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HOME OWNERSHIP & UNEMPLOYMENT:

A Panel Data Study on Australia

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ABSTRACT

Home ownership has for long been welcomed and subsidized across most Western countries. Earlier macro studies on the linkages between home ownership rates and unemployment rates have shown a fairly strong support of the Oswald hypothesis. However, these results have been contradicted by micro level evidence on the topic. In this paper the Oswald hypothesis will be analysed by conducting a panel data study on Australia. Earlier methodological issues of endogenous home ownership rates will be reduced by using instrumental variables methods to partly control for the issues that have shed doubt in earlier findings. The obtained results are in support of the Oswald hypothesis, and indicate that a 1 % increase in home ownership rates are followed by an increase of 0.1 - 0.3 % in unemployment rates. The paper also finds evidence of a strong link between trade union membership rates and unemployment rates. The results implicate that a 1 % increase in the trade union membership rate is followed by a 0.15 - 0.25 % increase in unemployment rates. No matter what mechanisms lie behind the findings it is sufficing to say that economies benefit from a highly mobile workforce and that housing markets that are not flexible enough will prevent workers' to be mobile and move to where the jobs are.

KEYWORDS: the Oswald hypothesis, home ownership, unemployment, panel data, Australia

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1 Introduction

1.1 Background and Motivation

Home ownership has for long been welcomed and subsidized across most Western countries. The favourable tax treatments with regards to home ownership combined with the exceptionally low interest rates after the 2008 financial crisis has made home ownership a very attractive and achievable alternative for the common man of today. Home owners are often associated with greater local engagement, more investment in their local communities and children that perform better in school (Dietz & Haurin, 2003). However, despite these benefits there may be potential costs of home ownership as well, something that will be examined in this paper. When you buy a home you are effectively putting down roots in your local community. Hence, imposing geographical restrictions on future employment opportunities. The high transaction costs of switching homes and the fact that people may be unable or unwilling to sell at market prices in economic downturns makes home owners less mobile than renters. The effects might be even more severe in countries where family ties and ties to your local community are highly important than in more "individualistic" countries. Furthermore, countries with high safety nets in terms of benefits when becoming unemployed, should be more affected by too high home ownership rates since people then may have the financial possibility to stay unemployed longer and look for jobs in their neighbourhood instead of being "forced" to move.

This lack of mobility, in terms of being limited to search for jobs within commuting reach may be a significant explanatory factor to varying unemployment rates in developed countries. The importance of workers' mobility depends largely on the geographical structure of the country of interest. Large countries with huge distances between important job centres and worse infrastructure should be much more vulnerable to having workers with a lower mobility than small well-connected countries. The linkage between home ownership rates and unemployment rates was first investigated by Oswald (1996), a paper which gave name to the *Oswald hypothesis*; suggesting a positive link between home ownership rates and unemployment rates.

In this paper the Oswald hypothesis will be revisited by conducting a panel data study on Australia. So far no macro level studies of this kind have been done on Australia, although it is one of few countries that has kept records of home ownership rates on a regional level over an extensive time period. The dataset at hand makes it possible to study the effect of evolvements over time in home ownership rates on a regional level and its linkages with labour market outcomes in the respective region. Earlier research on the area has with few exceptions shown a positive link between home ownership rates and unemployment rates on a macro level. Thus, creating doubts upon the somewhat uniform approach of promoting home ownership in developed countries. However, the relationship to this date is poorly evaluated mostly due to scarce recordkeeping of regional home

ownership rates, but also due to methodological issues when examining the data available.

Australia is one of few exceptions where regional home ownership rates have been recorded over the last 20 years, making it a perfect candidate for an extensive panel data study in line with Oswald and Blanchflower (2013) who conducted a similar study on the USA. Furthermore it is a large country with a sparsely allocated population and long distances between job centres, why labour force mobility should be of utmost importance for Australia. In addition to further evaluating the Oswald hypothesis in a previously unexplored setting, this paper will also reduce earlier methodological issues of endogenous home ownership rates by using instrumental variables methods to partly control for these issues that have shed doubt in earlier findings. The obtained results are in support of the Oswald hypothesis and indicate that a 1 % increase in home ownership rates are followed by an increase of 0.1 - 0.3 % in unemployment rates. The paper also finds evidence of a strong link between trade union membership rates and unemployment rates. The results implicate that a 1 % increase in the trade union membership rate is followed by a 0.15 - 0.25 % increase in unemployment rates.

1.2 The Housing Market in Australia

Home ownership is in general more desirable and common in comparison to private rental in Australia. This is because owning a property is seen as an efficient way of building wealth, and compared to renters home owners have larger security of tenure and more freedom over their dwellings. Moreover, as owner-occupied housing is considered as a private good rather than an investment, home owners are not obliged to pay tax on their housing returns (e.g., capital gains taxes). However, unlike many other Western countries Australia does not have any interest rate deduction scheme for home loans. Anyhow, home ownership is usually being considered more profitable than renting (ABS, 2013; Australian Residential Property Planners, 2014; CBA, 2009; Commonwealth of Australia, 2008; eChoice, 2014; Irvine, 2014). High-income Australians with their higher marginal tax rates and normally more expensive houses with larger capital gains and higher imputed rents, are those who benefits the most from tax exemptions. Thus, the current tax system is not as beneficial for home buyers as it is for current home owners (Commonwealth of Australia, 2008). Being a renter on the other hand can also be advantageous since you are more flexible to move elsewhere and you can invest in other assets that could gain higher profits. Furthermore, as housing prices are rising, choosing to buy a house rather than rent is no longer a certainty (CBA, 2009; GPG, 2014).

The Australian property market has been performing well in recent years. The escalating property prices could be explained by the lack of property supply and as mentioned above, a tax regime that benefits existing property owners (Dennes, 2014). Despite being one of the most expensive countries to live in, the demand and residential construction are continuously rising in Australia (AHURI, 2014; CBA, 2009; GPG, 2014; Property Wire, 2014). The population growth over the

past ten years could be a possible explanation for the strong demand for both purchasing and renting properties (HIA, 2013). While the housing construction is growing more rapidly in bigger cities, with Sydney and Melbourne being examples, the growth of housing construction in other cities is less or not growing at all. Hence, the demand for inner city apartments is greater than the demand for apartments in smaller cities (Dennes, 2014).

Since housing prices are increasing, as mentioned earlier, people are more willing to rent a property rather than buying one. There has been a strong growth in the Australian private rental market over recent decades and as of 2011, 23.4 % of the Australian households privately rent their housing. At the same time a gradual decline has been seen in home ownership rates that were around 68 % in 1994 and reached 66 % in 2014 (ABS, 2014). Because many renters cannot afford entering the housing market, long term renting is not unusual. In fact, about one third of all private renters are long-term renters (defined as people who rent for more than ten years continuously) (AHURI, 2014; Australians for Affordable Housing, 2011; Just Landed, 2014).

The net gain or loss of population through the movement of individuals from one state or territory of residence to another over a given time period, known as the *net interstate migration (NIM),* has been growing in the past several years. From 2009-2010 to 2010-2011 it increased with 2 %. Between 2010-2011 and 2011-2012 and from 2011-2012 to 2012-2013 the NIM increased with 0.3 % and 1.8 % respectively. Regarding the *net overseas migration (NOM)*, which is the net gain or loss of population through migration to Australia and emigration from Australia, annual rates have also been rising. There was a rise of 24.8 % from 2010-2011 to 2011-2012 and during 2011-2012 to 2012-2013 the NOM grew with 8.6 % (ABS, 2013). The improvement of regional mobility seen over the last years in Australia may have something to do with the increased importance of the private rental market and the overall decline in home ownership rates seen over the last decades.

Because the tax regime has encouraged people to own a property, the number of people investing in properties has escalated, resulting in accelerating property prices and housing costs and creating difficulties for first home buyers to enter the property market (Dennes, 2014). In order to help first home buyers with purchasing or constructing their first home, the Australian Federal or State Government introduced the so-called *First Home Owners Grant (FHOG)* in 2000. Only those who fulfill the eligibility criteria can receive this grant (Government of South Australia, 2014; Government of Western Australia, 2013; NAB, 2014; NSW Government, 2013; State Government of Victoria, 2013). A *First Home Owner Boost Scheme* was also implemented with the purpose of increasing the grants for first home buyers during a limited time period (NAB, 2014). Programs, services, benefits, payments, grants and funds provided by the Australian Department of Social Services (DSS) are other ways of assisting first home buyers and making housing more available. One example is the *Housing Affordability Fund*, which was a five year $500 million investment established in

2008 to reduce housing costs for new home buyers (Australian Government, 2008; DSS, 2014; LGA, 2008; Renwick Living, 2011). The government also gives housing assistance to the rental sector through programs such as the *CRA Program* (a demand-based tax free income supplement), the *Private Rent Program* (helps low-income households that have difficulties with securing or maintaining their rents), and the *National Rental Affordability Scheme* (designed to make housing more available for low- and moderate income households (Australian Institute of Health and Welfare, 2013; DSS, 2014; Government of Western Australia, 2014).

To sum up, with its lack of capital gains taxes the housing market in Australia should in theory be more flexible than in countries where transaction costs of moving residency are higher. However, with one of the world's highest property prices the dream of becoming a homeowner is hard to attain for the people of Australia, especially since there are no interest rate deductions as in many other developed economies (such as Sweden). As home ownership has become more and more expensive, Australia has seen a decline in home ownership rates over the last decades and consequently a rise in importance of the private rental market. Today almost one fourth of the households in Australia are private renters. According to the underlying theory of this paper, this development should be associated with a movement towards a more mobile workforce and possibly lower unemployment rates, which will be analysed later on in this paper.

The study is divided into six different sections. The next section will introduce earlier research on the topic followed by section 3, which describes the methodology used in this study. In section 4 a description of variables and data will be provided and section 5 will present the empirical results. The last section of the study presents the conclusion, discussion and policy implications.

2 Hypothesis and Literature Review

This section introduces the hypothesis of the interactions between home ownership rates and unemployment. Furthermore, a brief overview of results from earlier empirical studies and the methodological issues faced by most researchers in this area will be provided.

Research on a potential destructive effect of too high home ownership rates on the labour market began in the 1990s when Andrew J. Oswald (1996) wrote "A Conjecture on the Explanation for High Unemployment". In order to prove his hypothesised connection, Oswald performed cross-sectional regressions of unemployment rates and home ownership rates for regions in the UK, Sweden, France, Italy and the US. The findings implied that a 10 percentage point increase in home ownership rate in one region was associated with nearly 2 percentage points higher unemployment rates. Both pure cross-sectional models and

correlations between yearly changes in home ownership and unemployment were performed. According to Oswald, this positive relationship between home ownership and unemployment arises due to home owners' lower mobility and lower willingness of moving in search for jobs compared to private-sector renters. Reasons such as high costs faced by homeowners regarding buying, financing and selling a house could be an explanation for this outcome. Effects from too large a share of owner-occupied housing could according to Oswald also lead to less business activity in that region and/or a decline in consumption, particularly for those home owners with loans. Since cross-sectional regressions of this kind often lead to nonsense correlations, Oswald later developed his research towards using panel data and more researchers around the world followed in his footsteps.

Oswald's argument that a higher share of home ownership causes a higher unemployment, known as the *Oswald hypothesis*, led to further studies both on macro levels and on micro levels. In the former case, studies performed in for example Germany (Lerbs, 2010), New Zealand (Cochrane & Poot, 2007) and Finland (Laamanen, 2013) show similar findings as the ones found by Oswald. Perhaps the most comprehensive study on a macro level was the one conducted by Blanchflower and Oswald (2013) where the authors used a fixed effects panel data model to pin down the effect of rising/declining home ownership rates using data on American states during a 25-year period. The results indicated that the long-term elasticity seemed to lie between one and two. Put differently, in the long run, doubling the rate of home ownership would result in more than a doubling of the unemployment rate. In addition, the lags between cause and effect were found to be long. According to his results it could take up to four years for the effect of a rise in home ownership to affect the labour market.

Conversely, micro level studies usually find contradicting results where home owners tend to be associated with better labour market outcomes than renters (Coulson & Fisher, 2008; Flatau et al., 2003; Flatau et al., 2002; Munch et al., 2003; Taskin & Yaman, 2013;). In these studies, probit models and duration models are used to pin down the differences in risks of being unemployed and length of unemployment spells between home owners and renters. The results mostly point to the fact that home owners have lower risks of becoming unemployed, and in addition, shorter spells of unemployment than renters. One exception being Taskin and Yaman (2013) who found evidence in support of the Oswald hypothesis in the US after controlling for endogeneity of home ownership.

The only known study that tries to find evidence that were in conjunction with both micro and macro level findings was executed by Jani-Petri Laamanen (2013), "Home-ownership and the Labour Market: Evidence from Rental Housing Market Deregulation". The author shows using a natural experiment that home owners on the micro level are less likely to be unemployed, but at the same time, those living in regions with high home ownership rates are more likely to be unemployed than others. Laamanen uses micro data between 1990 and 1992, when a reform that encouraged private renting was implemented in Finland. The

reform had a strong effect on regional home ownership rates and could therefore be used as an instrument to isolate the causal effect of regional home ownership rates. When the instrumental approach was used, the marginal effect of a higher regional home ownership rate on risk of being unemployed was almost the double compared to the result where the instrument was not used. The author argues that this finding was an implication of a possible simultaneity issue causing downward biased parameters between home ownership rates and unemployment rates due to the fact the direction of causality between the two may run in both directions. High unemployment rates may lead to lower demand of owner-occupied housing and low unemployment rates have the opposite effect, thus implicating an inverse relationship in the opposite direction of causality. The results from Laamanen's study show that a 1 percentage point rise in home ownership in a region leads to a 9 percentage point higher risk of being unemployed.

The methodological issues faced on the area are not restricted to the possible double causality between the variables of interest. Measurement errors in home ownership rates are another methodological issue that gets magnified especially in empirical approaches where fixed effects panel data models are used. Measurement errors may cause further downward bias in the estimates of the home ownership variable, and thus further magnifying the downward bias due to simultaneity (Hsiao, 2003). The common approach trying to mitigate the simultaneity issue has been to use lags of home ownership rates in the modelling attempts (for example Cochrane & Poot, 2007). The issue of measurement errors has not gotten the same attention in earlier studies. In general, most studies rely on the fact that home ownership rates are not endogenous as it is hard to come by external instruments that can isolate the effect of exogenous changes in the housing market with the exception being Laamanen (2013). Therefore the question is to what extent earlier macro evidence is spurious or whether the linkages in fact have been underestimated in previous studies.

The diverging results from previous literature have led to discussion about the possible mechanism underlying the patterns shown in the data. It is of general belief that, in comparison to renters, homeowners are less willing or unable to relocate to areas where possibilities of finding a new job could be greater. This in turn makes them less mobile than renters all else being equal, resulting in possibly longer unemployment spells. However, the micro evidence showed that this was not the case; in fact homeowners were associated with shorter unemployment spells (for example Munch et al., 2003). The discussion about these contradicting micro and macro evidence has therefore led towards the belief that home ownership has effects above and beyond the effects on the individual level (externalities). While home owners are less likely to experience unemployment, external effects counteract the positive effects of home ownership on the aggregate level (Laamanen, 2013). Laamanen also proposed some plausible mechanisms behind these externalities such as consumption reductions due to mortgage financed home purchases. Also, home owners are more likely to be indebted with home loans, and therefore more vulnerable in the event of

becoming unemployed (Lerbs, 2010; Schmid, 2010). This may imply that homeowners have lower reservation wages resulting in an increased local job competition and possible displacement effects on other individuals. Furthermore, as the rental market in a region becomes smaller, it is harder to attract talent from other locations due to their issues in finding a place to reside. Yet, as the research area is relatively new the linkages between the housing and labour market are still poorly understood. Lastly, a useful review of the above mentioned studies and other relevant studies on the area is provided in Table 2.1 (see Appendix A).

3 Methodology

This section briefly explains the econometric techniques and principles employed in this paper. A brief overview of the notion of stationarity and methods of testing this assumption will be included. Furthermore, the section provides an overview of how to choose an appropriate panel data model, and a more detailed introduction of the panel data models used in the analysis.

3.1 Stationarity

Granger and Newbold (1974) showed that if ordinary OLS methods are applied to non-stationary data, one is highly likely to obtain very misleading estimates of the parameters of interest. This situation is known as *spurious regression,* where the OLS results show a strong link between variables even though there may be no relationship between them at all. Although the original research on spurious regressions was intended for time series models, the notion of spurious regressions can be applied to a panel data setting as well. There has been numerous research papers on the impact of non-stationary variables in a panel data setting, and since the time series are averaged over more than one cross-sectional unit in a panel, the problem of non-stationarity is not as damaging as in the single time series case. When the number of cross-sections is smaller and the time series dimension gets larger it becomes more important to test for stationarity to avoid possible spurious results (Hsiao, 2003, p. 298; Verbeek, 2012, p. 410).

The dataset in this paper contains fewer cross-sections and more time observations making it necessary to check for non-stationarity in the data. There are a numerous set of tests for stationarity available today with different structures depending on the assumptions you are willing to make about the data at hand. Levin, Lin and Chu (2002) propose a test where the null hypothesis is that each time series contains a unit root, and an alternative that each time series is stationary. This test is however restrictive because it assumes that the unit root process is the same across the cross-sections. Im, Pesaran and Shin (2003) propose a less restrictive test where they allow the unit root process to differ for the cross-sections. The test is conducted by averaging the augmented Dickey-Fuller (ADF) test statistics across cross-sections. Hence, allowing for different

orders of serial correlation and different unit root processes for each cross-section. The general ADF test equation looks like Equation 1:

$$1. \qquad \Delta y_{it} = \beta y_{i,t-1} + \beta 1 \Delta y_{i,t-1} + \beta 2 \Delta y_{i,t-2} + \beta 3 \Delta y_{i,t-3} + \beta k \Delta y_{i,t-k} + \varepsilon_{it}$$

The parameter in front of the sequence in levels will be tested in order to find out if it is equal to zero, such that the process must be described entirely in first-differences. Under the null hypothesis, the only non-stationary part of the equation above is the level variable. Thus, it makes sense that this variable should not appear in the equation under the null. A high average test statistic across the cross-sections therefore implies stationarity and vice versa. Another intuitive explanation for the reason of testing if β is equal to zero is that there is no correction mechanism towards a long run mean if the y_t sequence tend to meander away. There is also a Fisher type test proposed by Maddala and Wu (1999) that is based on combining the p-values from the ADF test on each cross-section. Thus, a similar approach as the test proposed by Im, Pesaran and Shin. All tests described above require cross-sectional independence, which is a strong assumption to make in macroeconomic contexts. However, there are ways to deal with this issue, for example by assuming that the cross-sectional dependence is following a common trend across cross-sections. Therefore the issue might be mitigated by subtracting period means across cross-sections from each individual observation to eliminate a possible trend common to all cross-sections.

Furthermore, there are three different approaches to testing for unit roots. The simplest but also most powerful test (most likely to reject a false null hypothesis) is one where no constant and no deterministic time trend is included in the test equation. The ADF test equation then looks exactly as Equation 1 above. After visual inspection of the series in levels, there may be reason to include either a constant or a deterministic time trend in the test equation if the mean of the series tend to evolve in a certain direction over time. The testing procedure starts with determining whether each individual panel series contains a unit root in levels or not; if it does, the series will be differenced once to make it stationary. Also, in certain occasions it is necessary to difference the series once more to make it stationary. The series is then said to be integrated of order one and two respectively. Examining relationships between variables of different order of integration is often pointless (Enders, 2009, p. 199). This explains why the first step in any study on time series data and panel data with a long time dimension should be to determine the order of integration of the variables, and if needed, making the necessary adjustments to ensure that every variable are integrated of the same order.

3.2 Panel Data Model Selection

3.2.1 Static Panel Models

Panel data models can in general be divided into two subsections; static and dynamic models of which the static models do not contain a lagged dependent variable as in dynamic models. The dynamic models are a bit more advanced, and will be explained in more detail after the concepts regarding static panel models have been introduced. The first necessary assumption to make regarding the data is whether or not the dependent variable is a random sample from an identical population. A pooled panel model combines the data from all cross-sections and assumes that there is no systematic time independent component that distinguishes the different cross-sectional units. This is an illogical assumption to make when handling regional unemployment models, since the average unemployment over time indeed in most cases differs between different regions. This is also the case for Australia where some regions are highly industrialized urban areas and some are less developed rural areas. It would therefore be of use to include a single intercept for every region to account for such time independent regional differences in unemployment. This model is called a LSDV model (Least Square Dummy Variable model).

In addition to the cross-sectional fixed effects, period specific fixed effects might be incorporated into the fixed effects model. If unemployment is assumed to follow the business cycles in a similar way across the regions, it would be of use to account for these time specific effects by including single intercepts for every time period in the model. If these business cycle effects are not accounted for, it may also result in biased estimates of the parameters of interest, should these variables be correlated with the business cycles.

The need to include cross-sectional or period fixed effects can be tested with a redundant fixed effects test that uses an F-statistic to check if the cross sectional, period or both fixed effects are contributing to the explanation of the dependent variable. The null hypothesis in such a test is that all cross-sectional or period dummies are zero versus the alternative that at least one of these differs from zero. Another common approach to remove fixed effects is to use a model in first-difference (FD model). Since it is assumed that the fixed effects are time independent, this manipulation will remove the fixed effects in a similar manner as the LSDV model.

3.2.2 Dynamic Panel Models

In many cases the dependent variable of interest depends highly on past realizations of itself. Periods with high unemployment are usually very persistent and it will take time for the level of unemployment to reach its long-term equilibrium level again. If a static model produces highly autocorrelated residuals, it might be needed to add a lagged dependent variable to account for the persistence in the dependent variable. Also, if the lagged dependent variable is wrongly omitted and correlated with any of the other explanatory variables, biased parameter estimates may be the result. A problem of biased and inconsistent parameter estimates arises when estimating such a model with an ordinary LSDV or first-difference approach as shown by Nickell (1981). The direction of the bias is always negative, resulting in too low estimates of the

parameter for the lagged dependent variables (see Nickell, 1981). If the other regressors are correlated with the lagged dependent variable it will result in biased estimates for their parameters as well, why it is important to try and overcome this issue. The problem of Nickell Bias is easiest shown in the FD model context where a lagged dependent variable is added to the model as Equation 2:

$$2. \qquad y_{it} - y_{i,t-1} = \gamma(y_{i,t-1} - y_{i,t-2}) + \beta\, x_{it}(x_{it} - x_{i,t-1}) + u_{it} - u_{i,t-1}$$

Since the realization of the lagged dependent variable depends on the error term in time period t-1, there is correlation between the error term and the repressors, resulting in biased estimates. The problem is not solely present in FD models but also in LSDV models. The bias gets smaller as the number of time periods in the sample goes to infinity, but may in this case be quite sizable, which requires finding a way to overcome this bias (see Verbeek, 2012, p. 397). There are two main approaches to overcome the Nickell bias where the simplest one is an IV approach as proposed by Anderson and Hsiao (1981) that uses past levels or differences of the y sequence as instruments for the lagged dependent variable. For instance, the second or third lagged levels of the y sequence do not depend on u_{it-1}, but may be highly correlated with (y_{it-1} - y_{it-2}). Thus, these may serve as a valid instrument if there is no severe autocorrelation in the differenced residual.

An extension of the Anderson-Hsiao approach may also be used in a GMM estimation framework as shown by Arellano and Bond (1991). They argued that a more efficient estimator could be found by using more available instruments of the lagged dependent variables either in differences or in levels. In addition, the other variables of the model can be instrumented if they are presumed to be endogenous. The fact that causality between home ownership and unemployment may run in both directions suggests a possible simultaneity problem. Also, the frequent problem of downward biased parameter estimates caused by measurement errors in FE and FD models may be significantly reduced by instrumenting the variables, which are assumed to suffer from large measurement errors (Hsiao, 2003, p.305). By using the Arellano-Bond method it is possible to instrument home ownership with past levels or differences of itself to reduce the simultaneity bias and the measurement error bias. This works if it is assumed that previous observations of home ownership are uncorrelated with future error terms (i.e. that future measurement errors are uncorrelated with past recordings of home ownership rates and that past home ownership rates are not simultaneously determined with future unemployment rates). In comparison to an ordinary FE or FD model, assuming that this exogeneity restriction holds, more consistent estimates of the true parameter might be found. Of course the instruments must also have a strong first-stage effect on the instrumented variable. In fact, the only difference between the Arellano-Bond method and 2SLS is the choice of weighting matrix. The one step weighting matrix will be used later on, which

implies that the two methods are equal, allowing interpretation of the model and its assumptions in the same manner as in 2SLS (see Cameron and Trivedi, 2005, p. 746).

Although the original Arellano-Bond approach was intended for panels with a large number of cross-sections and a smaller time dimension, later research showed that the estimator is also consistent as both the number of cross-sections and time series dimensions tend to infinity (Alvarez & Arellano, 2003). However, as the time series dimension gets larger the number of instruments might need to be restricted, since observations too far back in time may have a very weak correlation with present observations (Roodman, 2009; Verbeek, 2012, p. 404). To handle the unobserved fixed effects, either the differencing approach as in the Anderson-Hsiao method can be used, or orthogonal deviations that subtracts the average of all available future observations from the current value for every cross-sectional series to take the fixed effects into account. The differencing approach will be used later on.

There are two main specification tests for the GMM approach, namely to check for second-order autocorrelation in the residuals (first-order serial correlation in the residuals in Equation 2 is expected as both differenced residuals will contain $u_{i,t-1}$). Nevertheless, second-order serial correlation is unwanted as this implies autocorrelation in the level equation and would make the proposed instrument invalid. Second, Sargan test will be used, which tests whether the remaining instruments after having assumed that all the necessary instruments are valid, are correlated with the error term. It is therefore a somewhat weak test of the exogeneity restriction, where common sense must be used in order to validate exogeneity of the necessary instruments. If the model passes these tests there is no reason to assume that the instruments are invalid, and the Arellano-Bond GMM estimator will in this case provide consistent parameter estimates. Furthermore, it must be ensured that the instruments have a strong first-stage effect on the instrumented variable, which can easily be tested by examining t- or F-statistics from the first stage regression. Lastly, the exclusion restriction may be tested by including the instruments directly in the original model. A more detailed overview of these methods can be found in Hsiao (2003) or Verbeek (2012).

4. Variables and Data

In this section the variables chosen to model regional unemployment rates will be described in more detail. Having outlined the structure and relevance of the variables, the general panel model will be specified. Thereafter the data source will be reported followed by a section testing for stationarity. Finally, some descriptive statistics and correlations will be reported.

Unlike research using for example unemployment benefits or labour taxes to pin down differences in unemployment between countries, such standard approaches are not of interest in the context of explaining regional unemployment differences, as they are not varying across regions (even if there are such differences they will be incorporated in the intercept of a LSDV model). Since this study has chosen a fixed effects approach, all non-time varying determinants of regional unemployment will be incorporated in the intercept. It is therefore important to choose explanatory variables that are likely to evolve over time within regions. Because the purpose of this paper is to explicitly find the linkages between unemployment and home ownership, another goal when choosing control variables has been to find variables that are likely to be correlated with both of the above, this to reduce the issue of omitted variables bias. Following this reasoning the following explanatory variables are included along with regional home ownership rates:

Proportion of Trade Union Members of Total Workforce (T)
That trade union participation rates affect the wage bargaining between employers and employees, such that disequilibrium may take place in the labour market, is a well-known economic concept. To capture different evolvements over time in the strength of trade unions between regions, this variable is chosen as a possible determinant of regional unemployment rates. The expected relationship between the trade union participation rate and unemployment is positive.

Proportion of People in the Age Bracket 15 - 34 (Y)
Demographic patterns may evolve differently across regions over time and is also a well-known determinant of unemployment. As younger people have a weaker position on the labour market it is expected that the relationship between this variable and unemployment is positive. It is also highly likely that there is a correlation between the regional age structure and regional home ownership rates, why this variable is of great importance to the model. The expected coefficient sign is positive.

Proportion of People in the Age Bracket 45 - 64 (O)
In the age bracket 45 - 64 people usually have their strongest position on the labour market. Having reached such an age, people are also more likely to be home owners, why this variable fits the criteria very well. The expected coefficient sign is negative.

Percentage of People Over 15 years of Age with a Bachelor Degree (BD)
This variable is self-explanatory; a better educated workforce is associated with both lower unemployment rates and potentially higher home ownership rates. The expected coefficient sign is negative.

Percentage of People Born Overseas (BO)
To capture the effects of different immigration rates between regions, this variable is included to control for the potential relationship between the rate of people born overseas and unemployment. It is also highly likely that there is a connection between this measure and home ownership rates. The expected coefficient sign is negative.

People Working in Manufacturing (as a percentage of total workforce) (M)
This variable controls for the sectorial structure of the region. Though there may not be an apparent link between this variable and home ownership rates, it will still be included in the analysis as it may be strongly correlated with unemployment rates. The importance of trading industries (export-oriented industries) to the employment situation in a region is most likely strong, see for example Porter (2003).

Having specified the full set of control variables it is now time to outline the full model. As pointed out by Oswald (2013), a possible explanation as to why the linkages between home ownership and unemployment are so little known is the long time lags between cause and effect. In this modelling attempt, lags of the home ownership rates will therefore be used to ensure that no possible linkages over a larger time span are missed out on. Of course for each and every further lag, observations are lost and the issue of multicollinearity gets magnified, why the number of lags are restricted to two. The full model will look like this:

3. *Unemployment rate in a region* (U_{it}) = $U_{i,t-1}$ + *regional intercept dummies*$_i$ + *control variables*$_{it}$ + *regional homeownership rates*$_{it}$ *(from lag 1 to lag 2)* + *time period dummies*$_t$ + e_{it}

Where i is the regional index and t is the time index and e_{it} is the stochastic error term. Here the unemployment rate is modelled as an autoregressive process where it depends on its last recorded value as well as regional time invariant effects, national business cycle effects as recorded in the time period dummies, the lags of home ownership rates and the control variables as specified above. The model above is an LSDV model with both time period and cross-sectional fixed effects accounted for. In a first step static LSDV models will be run, excluding the lagged dependent variable. In the second step the lagged dependent variable will be added to the LSDV model. The third step will be to correct for the Nickell bias and possible endogeneity of home ownership rates as explained in the methodology section by using the Arellano-Bond GMM estimation approach.

4.1 Data Source

The data is solely collected from the Australian Bureau of Statistics. Regional home ownership rates were available from the year of 1994 until 2011 from the publication ”Housing occupancy and costs”. For the years of 1998, 2001, 2004, 2006, 2008, 2010, 2012 and 2013 no estimates of regional home ownership rates were available, why values for these years had to be interpolated using a simple linear interpolation method (for 1998 the value was interpolated as the mean of the estimate in 1997 and 1999 and so on). Details on survey size, standard errors of the estimates and more can be found in (”Housing occupancy and costs”, ABS, 2014). Regional unemployment rates were collected yearly from 1994 to 2013 from the Macrobond database (which in turn collects their data from ABS). Data on trade union membership rates, proportion of young people and proportion of old people were available for every year during the time span 1994 - 2013 with the simple exception of there being no estimate on trade union membership for 2013 (this was interpolated as the value of 2012). As for the proportion of people working in manufacturing data was missing for 2002-2006 as well as for 2013 (here linear interpolation techniques had to be used as well to fill out the missing data). Regional data on people born overseas and proportion of people with a bachelor degree is only collected every fifth year, why missing values had to be interpolated as well using the same linear interpolation techniques. Exact descriptions of the data and where to find the data for future regressions can be found by navigating the website of ABS, the relevant surveys are listed in the reference section of the paper.

4.2 Stationarity Testing

As pointed out in the methodology section, the first step in any study on time series data should be to determine the order of integration of all variables used. The case of panel data is no different, especially when the number of cross-sections is small and the number of time period observations is large. In this section three commonly used tests are chosen to formally test whether or not the variables are stationary. All tests rely on cross-sectional independence, a very strong assumption to make when dealing with macro data. The cross-sectional dependence will be assumed to be the result of a common national time trend, which is a reasonable assumption bearing in mind that the study is working with aggregate macro variables. To remove the cross-sectional dependence from the individual panels the data is averaged over cross-sectional units for each time period, the period specific element is thereafter subtracted from the data yielding ($y_{it}^* = y_{it} - (Sum(y_{it}))/N$), where $(Sum(y_{it}))/N$ is the mean value for variable ”y” across all regions in each specific time period. The time trend that is common to all regions will therefore be removed from the data. Thereafter, the adjusted data can be used to test for unit roots (see Enders, 2009, p. 246).

Having dealt with the cross-sectional dependence, the deterministic components to include in the test equation must be chosen. Since the paper is

dealing with ratios or percentage rates, a deterministic time trend seems unreasonable to include as it implies that the variables will reach above or under 100 % and 0 % over time. After visually inspecting the data there was a tendency for the mean of the individual series to evolve in certain directions over time. Therefore, an intercept or drift term is included in the test equation. Under the null hypothesis the variable contains a unit root, and non-stationarity can therefore not be ruled out. The p-values for each test and for each variable is reported in Table 4.1, full test results are to be found in Appendix B.

Table 4.1: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Unit Root Test Results	Levin, Lin & Chu	Im, Pesaran & Shin W-stat	ADF - Fisher Chi-Square
Home Ownership (H)	0.0024***	0.0000***	0.0000***
Unemployment (U)	0.0509*	0.0158**	0.0386**
Bachelor Degree (BD)	0.6646	0.9889	0.9810
Born Overseas (BO)	1.0000	1.0000	0.9826
Manufacturing (M)	0.9804	0.9994	0.9824
Old People (O)	0.1297	0.5085	0.0916*
Trade Union (T)	0.0000***	0.0000***	0.0000***
Young People (Y)	0.1233	0.6465	0.1752

The tests suggest that the two main variables of interest, which are home ownership rates and unemployment rates, are stationary and no further adjustment is needed to make them stationary. Additionally, trade union membership rates seems to be stationary, meaning that this variable can be used in levels from now on. The rest of the variables are clearly non-stationary and the necessary adjustments must be made to make sure that they will not complicate the modelling attempts. As has been pointed out in the methodology section, first-differencing the data will in most cases make it stationary and to confirm that this is the case for these variables, the same unit root tests will be run for the variables in first-differences. The p-values for the unit root tests of the non-stationary variables after differencing are shown in Table 4.2:

Table 4.2: Panel unit root in first-difference test results. Note: calculations made in EViews. Source: ABS

Unit Root Test Results, First-difference	Levin, Lin & Chu	Im, Pesaran & Shin W-stat	ADF - Fisher Chi-Square
D_Bachelor Degree (BD)	0.7566	0.8848	0.9713
D_Born Overseas (BO)	0.8422	0.5147	0.3197

Unite Root Test Results, First-difference	Levin, Lin & Chu	Im, Pesaran & Shin W-stat	ADF – Fisher Chi Square
D_Manufacturing (M)	0.0000***	0.0000***	0.0000***
D_Old People (O)	0.0000***	0.0000***	0.0000***
D_Young People (Y)	0.1413 0.0000***	0.0000***	0.0001***

Even after differencing, both BD and BO do not pass the test, but the rest of the variables are now stationary (Y do not pass the LLC test but passes the less restrictive IPS and Fisher tests). At this stage, the relevance of including BD and BO as control variables is questioned. Twice differencing the data will result in losing a lot of information and it is hard to justify from a theoretical viewpoint that the ”difference in the difference” of BD and BO will have anything to do with unemployment rates in levels. Furthermore, most of the data was interpolated for these two variables in the first place, making it hard to draw reliable conclusions using these variables in differences. It therefore makes sense both from a theoretical and statistical viewpoint to drop these variables completely. From now on, only M, O and Y will be used in first differences and H, U and T in levels.

4.3 Descriptive Statistics and Correlations

To get a first sense of the looks of the data and the possible linkages between the variables of interest simple descriptive statistics, correlations and pooled regressions of the variables will be introduced.

Table 4.3: Australian national averages of chosen variables during a 20-year period. Notes: calculations performed in EViews. Source: ABS

Variable	Mean	Std. Dev.	Min	Max	N
Unemployment	0.061	0.019	0.027	0.11	160
Home Owners	0.678	0.061	0.448	0.759	160
Manufacturing	0.061	0.024	0.0159	0.103	160
Born Overseas	0.223	0.06	0.10	0.41	160
Bachelor Degree	0.146	0.061	0.071	0.34	160
Old People	0.233	0.023	0.155	0276	160
Young People	0.294	0.0285	0.231	0.374	160
Trade Union	0.238	0.064	0.13	0.43	160

The table above describes the national averages over the 20 year time period. The average unemployment rate was around 6 %, whilst the average home ownership rate was around 68 %. The national unemployment rate was around 9.3 % in 1994 and has declined to around 5.6 % by 2014. The same gradual decline can be seen

in home ownership rates that were around 68 % in 1994 and reached 66 % in 2014 (ABS, 2014).

Table 4.4: Correlation between home ownership and unemployment. Notes: calculations performed in EViews. Source: ABS

Correlation	Home Ownership
Unemployment	0.2798

Table 4.5: Cross-sectional pooled regression results. Notes: calculations performed in EViews. Source: ABS

Dependent variable: Unemployment rate	Coefficient	Std. error	P-value
Constant	0.001571	0.016415	0.9239
Home Ownership Rate	0.088381	0.024121	0.0003

Switching the focus towards the linkages between the two measures, a positive correlation between home ownership rates and unemployment rates is found when the entire dataset over the whole sample period is pooled. A simple pooled OLS regression in the same manner further supports the positive link between the two variables. This finding surprisingly contradicts earlier studies, which often finds a negative connection between the two in this simple cross-sectional setting (see for example Lerbs, 2010). To see the pattern graphically the average unemployment rates for each region is plotted against the average home ownership rates (average over the entire time dimension) and indeed the same pattern arises here. The relationship looks very similar to the plot of the average unemployment rate against the average home ownership rate between 2010-2012 for the EU countries, but the opposite relationship is found for US states and Swedish counties using rates for 2012.

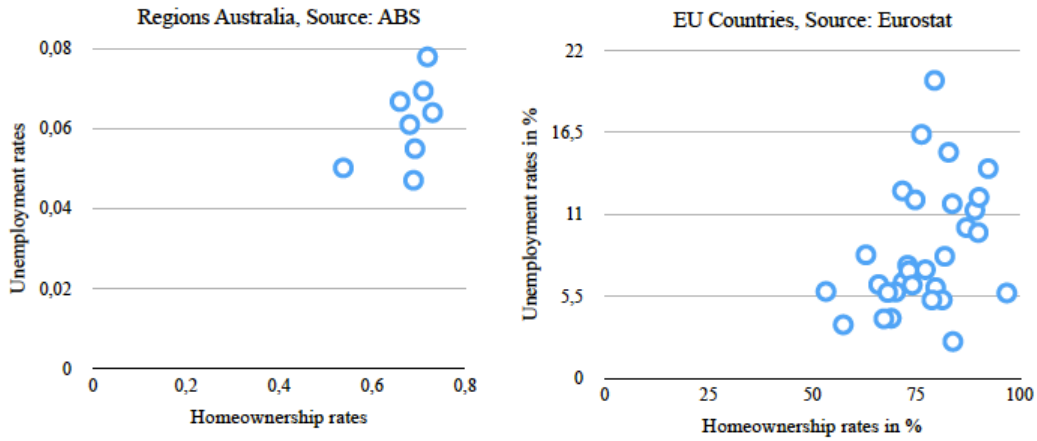

Figure 4.1: Relationship between home ownership and unemployment in Australian regions and EU countries. Notes: calculations performed in Excel.

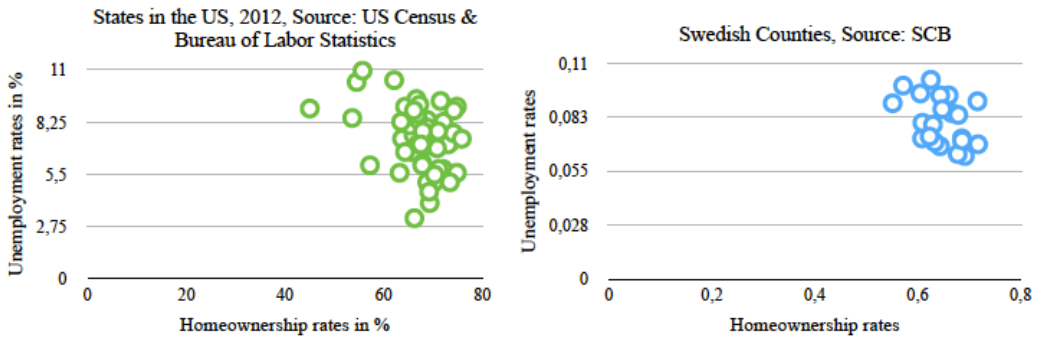

Figure 4.2: Relationship between home ownership and unemployment in states in the US and Swedish counties. Notes: calculations performed in Excel.

Conclusions of the linkages cannot be drawn at this stage, since cross-sectional relationships of this kind are highly likely to produce nonsense correlations due to the heterogeneity of regions or countries. For instance, countries or regions with a high home ownership rate tend to be more economically prosperous in the first place, and may therefore have lower average unemployment rates, which may be a reason as to why cross-sectional studies have tended to find a negative linkage between the two variables. The opposite may be the case for the EU union where countries that were severely hit by the financial crisis such as Spain, Portugal and Greece, and financially weaker Eastern European countries such as Romania, Bulgaria and Hungary, have very high home ownership rates (Eurostat, 2012). With panel data however, it is possible to isolate the linkages within each homogeneous region and therefore substantially reduce the issue of heterogeneity.

5 Panel Model Results

Having tested the variables for stationarity and made the necessary adjustments to make sure that the variables enter the model with the same order of integration, the models described earlier in the ”panel data model selection” section are now ready to be run. To start the empirical analysis, the most basic static LSDV model with period and cross-section fixed effects will be estimated. Thereafter, this model will be developed into a dynamic one, and lastly an attempt to try and mitigate possible biased parameter estimates will be made by using the Arellano-Bond approach.

5.1 Static LSDV Model

After testing for stationarity, it was concluded that it would be best to drop BD and BO from the model. Additionally, M, O and Y had to be first-differenced before running the regression. Bearing this in mind the final LSDV model will look like Equation 4:

4. $U_{it} = regional\ dummies_i + time\ period\ dummies_t + \beta 1H_{it-1} + \beta 2H_{it-2} + \beta 3T_{it} + \beta 4D\_M_{it} + \beta 5D\_O_{it} + \beta 6D\_Y_{it} + e_{it}$

Here the regional unemployment rates are modelled as a function of regional time invariant intercepts, time period specific national business cycle effects, former regional home ownership rates, the trade union participation rate and the year-to-year difference of the proportion of people working in manufacturing, the proportion of old people as well as the proportion of young people. All variables have been formally tested for non-stationarity and there is no evidence of non-stationarity for any of these variables. In the model specification (*i*) stands for the cross-section index, (*t*) stands for the time period index, (D_) indicates that the variable has been differenced and e_{it} is the stochastic error term. White period standard errors are used to allow for cross-sectional clustered serial correlation and heteroskedasticity in the residuals. Only the most relevant findings will be reported here. For a full regression table, please turn to Appendix C of this paper.

Table 5.1: Static panel least squares model results with period and cross-section dummies. Notes: calculations performed in EViews. Source: ABS

Static LSDV Model results	Coefficient	White Period Std. Error	P-Value
Home ownership(-1)	−0.0097	0.0273	0.7220
Home ownership(-2)	0.0978	0.0861	0.2581
D_Manufacturing	0.2608	0.271	0.3380
D_Old people	0.0831	0.0573	0.1499
D_Young People	−0.0156	0.0452	0.7314
Trade Union	0.1433***	0.0296	0.0000
Adj. R-Squared	0.8630		
Durbin-Watson Stat	0.6980		
Redundant fixed effects test	0.0000***		

As can be seen in Table 5.1, the coefficient estimates are quite unsatisfying. Twice lagged home ownership rates have the expected coefficient sign, but the standard error is large, making the coefficient insignificant. Manufacturing, Old People and Young People all have the opposite coefficient sign as compared to what was expected. Trade Union Membership rates enter with the expected coefficient sign and is highly significant. To check if the cross-section and period fixed effects are significant, a redundant fixed effects test was performed, where the null was strongly rejected.

The test checks if all cross-section specific and time period specific dummies are significant as a whole. The results suggest that the fixed effects dummies are correctly included in the regression. Therefore a pooled model approach would not be of interest in this case. The most disturbing result from this static LSDV model can be seen from the extremely low Durbin-Watson statistic. The Durbin-Watson test for panels, tests if there is first-order autocorrelation in the residuals. The rule of thumb is to conclude that there is positive first-order autocorrelation in the residuals when the Durbin-Watson statistic is much smaller than 2 (see Verbeek, 2012, p. 391). OLS is still consistent in this case, but the standard errors will have to be corrected by using a robust standard error calculation approach. The White Period standard errors are therefore used to make the necessary adjustments when estimating the standard errors with residuals that are correlated within each cross-section. To further show the autocorrelation pattern, the correlogram of the residuals will also be reported. Here each estimated residual is simply regressed on former estimated residuals to pin down the autocorrelation pattern. The test regression is specified below and is followed by the correlogram table that reports the PAC, which are the corresponding coefficients for each lagged residual in the auxiliary regression. The q-stat and p-value that tells whether or not all lagged residuals up until lag (*i)* (where *i* simply indicates lag 1, 2, 3 and 4) are significant as a whole are also reported:

$$\hat{e}_{it} = c + \hat{e}_{it-1} + \hat{e}_{it-2} + \hat{e}_{it-3} + \hat{e}_{it-4}$$

Table 5.2: Correlogram of residuals for static LSDV model. Notes: calculations performed in EViews. Source: ABS

Correlogram	PAC	Q-stat	P-value
1st	0.651***	62.218	0.0000
2nd	-0.070*	83.943	0.0000
3rd	-0.163*	86.377	0.0000
4th	-0.086*	86.746	0.0000

As expected from the low Durbin-Watson statistic the correlogram also suggests strongly autocorrelated residuals. Here the p-value for the first lagged residuals indicates that the AR(1) term is highly significant with a positive coefficient of 0.651. Even though all of the PAC: s are significant at the 10 % level it seems as though most of the autocorrelation issues may be resolved by appropriately dealing with the AR(1) process in the residuals. Instead of trying to quick fix the issue only by using robust standard errors the residual autocorrelation issue will be dealt with in the next section when estimating the dynamic models.

5.2 Dynamic LSDV Model

As can be seen in Table 5.2, the autocorrelation in the static model seem to be concentrated of the first order, why the inclusion of the first order AR(1) term in the model might be enough to resolve the autocorrelation issue. Not only is this a statistical judgement but also a theoretical one. It seems unreasonable that unemployment rates are not persistent and highly dependent on former realizations in its nature, something that was noted by Oswald and Blanchflower in their 2013 study. They also included a lagged dependent variable in their modelling attempts of the regional unemployment rates in the US. This section runs a similar model as in the above mentioned study. However the results from this section should serve more as a reference or baseline for the upcoming GMM models since the estimators are inconsistent due to Nickell Bias (Verbeek, p. 397). The period and cross-sectional fixed effects are included just as in the static model and the same set of control variables as well. Yielding the full dynamic specification as in Equation 5:

5. $$U_{it} = \beta 1 U_{it-1} + regional\ dummies_i + time\ period\ dummies_t + \beta 2 H_{it-1} + \beta 3 H_{it-2} + \beta 4 T_{it} + \beta 5 D\_M_{it} + \beta 6 D\_O_{it} + \beta 7 D\_Y_{it} + e_{it}$$

The regression results are given in Table 5.3:

Table 5.3: Dynamic panel least squares model results with period and cross-section dummies. Notes: calculations performed in EViews. Source: ABS

Dynamic LSDV Model (1 lag)	Coefficient	White Period Std. Error	P-value
Unemployment(-1)	0.7508***	0.0486	0.0000
Home ownership(-1)	0.0108	0.0221	0.6266
Home ownership(-2)	0.0432*	0.0254	0.0909
D_Manufacturing	−0.374**	0.1150	0.0015
D_Old people	0.0184	0.0447	0.6818
D_Young People	−0.0534**	0.0266	0.0471
Trade Union	0.0634***	0.0118	0.0000
Adj. R-Squared	0.9415		
Durbin-Watson Stat	1.6371		

The results from the dynamic LSDV model show, as expected, that the lagged dependent variable enters very significantly, and with a relatively high parameter indicating a high persistence in unemployment rates. Switching the focus towards the other parameters, it can be seen that the increased explanatory power in the

dynamic model and the lower autocorrelation in the residuals has reduced the standard errors of all parameters. The twice-lagged home ownership rates are now significant at the 10 % level, but the parameter is fairly low. A 10 % increase of home ownership rates should according to this model lead to a 0.4 % increase in unemployment rates (to clarify; if homeownership rates were to rise from 60 % to 70 % the result implies that this would be associated with with a 0.4 % increase in unemployment rates). However the persistence will result in home ownership rates having a long run effect on unemployment of (0.0432/(1-0.7508)) = 0.1733. Hence, the results are in fact of economic significance as it implies that a 10 % increase in home ownership rates would be associated with almost a 2 % increase in unemployment rates. Still, the results are not statistically significant enough to draw any reliable inference on the regression above, especially as the Nickell bias has not yet been dealt with. However, it can be confirmed that the lagged dependent variable should be included in the model. To further check whether the inclusion of a lagged dependent variable helped in getting rid of the autocorrelation issue, the correlogram of the residuals from this model is plotted as well. The correlogram is shown in Table 5.4:

Table 5.4: Correlogram of residuals from the dynamic LSDV model with one lagged dependent variable. Notes: calculations performed in EViews. Source: ABS

Correlogram	PAC	Q-stat	P-value
1st	0.171**	4.2819	0.039
2nd	−0.041	4.2992	0.117
3rd	−0.048	4.7647	0.190
4th	−0.072*	5.9185	0.205

The correlogram looks more pleasing. However, there is still some autocorrelation, particularly for the first lagged residual leading to inconsistency of OLS when having a lagged dependent variable (see Verbeek, 2012, p.141). A second lag of the dependent variable will therefore be added to the model, yielding results as shown in Table 5.5:

Table 5.5: Dynamic panel least squares model results with period and cross-section dummies. Notes: calculations performed in EViews. Source: ABS

Dynamic LSDV Model (2 lag)	Coefficient	White Period Std. Error	P-Value
Unemployment(-1)	0.931***	0.0505	0.0000
Unemployment(-2)	−0.2438***	0.0531	0.0000
Home ownership(-1)	0.0150	0.0265	0.5715

Dynamic LSDV Model (2 lag)	Coefficient	White Period Std. Error	P-Value
Home ownership(-2)	0.0403*	0.0210	0.0576
D_Old people	0.0002	0.0425	0.9967
D_Young People	−0.0311	0.0287	0.2803
Trade Union	0.0703***	0.0157	0.0000
Adj. R-Squared	0.9452		
Durbin-Watson Stat	2.0325		

As seen in Table 5.5, nothing much changes when adding the second lag of unemployment rates to the model. The parameters have the same sign and similar magnitudes, however the standard errors for home ownership shrinks even further and Home Ownership(-2) is now almost significant at the 5 % level. The persistence in unemployment rates is not as high when adding the second lag. Instead of being around 0.75 in the one lag model it is now (0.931-0.2438) = 0.6872. The long run parameter of twice lagged home ownership rates is in this case: (0.0403/(1-0.6872)) = 0.127, thus slightly lower than in the previous model.

There is however further issues to resolve. The Nickell bias is present in this model, which must be mitigated in the following models. Furthermore, the possible endogeneity of home ownership rates due to simultaneity or measurement errors will be dealt with by using appropriate instrumental variables techniques. It must however be noted that the model at this stage looks fairly reasonable. On the other hand, Verbeek (2013) shows that the Nickell bias can be quite sizable even for moderate time dimensions, why the results from Table 5.3 and Table 5.5 should serve more as a baseline for the next section. Anyhow, the long run parameter for home ownership rates is strikingly close to the stylized fact that a 1 % increase in home ownership rates is associated with a 0.2 % increase in unemployment rates as proposed by Oswald (1996). In the next section a GMM approach will be used to investigate whether there will be any significant change in the magnitude of the homeownership parameter by using methods to control for endogeneity and Nickell bias.

5.3 Arellano Bond GMM Model

The methodology section of this paper briefly described the possible bias of the lagged dependent variable when estimating a dynamic LSDV or FD model and the most common approaches to overcome this issue. The Anderson-Hsiao approach that uses lagged values of the lagged dependent variable as instruments for itself was introduced as a possible solution to this so-called Nickell bias. However, this method will not be of any help if the purpose is to control for endogeneity in some of the other regressors. The Arellano-Bond method was

introduced as an extension of the Anderson-Hsiao approach where more instruments for the lagged dependent variable might be used as well as for other regressors that are assumed to be endogenous. Moreover, the model will be estimated using GMM. The main purpose of this section is therefore not only to control for the Nickell bias, but to evaluate whether or not home ownership rates are endogenous and, if that is the case, in what direction the bias may be.

Most earlier studies on the linkages between home ownership rates and unemployment rates have acknowledged the possibility of double causality or measurement errors in home ownership rates that may invalidate the consistency of the estimates in a normal LSDV model. It is widely known that measurement errors are more harming in a LSDV model than in an ordinary OLS models, as the part of variation in the explanatory variable due to measurement errors is larger when using deviations from means instead of the all variation in the data (see for example Hsiao, 2003, p. 305). The bias induced by measurement errors often leads to too low and insignificant estimates of the parameter of interest. In other words, there tends to be attenuation towards zero of the explanatory variable when measurement errors are present. Furthermore, the simultaneity bias arises in theory because the demand for owner-occupied housing depends largely on the situation of the labour market. High unemployment rates may lead to lower demand of owner-occupied housing and low unemployment rates has the opposite effect. In theory, it will therefore be expected that this simultaneity will further downward bias the estimates of home ownership rates due to the negative correlation in the opposite causality direction. However, by lagging home ownership rates in the first place the problem should not be too severe. The simultaneity issue is mentioned and controlled for in the paper by Laamanen (2013) where the author used a natural experiment of the deregulation of the housing rental market to evaluate the possible endogeneity bias of home ownership rates. Indeed his suspicion of the possible downward bias due to measurement errors and simultaneity was proved right and his instrumental variables approach more than doubled the magnitude of the parameter for home ownership rates.

Other studies have been aware of the possibility that the relationship found between home ownership rates and unemployment rates may be underestimated, but the issue of finding appropriate instruments have resulted in no further attempts to overcome the problem other than that of Laamanen. In absence of appropriate external instruments, internal instruments will instead be used here to control for measurement errors and simultaneity. This approach is based upon the assumptions that earlier recordings of home ownership rates are uncorrelated with future error terms. Therefore, it must be assumed that the measurement errors are uncorrelated over time. Also, it will be assumed that the simultaneity as well as the issue of omitted variables decreases when lagging home ownership rates even further. To limit the number of instruments for home ownership rates, the lags to be used as instruments will be restricted to the second lag for each observation. For the lagged dependent variable, the third lagged level of unemployment rates

will be used as instrument. The rest of the variables are assumed to be exogenous and will instrument themselves. The estimation procedure is the one step GMM procedure and the standard errors are corrected for heteroskedasticity and autocorrelation in the same manner as earlier models. The fixed effects are handled by the first- differencing method. The regression results for this model with one lagged dependent variable is shown in Table 5.6. Full output results are reported in Appendix D.

Table 5.6: One step panel GMM model results (1 lagged dependent variable). Notes: calculations performed in EViews. Source: ABS

One step GMM Model (1 lag)	**Coefficient**	**White Period Std. Error**	**P-value**
Unemployment(-1)	0.5552***	0.1041	0.0000
Home ownership(-1)	0.0483	0.0307	0.1187
Home ownership(-2)	0.1425***	0.0299	0.0000
D_Manufacturing	−0.1964	0.1776	0.2713
D_Old people	−0.0283	0.0374	0.4520
D_Young People	−0.0017	0.0282	0.9518
Trade Union	0.0621**	0.0292	0.0358
J-test	0.3069		
2nd order serial correlation test	0.0956*		

There are two major changes in the results compared to earlier LSDV models. First, the magnitude of the parameter for the lagged dependent is significantly smaller and second, the parameter for twice lagged home ownership rates is significantly larger. The fact that the lagged dependent variable coefficient is smaller was not expected since the Nickell bias is supposed to be downwards in the LSDV model. The fact that home ownership grew in magnitude and became much more significant was expected, as it was assumed to be downward biased due to the possible endogeneity of it. The long run effect of Home Ownership(-2) is (0.1425/(1-0.5552)) = 0.3204, which is almost a doubled effect as compared with the dynamic LSDV model with one lagged dependent variable.

For the model to be valid it must be ensured that the model passes the J-test and the Arellano-Bond test for second-order serial correlation in the residuals. The J-test checks whether the overidentifying instruments are uncorrelated with the residuals (also known as Sargan test). The relatively large p-value from this test tells that there is no evidence in support of these instruments being correlated with the error term. Secondly, it must be ensured that there is no second-order

autocorrelation in the residuals, as this will imply that the instruments used are invalid. The fairly low p-value of this test is quite worrisome as it may invalidate the exogeneity restriction of the instruments, but the null of no second-order autocorrelation cannot be rejected at the 5 % level. All in all, the model looks fairly satisfying at first glance. Yet, the fact that the home ownership rates enters with such high magnitude and that the lagged dependent variable is so much lower than previous models deserves further attention.

Next a second lagged dependent variable is added to see whether the second order autocorrelation test could be improved and to see if the parameter estimates changed. Here it is assumed that Unemployment(-2) is uncorrelated with the error term,, why it will instrument itself (more on the theory behind this assumption is found in the methodology section earlier in this paper). The results from this specification are given in Table 5.7:

Table 5.7: One step GMM model results with period dummies and first-differences transformation (2 lagged dependent variables). Notes: calculations performed in EViews. Source: ABS

One step GMM Model (2 lags)	**Coefficient**	**White Period Std. Error**	**P-value**
Unemployment(-1)	0.7338***	0.0846	0.0000
Unemployment(-2)	−0.1805**	0.0794	0.0250
Home ownership(-1)	0.0526**	0.0224	0.0203
Home ownership(-2)	0.1238***	0.0265	0.0000
D_Manufacturing	−0.2599	0.1780	0.1471
D_Old people	−0.0385	0.0371	0.3008
D_Young People	−0.0062	0.0347	0.8594
Trade Union	0.0675**	0.0320	0.0372
J-test	0.3230		
2nd order serial correlation test	0.4526		

The results did not change much and the combined persistence in unemployment is very similar to the one lag model more precisely: (0.7338-0.1805) = 0.5533 and the long run effect of Home Ownership(-2) is therefore (0.1238/(1-0.5533)) = 0.2771, a bit lower than in the last model, but still a far higher magnitude than in the dynamic LSDV models. Als,o the second-order serial correlation test looks more pleasing when adding a second lag of unemployment to the list of explanatory variables.

5.4 Robustness Checks

The last step in evaluating the validity of the GMM results will be to run a set of robustness checks to see whether the results stay stable over different model specifications. Furthermore, there is serious doubt of the result from the GMM models in Table 5.6 and 5.7. First, due to the fact that the lagged dependent variable parameter shrinks as opposed to the expected direction of the Nickell bias (see Nickell (1981)), second, the parameter for home ownership gets largely magnified. Therefore this section is dedicated to evaluating the validity of these results.

The fact that the model passed the J-test only implies that the instruments are most likely exogenous, which is good. However, the fact that the instruments must have a strong first-stage effect on the instrumented variables has not been evaluated yet. Weak instruments can lead to very misleading and biased results (Verbeek, 2012, p. 165). Verbeek also mentions that the GMM estimators may be very sensitive to a change in the number of instruments when these are weak. Therefore, a good robustness check can be to experiment with different instruments (Verbeek, 2012, p. 171).

As mentioned in the methodology section related to this topic, the GMM estimation method used in this paper is the same as running 2SLS. The first-stage may then be appropriately checked by running the first-stage regression (where the endogenous variables is used as dependent and all instruments plus all exogenous variables as independent) just as in 2SLS. A commonly used rule of thumb is to check whether the F-statistic on the instruments in this first-stage regression is above ten to ensure that the instruments explains a lot of the variation in the endogenous variables (Verbeek, 2012, p. 165). The bias due to weak instruments is in many cases towards OLS (or in this case towards the GMM results without instruments), and as more weak instruments are added, the closer to OLS it should get (see Roodman, 2009). However, if there is a combination of weak instruments and a violation of the exclusion restriction (meaning that the instruments explain the dependent variable directly or is correlated with the error term) it might lead to a strong positive biased 2SLS estimate, particularly if the first stage effect is fairly low (for further details see Wooldridge, 2008, p. 515). A last robustness check should therefore be to include the instruments directly in the model and see whether they themselves should be included as regressors. The first-stage F-statistics, which is simply calculated as the square of the t-statistic of the instrument in the first-stage regression will be reported in Table 5.8. The rest of the robustness checks that were performed will be reported in Appendix E. Here, the following regression was run to check the first-stage effect:

$$D(U) = C + U(-2) + D(T) + D(D\_M) + D(D\_O) + D(D\_Y) + D(H(-2)) + D(H(-3))$$

$$D(H) = C + D(H(-2)) + D(T) + D(D\_M) + D(D\_O) + D(D\_Y) + U(-2)$$

Where D(*) is the first difference operator and D_(*) means that variable * is already first-differenced once before entering the difference operator once more. This is just an indicator for the first-stage since all instruments are not included in these first-stage regressions. Still, it is important to check whether the second lagged level of unemployment rates and the second lagged difference of home ownership rates are correlated with its presumed endogenous counterparts.

Table 5.8: First stage F-statistics for instruments used in GMM. Notes: calculations performed in EViews. Source: ABS

First stage F-statistics for instruments used in GMM (Squared t-statistic from the respective regression shown above)	F-statistic
U(-2)	29.15
D(H(-2))	39.19

The first stage F-statistics are well above the ”10 limit” as was the rule of thumb when evaluating the instrument relevance condition. But the fact that lagged levels of the unemployment rates may violate the exclusion restriction because this instrument itself affects the independent variable (most likely in a negative direction since high levels of unemployment rates are likely to be associated with negative future differences in unemployment rates and vice versa), may be the reason as to why the estimated persistence parameters in the GMM (1 and 2 lag) models seemed to be downward biased. Therefore, the models were run by using lagged differences instead of levels as instruments for the lagged dependent variable. Here, the results were more in line with the expected magnitude of the parameter for the lagged dependent variable and the parameters for home ownership rates were pretty much unchanged (see Table 5.18 in Appendix E).

More robustness checks in the form of changing the instrument count and evaluating the exclusion restriction were also run. The general conclusion from these tests is that the instruments for home ownership rates may be violating the exclusion restriction as well. However, this is not a big of a problem since this further strengthens the assumed view of a positive link between the two (the excluded instruments are of a positive magnitude when included in the regression). Additionally, as more instruments are added, the results go towards the ones in the Dynamic LSDV model as expected, but the J-test gets rejected in these cases.

To check whether the coefficients for home ownership rates are robust to changes in the list of exogenous covariates the models were run without any exogenous covariates resulting in no significant change in the parameters for home ownership. Lastly, the GMM model was run by using the second and fourth lag of hom eownership rates and treating these as exogenous (they are of such deep lags that the simultaneity issue should not be a big problem) with two different kinds of instrument specifications for the lagged dependent variable. The

results were more in line with the expected direction of bias for the lagged dependent variable, although the coefficient for homeownership shrank to a long run effect of about 0.10 (see Table 5.23 in Appendix E for these results). All the above mentioned robustness checks are reported in Appendix E.

Summing up, the results from Table 5.6 and Table 5.7 should be cautiously evaluated as they do not seem to be entirely robust. On the other hand, the results obtained in this paper generally suggests that the true parameter of home ownership rates should lie somewhere in between the static LSDV estimates and the GMM estimates (i.e., a long run parameter of somewhere in between 0.1 and 0.3).

6. Concluding Remarks

If too high homeownership rates have negative effects upon the labour market, serious doubt arises upon the uniformly encouraging policies towards home ownership in developed countries. Thorough investigation is therefore needed to pin down not only the effects of home ownership on an individual level but the aggregate effects on a macro level. A lot of serious economic issues have its roots in the housing market such as the financial crisis in 2008, where the housing market bubble in the USA collapsed. Still, today there are many potential threats for the housing markets in many Western countries such as Sweden and Norway, where housing prices have risen to very high levels. The promotion of home ownership due to various tax incentives in combination with the low interest rates of today makes home ownership the most financially attractive alternative of tenure for those with resources to afford it.

This paper investigates the possible negative effects when too many individuals become home owners, not by looking at the effects on housing prices, but on the structural effects it may have on the mobility of the workforce and therefore on unemployment rates. A panel data set covering 19 years of regional unemployment and home ownership rates in Australia is used to model the relationships between the two. The results of this paper gives further macro evidence to the Oswald hypothesis of a positive link between home ownership and unemployment after controlling for covariates as well as simultaneity and measurement errors in home ownership rates. The results from a static model only controlling for fixed effects, period effects and covariates suggests a positive but insignificant link between the two. When developing the model into a dynamic one, and controlling for Nickell bias, as well as possible endogeneity of home ownership rates, the relationship gets magnified suggesting that simultaneity or/and measurement errors may work towards underestimating the effect of regional home ownership rates on unemployment rates. The results from these models indicates that a 1 % increase in home ownership is associated with a 0.2 % - 0.3 % increase in unemployment rates, thus is of strong economic importance. These results were however not entirely robust, but the evidence of this paper suggest that the link between the two is positive and statistically significant. Something that in itself should be worrying for policy makers given the fact that

the large amount of subsidies with regards to promoting home ownership may be of better use elsewhere.

The results also show a strong positive link between trade union strength and unemployment. As in every empirical study the tricky part is to difference between causality and nonsense correlations. Earlier macro studies on the linkages between home ownership rates and unemployment rates have shown a fairly strong support of the Oswald hypothesis. However, these results have been contradicted by micro level evidence on the topic. The question is then whether the macro level evidence is spurious, the micro level evidence is spurious or whether the micro and macro level evidence can be true at the same time. The macro level evidence in support of the Oswald hypothesis have now been found in a variety of countries such as USA (Oswald & Blanchflower, 2013), Germany (Lerbs, 2010), New Zealand (Cochrane & Poot, 2007), and here in Australia under different econometric specifications suggesting that the results may not be spurious after all. One possible explanation as to why macro studies could be spurious may result from the fact that five year lags of home ownership rates often are used in the analysis, for example in Oswald and Blanchflower (2013) and Cochrane and Poot (2007). The strong correlations appearing in these studies may be the result of underlying business cycles implicating that home ownership rates rise in periods of economic growth and are followed by higher unemployment rates five years later during economic contractions. This paper finds linkages that are shorter than in the previous mentioned studies, more exactly the linkages arise already after two years suggesting that the business cycle counter-argument should not be valid in this case.

Additionally, it cannot be assumed that the micro level evidence is spurious (even though many of these studies may suffer from significant omitted variables bias (Taskin & Yaman, 2013)). Home owners generally seem to be associated with better labour market outcomes. Still, the micro level evidence is disputable since studies controlling for endogeneity of home ownership are few, and the ones that do are not as opposing to the Oswald hypothesis (for example Taskin & Yaman, 2013). One exception is the study by Munch et al., (2002) who found a negative correlation between unemployment duration and home ownership in Denmark. However, the fact that Denmark is a relatively small country may diminish the importance of mobility. Another explanation to the puzzle, is the one of coexisting micro and macro level evidence as was further investigated by Laamanen (2013). It could be the case that home ownership has significant external effects that counteracts the possibly positive individual effects. No matter what mechanisms lie behind the findings it is sufficing to say that economies benefit from a highly mobile workforce and that housing markets that are not flexible enough will prevent workers to be mobile and move to where the jobs are. More empirical research is needed to further understand the linkages between the housing and labour market.

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APPENDIX A

Table 2.1: Former empirical research examining the Oswald hypothesis. Notes: MSAs is an abbreviation for Metropolitan Statistical Areas.

Author and year	**Country**	**Methodology**	**Results**	**Effect**
Blanchflower & Oswald, 2013	The US (states)	Fixed effects panel model with data from 1985 - 2011	Long term elasticity between 1 and 2, doubled home ownership rate leads to more than doubled unemployment	+
Cochrane & Poot, 2007	New Zealand (regions)	Fixed effects panel model with data from 1986 - 2001, controls for simultaneity by using 5 years lagged home ownership rates as an explaining variable	1 % rise of homeownership rate in a specific region increases unemployment with 0,2 %	+
Coulson & Fisher. 2008	The US (MSAs)	Micro probit models	Negative correlation	-
Flatau et al., 2002	Australia (regions)	Probit micro level model	Homeowners quicker to exit unemployment & are 30 % less likely to be unemployed long term.	-
Flatau et al. 2003	Australia (regions)	Probit micro level model	Strong evidence for counter-Oswald results, leveraged owners tend to become reemployed faster than renters	+/-
Garcia & Hernandez, 2004	Spain (province s)	Cross-section	Negative correlation	-
Glaeser & Shapiro, 2003	The US (MSAs)	Cross-section on metropoles	Negative correlation, higher home ownership leads to lower unemployment	-
Laamanen, 2013	Finland (labour districts)	Micro probit model - models the probability for an individual being unemployed under a certain period, uses a reform as an instrument.	1 % rise in homeownership rate in a specific region increases the risk of being in a period of unemployment with 9 %	+

Author and year	Country	Methodology	Results	Effect
Lerbs, 2010	Germany (regions)	Panel model, Fixed effects	Positive correlation, 10 % increase of home ownership rate leads to 0.5 % increase of unemployment	+/-
Munch et al., 2003	Denmark	Unemployment duration model, controlling for endogeneity of homeownerhsip	Homeowners exit unemployment quicker	-
Taskin & Yaman, 2013	USA	Same as above	Homeowners have longer unemployment spells	+

APPENDIX B

Tables with full panel unit root test results:

Table 4.6: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: BD_CSD
Date: 04/21/14 Time: 15:33
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	0.42514	0.6646	8	144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	2.28749	0.9889	8	144
ADF - Fisher Chi-square	6.54801	0.9810	8	144
PP - Fisher Chi-square	10.8811	0.8168	8	152

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.7: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: BO_CSD
Date: 04/21/14 Time: 15:33
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 1
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	4.15330	1.0000	8	144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	4.09912	1.0000	8	144
ADF - Fisher Chi-square	6.44129	0.9826	8	144
PP - Fisher Chi-square	2.52371	0.9999	8	152

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.8: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: H_CSD
Date: 04/21/14 Time: 15:34
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-2.82124	0.0024	8	139
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-4.36988	0.0000	8	139
ADF - Fisher Chi-square	50.2784	0.0000	8	139
PP - Fisher Chi-square	30.0073	0.0180	8	152

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.9: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: M_CSD
Date: 04/21/14 Time: 15:34
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	2.06216	0.9804	8	151
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	3.21867	0.9994	8	151
ADF - Fisher Chi-square	6.45777	0.9824	8	151
PP - Fisher Chi-square	5.11569	0.9951	8	152

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.10: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: O_CSD
Date: 04/21/14 Time: 15:34
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections
Null: Unit root (assumes common unit root process)			
Levin, Lin & Chu t*	-1.12768	0.1297	8
Null: Unit root (assumes individual unit root process)			
Im, Pesaran and Shin W-stat	0.02136	0.5085	8
ADF - Fisher Chi-square	23.9069	0.0916	8
PP - Fisher Chi-square	24.0101	0.0893	8

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.11: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: T_CSD

Date: 04/21/14 Time: 15:35
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 1
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections
Null: Unit root (assumes common unit root process)			
Levin, Lin & Chu t*	-4.17979	0.0000	8
Null: Unit root (assumes individual unit root process)			
Im, Pesaran and Shin W-stat	-4.15229	0.0000	8
ADF - Fisher Chi-square	48.1694	0.0000	8
PP - Fisher Chi-square	53.1086	0.0000	8

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.12: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: U_CSD
Date: 04/21/14 Time: 15:35
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections
Null: Unit root (assumes common unit root process)			
Levin, Lin & Chu t*	-1.63576	0.0509	8
Null: Unit root (assumes individual unit root process)			
Im, Pesaran and Shin W-stat	-2.14897	0.0158	8
ADF - Fisher Chi-square	27.2635	0.0386	8
PP - Fisher Chi-square	23.3872	0.1038	8

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.13: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: Y_CSD
Date: 04/21/14 Time: 15:35
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 4
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections
Null: Unit root (assumes common unit root process)			
Levin, Lin & Chu t*	-1.15869	0.1233	8
Null: Unit root (assumes individual unit root process)			
Im, Pesaran and Shin W-stat	0.37593	0.6465	8
ADF - Fisher Chi-square	21.0880	0.1752	8
PP - Fisher Chi-square	24.1422	0.0864	8

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.14: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: D(BO_CSD)
Date: 04/21/14 Time: 15:31
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	1.00368	0.8422	8	141
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	0.03685	0.5147	8	141
ADF - Fisher Chi-square	18.0716	0.3197	8	141
PP - Fisher Chi-square	22.2440	0.1355	8	144

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.15: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: D(M_CSD)

Date: 04/21/14 Time: 15:32
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-8.88134	0.0000	8	144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-6.95465	0.0000	8	144
ADF - Fisher Chi-square	73.0078	0.0000	8	144
PP - Fisher Chi-square	72.7394	0.0000	8	144

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.16: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: D(O_CSD)
Date: 04/21/14 Time: 15:32
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0
Newey-West automatic bandwidth selection and Bartlett kernel
Balanced observations for each test

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-16.2064	0.0000	8	144
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-13.2574	0.0000	8	144
ADF - Fisher Chi-square	140.646	0.0000	8	144
PP - Fisher Chi-square	303.318	0.0000	8	144

** Probabilities for Fisher tests are computed using an asymptotic Chi -square distribution. All other tests assume asymptotic normality.

Table 4.17: Panel unit root test results. Notes: calculations performed in EViews. Source: ABS

Panel unit root test: Summary
Series: D(Y_CSD)
Date: 04/21/14 Time: 15:32
Sample: 1994 2013
Exogenous variables: Individual effects
Automatic selection of maximum lags
Automatic lag length selection based on SIC: 0 to 3
Newey-West automatic bandwidth selection and Bartlett kernel

Method	Statistic	Prob.**	Cross-sections	Obs
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-1.07450	0.1413	8	130
Null: Unit root (assumes individual unit root process)				

APPENDIX C

Tables with full static and dynamic LSDV model results:

Table 5.9: Static Panel least squares test results. Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Least Squares
Date: 04/21/14 Time: 15:39
Sample (adjusted): 1996 2013
Periods included: 18
Cross-sections included: 8
Total panel (balanced) observations: 144
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.033950	0.066320	-0.511914	0.6097
H(-1)	-0.009739	0.027302	-0.356706	0.7220
H(-2)	0.097820	0.086066	1.136571	0.2581
D_M	0.260755	0.270995	0.962214	0.3380
D_O	0.083056	0.057288	1.449796	0.1499
D_Y	-0.015564	0.045224	-0.344159	0.7314
T	0.143252	0.029613	4.837421	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.891712	Mean dependent var	0.058455
Adjusted R-squared	0.862963	S.D. dependent var	0.017379
S.E. of regression	0.006434	Akaike info criterion	-7.066453
Sum squared resid	0.004677	Schwarz criterion	-6.427118
Log likelihood	539.7846	Hannan-Quinn criter.	-6.806663
F-statistic	31.01721	Durbin-Watson stat	0.698002
Prob(F-statistic)	0.000000		

Table 5.10: Dynamic Panel least squares model results (1 LDV). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Least Squares
Date: 04/21/14 Time: 15:39
Sample (adjusted): 1996 2013
Periods included: 18
Cross-sections included: 8
Total panel (balanced) observations: 144
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.038094	0.027305	-1.395109	0.1657
H(-1)	0.010796	0.022131	0.487842	0.6266
H(-2)	0.043222	0.025349	1.705104	0.0909
D_M	-0.373955	0.114974	-3.252519	0.0015
D_O	0.018367	0.044687	0.411016	0.6818
D_Y	-0.053381	0.026589	-2.007607	0.0471
T	0.063404	0.011872	5.340514	0.0000
U(-1)	0.750865	0.048597	15.45072	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.954165	Mean dependent var	0.058455
Adjusted R-squared	0.941478	S.D. dependent var	0.017379
S.E. of regression	0.004204	Akaike info criterion	-7.912302
Sum squared resid	0.001980	Schwarz criterion	-7.252344
Log likelihood	601.6858	Hannan-Quinn criter.	-7.644132
F-statistic	75.21077	Durbin-Watson stat	1.637129
Prob(F-statistic)	0.000000		

Table 5.11: Dynamic Panel least squares model results (2 LDV: s. Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Least Squares
Date: 04/23/14 Time: 14:14
Sample (adjusted): 1996 2013
Periods included: 18
Cross-sections included: 8
Total panel (balanced) observations: 144
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.035976	0.027901	-1.289409	0.1999
U(-1)	0.931007	0.050466	18.44821	0.0000
H(-1)	0.015026	0.026475	0.567564	0.5715
H(-2)	0.040278	0.020997	1.918282	0.0576
D_M	-0.266947	0.113687	-2.348089	0.0206
D_O	0.000178	0.042571	0.004173	0.9967
D_Y	-0.031142	0.028703	-1.084971	0.2803
T	0.070335	0.015722	4.473664	0.0000
U(-2)	-0.243893	0.053051	-4.597378	0.0000

Effects Specification

Cross-section fixed (dummy variables)
Period fixed (dummy variables)

R-squared	0.957441	Mean dependent var	0.058455
Adjusted R-squared	0.945172	S.D. dependent var	0.017379
S.E. of regression	0.004069	Akaike info criterion	-7.972576
Sum squared resid	0.001838	Schwarz criterion	-7.291994
Log likelihood	607.0255	Hannan-Quinn criter.	-7.696026
F-statistic	78.03577	Durbin-Watson stat	2.032547
Prob(F-statistic)	0.000000		

APPENDIX D

Tables with full panel GMM estimation results:

Table 5.12: Panel GMM model results (1 lag model). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 04/21/14 Time: 15:43
Sample (adjusted): 1997 2013
Periods included: 17
Cross-sections included: 8
Total panel (balanced) observations: 136
Difference specification instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Instrument specification: @DYN(H, -2, -2) T D_M D_O D_Y @LEV(U(-3)) @LEV(@SYSPER)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.555165	0.104094	5.333308	0.0000
H(-1)	0.048273	0.030702	1.572322	0.1187
H(-2)	0.142453	0.029855	4.771540	0.0000
T	0.062131	0.029247	2.124361	0.0358
D_M	-0.196418	0.177660	-1.105582	0.2713
D_O	-0.028227	0.037398	-0.754769	0.4520
D_Y	-0.001705	0.028154	-0.060550	0.9518
@LEV(@ISPERIOD("1997"))	-0.000306	0.002552	-0.119783	0.9049
@LEV(@ISPERIOD("1998"))	-0.003303	0.002264	-1.459238	0.1473
@LEV(@ISPERIOD("1999"))	-0.005298	0.001695	-3.125007	0.0023
@LEV(@ISPERIOD("2000"))	0.000246	0.002032	0.121164	0.9038
@LEV(@ISPERIOD("2001"))	0.007960	0.001840	4.326876	0.0000
@LEV(@ISPERIOD("2002"))	-0.008911	0.002478	-3.596851	0.0005
@LEV(@ISPERIOD("2003"))	-0.000280	0.001584	-0.176608	0.8601
@LEV(@ISPERIOD("2004"))	-0.003409	0.001933	-1.763466	0.0805
@LEV(@ISPERIOD("2005"))	7.98E-06	0.002444	0.003266	0.9974
@LEV(@ISPERIOD("2006"))	0.000903	0.000891	1.013256	0.3131
@LEV(@ISPERIOD("2007"))	-0.001357	0.001701	-0.797872	0.4266
@LEV(@ISPERIOD("2008"))	0.000297	0.001165	0.254464	0.7996
@LEV(@ISPERIOD("2009"))	0.010848	0.001978	5.485535	0.0000
@LEV(@ISPERIOD("2010"))	-0.007142	0.002111	-3.382861	0.0010
@LEV(@ISPERIOD("2011"))	0.001459	0.002000	0.729398	0.4673
@LEV(@ISPERIOD("2012"))	0.004442	0.002693	1.649822	0.1018
@LEV(@ISPERIOD("2013"))	0.005049	0.001230	4.103366	0.0001

Effects Specification

Cross-section fixed (first differences)
Period fixed (dummy variables)

Mean dependent var	-0.001696	S.D. dependent var	0.006309
S.E. of regression	0.005206	Sum squared resid	0.003036
J-statistic	17.20220	Instrument rank	39
Prob(J-statistic)	0.306921		

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 04/21/14 Time: 15:43
Sample: 1994 2013
Included observations: 136

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	-1.734877	-0.000608	0.000351	0.0828
AR(2)	-1.666440	-0.000450	0.000270	0.0956

Table 5.13: Panel GMM model results (2 lag model). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U

Method: Panel Generalized Method of Moments

Transformation: First Differences

Date: 04/29/14 Time: 17:40

Sample (adjusted): 1997 2013

Periods included: 17

Cross-sections included: 8

Total panel (balanced) observations: 136

Difference specification instrument weighting matrix

White period standard errors & covariance (d.f. corrected)

WARNING: estimated coefficient covariance matrix is of reduced rank

Instrument specification: @DYN(H, -2, -2) U(-2) T D_M D_O D_Y @LEV(U(
-3)) @LEV(@SYSPER)

Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.733812	0.084597	8.674230	0.0000
U(-2)	-0.180478	0.079440	-2.271877	0.0250
H(-1)	0.052695	0.022370	2.355554	0.0203
H(-2)	0.123757	0.026496	4.670868	0.0000
T	0.067573	0.032048	2.108471	0.0372
D_M	-0.259943	0.178024	-1.460155	0.1471
D_O	-0.038588	0.037117	-1.039632	0.3008
D_Y	-0.006177	0.034787	-0.177574	0.8594
@LEV(@ISPERIOD("1997"))	-0.002030	0.003113	-0.652034	0.5157
@LEV(@ISPERIOD("1998"))	-0.002768	0.002280	-1.214389	0.2272
@LEV(@ISPERIOD("1999"))	-0.004475	0.002156	-2.075654	0.0402
@LEV(@ISPERIOD("2000"))	0.000860	0.002125	0.404743	0.6864
@LEV(@ISPERIOD("2001"))	0.007717	0.002003	3.853103	0.0002
@LEV(@ISPERIOD("2002"))	-0.010932	0.002405	-4.546186	0.0000
@LEV(@ISPERIOD("2003"))	0.001655	0.002240	0.738893	0.4615
@LEV(@ISPERIOD("2004"))	-0.003747	0.001862	-2.012631	0.0466
@LEV(@ISPERIOD("2005"))	0.000589	0.002591	0.227406	0.8205
@LEV(@ISPERIOD("2006"))	0.000518	0.001066	0.485412	0.6283
@LEV(@ISPERIOD("2007"))	-0.001565	0.001734	-0.902197	0.3689
@LEV(@ISPERIOD("2008"))	0.000503	0.001249	0.403086	0.6877
@LEV(@ISPERIOD("2009"))	0.010150	0.001865	5.443609	0.0000
@LEV(@ISPERIOD("2010"))	-0.009195	0.002503	-3.673068	0.0004
@LEV(@ISPERIOD("2011"))	0.003752	0.002717	1.380748	0.1701
@LEV(@ISPERIOD("2012"))	0.003958	0.003234	1.223801	0.2236
@LEV(@ISPERIOD("2013"))	0.004412	0.001512	2.918381	0.0043

Effects Specification

Cross-section fixed (first differences)

Period fixed (dummy variables)

Mean dependent var	-0.001696	S.D. dependent var	0.006309
S.E. of regression	0.005428	Sum squared resid	0.003270
J-statistic	16.93036	Instrument rank	40
Prob(J-statistic)	0.323044		

Arellano-Bond Serial Correlation Test

Equation: Untitled

Date: 04/29/14 Time: 17:40

Sample: 1994 2013

Included observations: 136

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	-3.394411	-0.001105	0.000326	0.0007
AR(2)	-0.751164	-0.000195	0.000260	0.4526

APPENDIX E

Tables with full robustness checks results:

Table 5.14: Instrument relevance test, first stage regressions for unemployment rates. Notes: calculations performed in EViews. Source: ABS

Dependent Variable: D(U)
Method: Panel Least Squares
Date: 05/07/14 Time: 13:48
Sample (adjusted): 1998 2013
Periods included: 16
Cross-sections included: 8
Total panel (balanced) observations: 128

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.008144	0.001763	4.619394	0.0000
U(-2)	-0.158644	0.029384	-5.399057	0.0000
D(H(-2))	0.037307	0.028625	1.303295	0.1950
D(H(-3))	0.000155	0.026853	0.005766	0.9954
D(D_M)	0.053094	0.164412	0.322933	0.7473
D(D_O)	-0.012104	0.056523	-0.214143	0.8308
D(D_Y)	0.016620	0.046995	0.353659	0.7242
D(T)	0.054086	0.032638	1.657122	0.1001

R-squared	0.250092	Mean dependent var	-0.001691
Adjusted R-squared	0.206348	S.D. dependent var	0.006436
S.E. of regression	0.005734	Akaike info criterion	-7.424503
Sum squared resid	0.003945	Schwarz criterion	-7.246251
Log likelihood	483.1682	Hannan-Quinn criter.	-7.352078
F-statistic	5.717104	Durbin-Watson stat	2.138781
Prob(F-statistic)	0.000010		

Table 5.15: Instrument relevance test, first stage regressions for homeownership rates. Notes: calculations performed in EViews. Source: ABS

Dependent Variable: D(H)
Method: Panel Least Squares
Date: 05/07/14 Time: 13:23
Sample (adjusted): 1997 2013
Periods included: 17
Cross-sections included: 8
Total panel (balanced) observations: 136
White period standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.009659	0.001794	-5.385387	0.0000
U(-2)	0.141919	0.039707	3.574164	0.0005
D(H(-2))	-0.255526	0.040782	-6.265658	0.0000
D(D_M)	0.095533	0.288827	0.330762	0.7414
D(D_O)	0.077425	0.047950	1.614706	0.1088
D(D_Y)	0.001992	0.038101	0.052291	0.9584
D(T)	-0.012739	0.082465	-0.154474	0.8775

R-squared	0.105489	Mean dependent var	-0.000687
Adjusted R-squared	0.063884	S.D. dependent var	0.017155
S.E. of regression	0.016598	Akaike info criterion	-5.309019
Sum squared resid	0.035537	Schwarz criterion	-5.159103
Log likelihood	368.0133	Hannan-Quinn criter.	-5.248097
F-statistic	2.535472	Durbin-Watson stat	2.290631
Prob(F-statistic)	0.023603		

Table 5.16: Panel GMM robustness check results (excluded instruments H(-3) and H(-4) included as regressors). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U

Method: Panel Generalized Method of Moments

Transformation: First Differences

Date: 04/29/14 Time: 17:43

Sample (adjusted): 1999 2013

Periods included: 15

Cross-sections included: 8

Total panel (balanced) observations: 120

Difference specification instrument weighting matrix

White period standard errors & covariance (d.f. corrected)

WARNING: estimated coefficient covariance matrix is of reduced rank

Instrument specification: @DYN(H, -2, -2) U(-2) T D_M D_O D_Y @LEV(U(-3)) H(-3) H(-4) @LEV(@SYSPER)

Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.837172	0.089239	9.381278	0.0000
U(-2)	-0.164349	0.130836	-1.256145	0.2121
H(-1)	-0.003039	0.027341	-0.111155	0.9117
H(-2)	0.163179	0.032279	5.055252	0.0000
T	0.030217	0.041836	0.722256	0.4719
D_M	-0.307401	0.215119	-1.428978	0.1563
D_O	-0.048587	0.036171	-1.343264	0.1824
D_Y	-0.006731	0.037309	-0.180417	0.8572

H(-3)	-0.012597	0.048684	-0.258753	0.7964
H(-4)	0.063802	0.032293	1.975715	0.0511
@LEV(@ISPERIOD("1999"))	-0.003609	0.001594	-2.264043	0.0258
@LEV(@ISPERIOD("2000"))	0.001646	0.001615	1.019216	0.3107
@LEV(@ISPERIOD("2001"))	0.007613	0.002899	2.626309	0.0101
@LEV(@ISPERIOD("2002"))	-0.012136	0.002824	-4.297855	0.0000
@LEV(@ISPERIOD("2003"))	0.001429	0.002634	0.542546	0.5887
@LEV(@ISPERIOD("2004"))	-0.003264	0.001685	-1.937059	0.0557
@LEV(@ISPERIOD("2005"))	0.000815	0.002888	0.282169	0.7784
@LEV(@ISPERIOD("2006"))	0.000577	0.001474	0.391658	0.6962
@LEV(@ISPERIOD("2007"))	-0.002054	0.002006	-1.023558	0.3086
@LEV(@ISPERIOD("2008"))	0.001075	0.001263	0.851062	0.3969
@LEV(@ISPERIOD("2009"))	0.010952	0.002319	4.722763	0.0000
@LEV(@ISPERIOD("2010"))	-0.010395	0.003293	-3.156469	0.0021
@LEV(@ISPERIOD("2011"))	0.003510	0.003414	1.028217	0.3065
@LEV(@ISPERIOD("2012"))	0.003742	0.003260	1.148041	0.2538
@LEV(@ISPERIOD("2013"))	0.004036	0.001635	2.468397	0.0154

Table 5.17: Panel GMM robustness check results (additional instruments for homeownership rates). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U

Method: Panel Generalized Method of Moments

Transformation: First Differences

Date: 04/29/14 Time: 17:47

Sample (adjusted): 1997 2013

Periods included: 17

Cross-sections included: 8

Total panel (balanced) observations: 136

Difference specification instrument weighting matrix

White period standard errors & covariance (d.f. corrected)

WARNING: estimated coefficient covariance matrix is of reduced rank

Instrument specification: T D_M D_O D_Y @LEV(U(-3)) @DYN(H, -2, -4) @LEV(@SYSPER)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.602198	0.059053	10.19766	0.0000
T	0.049839	0.020511	2.429879	0.0167
D_M	-0.345471	0.116096	-2.975739	0.0036
D_O	-0.016805	0.042361	-0.396703	0.6923
D_Y	-0.034174	0.027958	-1.222322	0.2242
H(-1)	0.032480	0.021670	1.498853	0.1367
H(-2)	0.048441	0.030557	1.585275	0.1157
@LEV(@ISPERIOD("1997"))	-0.001258	0.002061	-0.610467	0.5428
@LEV(@ISPERIOD("1998"))	-0.003788	0.002111	-1.794569	0.0754
@LEV(@ISPERIOD("1999"))	-0.005031	0.001970	-2.554271	0.0120
@LEV(@ISPERIOD("2000"))	0.001672	0.001848	0.904768	0.3675
@LEV(@ISPERIOD("2001"))	0.009469	0.001444	6.556448	0.0000
@LEV(@ISPERIOD("2002"))	-0.009854	0.002125	-4.636680	0.0000

@LEV(@ISPERIOD("2003"))	-0.000319	0.001470	-0.217080	0.8285
@LEV(@ISPERIOD("2004"))	-0.003440	0.001402	-2.453435	0.0157
@LEV(@ISPERIOD("2005"))	0.000267	0.002254	0.118425	0.9059
@LEV(@ISPERIOD("2006"))	0.000596	0.000943	0.632276	0.5285
@LEV(@ISPERIOD("2007"))	-0.001744	0.001590	-1.097241	0.2749
@LEV(@ISPERIOD("2008"))	0.000116	0.000887	0.131044	0.8960
@LEV(@ISPERIOD("2009"))	0.010274	0.002060	4.987322	0.0000
@LEV(@ISPERIOD("2010"))	-0.007245	0.002297	-3.154032	0.0021
@LEV(@ISPERIOD("2011"))	0.001577	0.001952	0.808005	0.4208
@LEV(@ISPERIOD("2012"))	0.003975	0.002515	1.580284	0.1169
@LEV(@ISPERIOD("2013"))	0.003924	0.001537	2.553226	0.0120

Effects Specification

Cross-section fixed (first differences)

Period fixed (dummy variables)

Mean dependent var	-0.001696	S.D. dependent var	0.006309
S.E. of regression	0.004887	Sum squared resid	0.002675
J-statistic	76.42738	Instrument rank	66
Prob(J-statistic)	0.000918		

Table 5.18: Panel GMM robustness check results (lagged differences instrumenting the LDV instead of lagged levels). Notes: calculations performed in EViews. Source: ABS

Periods included: 17

Cross-sections included: 8

Total panel (balanced) observations: 136

Difference specification instrument weighting matrix

White period standard errors & covariance (d.f. corrected)

WARNING: estimated coefficient covariance matrix is of reduced rank

Instrument specification: T D_M D_O D_Y @DYN(U, -2, -2) @DYN(H, -2, -2) @LEV(@SYSPER)

Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.789394	0.150275	5.253006	0.0000
T	0.055955	0.024687	2.266585	0.0253
D_M	-0.284289	0.138238	-2.056519	0.0421
D_O	-0.038863	0.045898	-0.846717	0.3990
D_Y	-0.011074	0.024267	-0.456334	0.6490
H(-1)	0.028604	0.019076	1.499427	0.1366
H(-2)	0.102747	0.033383	3.077793	0.0026
@LEV(@ISPERIOD("1997"))	-0.000827	0.002834	-0.291995	0.7708
@LEV(@ISPERIOD("1998"))	-0.003057	0.002392	-1.277902	0.2039
@LEV(@ISPERIOD("1999"))	-0.003723	0.002634	-1.413514	0.1603
@LEV(@ISPERIOD("2000"))	0.002750	0.001569	1.752544	0.0824
@LEV(@ISPERIOD("2001"))	0.009613	0.001846	5.207891	0.0000
@LEV(@ISPERIOD("2002"))	-0.010614	0.002228	-4.764751	0.0000
@LEV(@ISPERIOD("2003"))	0.000840	0.001635	0.513578	0.6086
@LEV(@ISPERIOD("2004"))	-0.002616	0.001943	-1.346247	0.1809
@LEV(@ISPERIOD("2005"))	0.001497	0.002891	0.517724	0.6057
@LEV(@ISPERIOD("2006"))	0.001530	0.001209	1.266061	0.2081
@LEV(@ISPERIOD("2007"))	-0.000995	0.001901	-0.523258	0.6018

@LEV(@ISPERIOD("2008"))	0.001107	0.001379	0.802825	0.4238
@LEV(@ISPERIOD("2009"))	0.011084	0.002200	5.037625	0.0000
@LEV(@ISPERIOD("2010"))	-0.009291	0.002966	-3.133111	0.0022
@LEV(@ISPERIOD("2011"))	0.001861	0.002244	0.829610	0.4085
@LEV(@ISPERIOD("2012"))	0.004050	0.002769	1.462951	0.1463
@LEV(@ISPERIOD("2013"))	0.003952	0.001781	2.218917	0.0285

Effects Specification

Cross-section fixed (first differences)

Period fixed (dummy variables)

Mean dependent var	-0.001696	S.D. dependent var	0.006309
S.E. of regression	0.005408	Sum squared resid	0.003275
J-statistic	51.02488	Instrument rank	55
Prob(J-statistic)	0.013199		

Table 5.19: Panel GMM robustness check results (dropping the exogenous covariates (1 lag model)). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 05/13/14 Time: 12:34
Sample (adjusted): 1997 2013
Periods included: 17
Cross-sections included: 8
Total panel (balanced) observations: 136
Difference specification instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Instrument specification: @DYN(H,-2, -2) @LEV(U(-3)) @LEV(@SYSPER)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.562948	0.099291	5.669653	0.0000
H(-1)	0.058028	0.022878	2.536404	0.0125
H(-2)	0.120436	0.028125	4.282147	0.0000
@LEV(@ISPERIOD("1997"))	-0.000567	0.002881	-0.196835	0.8443
@LEV(@ISPERIOD("1998"))	-0.005577	0.002010	-2.774293	0.0064
@LEV(@ISPERIOD("1999"))	-0.005511	0.001331	-4.141264	0.0001
@LEV(@ISPERIOD("2000"))	-0.001249	0.001764	-0.707905	0.4804
@LEV(@ISPERIOD("2001"))	0.006947	0.001816	3.825917	0.0002
@LEV(@ISPERIOD("2002"))	-0.008194	0.001550	-5.285076	0.0000
@LEV(@ISPERIOD("2003"))	-0.000472	0.001511	-0.312654	0.7551
@LEV(@ISPERIOD("2004"))	-0.003746	0.001593	-2.351612	0.0204
@LEV(@ISPERIOD("2005"))	-0.000749	0.001813	-0.413222	0.6802
@LEV(@ISPERIOD("2006"))	0.000104	0.001288	0.080742	0.9358
@LEV(@ISPERIOD("2007"))	-0.002368	0.001774	-1.334547	0.1846
@LEV(@ISPERIOD("2008"))	0.000459	0.001189	0.385908	0.7003
@LEV(@ISPERIOD("2009"))	0.011954	0.002277	5.249038	0.0000
@LEV(@ISPERIOD("2010"))	-0.008424	0.002382	-3.536494	0.0006
@LEV(@ISPERIOD("2011"))	0.001625	0.001818	0.893629	0.3734
@LEV(@ISPERIOD("2012"))	0.004318	0.002303	1.874839	0.0633
@LEV(@ISPERIOD("2013"))	0.004803	0.001098	4.375268	0.0000

Effects Specification

Cross-section fixed (first differences)
Period fixed (dummy variables)

Mean dependent var	-0.001696	S.D. dependent var	0.006309
S.E. of regression	0.005097	Sum squared resid	0.003013
J-statistic	20.05376	Instrument rank	35
Prob(J-statistic)	0.169880		

Table 5.20: Panel GMM robustness check results (dropping the exogenous covariates (2 lag model)). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 05/13/14 Time: 12:34
Sample (adjusted): 1997 2013
Periods included: 17
Cross-sections included: 8
Total panel (balanced) observations: 136
Difference specification instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Instrument specification: @DYN(H,-2, -2) @LEV(U(-3)) U(-2)

@LEV(@SYSPER)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.716550	0.071484	10.02395	0.0000
H(-1)	0.061896	0.017776	3.482012	0.0007
H(-2)	0.104304	0.030962	3.368827	0.0010
U(-2)	-0.150782	0.066901	-2.253799	0.0261
@LEV(@ISPERIOD("1997"))	-0.002048	0.003460	-0.591996	0.5550
@LEV(@ISPERIOD("1998"))	-0.005324	0.002015	-2.641939	0.0094
@LEV(@ISPERIOD("1999"))	-0.004686	0.001550	-3.023792	0.0031
@LEV(@ISPERIOD("2000"))	-0.000904	0.001787	-0.505957	0.6139
@LEV(@ISPERIOD("2001"))	0.006518	0.002006	3.248531	0.0015
@LEV(@ISPERIOD("2002"))	-0.009698	0.001774	-5.468051	0.0000
@LEV(@ISPERIOD("2003"))	0.001149	0.002083	0.551662	0.5823
@LEV(@ISPERIOD("2004"))	-0.004006	0.001585	-2.526602	0.0129
@LEV(@ISPERIOD("2005"))	-0.000355	0.001875	-0.189267	0.8502
@LEV(@ISPERIOD("2006"))	-0.000229	0.001394	-0.164630	0.8695
@LEV(@ISPERIOD("2007"))	-0.002599	0.001781	-1.459425	0.1472
@LEV(@ISPERIOD("2008"))	0.000694	0.001351	0.513690	0.6085
@LEV(@ISPERIOD("2009"))	0.011619	0.002226	5.219066	0.0000
@LEV(@ISPERIOD("2010"))	-0.010365	0.002649	-3.912889	0.0002
@LEV(@ISPERIOD("2011"))	0.003585	0.002445	1.466159	0.1453
@LEV(@ISPERIOD("2012"))	0.003855	0.002697	1.429515	0.1556
@LEV(@ISPERIOD("2013"))	0.004254	0.001309	3.249146	0.0015

Effects Specification

Cross-section fixed (first differences)
Period fixed (dummy variables)

Mean dependent var	-0.001696	S.D. dependent var	0.006309
S.E. of regression	0.005337	Sum squared resid	0.003275
J-statistic	19.93637	Instrument rank	36
Prob(J-statistic)	0.174387		

Table 5.21: Panel robustness check results (dropping the exogenous covariates (static model)). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Least Squares
Date: 05/13/14 Time: 12:38
Sample (adjusted): 1996 2013
Periods included: 18
Cross-sections included: 8
Total panel (balanced) observations: 144

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003411	0.015937	0.214040	0.8308
H(-1)	0.023188	0.076528	0.302997	0.7623
H(-2)	0.057818	0.075874	0.762025	0.4473

R-squared	0.079129	Mean dependent var	0.058455
Adjusted R-squared	0.066067	S.D. dependent var	0.017379
S.E. of regression	0.016795	Akaike info criterion	-5.314814
Sum squared resid	0.039774	Schwarz criterion	-5.252942
Log likelihood	385.6666	Hannan-Quinn criter.	-5.289673
F-statistic	6.057953	Durbin-Watson stat	0.155799
Prob(F-statistic)	0.002992		

Table 5.22: Panel robustness check results (using H(-2) and H(-4) as explanatory variables and treating them as exogenous, lagged levels instrument for the LDV). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 05/14/14 Time: 22:11
Sample (adjusted): 1999 2013
Periods included: 15
Cross-sections included: 8
Total panel (balanced) observations: 120
Difference specification instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Instrument specification: @LEV(U(-3)) D_M D_O D_Y T H(-2) H(-4)
@LEV(@SYSPER)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.930190	0.083736	11.10866	0.0000
D_M	-0.425889	0.186575	-2.282668	0.0246
D_O	-0.034180	0.026752	-1.277651	0.2044
D_Y	-0.018760	0.038353	-0.489145	0.6258
T	-0.031986	0.039304	-0.813794	0.4177
H(-2)	0.054176	0.034864	1.553917	0.1234
H(-4)	0.027571	0.017556	1.570490	0.1195
@LEV(@ISPERIOD("1999"))	-0.003800	0.001713	-2.217871	0.0289
@LEV(@ISPERIOD("2000"))	0.003233	0.001043	3.098809	0.0025

@LEV(@ISPERIOD("2001"))	0.010415	0.002137	4.873459	0.0000
@LEV(@ISPERIOD("2002"))	-0.012303	0.001546	-7.955657	0.0000
@LEV(@ISPERIOD("2003"))	0.000921	0.001880	0.489844	0.6253
@LEV(@ISPERIOD("2004"))	-0.002630	0.001628	-1.615528	0.1094
@LEV(@ISPERIOD("2005"))	0.001481	0.002188	0.676973	0.5000
@LEV(@ISPERIOD("2006"))	0.000652	0.001340	0.486603	0.6276
@LEV(@ISPERIOD("2007"))	-0.002327	0.002508	-0.927636	0.3559
@LEV(@ISPERIOD("2008"))	0.001477	0.000981	1.504665	0.1356
@LEV(@ISPERIOD("2009"))	0.011492	0.001997	5.755151	0.0000
@LEV(@ISPERIOD("2010"))	-0.011354	0.003132	-3.624886	0.0005
@LEV(@ISPERIOD("2011"))	0.002329	0.002278	1.022101	0.3092
@LEV(@ISPERIOD("2012"))	0.003442	0.002655	1.296785	0.1978
@LEV(@ISPERIOD("2013"))	0.002980	0.002123	1.403542	0.1636

Effects Specification

Cross-section fixed (first differences)
Period fixed (dummy variables)

Mean dependent var	-0.001350	S.D. dependent var	0.006448
S.E. of regression	0.005351	Sum squared resid	0.002806
J-statistic	1.03E-25	Instrument rank	22

Table 5.23: Panel robustness check results (using H(-2) and H(-4) as explanatory variables and treating them as exogenous, lagged differences instrument for the LDV). Notes: calculations performed in EViews. Source: ABS

Dependent Variable: U
Method: Panel Generalized Method of Moments
Transformation: First Differences
Date: 05/14/14 Time: 22:13
Sample (adjusted): 1999 2013
Periods included: 15
Cross-sections included: 8
Total panel (balanced) observations: 120
Difference specification instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
WARNING: estimated coefficient covariance matrix is of reduced rank
Instrument specification: @DYN(U, -2, -2) D_M D_O D_Y T H(-2) H(-4)
@LEV(@SYSPER)
Constant added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
U(-1)	0.926844	0.111283	8.328739	0.0000
D_M	-0.411470	0.141485	-2.908226	0.0045
D_O	-0.038964	0.033725	-1.155357	0.2508
D_Y	-0.019318	0.033051	-0.584490	0.5602
T	-0.026944	0.030972	-0.869951	0.3865
H(-2)	0.068250	0.025794	2.645978	0.0095
H(-4)	0.035366	0.021496	1.645212	0.1031
@LEV(@ISPERIOD("1999"))	-0.003692	0.002201	-1.677342	0.0967
@LEV(@ISPERIOD("2000"))	0.003189	0.001078	2.958905	0.0039
@LEV(@ISPERIOD("2001"))	0.010219	0.002346	4.355354	0.0000
@LEV(@ISPERIOD("2002"))	-0.012277	0.001763	-6.962614	0.0000
@LEV(@ISPERIOD("2003"))	0.000887	0.002095	0.423470	0.6729
@LEV(@ISPERIOD("2004"))	-0.002588	0.001540	-1.680871	0.0960
@LEV(@ISPERIOD("2005"))	0.001537	0.002613	0.588108	0.5578
@LEV(@ISPERIOD("2006"))	0.000755	0.001403	0.538028	0.5918
@LEV(@ISPERIOD("2007"))	-0.002231	0.002552	-0.874198	0.3841
@LEV(@ISPERIOD("2008"))	0.001539	0.001289	1.193439	0.2356
@LEV(@ISPERIOD("2009"))	0.011568	0.002260	5.118413	0.0000
@LEV(@ISPERIOD("2010"))	-0.011278	0.003327	-3.390042	0.0010
@LEV(@ISPERIOD("2011"))	0.002257	0.002292	0.984680	0.3272

@LEV(@ISPERIOD("2012"))	0.003551	0.002674	1.327768	0.1873
@LEV(@ISPERIOD("2013"))	0.003084	0.002022	1.525689	0.1303

Effects Specification

Cross-section fixed (first differences)
Period fixed (dummy variables)

Mean dependent var	-0.001350	S.D. dependent var	0.006448
S.E. of regression	0.005348	Sum squared resid	0.002803
J-statistic	14.55817	Instrument rank	36
Prob(J-statistic)	0.409008		

Arellano-Bond Serial Correlation Test
Equation: Untitled
Date: 05/14/14 Time: 22:14
Sample: 1994 2013
Included observations: 120

Test order	m-Statistic	rho	SE(rho)	Prob.
AR(1)	-3.291475	-0.000946	0.000287	0.0010
AR(2)	-1.292148	-0.000373	0.000289	0.1963