntary job loss tends to be skewed — relative to the employed population — toward males, workers with shorter job tenure, casual employees, and in occupations that are typically more 'blue collar'. Around 70 per cent of employees experiencing involuntary job loss were re-employed within 12 months. Those who left the labour force altogether were more likely to be female, perhaps an indicator of different labour market expectations between genders.

The paper examined three self-assessed indicators of job satisfaction for individuals who found employment again following involuntary job loss. Those who lost a permanent or ongoing role and were re-employed in a casual capacity by a new employer exhibited the most pronounced falls in job satisfaction. Those who lost a casual role but were re-employed in a permanent capacity by a new employer exhibited higher self-assessed job satisfaction ratings. A more rigorous analysis using micro-econometric techniques would be needed to properly isolate the effect of job loss on these sorts of wellbeing indicators. However, these findings are consistent with the literature on job displacement having a more deleterious impact on wellbeing for established workers in permanent roles.

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