DEMOGRAPHICS AND ASSET PRICES IN AUSTRALIA

DO THE DYNAMICS OF POPULATION AGEING MATTER?

Wasanthi Thenuwara Hennadige

MA (UW, Canada), MAIF (Advanced) (UQ, Australia), BSc (Honours) (USJP, SL)

A thesis submitted for the degree of Doctor of Philosophy
University of New England
Australia

December 2016

CANDIDATE'S CERTIFICATION

I certify that the substance of this thesis has not been submitted for any degree and it is not currently being submitted for any other degree or qualification.

I also certify that the any help received in preparing of this thesis and all sources used have been acknowledged in this thesis.

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ABSTRACT

The effects of population ageing on asset markets are complex. Recent literature has raised concerns of significant downward pressure on asset prices, housing and financial, due to the rapid demographic transition associated with retiring Baby Boomers. Awareness of this demographic transition and speculation over the consequent effects on asset markets prompted the asset meltdown debate. This thesis contributes to the asset meltdown debate and addresses the question whether demographic transitions, particularly the increasing proportion of the population in the old age cohort due to the retirement of Baby Boomers, will precipitate a dramatic decline in house and stock price in Australia.

The structural vector autoregressive model used for the empirical analysis is an important improvement over the reduced-form regression strategies usually employed in the literature. Both the demographic and non-demographic variables used in the empirical analysis are treated as endogenous and reverse causality between the variables is taken into account. The population ageing dynamics are modelled using impulse response functions and, thus, an insight into the potential magnitude of demographic shocks, particularly retirement shocks, is obtained. The analysis quantifies the responses in real house and stock prices to such shocks. The structural shocks are characterised as a sequence of shocks, often with different signs at different points in time, rather than one-off shock. The cumulative effect of such a sequence of shocks on the evolution of real house and stock prices over time is examined using historical decomposition. In addition, the forecast error variance decomposition is used to quantify the percentage contribution of the total variation in real house and stock prices to each structural shock in the models for different forecast periods.

The findings support the optimists' view in the asset meltdown debate. Predictions that population ageing, or more specifically, changes in age structure particularly due to retiring Baby Boomers, will lead to pronounced downward pressure on real house or real stock price in Australia are rejected. The findings suggest that Baby Boomers are unlikely to sell enough housing and financial assets in retirement to precipitate a market

meltdown, or a sudden and sharp decline in real house or stock prices. With the benefit of hindsight, we also see that the one fourth of the Baby Boomers are already retired and the Australian housing market and stock market does not show signs of collapse or substantial price decreases. Poterba (2001) provides a possible explanation for these findings, namely, even though changes in age structure affect asset demand, these effects are simply too small to be detected among the other shocks to house and stock prices. Moreover, the anomaly as revealed by asset ownership statistics, that the older population cohort continues to hold or accumulate assets rather than de-accumulate as originally predicted by the life cycle hypothesis sheds light on why population ageing does not exert a pronounced downward pressure on asset prices in Australia.

ACKNOWLEDGEMENTS

First and foremost I am very grateful to my principal supervisor Dr. Nam Hoang and co-supervisor Professor Mahinda Siriwardana for their consistent guidance, encouragement, invaluable support and mentorship throughout my study. The patience, kindness and friendship I received from them made my PhD experience an enjoyable one. Thank you.

I am indebted to Dr. Bryan Morgan from the University of Queensland for his kindness in undertaking the final editorial checking of my thesis. Thank you Dr. Morgan.

I give my special thanks to Professor Oscar Cacho and Associate Professor Renato Villano for their guidance as the research coordinators.

I also extend my gratitude to Professor Derek Baker, Associate Professor Renato Villano, Dr. George Chen, Dr. Emilio Morales, Dr. Stuart Mounter, Dr. Tony Ramsay and Dr. Samuel Meng for offering teaching/tutoring/marking/RA opportunities to overcome the financial hardship I faced and to obtain experience. Being a student without a stipend your support was invaluable. My special thanks goes to Dr. Chen who offered me my first job as a tutor and spoke well of me to other staff.

My special thanks to the head of the Business School, Professor Alison Sheridan for providing necessary institutional support. I would also like to thank administrative staff of the Business School for their generous support in various ways whenever I needed.

I should not forget Dr. Reddy Yarram for his support and time to instructing me how to use DataStream and downloading some data I required. Thank you.

My very special thanks to Dr. Neil Karunaratne and Dr. Bryan Morgan from the University of Queensland for their encouragement to commence a PhD and providing reference letters supporting to my application. The writing techniques that I learnt from Dr. Morgan when he supervised my Masters thesis at the UQ were incredibly useful in making my PhD thesis a success. I gratefully appreciate that. Thank you.

My mother has been my greatest source of inspiration for completing my PhD thesis. I express my sincere gratitude to my brothers, sisters and in-laws who have been looking after my mother after she became very ill in March 2016.

Finally, I dedicate this thesis to my late father and my mother.

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ABBREVIATIONS

ABS	Australian Bureau of Statistics
ADF	Augmented Dicky-Fuller
ADPI	Attached Dwelling Price Index
AIC	Akaike Information Criterion
AMH	Asset Meltdown Hypothesis
APM	Australian Property Monitors
ASX	Australian Stock Exchange
AUD	Australian Dollar
CBA	Commonwealth Bank of Australia
CGT	Capital Gains Tax
EMH	Efficient Market Hypothesis
EPS	Earnings Per Share
FEVD	Forecast Error Variance Decomposition
GDP	Gross Domestic Product
GLS	Generalised Least Square
GMM	Generalised Method Moments
HAA	Housing and Ageing Alliance
HD	Historical Decomposition
HPI	House Price Index
IRF	Impulse Response Function
KPSS	Kwiatkowski Phillips Schmidt Shin
LM	Lagrange Multiplier
LR	Likelihood Ratio
LTO	Land Title Office
MLC	Marketing Leadership Council
OECD	Organization of Economic Cooperation and Development
OLG	Overlapping Generations Model
OLS	Ordinary Least Square

OY	Old Young
PP	Phillips Perron
RBA	Reserve Bank of Australia
RATS	Regression Analysis for Time Series
REIA	Real Estate Institute of Australia
RPPI	Residential Property Price Index
SC	Schwarz Information Criterion
S&P	Standard & Poor’s
SMSF	Self- Managed-Superannuation-Fund
SVAR	Structural Vector Autoregressive
TFR	Total Fertility Rate
VAR	Vector Autoregressive
WHO	World Health Organization

CHAPTER 1 INTRODUCTION

1.1 General Background to the Study

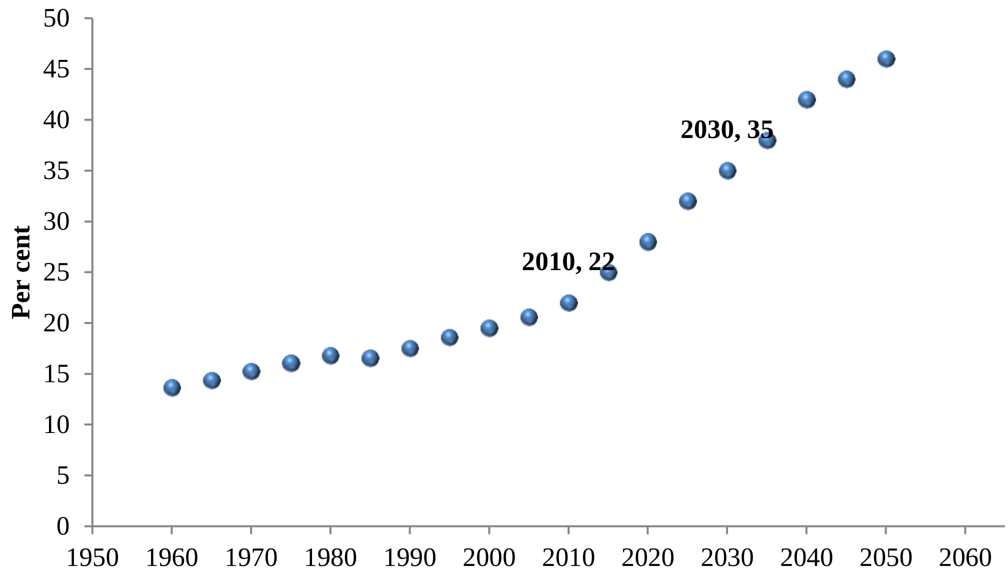
Ageing of the population is an emerging phenomenon in many countries around the world. Since the late 1980s academic researchers, analysts and investors have been studying the pressure exerted by demographic transitions, particularly the rapid ageing of the population, on various sectors in the economy. Among these effects, the impact on economic growth, consumption, savings, capital flows, government expenditure and asset prices are of particular significance. A substantial number of studies focus on the link between changing demographic structure and trends in macroeconomic variables such as consumption, growth, savings, exchange rates, capital flows and public expenditure (Cutler, Louise and Lawrence, 1990; Taylor and Williamson, 1994; Higgins and Williamson, 1997; Miles, 1998; Bloom, Canning and Graham, 2003; 2003; Kim and Lee, 2008; Karras, 2009). There is an extensive literature on the effect of ageing on public pension and social security (see Hviding and Merette, 1998; DeNardi, Imrohologlu and Sargent, 1999; Fehr, 2000; Borsch, Ludwig and Winter, 2006; Kotlikoff, Smetters and Walliser, 2007). Meanwhile, a notable number of studies focus on the effect of changing demographics on asset prices resulting from the Baby Boom (see chapter 3).

The *life cycle theory* of consumption and savings (Modigliani and Brumberg, 1954; Ando and Modigliani, 1963) analyses the saving and consumption behaviour of individuals over the different stages of their lives. The theory posits that the saving behaviour of the households (save during the working age and dis-save during the retirement) exhibits a demographic transition not a steady state growth. Young people (aged 20-39) are net borrowers, while middle aged people (aged 40-64) actively accumulate assets and as people enter retirement (aged > 65) they start to de-accumulate wealth. The overlapping generations framework (OLG) suggests that working aged people buy assets to save for old age and sell when they are old to finance their retirement. In this context, the changes in relative numbers of asset buyers and sellers have consequences for asset prices. Hence, when the proportion of working aged people is large, it drives up the demand for assets and exerts an upward pressure on asset prices and conversely, if the population is ageing the demand reduces and thus put a downward pressure on asset prices.

The Baby Boom generation, those born between 1946 and 1964, is a significant demographic group in developed countries. Conversely, the Baby Bust generation (born 1967-1979) is a much smaller group. The significant differences in the numbers in the boom and bust groups along with increasing life expectancy have brought OECD countries to the onset of a rapid demographic transition. The average and median ages of populations across the OECD countries have been increasing. The declining birth rates coupled with increasing life expectancy also contributes to the observed demographic transition. Average life expectancy at birth in OECD countries rose from 70 years in 1970 to 80.5 years in 2013 ("Health at a Glance", 2015). The first of the Baby Boom generation reached retirement age in 2011 leading to a rapid increase in the existing and projected populations of those aged 65 and above. Thus, a steep increase is projected for the old age dependency ratio during the 2011 to 2030 period as this is the time when the entire Baby Boomer generation reaches the retirement age (see Figure 1.1). The average old age dependency ratio for OECD countries was 22% in 2010 and it is projected to increase to 35% and 46% in 2030 and 2050 respectively.

When Baby Boomers initially entered the labour market there were fears about increases in unemployment levels and the reduced wage rates. However, the debate turned to the impact on asset markets as the Baby Boom cohort aged. For example, a substantial number of researchers link the rise in the U.S. stock prices in the 1990s to the increase in savings as the working-age Baby Boomers saved for their retirement. It is argued that this led to an increase in the demand for financial assets and a dramatic rise in financial asset prices. With the present need to provide for an increasing proportion of the population who are retired, a concern has arisen about a downward pressure on asset prices. This intuition has given rise to the asset meltdown hypothesis (AMH). Siegel (1998, p. 41) describes this scenario as:

> The words "Sell? Sell to whom?" might haunt the Baby Boomers in the next century. Who are the buyers of the trillions of dollars of boomer assets? The [Baby Boomer generation]... threatens to drown in financial assets. The consequences could be disastrous for the boomers' retirement but also for the economic health of the entire population.



Source(s): United Nations Population division, World Population Prospects

Figure 1.1: Average old age dependency ratio (65+/15-64 years) in OECD countries

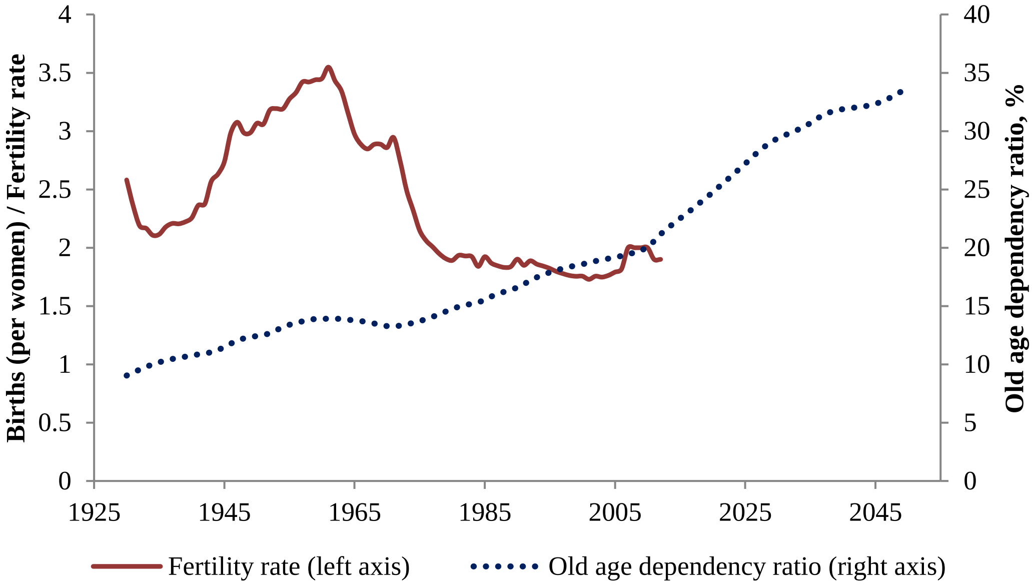
The theoretical and empirical research exploring the direction and magnitude of the impact of ageing on asset markets has been evolving since the end of the 1980s prompting the asset meltdown debate. These studies are highly diversified in terms of the theoretical model specification, data, empirical methodology and results. Many theoretical and empirical studies use the life cycle hypothesis to investigate the effect of a changing population age structure on asset markets. The population age structure primarily affects savings though rational economic agents investing in housing and financial assets. Furthermore, overlapping generations models (OLG) are the natural framework to model an individual's distinct financial needs at different periods of life, such as borrowing when young, saving for the retirement in the middle-aged life and dis-savings at the retirement (Samuelson, 1958; Diamond, 1965). It is, therefore, likely that the changing demographic structure may have an impact on asset markets.

However, the motivation for the empirical research on demographics and asset prices is the Mankiw and Weil (1989) research paper on the effect of Baby Boomers on house prices in the United States. They predicted a house price meltdown in the United States when Baby Boomers begin to retire. However, Mankiw and Weil's (1989) startling result of real house prices falling by 47% in the United States within 20 years from 1990s provoked considerable criticism and questioning of the validity of their forecast. For example, volume *21* of the *Journal of Regional Science and Urban Economics* published in 1991 presents many studies on the topic, including replications and extensions to Mankiw and Weil's (1989) analysis. Among those, Engelhardt and Poterba (1991) compare the results with Canadian data which had a similar demographic pattern to the United States and reaches contradictory conclusions. Woodward (1991) highlights the lack of supply side considerations in Mankiw and Weil's (1989) analysis and the overly simple relation between a demographic housing demand and real house prices. With the benefit of hindsight, we also see that their prediction of a decline in real house prices by 3% annually did not eventuate in the United States.

Subsequent research contributed to the asset meltdown debate investigating the influence of changing demographic structure on financial asset prices and asset returns from theoretical bases and on empirical grounds. Pessimists, those who believe in an asset meltdown, presume that retiring Baby Boomers will cause asset prices to plummet by selling their assets to a smaller group of young investors. In contrast, optimists believe such that the economic mechanism of forward looking asset markets will reflect the impact of the predictable retirement of Baby Boomers, so the impact would be softened or perhaps even be totally offset. The smaller size of younger population compared to the old aged population creates scarcity of human capital. The falling labour force may be offset by increased use of capital financed by savings of old people. As a consequence asset prices will not collapse and returns on financial assets will not fall sharply contrary to the pessimists' fear.

1.2 An Overview of the Australian Situation

Similar to other developed countries, Australia has experienced a changing demographic structure due to the Baby Boom and over the next four decades a further substantial change is projected. Australia has one of the highest life expectancies in the world. Male life expectancy is projected to increase from 91.5 years 2015 to 95.1 years in 2055 and female life expectancy is projected to increase from 93.6 years in 2015 to 96.6 years in 2055 (Intergenerational Report, 2015, p. 8). In Australia, the terms Baby Boom generation and Baby Boomers generally relate to all Australian residents born in the years 1946 to 1965, including those who migrated to Australia from countries which did not experience a baby boom ("Australian social trends", 2004).



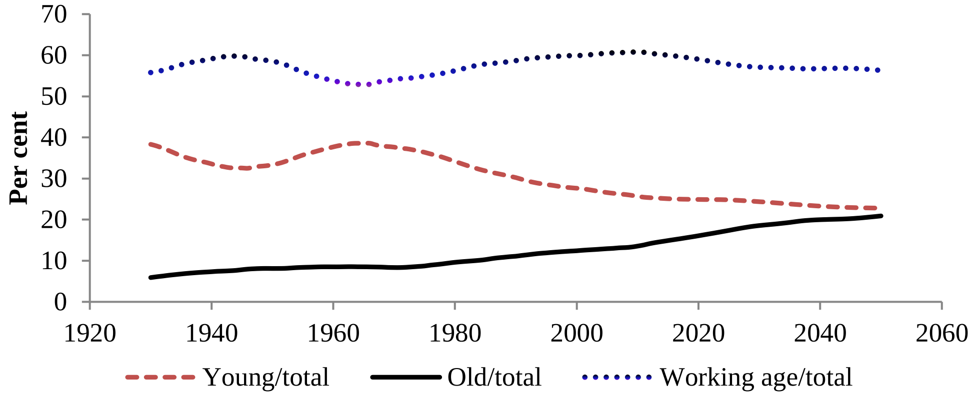
Source(s): Australian Bureau of Statistics (ABS) Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001); ABS Births, Australia, 2012 (cat. no. 3301); ABS Australian Demographic Statistics, 2013 (cat. no. 3101.0); ABS Australian Population Projections (cat. no. 3222.0) and author's calculation for old age dependency ratio

Figure 1.2: Australia's fertility rates and old age dependency ratios, 1930-2050

Figure 1.2 depicts the impact of the Baby Boom in Australia. The fertility rates were significantly high during this period. The average fertility rate during 1946-1965 increased to 3.23 babies per woman and more than 4 million of the current population were born during this period. Further, Australia recorded a birth bubble in

1971, the largest number of births of 276,400 babies in its history as a result of the first Baby Boomers reaching reproductive age. The ageing of the Baby Boom generation, increasing adult life expectancy and declining fertility trends in Australia contribute to an increase in the old age dependency ratio. The old age dependency ratio in 2013 was 21.6% and it is projected to increase to 29% in 2030 and 34% in 2050.

Demographic shifts in Australia increase the fraction of the old population and decrease the young and working age population. Figure 1.3 shows the historical and projected young (0-19 years), working age (20-64 years) and old (65 years and above) population ratios. The young age population increased to 5.84 million in 2013 from 2.73 million in 1950. In 2013, 60.3 % of the Australian population was aged between 20-64 years, however by 2030, this proportion is predicted to decline to 57%. The increase in the old age population was to 3.33 million in 2013 from 0.66 million in 1950. In 2011 the first of the Baby Boom generation in Australia reached age 65 years and by 2031 all the Baby Boomers will have reached retirement age. With the additional impact of the increase in longevity, the number of population aged 65 and above increased significantly during 2011-2013 and a steep increase is projected.



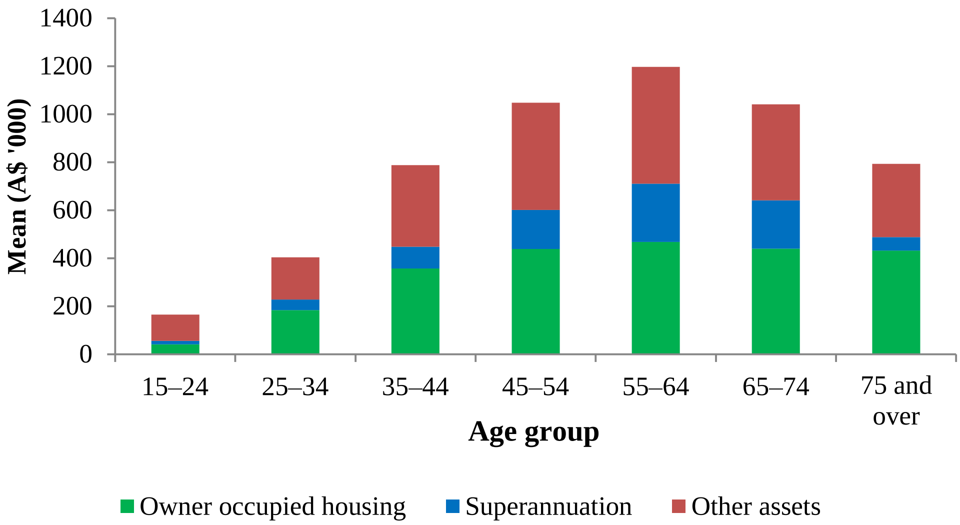
Source(s): Australian Bureau of Statistics (ABS) Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001); and ABS, Australian Population Projections (cat. no. 3222.0) and author's calculation for ratios

Figure 1.3: Australia's historical and projected young, working age and old population ratios, 1930-2050

The number of the old population is projected to increase to 5.58 million in 2030 from 2.99 million in 2010. That is, the projected growth is 87% over 2010. However, the size of the young population increases at a substantially slower rate compared to the old population. The young population is projected to increase by 1.68 million to 7.33 million in 2030, which is a 29% growth over 2010. The slower historical and projected growth in the young population compared to the old population implies that fewer young persons will enter into the labour force compared to the growing old population with a consequent increase in the burden on the working age population. The higher old age dependency ratios and lower labour market participation is expected to lead to reduced economic output. The intergenerational report of 2015 indicates that the number of people aged between 15 and 64 years for every person 65 years and above has fallen from 7.3 people in 1975 to 4.5 people in 2015. Kudrna, Tran and Woodland (2015) project a 6.2% decline in GDP per capita and increases in sizes of health care, age care and pension programmes by 24.5%, 125.9% and 62.9% respectively in 2050 as a result of the projected demographic shift.

The ABS survey publication of Household Wealth and Wealth Distribution, Australia, 2011–12 reveals that the largest share (43%) of assets held by Australian households is owner occupied housing (see Figure 1.4). The survey further reveals that the Baby Boom generation which comprise 25% of the Australian population have around 50% of housing wealth and thus they control a large component of the housing wealth in Australia. This implies that the elderly will have high level of housing wealth in the next two decades. Thus the elderly population will be asset rich and they will have high potential values of housing equity compared to the current elderly population.

Further, the survey findings reveal that the households with the age group of 55-64 years have the highest mean total financial assets. Of those financial assets more than 50% is in the form of superannuation that potentially can be converted into income in retirement. Moreover, the Baby Boomers which represent one-fourth of the Australian population own around one-half of the nation’s total assets. These figures provide some support for the hypothesis that elderly population run down their assets either by selling housing and financial assets and/or moving to cheaper dwelling to fund their future income needs in retirement.



Source(s): Australian Bureau of Statistics (ABS), Household Wealth and Wealth Distribution, 2011-12 (cat. no. 65540DO001)

Figure 1.4: Mean value of assets ownership by age group

Even though there are number of studies which focus on the fiscal implications of ageing (Guest and McDonald, 2000; Giesecke and Meagher, 2008; AIWH, 2010), national savings (Guest and McDonald, 2001), pension reforms (Warren, 2008; Clare, 2009; Kulish et al., 2010), international capital flows (Borsch-Supan et al., 2006) and economic growth (Kudrna et al., 2015), the literature on the topic of demographic change and asset prices for Australia is very limited. Three recent studies are related to the question of the effect of demographics on house prices in Australia (Guest and Swift, 2010; Otto, 2007; Bodman and Crosby, 2003). In relation to the stock prices, Huynh et al. (2006) investigate the effect on stock prices in Australia from the population in the 40-64 years cohort using annual data from 1965-2002. In addition, Takats (2012), Brooks (2006), Ang and Maddaloni (2005) and Erb et al. (1997) consider Australia in their cross country studies. However, these studies are subject to shortcomings which are discussed in detail in chapter 3.

Among the studies for house prices neither Bodman and Crosby (2003) nor Otto (2007) directly addresses the effects of demographic changes on house prices. Their focus is to analyse the growth of house prices in Australian capital cities and include population growth as an explanatory demographic variable. Guest and Swift (2010) examine house prices in terms of demographics but base the analysis to a 35-59 years cohort which limits its usefulness in the context of predictions of an asset price meltdown when Baby Boomers retire. Huynh et al. (2006, p. 695) infer that '… it is possible that, when the Baby Boomers start to retire from the workforce, they will withdraw their money from their stock market investments… essentially the economy may be in crisis'. However, the cohort who was aged 40-64 years during 1965-2002 have already passed their retirement age and the Australian stock market does not show signs of a collapse due to high volume of withdrawals.

1.3 Motivation for the Study

The motivation for this line of research is the ongoing and extensive discussions about the effect of the Baby Boom generation on asset markets since the 1990s, both in popular media and the academic literature. For example, New York Times (05 January, 1998) wrote that 'in the 1990s the performance of the American stock market has been nothing short of amazing ... Most of that performance has come from demographics as the Baby Boom reaches the age when it seems wise to invest for retirement...' quoted in Lim and Weil, 2003, *The Baby Boom and the Stock market Boom*, p. 2. As the first cohort of the Baby Boomers began to retire in 2011 those who believe this proposition have questioned whether the retired Baby Boomers will sell their assets and cause downward pressure on asset prices, particularly whether this will cause a significant fall in the stock market?

The existing literature establishes the relationships between demographic changes and asset prices/returns where the proportion of old aged and retired people was comparatively low. With the first Baby Boomers reaching 65 years of age in 2011 this proportion is projected to increase substantially and hence the effect is reinforced. Policy changes are being made to counter this trend, with 28 out of 34

OECD countries having increased or planning to increase retirement ages due to increases in life expectancy ("OECD Pension Outlook", 2012). With updated data results may change substantially in future research. Moreover, in contrast to the experiences of population ageing in developed countries, developing countries are still experiencing rapid population growth with low average ages. These divergent demographic trends along with the increasing globalisation of financial markets may exert changes in savings patterns and on asset markets. In addition, asset ownership statistics reveals an anomaly in the behaviour of the older populations' savings as they continue to accumulating savings rather than dis-saving as originally predicted by the life cycle theory. These factors raise the questions whether the increasing number of the population who are over 65 years dis-save and sell their assets to fund their retirement and whether that will cause a fall in asset prices?

In Australia a substantial demographic transition is in progress caused by the ageing Baby Boomers in conjunction with increasing life expectancy and low fertility rates. The Productivity Commission of Australia (2005, p. 1) states that 'ageing of our population is one of the biggest policy challenges facing'. As described in section 1.2, the shortcomings in the existing literature investigating the implications of ageing on asset markets in Australia are the motivation for a new study. The previous studies do not provide clear answers as to how the demographic shift, or more specifically, rapidly increasing proportion of the old population particularly due to retiring Baby Boomers, affects house prices and stock prices.

The review of the literature (see chapter 3) confirms that the findings are sensitive to the econometric techniques used. A substantial number of studies assume the direction of the causal relationship to be from the demographic variable and macroeconomic variable to asset prices without considering the possibility of a relationship in the opposite direction. Sims (1980) argues that macroeconomic variables have a substantial endogenous component and stresses the need to discard empirically implausible exogeneity assumptions. Further the studies in the literature ignore the dynamic interrelationships between a number of variables. Shambora (2007) uses a semi-structural VAR model to investigate the effect of demographics on equity prices in the United States, which is the only study that takes into account the reverse causality of the variables. Thus it is clear more sophisticated techniques are required to investigate the effects of population ageing dynamics on asset markets in Australia as well, thus motivating this new study.

1.4 Research Objectives

The objective of this thesis is to contribute to the asset meltdown debate by examining whether demographic transitions, particularly the increasing proportion of the population in the old age cohort due to the retirement of Baby Boomers, will precipitate a dramatic decline in asset prices in Australia. More specifically the study investigates how the changes in age distribution affect real house prices and real stock prices. Thus, the study focuses on the shift of a large cohort (Baby Boomers) from working age (20-64 years) to retirement age and the consequent implications for house and stock prices. Baby Boomers comprise a demographical bulge and the entire generation was of working age (20-64 years) during the period 1986 to 2010. Between 2011 and 2031 this cohort will all reach 65 years and living members will be in retirement. The life cycle theory suggests that the shift of such a large cohort from the working age to retirement age will impact on asset markets. Thus the specific research objectives of this study are as follows:

For Australian markets,

1. to analyse the historical and projected demographic changes
2. to analyse the asset ownership over the life cycle
3. to estimate the effects population ageing on real house prices
4. to estimate the effects of population ageing on real stock prices
5. to investigate whether the effects of population ageing on house prices are sensitive to any interaction effects between house prices and stock prices
6. to investigate whether the effects of population ageing on stock prices are sensitive to any interaction effects between house prices and stock prices

1.5 Research Questions

To establish the broad research theme and the research objectives, the overall research question is specified as follows:

To what degree do demographic transitions, particularly the increasing proportion of the population in the old age cohort due to retirement of Baby Boomers, affect real house and stock prices in Australia?

The overall research question is investigated empirically through the following research questions.

RQ1: Do the dynamics of population ageing affect real house prices?

RQ2: Do the dynamics of population ageing affect real stock prices?

RQ3: Do the dynamics of population ageing on real house and stock prices for RQ1 and RQ2 respectively have an impact through the interaction between the two classes of assets?

1.6 Research Approach

To achieve the objectives of this research, descriptive statistics analyses and econometric models are developed using secondary data. The broad research question is addressed using two approaches. The first assumes that there is no impact on house prices from stock prices and vice versa. That is, house prices and stock prices are treated as independent to each other and assume that there is no interaction effect. Thus, two separate empirical models are formulated, one for house prices and the other for stock prices. This enables a direct comparison of the results with the literature. The second approach assumes that if the financial asset markets and housing markets are in equilibrium, the possibility of interaction should be considered. Therefore a model in which the joint dynamics of two assets are included to test whether the effects of population ageing on house prices and stock prices estimated using the first approach are attenuated or intensified.

The empirical models used in this research include asset price variables (real house prices and real stock prices), demographic variables (old population, old age ratio) and macroeconomic variables (GDP, the unemployment rate and the interest rate). The dynamic relationships among the variables are modelled using a structural vector autoregressive (SVAR) approach. This method has the advantage that it does not rely on ad hoc dynamic exclusion restrictions in the regression model and empirically implausible exogeneity assumptions. Also, in formulating SVAR models, the researcher does not have to dichotomise variables into endogenous and exogenous. Moreover, the likely lag effects of the variables are considered, which is an important improvement over the existing models used to examine demographic effects on asset prices as they only take contemporaneous effects of the variables into account.

In econometrics a variable is called exogenous if that variable is not affected by any other variables in the model (for a statistical interpretation of exogeneity of variables see Engle, Hendry and Richard, 1983). In this research it can be argued that demographic variables such as the old population and/or the old age ratio are not purely exogenous in a model which includes macroeconomic variables and asset price variables. There are a number of ways in which economic conditions can affect the demographic variables that will be used in this study. High income per capita countries are experiencing increasing longevity leading to an increase the size of the old age population. Also studies related to fertility scheduling state that the child bearing decisions of women are affected by the opportunity cost (see Ben-Porath, 1973; Becker, 1960). Further, Schaller (2016) examines this issue considering labour market conditions for both males and females and concludes that there exists a negative relationship between the unemployment rate and birth rates. In a recent study, Dettling and Kearney (2014) find a negative relationship going from house prices to fertility rates in the United States. Further, the World Health Organization [WHO] (2012) finds a causal link between housing quality and long-term health conditions of older people. Supporting these findings, the Housing and Ageing Alliance [HAA] (2014) argues that suitable housing for older people leads to reduced health care costs. Thus the affordable prices of quality houses suitable for old people will have an impact on the number in the old age cohort through reduced mortality rates at older ages.

In order to answer the research questions specified in section 1.5, SVAR models are formulated. Demographic variables are treated the same as macroeconomic variables and reverse causality is controlled for. This means that cause and effect between asset market variables, demographic and non-demographic variables are not well defined. In other words, the empirical specification treats all variables as endogenous and models each variable as a function of all other variables. The appropriate identification restrictions are used in each SVAR model.

In this research, each of the research questions is addressed by applying the SVAR methodology in three ways, following Kilian (2011). The first is to examine the expected response of the variables in each empirical model to a given one-time structural shock. Impulse response functions are used in VARs to assess the timing and magnitude of responses in a system of variables when one of those variables is subject to a structural shock or impulse. As Lütkepohl (2005, p. 51) states '... one would like to investigate the impulse response relationships between two variables in a higher dimensional system. ... if there is a reaction of one variable to an impulse in another variable we may call the latter causal for the former'.

However, structural shocks are not limited to a one-time shock. Rather they involve a sequence of shocks, often with different signs at different points in time[1]. Therefore, the second way of addressing the research questions is to quantify the cumulative effect of such a sequence of shocks on the evolution of each variable over time. Historical decompositions are constructed for this application. Accordingly, this research will be able to answer the empirical question of whether shocks to demographic variables drove real stock and house prices historically. The third way the research question is addressed is to quantify the average contribution of a given structural shock to the variability of the data using forecast error variance decompositions. For example, variance decomposition will be used to quantify on

[1]See Kilian and Park (2009, p. 1272).

average how much of the variations in real stock prices and house prices are associated with shocks that drive demographic variables.

1.7 Significance of the Research/ Contribution to the Literature

This research contributes to the ongoing debate among academic and non-academic researchers concerning the effect of changing demographic structure, particularly the rapidly increasing old age population, on asset markets both housing and financial. The research makes a significant contribution to the literature in several ways mainly. The first is that instead of focusing on the average effect of the old population variable on asset prices, the structural VAR approach analyses impact of a shock to demographic variables. This takes into account the large cohort entering retirement age since 2011 due to retirement of the first of the Baby Boom generation. This is the first study in the literature that uses this methodology to address the effects of the dynamics of population ageing on asset prices.

There is a gap in the literature investigating the effects of demographics in particular whether the population age structure will have an impact on the joint relationship between house and stock prices. However as Otto (2007, p. 231) states ‘in particular for the Sydney, Brisbane, Hobart and Canberra markets, increases in real equity returns are associated with statistically significant declines in the growth rate of real house prices’. Thus this research takes into account the fact that asset prices may be jointly determined and hence, through substitution and wealth effects and in conjunction with population ageing dynamics, changes in house prices have implications for stock prices and vice versa. This approach is new to the literature and it contributes by clarifying any ambiguity as to whether the key findings are sensitive to any interaction effects between house prices and stock prices.

The impact of a changing demographic structure on stock prices in Australia has received little attention to date. Brooks (2006, p. 235) reports a possible impact of ageing on financial markets as follows:

> In fact in countries where stock market participation is greatest, including Australia, Canada, New Zealand, the United Kingdom and the United States, evidence suggests that real financial asset prices may continue to rise as populations age, consistent with survey evidence that households continue to accumulate financial wealth well into old age and do little to run down their savings in retirement.

According to Brooks (2006) ageing will not have a negative impact on financial asset prices in Australia. Contrary to this, Huynh et al. (2006) infer a large volume of withdrawals from stock market when Baby Boomers retire. One fourth of the Baby Boomers have already retired; hence the finding from the current research with respect to stock price is a significant contribution to the literature to clear any ambiguity of the mixed inferences of Brooks (2006) and Huynh et al. (2006).

Moreover, this research extends the previous Australian research on this issue by employing a much longer time series from 1950 to 2014. This is an advantage as demographic change is a slow moving fundamental which is better captured with a longer time span.

1.8 Structure of the Thesis

This thesis is divided into eight chapters. The first chapter is an introduction to the study, explaining the background in general and specific to Australia, the research objectives, the research questions, the approaches to answer the research questions and achieve objectives, the study's significance and the organisation of the thesis.

Chapter 2 provides the stylised facts of the demographic dynamics and asset ownership in Australia. Current and projected demographic statistics are analysed to understand Australia's changing demographic structure and the driving factors of the demographic transition. A review of asset ownership statistics across the life cycle provides some important information on which to build the conceptual framework for the empirical models and to strengthen the findings from the empirical analyses.

Chapter 3 surveys the theoretical and empirical literature investigating the effects demographic changes, particularly focusing on the effects of the Baby Boom generation on asset markets, both housing and financial. The review especially focuses on the question of the asset meltdown hypothesis including critical reviews of the methodologies used and an evaluation of contradictory results. The gaps in the literature thus identified were useful to develop a more rigorous approach to this research and to make a significant contribution to the existing literature.

Chapter 4 provides a relatively non-technical survey of finite order vector autoregressive (VAR) models since a comprehensive understanding of vector autoregressive models is important in order to apply this methodology and interpret the results in this research. It specifically focuses on the basic assumptions and properties of VAR and the fundamentals regarding interpretation of results. The chapter has a particular focus on structural VAR including various identification techniques.

Chapter 5 is the first empirical chapter and examines the effects of population ageing dynamics on real house prices and more specifically answers the question "Will retiring Baby Boomers cause a house price meltdown in Australia?". This chapter extends previous Australian research on this issue by employing a much longer time series from 1950 to 2013 and using a constant quality real house price series which controls for compositional and quality effects.

Chapter 6 examines the effects of population ageing dynamics on real stock prices. A theoretical link between demographics and asset prices following Poterba (2001) is developed as a starting point of analysing why population ageing shocks would affect stock prices. The structural VAR model which is formulated for the empirical analysis has a strong conceptual framework and produces a detailed description of the notion of relative stock market efficiency.

Chapter 7 analyses the effects of population ageing dynamics on house prices and stock prices in conjunction with the joint dynamics of the two classes of assets. The models developed in chapter 5 and chapter 6 are extended to incorporate the interaction between house prices and stock prices. Further, a small model is also developed with four variables, namely a demographic variable to represent the population ageing effect, a variable to represent the real economic forces, real house price and real stock price.

Chapter 8 presents an overall summary of the study. The main conclusions based on the findings from Chapters 2, 5, 6 and 7 and a discussion of the results is provided. The policy implications and recommendations along with a number of directions for further research are also presented.

CHAPTER 2 STYLISED FACTS OF DEMOGRAPHIC DYNAMICS AND ASSET OWNERSHIP IN AUSTRALIA

2.1 Introduction

Since the late 1990s, Australia has experienced a changing demographic structure and over the next four decades a further substantial change is projected. Ageing of Baby Boomers will be the driving factor for this change[2]. The ageing of the Baby Boom generation, increasing adult life expectancy and declining fertility trends in Australia contribute to an increase in the ratio of the old population (people aged 65 or over) to the working age population (people aged 20-64 years).

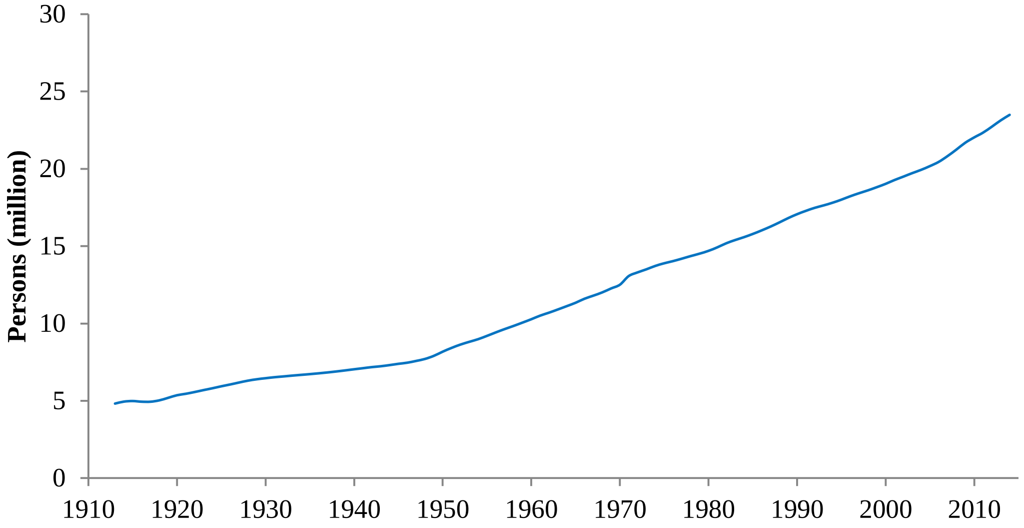
This chapter explores the stylised facts of Australia's changing age structure and the pattern of asset ownership over the life cycle. Sections 2.2 to 2.6 present an overview of Australia's historical and projected demographic changes, particularly focusing on the impact of the Baby Boomers. A measure of household's economic wellbeing is the ownership of assets. The patterns in asset ownership either through direct ownership of housing and financial assets or ownership of assets through superannuation/pension plans vary with age. Sections 2.7 to 2.9 examine Australian asset ownership patterns over the life cycle. Conclusions are provided in section 2.10.

2.2 Population Size and Growth Rates

Figures 2.1 and 2.2 show Australia's population size and population growth from 1913 to 2014. The changes in the population size and growth rate are attributable to the different social and economic events such as the World Wars, the Great Depression, the Baby Boom and the Baby Bust experienced during the past 100

[2]Baby Boomers in Australia are those who were born from 1945 to 1965. A more detailed discussion is provided in section 2.2.

years. The population size increased by approximately five times from 4.8 million in 1913 to 23.5 million in 2014.

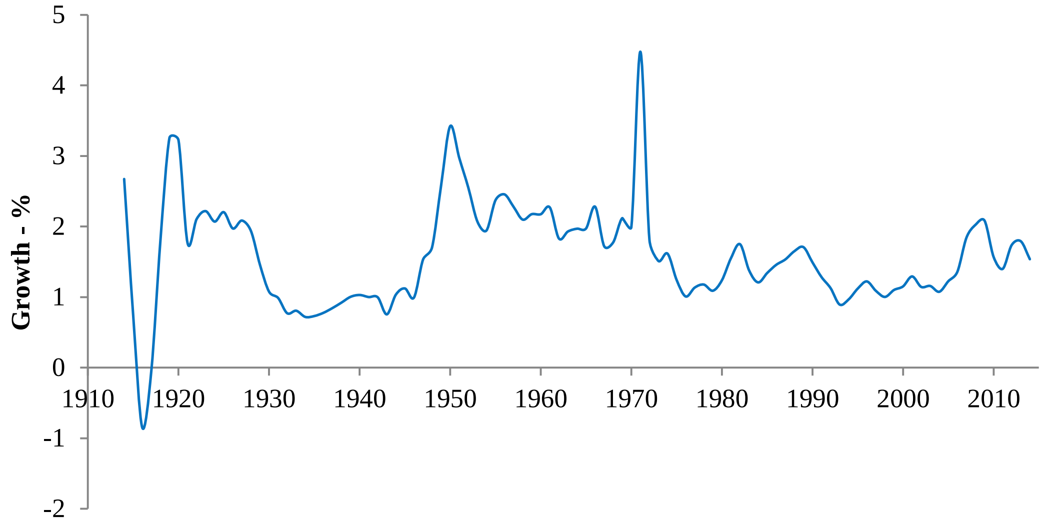


Source(s): Australian Bureau of Statistics (ABS) Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001) and ABS, Australian Demographic Statistics, 2013 (cat. no. 3101.0)

Figure 2.1: Australia's population, 1913-2014

The increase in the population growth rate between 1946 and 1970 can be seen clearly in Figure 2.2. The average growth rate during this period was 2.2% per annum against 0.9% average growth during the period 1929-1945. The period of a high fertility rate from 1946 to the mid-1960s came to be known as the Baby Boom. More than 4 million of the current population were born during the period of 1946-1965[3]. The year 1971 records the highest population growth rate of 4.5% as a result of the first echo of the Baby Boom[4]. Figure 2.2 further indicates a slower annual growth of population during 1970s due to slow economic growth, low levels of fertility and a slowing down of migration. For example, the annual population increase in 1975 fell to 170,424 from 560,000 in 1971 and stayed between 140,000 and 180,000 in each year till 1980.

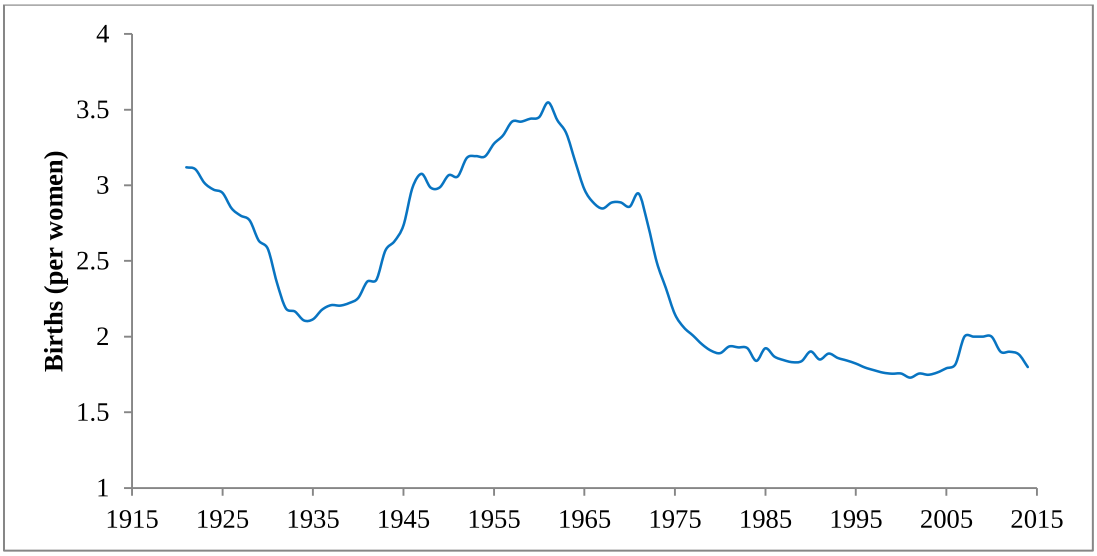
[3]The definition for Australian Baby Boom was given in section 1.2.
[4]Describe in detail in the subsequent sections.



Source(s): ABS Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS, Australian Demographic Statistics, 2013 (cat. no. 3101.0) and author's calculation for population growth

Figure 2.2: Australia's population growth, 1914-2013

2.3 Fertility Rates and Birth Rates in Australia



Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001) and ABS, Births, 2014 (cat. no. 3301.0)

Figure 2.3: Australia's total fertility rates (TFR), 1920-2014

In the early 1920s the total fertility rate (TFR) in Australia was slightly above 3 babies per woman, but during the Great Depression it fell and reached 2.1 babies per woman in 1934. In the aftermath of the World War II, the number of births in Australia showed a dramatic increase as seen in Figures 2.3 and 2.4. In 1947 the fertility rate exceeded three babies per woman resulting in 182,400 births. This year is the first peak of the Baby Boom. During the 1950s and early 1960s total fertility rates exceeded 3 babies per woman, with the highest being 3.55 in 1961. Since then there has been a declining trend and from 1978 to 2006 the rate was below 2 births per woman. A sharp decline occurred during 1972-1980 followed by stable rates in the 1980s and 1990s albeit with slight fluctuations.

The average fertility rate during 1946-1965 stands at 3.23 babies per woman. The preceding and succeeding twenty years averages are 2.42 and 2.32 respectively (Table 2.1). In accordance with the fertility rates, the number of births shows an increasing trend during the Baby Boom with the peak of 240,000 births in 1961.

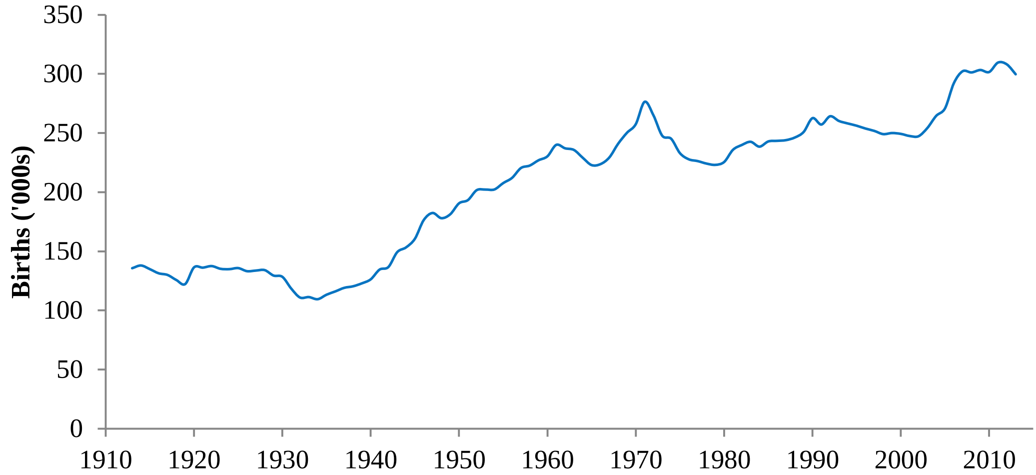
Table 2.1: Average fertility rate (per woman)

Time period	**Average fertility rate**
1926-1945	2.42
1946-1965	3.23
196-1985	2.32
1986-2005	1.81

Source(s): Australian Bureau of Statistics (ABS) Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001) and ABS, Births, 2014 (cat. no. 3301.0)

Figure 2.4 further demonstrates the effects of the Baby Boom on the number of births. The large cohort of female babies born in 1947 resulted in the median age of mothers being 25 years in 1971. Australia records a birth bubble in 1971, the largest number of births of 276,400 babies in its history as a result of the first Baby Boomers reaching reproductive age. Australian Bureau of Statistics (ABS) defines this year as the first echo of the Baby Boom[5].

[5] Those who were born in 1971 were the children of the first Baby Boomers.

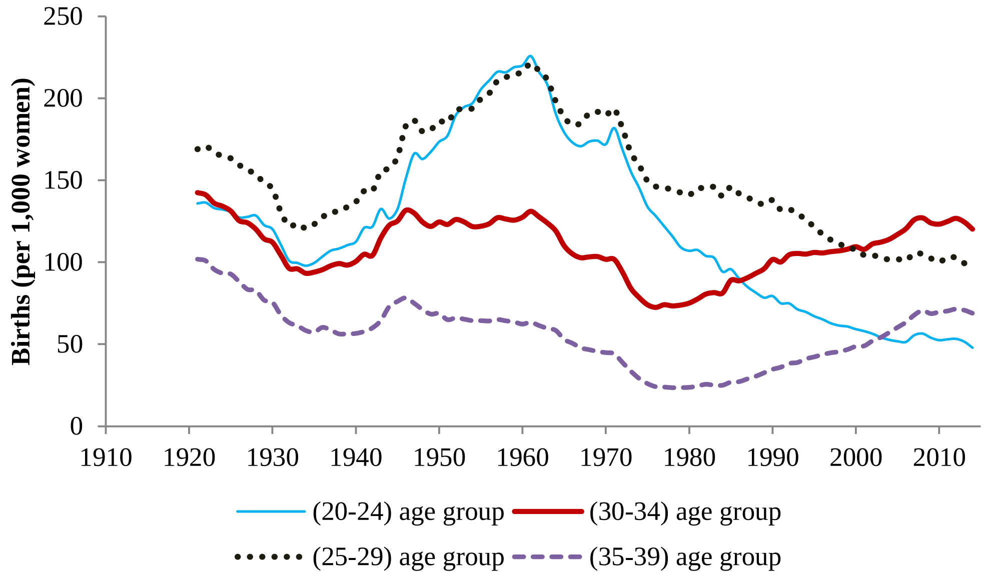


Source(s): ABS, Social Indicators, Australia, 1992 (cat. no. 4101.0), ABS, Australian Social Trends, 2002 (cat. no. 4102.0) and ABS, Australian Social Trends, 2012 (cat. no. 4102.0) and ABS, Births, 2014 (cat. no. 3301.0)

Figure 2.4: Australia's registered births, 1913-2014

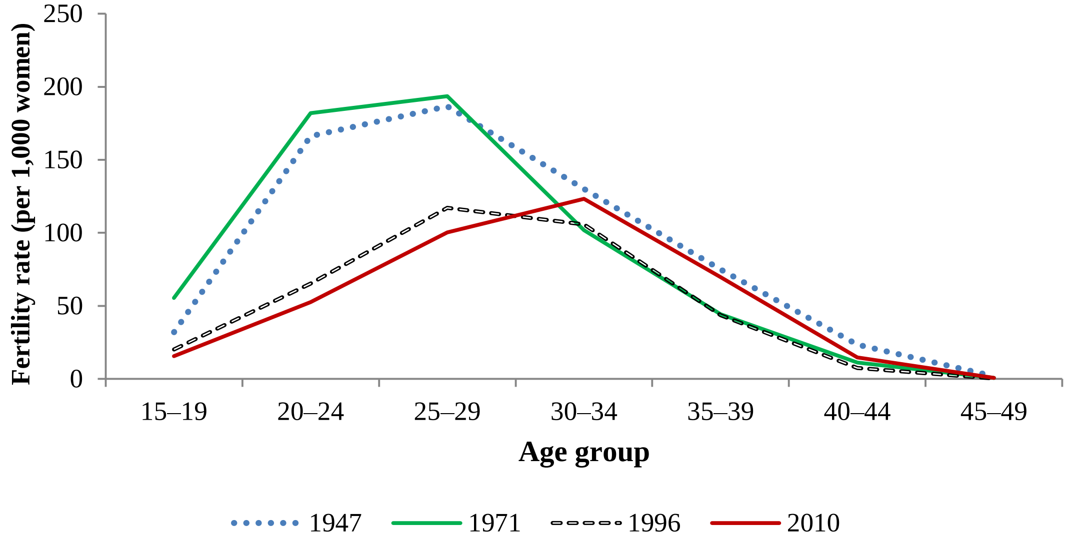
Figure 2.5 shows the age specific fertility rates. Four age groups are specified to record fertility: 20 – 24 years, 25 – 29 years, 30 – 34 years and 35 – 39 years. During the Baby Boom period, all four age groups showed their highest fertility rates. Women between 25-30 years show the highest fertility rates in most of the times. Whilst women aged 20-24 years had the second highest fertility rates during the Baby Boom, this age group exhibited a sharp decline compared to other age groups in the following years. From 1980s fertility rates were decreasing in the younger aged groups of 20-29 years but they were increasing in the 30-39 years age groups. That is, while the fertility rates of younger women have shown a declining trend since the mid1980s, older women have shown an increasing trend. For example, from 1947-1971 women aged 25-29 years had the highest fertility rates, but from 2001 onwards women aged 30-34 years have shown the highest fertility rates.

The average fertility rates of younger women aged 20-24 years declined by more than 100 to 72.1 births per 1,000 women during 1980-2010 from the average of 176.8 births per 1,000 women during the period of 1946-1979. Similarly, the corresponding averages of women between 25-29 years changed from 186.6 to 122.1. The average fertility rates of women aged 30-34 and 35-39 also declined though the magnitudes are substantially lower compared to the younger women. The declines are 7 and 10 per 1,000 women for the age groups 30-34 years and 35-39 years respectively.



Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001) and ABS, Births, Australia, 2014 (cat. no. 3301.0)

Figure 2.5 Australia's age specific fertility rates, 1921-2014

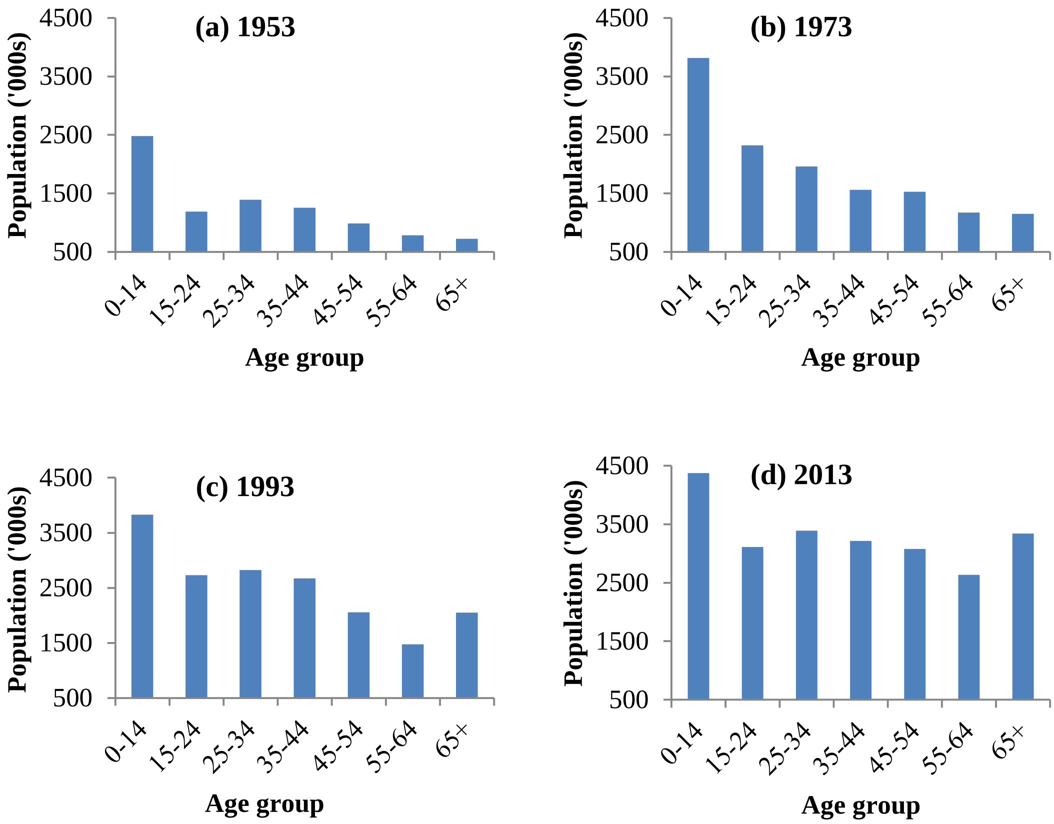


Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001) and ABS, Births, Australia, 2012 (cat. no. 3301)

Figure 2.6: Fertility rates for selected years

Figure 2.6 illustrates the changing pattern of fertility of Australian women. During and soon after the Baby Boom, early fertility is observed whereas the two most recent decades exhibit evidence of delayed fertility. As discussed above a baby echo is seen in 1971 as a result of the first Baby Boomers reaching reproductive age, but a second baby echo is not evident. The declining trend of fertility rates among younger women limits the likelihood of larger families leading to a slow population growth in the future.

2.4 Demographic Transition in Australia: 1953-2013



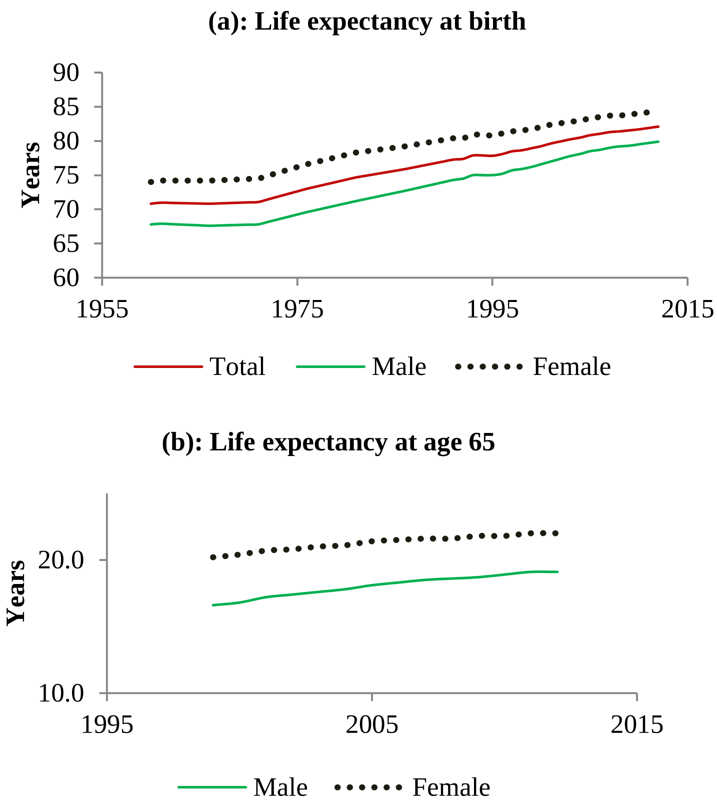
Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013 (cat. no. 3101.0) and author's calculation for population in different aged groups

Figure 2.7: Australia's changing demographic structure

The changing demographic structure in Australia towards a more aged population can be seen in Figure 2.7. The percentage of population aged 65 years or over (65+

hereafter) increased from 8% in 1953 to 14% in 2013. The number of people aged 65+ years was less than 1 million (725,400) in 1953. However, it reached above 2 million (2,052,648) in 1993 and above 3 million (3,338,168) in 2013. In contrast, the percentage of younger people in the population (0-24 years) declined from 42% in 1953 to 32% in 2013.

In 1953 and 1973 the population aged distributions are right skewed. However, the skewness has gradually disappeared and by 2013 the right tail has filled with middle and old aged population. In 2013, the third largest cohort consists of people 65+ years (3,338,168), which is slightly lower than the second largest cohort of those aged 25-34 years which is 3,387,285.

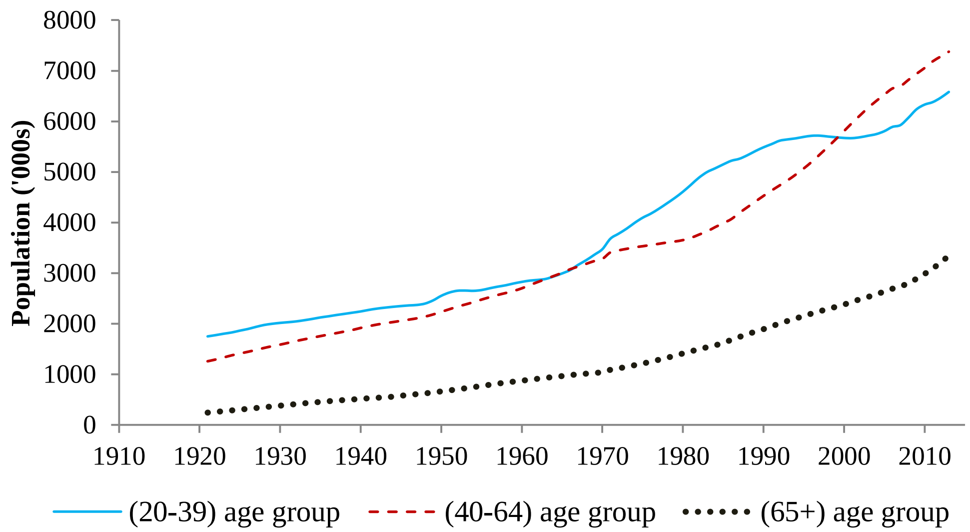


Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013 (cat. no. 3101.0) and ABS Deaths, 2012 (cat. no. 33302.0)

Figure 2.8: Australians' life expectancy

The increasing life expectancy among the Australians, both in life expectancy at birth and at age 65, is one of the key factors driving the demographic shift. Life expectancy at birth increased from 70.9 years in 1962 to 82.1 years in 2012. During the period 1982-2012 the life expectancy for females and males improved 0.2 years and 0.3 years respectively on average. This trend is further evident in the increased life expectancy at age 65 years. Life expectancy at age 65 increased to 19.1 and 22.0 years for males and females respectively in 2012 (Figure 2.8).

This changing demographic structure in Australia can also be seen in Figure 2.9.As the Baby Boom cohort moves through the age structure, it can be seen first that the youngest age group increases in size starting in mid-1960s, then the middle age group increases in sizes as the 20-39 age group shrinks in size. In 1966, the first of the Baby Boom cohort turned 20 and they turned to age 40 years in 1986. Similarly, the last cohort of the Baby Boomers who were born in 1965 turned to age 20 years in 1985 and to 40 years in 2005.



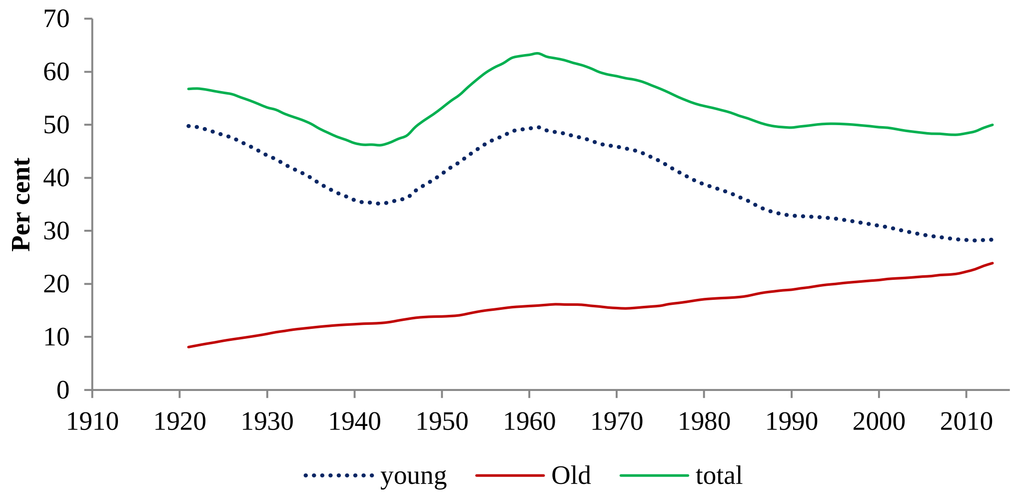
Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013 (cat. no. 3101.0) and author's calculation for different aged groups

Figure 2.9: Age distribution of Australia's adult population

Further, the effect of the baby echo that took place in 1971 began to alter size of the (20-39) aged group from 1991 to 2010. Thus, the combined effect of the Baby Boom and baby echo substantially alters the size of the two aged groups, (20-39) and (40-64). As a result, the period 1970-2000 show a considerable gap between populations in the aged groups (20-39) and (40-64) years compared to the time period before 1970. In 2000, the two population distributions for aged (20-39) and (40-64) groups intersects and the population in the aged group (40-64) increase in a higher rate than that of (20-39) aged group. Also, the population 65+ increased steadily. The number of retirees increased by 32% from 2.5 million in 2003 to 3.3 million in 2013. Thus the effects of the Baby Boom along with the changing fertility patterns (Figure 2.6) and increasing life expectancy drastically change the age structure of the Australia's population.

2.5 Age Dependency Ratios in Australia

A dependency ratio indicates the ratio of a non-working proportion of the population to the working proportion. The young age dependency ratio is defined as the population aged 0-14 divided by the population aged 15-64 years. Similarly old age dependency ratio is the population aged 65+ divided by the population aged 15-64 years. Age dependency ratio indicates the potential burden to those in the working age population of aged 15-64 years; the smaller the ratio, the smaller the burden.



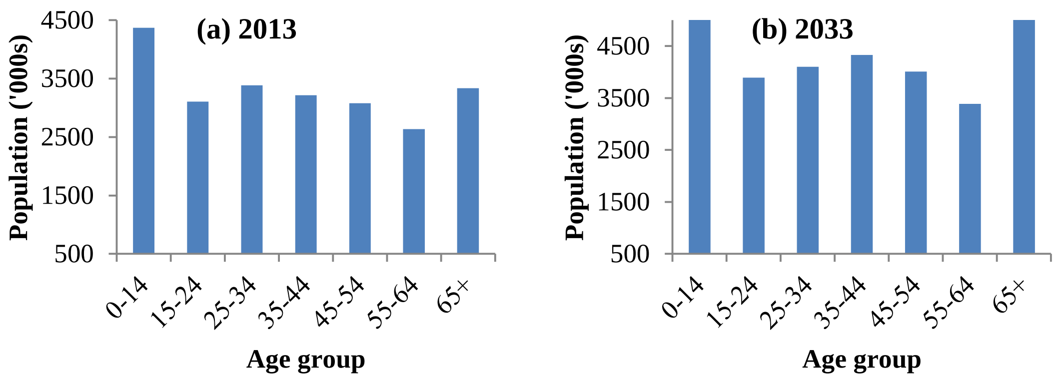
Source(s): ABS, Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013 (cat. no. 3101.0) and author's calculation for age dependency ratios

Figure 2.10: Australia's age dependency ratios, 1920-2014

The effects of the Baby Boom on these dependency ratios can be seen in Figure 2.10. During the Baby Boom, the young age dependency ratio shows a humped shape with the peak in the mid-1960s. After the mid-1960s the young age dependency ratio falls gradually. Over the period 1971 to 2013 the old age dependency ratio increased from 15.4% to 23.9% and young age dependency ratio fell from 48.5% to 28.3%. The declining young age dependency ratio implies that fewer young persons will enter into the labour force to support for growing old population. From the mid-1980s to 2010 all the Baby Boomers are of working age and the impact is a low total dependency ratio from 1985 to 2010.

2.6 Population Projections and Projected Effects of the Baby Boom in Australia

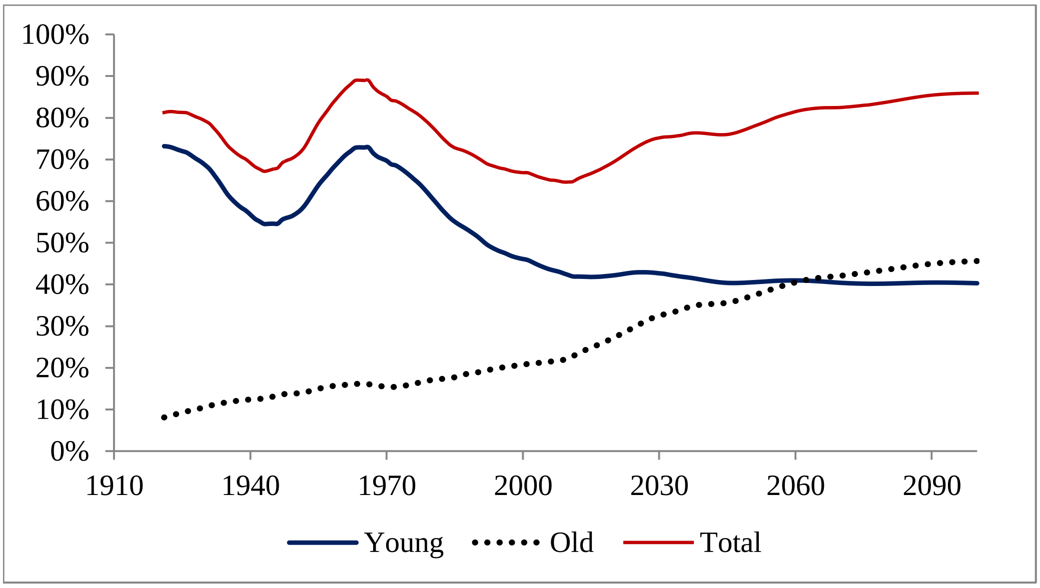
The Australian Bureau of Statistics presents population projections for the period 2012-2100 using three different sets of assumptions. The three series are series A, B and C. In this analysis series B population projections is used as the assumptions of this series relate closely to the research objectives. Series B largely reflects the current trends in fertility, life expectancy and net overseas immigration ("Population Projections Australia", 2012).



Source(s): Australian Bureau of Statistics (ABS), ABS Australian Demographic Statistics, 2013(cat. no. 3101.0), ABS Australian Population Projections (cat. no. 3222.0) and author's calculation for population in different aged groups

Figure 2.11: Demographic transition 2013-2033

The population is projected to grow by about 15 million over the next 50 years though the growth rate is expected to fall. Australia's average population growth rate for the period 2002-2012 stands at 1.5%. However, it is projected to decline to 1.0% by 2045 and 0.5% by 2100. The ageing of the population is projected to continue in the future. The percentage of population 65+ is expected to increase from 14% in 2012 to 22% and 25% in 2061 and 2100 respectively. Further, the proportion of the population aged 85 years and above was 2% in 2012. However, the ABS projects a rapid increase to 5% in 2061 and 6% in 2101 for the 85+ population group. Figure 15 depicts the future population transition from young to old. The largest population group is projected to be made up of people aged 65 and above in 2033, corresponding to the effects of the Baby Boom generation. The 65+ age group is projected to experience a 78% increase in size from 2013 to 2033.



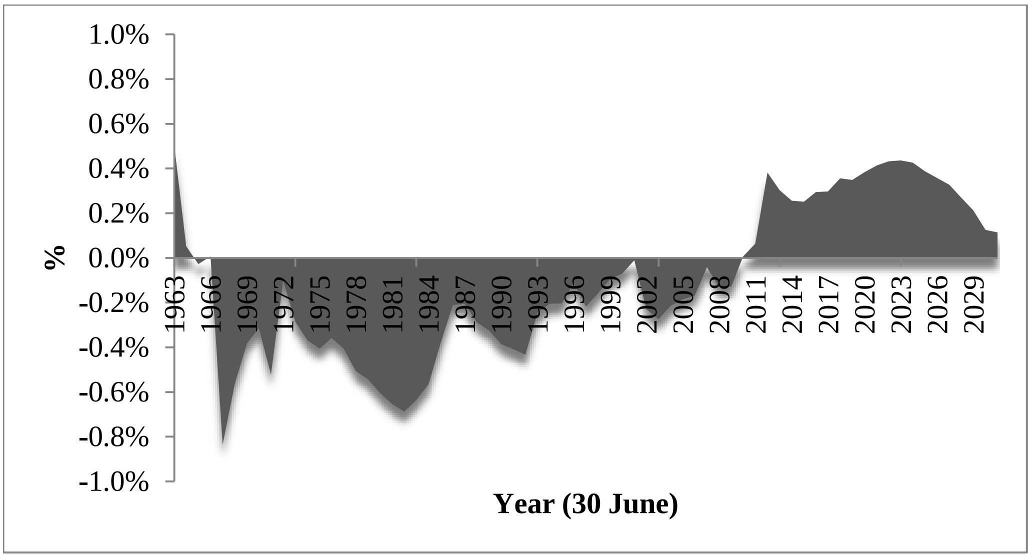
Source(s): Australian Bureau of Statistics (ABS) Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013 (cat. no. 3101.0), ABS Australian Population Projections (cat. no. 3222.0) and author's calculation for age dependency ratios

Figure 2.12: Historical and projected age dependency ratios

Whilst the old age dependancy ratio is projected to increase, the young age dependency ratio is projected to decrease (Figure 2.12). The old age dependancy ratio is projected to increase from 21% in 2010 to 33% in 2030 and 41% in 2060.

The total dependency ratio follows the trend of the old age dependancy ratio and it is projected to reach 76% and 82% by 2033 and 2063 respectively.

Figure 2.13 indicates the gap between the total population growth and growth rate of the segment of population aged 20-64 years, which was defined as the working age population in this research. The negative gap from 1966-2010 indicates the labour force was growing at a higher rate than the total population as a result of Baby Boomers entering the labour force. However, from 2011 to 2013 the gap is positive and it is projected to be positive in the next two decades. Also, the gap is projected to be more pronounced in 2020s. The positive gap indicates that the labour force will be growing in a slower rate than the population growth. This is because, as described in an earlier section, all the Baby Boomers will be over age 65 years in next two decades. The observed and projected changing ageing structure emphasizes the burden on the working age population in the future.

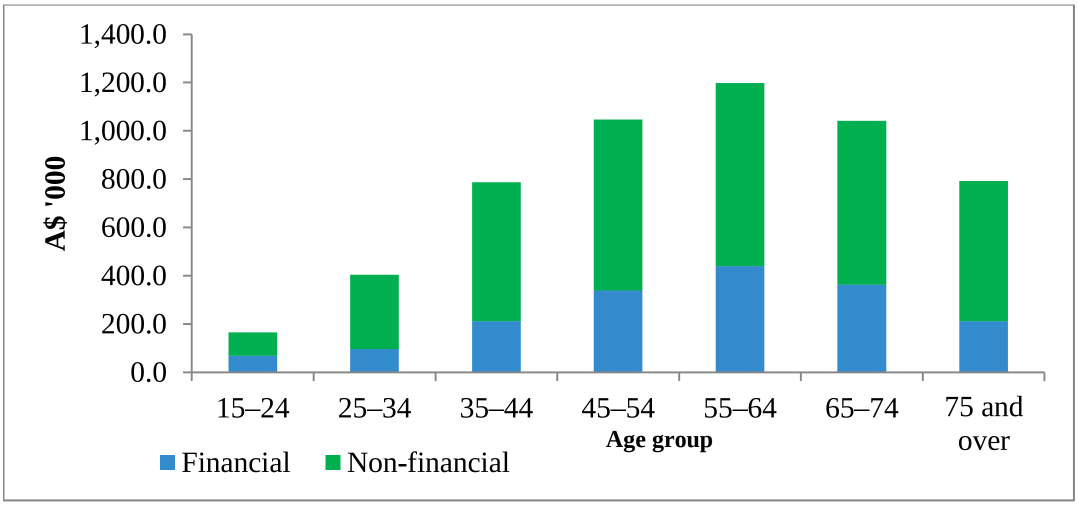


Source(s): Australian Bureau of Statistics (ABS) Australian Historical Population Statistics, 2008(cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013(cat. no. 3101.0), ABS Australian Population Projections (cat. no. 3222.0) and author's calculation for growth rates and the gap

Figure 2.13: Gap between total population growth and growth aged 20-64 years

2.7 Australian Asset Ownership Patterns across the Life Cycle

The survey reveals that the mean value of households' net worth of assets in 2011-2012 was A$ 728,000 compared to the mean value of A$ 759,000 in 2009-2010 in real terms (The net worth of assets is defined as the value of assets minus the value of liabilities). Out of the selected life cycle groups, those aged from 55 to 64 years have the highest mean household net worth of assets. Nearly all Baby Boomers were in this age category in 2011-2012. Also, households comprised of those over 65 years had lower net worth than those in the 55-64 years age group. This partly reflects the run-down of assets to support consumption in retirement. Households' assets include both financial and non-financial assets. As shown in Figure 2.14, on average households hold a higher percentage of non-financial assets than financial assets in each age group.

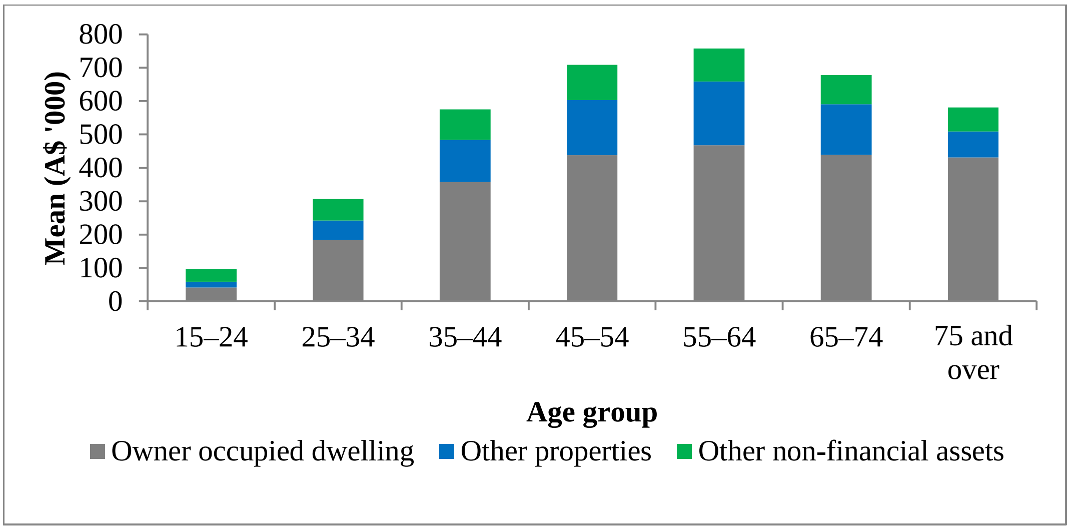


Source(s): Australian Bureau of Statistics (ABS), Household Wealth and Wealth Distribution, 2011-12 (cat. no. 65540DO001)

Figure 2.14: Mean value of asset ownership (2011-12)

2.8 Ownership of Non-Financial Assets

Non-financial assets include owner-occupied dwellings, other properties, contents of dwelling and vehicles. Owner occupied housing comprises 43% of households' total assets. This is the largest form of assets held by households. The tendency of buying houses after age of 25 years is apparent as over 60% non-financial assets are owner occupied housing for all the age groups other than the younger age group of 15-24 years (Figure 2.15).



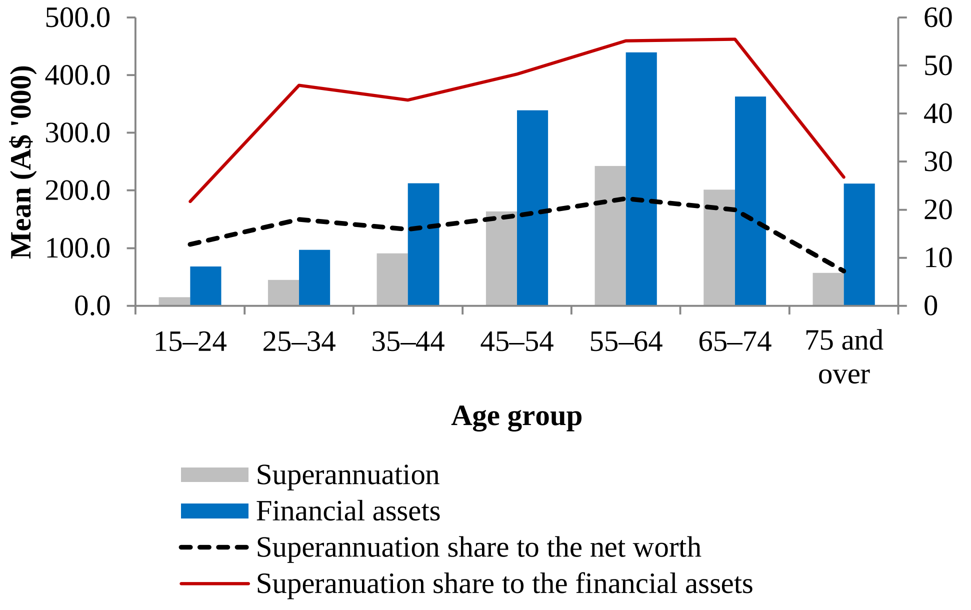
Source(s): Australian Bureau of Statistics (ABS), Household Wealth and Wealth Distribution, 2011-12 (cat. no. 65540DO001)

Figure 2.15: Mean value of non-financial assets (2011-12)

The 55-64 years age group has the largest mean value of owner occupied housing followed by the 45-54 years age group. Further, the age group 45-64 years holds the highest amount of housing assets, both the owner occupied and other, which includes private rental properties, holiday homes and some commercial property. The mean value of properties other than owner occupied housing is A$ 165,200 and A$ 191,100 for the age groups 45-54 and 55-64 years respectively. Also the mean value of owner occupied housing is A$ 437,600 and A$ 467,700 for these two age groups. That is, Baby Boomer households hold nearly 50% of Australia's owner occupied housing stock despite that these two age groups represent only 25% of the Australian population.

2.9 Ownership of Financial Assets

Similar to the picture for non-financial assets, Baby Boomers (45-64 years old) hold above 50% of financial assets. The largest proportion of financial assets is in the form of superannuation funds for each group between 25 and 74 years. Also, superannuation is the largest type of asset for each age category after the owner occupied housing. Figure 2.16 depicts the mean value of the superannuation and financial assets (left axis) and the shares of superannuation funds to the total financial assets as well as to the net worth (right axis) for each age group. The 54-64 years age group has the highest mean value of superannuation funds and it is becoming the most important source for generating retirement income for Australians.



Source(s): Australian Bureau of Statistics (ABS), Household Wealth and Wealth Distribution, 2011-12 (cat. no. 65540DO001)

Figure 2.16: Value of superannuation, financial assets and shares of the superannuation

2.10 Conclusion

The trend of ageing in the Australian population is evident over recent decades and it is predicted to be the most dramatic change in the population structure over the next fifty years. The key factor is the Baby Boomer generation's shift into retirement, beginning in 2011. In addition, increasing life expectancy and low fertility rates exacerbate the situation. The age dependency ratio is projected to increase rapidly to

33% by 2030, increasing the burden to the working age population. The median age of the Australian population is projected to increase from 37.3 years in 2012 to 43.3 years in 2061, while mortality continues to decline and life expectancy continues to increase. For example, a person born in 2012 is expected to live 29 years after she reaches 65 years. This raises questions about optimal retirement ages, and access to superannuation savings and government funded pensions. The positive gap between the growth rates in the total population and the working age population (between 20-64 years) from 2011 onwards indicates that the labour force will be growing at a slower rate than the population. The size of the gap will be more pronounced in the 2020s, indicating that the potential burden to the working age population will increase. Further, the likely consequences of the substantial increase in the ratio of retired population to the working age population would be a combination of higher taxes, reduced social security benefits and/or larger budget deficits.

The largest share of assets held by Australian households is owner occupied properties. The Baby Boom generation has a higher level of housing wealth than previous generations and over the next two decades this store of wealth will be in the hands of the elderly. The highest share of financial assets is in the form of superannuation funds and is the largest form of assets after the owner occupied housing. Baby Boomers, who represent 25% of the Australian population own approximately 50% of the assets and net worth, are moving into retirement from 2011.

CHAPTER 3: A REVIEW OF THE LITERATURE

3.1 Introduction

The post-World War II Baby Boom in developed economies has had a significant impact on demographic structures. This aroused a fear that asset markets will be severely affected as a result of the Baby Boomers' retirement. The relevant literature thus investigates the impact of demographic changes, focusing on the effects of the Baby Boom generation on asset prices from different perspectives, especially the question of the asset meltdown hypothesis (AMH). The AMH posits that an increasingly-large working age cohort will save through investing in asset markets and thereby exert an upward pressure on asset prices and then at their retirement will start to dis-save, primarily through selling previously accumulated assets and thus put downward pressure on asset prices.

The motivation for the research on demographics and asset prices is the possible house price meltdown, first predicted by Mankiw and Weil in 1989, and applied to the ageing of Baby Boomers in the United States. Mankiw and Weil (1989) related the increase in house prices during the 1970s and 1980s in the United States to the prime saving years of the Baby Boomers and then suggested a reverse effect on house prices when the Baby Boomers retired. Based on this simple intuition they predicted 47% decrease in the real house prices in the United States in 2010. This extreme prediction generated an important and sustained debate over the relationship between population ageing and house prices. Thus, since the end of the 1980s, theoretical and empirical research measuring the direction and magnitude of the impact of ageing on asset markets, both housing and financial, has been evolving. The studies are highly diversified in terms of the theoretical model specification, data, empirical methodology and results.

This chapter surveys both the theoretical and empirical literature examining the impact of population ageing on asset markets including critical reviews of the methodologies used, explanations, limitations and an evaluation of contradictory results. A survey of the literature is appropriate at this time to summarise what we already know about the dynamics of population ageing and the impact on housing and financial asset prices/returns and to identify the gaps and shortcomings in the existing studies. The identification of gaps and shortcomings provides a direction to develop research questions, formulate research objectives and to develop a more rigorous methodology for this study.

Following the introduction, section 3.2 of the chapter reviews the theoretical literature classified in two categories, simulations and analytical results. Section 3.3 reviews the empirical literature, which is divided into two parts. The empirical studies related to housing assets are discussed in section 3.3.1 and financial assets are discussed in section 3.3.2. The last section presents a summary of conclusions drawn from the chapter.

3.2 Review of the Theoretical Literature

To understand the effect of demographic changes stemming from the Baby Boom generation on asset markets, it is useful to start with theories that link an individual's age, consumption and saving decisions. Two such theories are the permanent income hypothesis (Friedman, 1957), and the life cycle hypothesis (Modigliani and Brumberg, 1954; Ando and Modigliani, 1963).

The permanent income hypothesis does not directly link consumption to ageing however it gives some insight into consumption decisions related to income. An individual's consumption depends on her permanent income rather than the current disposable income. Therefore, if an individual foresees a decline in future income she reduces consumption and saves for future. Similarly, if she predicts a temporary increase in their income she will save some of it rather than spending all additional income on consumption. Therefore, the core of the permanent income hypothesis is that individuals smooth consumption over their life cycle. With this foundation, the life cycle hypothesis posits that individuals consume a portion of their income during their working age and save for their retirement. Accordingly, it is plausible that the working-age cohort will save for retirement through investing in housing and financial assets and will fund their retirement by selling those assets when they come to retirement age. Thus the size of the working-age cohort will have an impact on asset prices. That is, an increase in the size of the working-age cohort will push up the asset prices and such prices will decrease when the size of the same cohort becomes small. This variation produces a relationship between asset prices and demographic structure.

Applying this idea to the ageing of Baby Boomers several researchers suggest that the steep increase in the U.S. asset prices in the 1990s is attributable to the growing demand for assets as Baby Boomers began to save for their retirement as they reached prime saving ages. The same reasoning implies the opposite effect when Baby Boomers reach retirement age. This intuition gave rise to the asset meltdown hypothesis.

Overlapping Generations (OLG) models (Samuelson, 1958; Diamond, 1965) are the natural framework to model an individual's distinct financial needs at different periods of life, such as borrowing when young, saving for the retirement in the middle-aged life and dis-savings at the retirement. Theoretical studies suggesting a plausible link between asset prices/returns and the demographics adopt different modelling structures. The results from such modelling can be either from simulations or analytical. The principal approaches are examined below according to these two categories.

3.2.1 Theoretical Models with Simulation Results

Yoo (1994a) develops a simple OLG model assuming that a given agent has three different time periods; childhood (T_c), retirement (T_a) and death (T_i). The agent maximises the lifetime utility subject to the budget constraint and in equilibrium aggregate consumption equals to the aggregate endowment.

$$max \sum_{s=1}^{T_i} (1+\delta)^{1-s} \frac{c_{t+s-1,s}^{1-\rho}}{1-\rho} \qquad (3.1)$$

Subject to

$$a_{t+s-1,s} = (1 + r_{t+s-1})a_{t+s-2,s-1} + e_s - c_{t+s-1,s} \quad (3.2)$$

In equilibrium

$$\sum_{s=1}^{T_i} \emptyset_t(s)\, e_s = \sum_{s=1}^{T_i} \emptyset_t(s) c_{t,s} \quad (3.3)$$

where $c_{t,s}$ and $a_{t,s}$ are consumption and asset holdings of an agent aged s years in period t, r_t is the rate of return of holding an asset between periods $t-1$ and t, e_s is the non-storable endowment of agent of s years, δ and ρ are the discount rate and the coefficient of risk aversion respectively and $\emptyset_t(s)$ is the age distribution of the population in period t.

Equations (3.1) and (3.3) are solved for different age distributions to find the relationship between age distributions and asset returns. The simulation results indicate that age structure has an influence on asset returns in the United States. Also, a 1% rise in the percentage of population over the age of 45 years leads to a reduction in asset returns of 2%. Yoo (1997) further develops the model to incorporate the age distributions generated by the stylised Baby Boom in the United States. The results show the clear impact of Baby Boomers on asset prices, raising asset prices by 33% above the steady state. In addition, the effects of the Baby Boom induce a 10% permanent increase in asset prices. However, Yoo's simulation results focus on a single steady state and ignore the adjustment process from one steady state to another.

When examining the impact of demographics on asset markets it is important to explore which factors are likely to augment or attenuate the impact on asset prices and asset returns. The rational expectations assumption poses a vital challenge to the simple model outlined above. Yoo (1997) extends the model to replace the static expectations assumption with one of perfect foresight. Accordingly, the model assumes that individuals take into account their predictions of future asset prices when they make their saving decisions. Simulations with the perfect foresight assumption imply that within the first 15 years asset prices rise 32% compared to

19% when the static expectation assumption is used. Baby Boomers depress asset prices sooner under rational expectations assumptions.

Further, the benchmark simulation model assumes that supply of assets is fixed. Yoo (1997) incorporates supply effects by replacing the non-storable endowments in equation (3.3) by total wages, which are derived using a Cobb-Douglas production function. This modification attenuates the effect of Baby Boomers on asset prices to 15%, compared to 33% in the benchmark model but without changing the sign or timing of the relationship between age distribution and asset prices.

In the context of a closed economy and assuming a fixed supply of capital (K) and saving rate (s), Poterba (2001) sketches a very simple OLG model of the effects of demographics on asset prices and asset returns in the United States. The two periods OLG model assumes that individuals work when they are young and retire when they are old. Assuming N_y number of young workers and the relative price of fixed assets in terms of a numeraire good (p), the demand for assets ($N_y \times s$) satisfies the following equilibrium condition.

$$N_y \times s = p \times K \tag{3.4}$$

The model assumes a fixed capital supply in each period. Hence the price of capital is derived using formula (3.4) directly and it is proportional to the number of workers in each period. As a result, this formulation leads to the conclusion that the high proportion of young workers due to the Baby Boom drives up the price of capital and hence asset prices. The subsequent shrinking of the size of the working age cohort and increase in the retired population leads to a decline in asset prices. However, Poterba (2001, p. 566) states that 'the foregoing model is simple, and it seems compelling in many popular accounts, but it neglects many important realities of asset pricing'.

Brooks (2002) augments a real business cycle model with an OLG model assuming an individual has four periods; childhood, young working age, old working age and retirement[6]. The assumption of four life periods allows the maximization of the expected utility function of a given young worker to be subject to three budget constraints. Assuming that agents are not active decision makers in childhood, the budget constraints correspond to young working age, old working age and retirement. Similar to Yoo's (1997) extended model, the endowments in the budget constraints consists of wages, assuming that output is generated by a Cobb-Douglas production function. The model incorporates both risky and risk free assets. This framework enables Brooks (2002) to investigate the effects of demographics on risk premiums. Brooks (2002) treats population growth and technology shocks as uncertain and exogenous.

The Brooks's (2002) simulation exercise measures the impact of changes in the U.S. population structure on asset prices, which the results show that old agents are risk aversion. Young workers invest in risky capital while old workers invest in safe bonds. Thus the results indicate that when the Baby Boom generation is young and working (the 1980s) risk-free returns rise and when they reach retirement the same falls. The retirement of Baby Boomers will raise the capital-labour ratio by 15% above the steady state value in 2020. The returns on stocks and bonds will be 0.47% and 0.55% below the steady state value in 2020 respectively. Overall, Brooks (2002) concludes that although returns on Baby Boomers' savings at their time of retirement is 1% lower compared to the current rates, they will not be worse off than their parents or children.

Rational agents anticipate the impact of the changing ageing structure on asset markets. Geanakoplos, Maggil and Quinzii (2004) apply this concept and augment the OLG model and show that irrespective of whether agents are myopic or far-sighted about the future demographics changes, a large middle-aged cohort will push up stock prices. They further show that agents' prior knowledge of the changing ageing structure reinforces the effect. This contradicts Poterba's (2001) argument that

[6] Each period represents 20 years.

incorporating rational expectations into the model negates the effects of demographics on asset prices.

Geanakoplos et al. (2004) consider a three periods (young childhood, middle age and retirement) OLG exchange economy with a single good. The model includes riskless bonds and risky assets. Individuals have the options to redistribute their income over these two financial instruments. Further, Geanakoplos et al. (2004) extend the model to allow for realistic age-income patterns, and accommodate the following; social security, bequests motives and dependent children for young agents, endogenous wages and dividends and the presence of adjustment costs. The results suggest that the effect of demographic changes on the price-earnings ratio is larger than the previous theoretical models suggest. The presence of children and social security reinforce the demographic effect on asset prices though bequests weaken the effect.

The theoretical literature and simulation evidence discussed so far only focuses on financial asset prices and financial asset returns. Guest and Swift (2010) develop a life cycle simulation model and investigate the dampening effect from ageing on house prices in Australia. The model is based on several assumptions and assumes a life cycle of thirteen periods of five years for each household. The starting age is 20 and the ending age is 85 years. The Guest and Swift (2010) model takes the housing supply elasticity as given. They focus only on the demand for housing services while aiming to isolate the effect of population ageing on house prices. Further, the model does not take into account any investment demand for housing and assumes that households purchase houses only as a source of housing services.

Households maximise lifetime utility given perfect foresight about their labour income and interest rates. At the same time they expect house prices will remain at current levels. The target bequest is exogenously given and is a constant fraction of lifetime income. Households’ preference over the ratio of housing to other consumption is not a constant and varies over the life cycle. Guest and Swift (2010) produce simulation results based on set of exogenous variables; labour productivity growth, the labour force participation rate, population shares and real interest rate.

The most crucial assumption in simulation is that, if there is no influence from demographic changes, housing supply and housing demand grow at the same rate. This rate equals to the labour productivity growth of 1.5% which is exogenously given.

The life cycle model shows a drop in house price during the 1960s and 1970s and a rise in the late 1980s and 1990s. However, the model predicts the house price increase in the 1990s at a lower rate compared the actual rates reported. Also, the house price peaks in 2005 and they predict a gradual fall of 3.5% to 2050. When the model assumes that households do not trade down but remain in at least the same-sized owner occupied housing from age 60 years to death, the ageing effect on house prices reduces to a fall of 1.8%.

3.2.2 Theoretical Literature with Analytical Results

Whilst studies in section 3.2.1 provide simulation based evidence for a plausible link between changing demographic structure and asset prices, the following studies produce analytical results.

Abel (2001) develops a rational expectations general equilibrium model with a bequest motive to investigate the effect of the Baby Boom on asset prices and hence the predicted AMH. The bequest motive implies that individuals hold assets at the time of their death. Thus at any given time in an economy the amount of savings and demand for capital will be higher in the presence of bequest motive than without it. In addition, the stock of capital is higher in each time period with a bequest motive. As a result in Abel’s (2001) model the price of capital at equilibrium does not change with the introduction of a bequest motive compared with the case of without bequest motive. Further, Abel’s model allows for endogenous production of capital in that the model includes an aggregate supply curve for capital.

The analytical results indicate that the Baby Boom generation drives up stock prices and anticipate a decline in stock prices when Baby Boomers retire in the United States. These results are not attenuated with the introduction of bequest motives to the model. This is because the bequest motive does not affect the equilibrium price of capital. However, Abel's (2001) conclusions contradict Poterba's (2001) empirical results that we discuss in section 3.3.2 of the chapter. This is despite that both (Poterba and Abel) having consistent observations about the asset holdings of retired people. Both observe that in retirement individuals hold on to a proportion of assets that they have accumulated during their working life. This held portion is considerably higher than that predicted by a simple life-cycle model.

Abel (2003) provides further analytical results using an OLG closed economy model. He modifies the Diamond's (1965) model with production and capital accumulation in two ways. The first is to allow for stochastic variation in the population growth rate in contrast to the assumption of a constant population growth rate in Diamond's model. Thus, the model treats the birth rate as an independently and identically distributed random variable. The second is to make the price of capital endogenous. Diamond's (1965) model assumes that one unit of capital is used either to produce one unit of consumption or to create one unit of capital. In the modified version, Abel (2003) capital goods are transformed into consumption goods assuming a convex adjustment cost of technology. The analytical results show that national income and investments are high when the working age group is a large proportion of the population. Therefore, the effect of the Baby Boom is to raise the price of capital leading to an increase in the price of stocks. However, the increase in price of capital is not persistent and when the working age group becomes small as a result of the retiring Baby Boomers, the price of capital falls. Thus, the price of capital is subject to mean reversion.

Further, Abel's model includes the effects of social security payments either on a pay-as-you-go basis or a fully-funded basis or a combination of both. The motivation to include social security payments is that the model does not have a bequest motive as it only has two periods, young and old. The model assumes that the social security system owns a trust fund to accumulate capital. The trust fund models the saving behaviour of consumers. This model does not show a long run impact on the price of capital due to the social security system. However, there is an effect on the investment-output ratio in the long-run because social security can be used to change national saving and investments.

Goyal (2004) uses a different theoretical approach that considers the impact of a changing demographic structure on both inflows and outflows from the asset markets and asset returns. He first analyses the intertemporal consumption-investment problem of a single agent and then aggregates the solution in an OLG framework.

The model has two aspects. First, Goyal assumes that the distribution of returns on risky assets is exogenous and hence a partial equilibrium analysis takes place. Second, the model incorporates endogenous asset returns. The former shows the effect of the changing demographic structure on inflows and outflows from the stock market, while latter measures the impact on stock prices. The results indicate a positive impact on asset market inflows from an increasing share of middle aged people. Also, the increase in the share of the old age population increases outflows from the asset market. With regard to asset returns, the increasing share of the middle aged drives up asset returns while the increase in the old aged cohort pushes down the asset returns.

In Abel's (2001) model with a variable aggregate supply of capital, the dynamic behaviour of price of capital shows the effect from demographic factors. This is shown in equation (3.5).

$$lnp_t = \frac{1}{1+\lambda} lnp_{t-1} - \frac{1}{1+\lambda} lnk + \frac{1}{1+\lambda} ln\mu_t \quad (3.5)$$

where λ is a constant, $k > 0$ is a positive constant, $\mu_t = \frac{No.of\ births\ at\ the\ beginning\ of\ time\ t}{No.of\ biths\ at\ the\ beginning\ of\ time\ t-1}$. If $\lambda > 0$, the equation shows that the increase in birth rate μ_t leads to increase in the price of capital, p_t.

Brunetti and Torricelli (2010) extend Abel's (2001) model so that an aggregate supply stock (K) is carried into period $t+1$. K_{t+1} is a function of both price of capital and lagged birth rate as given in equation (3.6). α is a real number which represents the sensitivity of the capital supply growth rate to the demographic change.

$$K_{t+1} = kK_t p_t^{\lambda} \mu_{t-1}^{\alpha} \tag{3.6}$$

With the above modification to the aggregate supply curve, the price of capital possesses the equilibrium dynamics as given in equation (3.7) below.

$$lnp_t = \frac{1}{1+\lambda} lnp_{t-1} - \frac{1}{1+\lambda} lnk + \frac{1}{1+\lambda}\left[ln\left(\frac{\mu_t}{\mu_{t-1}^{\alpha}}\right)\right] \tag{3.7}$$

In contrast to Abel's (2001) model, the third term of the right hand side in equation (3.7) implies that the price of capital is affected by the population dynamics rather than by its levels. The model output suggests that when the birth rate declines, resulting in progressively ageing population, a negative pressure on asset prices emerges. On the other hand, the opposite is true in the case of an increasing birth rate. Brunetti and Torricelli (2010, p. 199) further concludes that the '… result can explain the differences in empirical evidence between countries experiencing a smooth demographic dynamics (such as the U.S.) and countries with steeper ageing dynamics (such as Italy)'.

Takats (2012) constructs an OLG model in which an individual works for two periods; young and old. The model assumes that work income for young agents is exogenous and a portion of their income is saving through divisible fiat assets which are consumed when they are old. She updates the basic OLG model to introduce asset markets such that young agents buy a share of the assets at a unit price. Equation (3.8) gives the evolution of asset prices in terms of real economic and demographic factors in equilibrium.

$$1 + r_{t+1} = \frac{p_{t+1}}{p_t} = (1 + g_t)(1 + d_t) \tag{3.8}$$

where r_t is the interest rate, p_t is the unit price of assets, g_t is the real GDP growth rate, d_t is the demographic growth defined as $\frac{young\ generation\ at\ time\ t+1 - young\ generation\ at\ time\ t}{young\ generation\ at\ time\ t}$

The asset price evolution equation (3.8) implies that the when the generation size is large the demand for assets increases. Also if the economy is wealthier, that is GDP per capita is higher, there is an increase in demand for assets.

Applying this model to housing prices, Takats (2012) expects an increase in house price in response to a higher GDP per capita. She further defines the old age dependency ratio at time t as the inverse of demographic growth, $(1 + d_{t-1})$. She then predicts different of impacts of total population and the old age dependency ratio on housing prices. An increase in old age dependency ratio and total population leads to negative and positive impacts on real house prices respectively.

3.3 Review of the Empirical Literature

The standard theoretical models suggest a plausible link between the asset prices and demographic structure. The results are sensitive to the structure of the model, assumptions and chosen parameters. However, the theoretical models do not directly address a question whether demographic changes have an impact on asset prices, rather they produce simulation or analytical results suggesting a potential influence from demographic changes on equilibrium asset prices and asset returns. In contrast empirical model results quantify the magnitude of the effects and hence the economic implications. Sections 3.3.1 and 3.3.2 describe several strands of empirical evidence that measure the magnitude and direction of the effects of population age structure on housing assets and financial assets.

3.3.1 Housing Assets

Mankiw and Weil (1989) predicted a fall of about 47% in real house prices in the United States by 2010, for the first time in the literature. They examine the effect of the Baby Boomer cohort on the housing asset market both retrospectively and prospectively. Mankiw and Weil (1989) use cross sectional data from the 1970 U.S. census and argue that the house price increases in 1970 and 1980 are due to the increased demand by Baby Boomers. They predict a slow growth in housing demand from the 1990s leading to a substantial drop in real house prices over the next two decades and therefore predict an asset price meltdown coinciding with the Baby Boomers' retirement.

They begin the study by quantifying the age cohort effect on the quantity of housing demand using 1970 Census data. They first estimate the coefficients for each age from 0-99 using a household demand equation and plot against the age[7,8]. Looking at figure 3 in their paper Mankiw and Weil (1989, p. 240) conclude that '…a sharp jump in the demand for housing between the ages of 20 and 30. … to decline after age 40 by about one per cent per year'. However, such a declining trend after age 40 as observed by the authors in figure 3 is not readily apparent.

Mankiw and Weil (1989) assume that the above mentioned coefficient estimates are constant over time and only the size and age structure will change. Then they construct the demographically driven aggregate housing demand index for a given year as follows.

$$D_t = \sum_{i=0}^{99} \alpha_i N_{i,t} \qquad (3.9)$$

where D_t is the aggregate housing demand index, α_i is the estimated coefficient from the demand for housing for each age, $N_{i,t}$ is the number of people of age *i* in year *t*. They use this aggregate housing demand index in a series of regression analysis to assess the impact from demand on housing stock and price using time series data from 1947-1985. The estimated regression equation takes the following form.

$$\log(DV_t) = c + t + \alpha_1 \log(D_t) + \alpha_2 \log(GNP_t) + \alpha_3 \log(CF_t) \qquad (3.10)$$

where DV represent either housing stock or real house price, GNP is the gross national product and CF is the cost of funds. Whilst the result do not show a statistically significant relationship between demographically driven housing demand index and the stock of housing, the positive link between aggregate housing demand index and real housing price is highly significant. Further, based on this Mankiw and Weil (1989) concluded that demography is the major source of housing demand and housing prices and predict that real house price will decline by 3% a year with the ageing of the Baby Boomers. Also, their forecasting results predict an abrupt fall in

[7] 0 means less than 1 year.
[8] Figure 3 in the paper.

real house prices of the order of 47% by 2010. This prediction mainly derives from the negative coefficient of estimate for the linear time trend in their regression specification. It suggests that even if the demand remains constant, real house prices will drop by 8%, which was criticised by both Hamilton (1991) and Hendershott (1991).

This prediction was not only widely criticised, but the annual decrease of 3 per cent did not eventuate in the United States. Engelhardt and Poterba (1991) were the first to criticise Mankiw and Weil (1989) and emphasize the risk of extrapolating historical U.S. trends and forecasting a substantial real house price decline between 1990 and 2010. They show that the demographic pattern in Canada is similar to the United States and reproduce the Mankiw and Weil results for both the U.S. data and Canadian data. The estimates for the corresponding regressions demonstrate contradictory results. In the regressions which do not control for income effect, the coefficient estimates for the relationship between real house price and demographically driven housing demand index are negative and statistically insignificant for Canadian data. This is in contrast to the statistically significant positive coefficient for the United States. However, the regression equation that does control for the income effect provides a positive though statistically insignificant coefficient estimate with respect to the demand variable in Canada. This gives rise to ambiguity about the extent to which Engelhardt and Poterba’s (1991) findings of the negative relationship between real house prices and the demographic structure contradict those of Mankiw and Weil (1989).

It is worth considering the house price variable that both of the above studies used to examine the impact of demographics on house prices. The variable should be a measure of the market price of housing. However, in the studies of both Engelhardt and Poterba (1991) and Mankiw and Weil (1989), their index measures cost of residential construction. Moreover, both studies use cross sectional data and ignore the effects of income and the cohort groups when they analyse the demand for residential property.

Studies of the housing market suggest that, in the long-run, housing supply is elastic. This implies that responsiveness of housing demand should primarily result in the changes in the housing stock and comparatively less in the housing price. However, Mankiw and Weil (1989) reject these high elasticities. Based on their regression results they conclude that the substantial impact on real housing prices emerge from the shift in housing demand only if the supply elasticities are low. Woodward (1991) makes a note on this issue while considering the work of Hamilton (1991), Hendershott (1991) and Holland (1991) and argues that in the 1970s, on the supply side, the real cost of housing fell and supply increased, yet housing prices were high. This suggests that Mankiw and Weil's (1989) prediction of a substantial fall in real house prices is not credible as they ignore the supply side and consider only a simple relation between a demographic housing demand variable and real house prices.

DiPasquale and Wheaton (1994) focus on the importance of including both supply and demand factors in an aggregate housing model when examining the relationship between demographics and housing asset prices. First, they estimate demand and supply equations and use those estimates to forecast house prices with added assumptions about rates of ageing and household formation. In other words, they use a baseline forecast for house prices and then incorporate the effects of demographic factors. This enables them to isolate the impact of ageing of the population on house prices. The model estimates clearly suggests a negative shock to the housing demand in the 1990s resulting from an ageing population and slower household formation. However, the magnitude of the shock is relatively small. Therefore, even though demographics slow down house price appreciation, the long run housing supply elasticity dampens the impact, which is consistent with the findings of Woodward (1991). Therefore, a real house price decline as predicted by Mankiw and Weil (1989) is highly unlikely for the United States.

Unlike previous studies, Green and Hendershott (1996) use a different approach to construct the aggregate housing demand variable. They assume that real house prices are directly determined by the households' willingness to pay for a constant quality house. To measure this, they build a hedonic pricing model of household demand and obtain hedonic prices (q_i) with respect to each hedonic characteristic. Then they use those hedonic prices in a regression analysis as follows[9]. The analysis uses 17 age dummies for each 5 year age class running from 0-85 years.

$$q_i = \alpha_0 + \alpha_i z_i + \sum_{\alpha=1}^{17} \alpha_\alpha A_\alpha + \varphi X + \sum_{\alpha=1}^{17} \alpha_{y\alpha} Y A_\alpha + \varepsilon_i \qquad (3.11)$$

where A_α are age dummies, Y is the income less housing expenditure, α' s are individual coefficients, φ is a coefficient vector for other demographic variables of X. Green and Hendershott (1996) utilise these hedonic prices to compute the willingness to pay for a constant quality house for each age group and the housing demand. Also, they measure both total and partial derivatives. The total derivative takes into account all average characteristics such as income, marital status and education that vary with age. In contrast, the partial derivative measure holds constant the other characteristics associated with age.

The results indicate that the housing demand using total derivative is close to the Mankiw and Weil (1989) findings. However, the partial derivative method suggests that housing demand is flat or slightly changing with age. Therefore, Green and Hendershott (1996) conclude that the effect of ageing on real house prices in the United States in the future will not be economically significant, contrary to Mankiw and Weil (1989). Accordingly, these results suggest that if Mankiw and Weil also considered partial derivative rather than total derivatives they may not have made such a startling prediction for real house price decline.

Bergantino (1998) provides a different criticism of the Mankiw and Weil research. He points out that Mankiw and Weil (1989) ignore the effect of existing housing stock when they construct the demographically driven aggregate housing demand (equation (3.9)) and use gross housing demand in the regression analysis. Instead Bergantino suggests that flow of housing in a particular year as measured by $D_t - D_{t-1}$ would have been a more appropriate variable in the right hand side of their

[9]The hedonic characteristics include house age, number of bedrooms, number of bathrooms, number of other rooms, whether house is owned, whether it has central air-conditioning, gas heating, sewer and water, condominium, in an urban area and in which census area.

regressions. Accordingly, Bergantino (1998) uses the flow of housing to regress with real housing price appreciation ($P_{t+k} - P_t$) for different forecast horizons of k =1, 2, 3, 4, 5 and 10.

$$\frac{[\log(P_{t+k})-\log(P_t)]}{k} = \beta_0 + \beta_1 * \frac{[\log(D_{t+k})-\log(D_t)]}{k} + \varepsilon_t \qquad (3.12)$$

Also, to overcome the serially correlated error terms due to overlapping data in the multi-year regressions, Bergantino (1998) computes both Newey-West (1987) and Monte Carlo standard errors to make inferences from the OLS regression. The estimates from the regression are positive and statistically significant on the demographic housing demand variable. In addition, he uses both growth in housing flow and growth in real GDP per capita ($[\log(Y_{t+k}) - \log(Y_t)]$) as explanatory variables in the regression of growth in real house price to measure the income effect on real house prices. The estimated results show that demographic factors account for approximately 59% of the increased growth in annual housing prices from 1946-1986 in the United States.

$$\frac{[\log(P_{t+k})-\log(P_t)]}{k} = \beta_0 + \beta_1 * \frac{[\log(D_{t+k})-\log(D_t)]}{k} + \beta_2 * \frac{[\log(Y_{t+k})-\log(Y_t)]}{k} + u_t \qquad (3.13)$$

The studies discussed above examine the relationship between demographics and housing asset prices in the Unites States. Bodman and Crosby (2004) and Otto (2007) analyse the growth of house prices in Australian capital cities. The former includes population growth and the fraction of population who are 60-64 years and the latter includes population growth as demographic variables in their empirical analyses. Regarding Otto (2007), population growth does not capture the evolution of demographic changes, particularly the ageing effect, which is the concern in this literature review. However, Bodman and Crosby (2003) use the fraction of population between 60-64 years as a demographic variable though they do not explain the rationale behind it. In addition, Bodman and Crosby (2003) use an interest rate as one of the explanatory variables in the multiple regression analysis. It is logical to think house prices would be linked to interest rates, however including the interest rate as a regressor and estimating using OLS ignores the endogeneity problem in the variables, leading to biased estimates and hence incorrect inferences.

Both Bodman and Crosby (2003) and Otto (2007) run regressions for major cities in Australia individually. It would have been more appropriate to use panel regression analysis as the precision of estimates would be higher as a result of increased number of observations. Also, panel regression with fixed effects allows for unobserved city specific heterogeneity that may be correlated with other explanatory variables of the model. That is, the fixed effect model removes the time invariant characteristics from the real house prices, so that the net effect can be assessed. The individual city regressions do not correct for the unobserved heterogeneity and suffer from omitted variable bias. To correct this problem in the individual cross section data it is necessary to include instrumental variables, but authors have not considered this aspect. Given these points panel regression would have been a stronger econometric specification in the analysis of house prices for capital cities in Australia.

Guest and Swift (2010) model the house prices in both long-run and short-run and investigate population ageing and house prices in Australia. That is, they estimate the long-run equilibrium relationships using Dynamic Ordinary Least Squares (DOLS) represented by the error correction term. The results indicate that the population share of the 35-59 years cohort significantly affects real house prices in the long-run in Australia. Further, ceteris paribus, a 1% decline in the share of population between 35-59 years lead to a reduction in real house prices by 2.26%, on average. Also, based on the population projections, Guest and Swift (2010) predict that real house prices would be 27.1% lower in 2050 than they would be if the population share of the 35-59 years cohort remains constant. However, Guest and Swift (2010) also do not directly address the effect of retiring Baby Boomers and further according to the published population projections by the ABS it is highly unlikely that the number of people in this age group will remain constant.

Chen, Gibb, Leishman and Wright (2012) use a combination of a macro-level house price specification and a micro-level household formation specification to investigate the impact of population ageing on house prices in Scotland. They derive a house price specification model by combining an autoregressive distributed lag model and partial adjustment model, which is given in equation (3.14).

$$p_t = \beta_0 + \beta_1 hhds_t + \beta_2 uc_t + \beta_3 y_t + \beta_4 dpsh_t + \beta_5 p_{t-1} \qquad (3.14)$$

where p_t is the log of real median house price, $hhds_t$ is the log of the ratio of households to dwellings, $dpsh_t$ is an index of real capital asset returns, and uc_t is the user cost of capital and y_t is the log of real median household income. A binary Probit model was used in household formation specification. To evaluate the impact of population ageing on house prices, simulations drawn from the estimated house price equation (3.14) and a simplified household formation equation have been used. The results suggest that population ageing is not a key determinant of house prices in Scotland.

The studies examining demographics and house prices discussed so far are single country studies for the United States, Australia and Scotland. Takats (2012) examines the impact of demographics on house prices using a small model in a panel regression framework for 22 advanced economies with data from 1970-2009 and finds that ageing has a significant negative impact on house prices. The benchmark model includes both demographic (population size and old age dependency ratio[10]) and non-demographic (real GDP per capita) variables. The panel regression run on differences is given below.

$$\Delta \log(P_{it}) = \beta_0 + \beta_1 \Delta \log(gdp_{it}) + \beta_2 \Delta \log(dem1_{it}) + \beta_3 \Delta \log(demo2_{it}) + \alpha_t + \varepsilon_{it} \qquad (3.15)$$

where P denotes the real house price, β_0 is the intercept, gdp is real GDP per capita, $dem1$ is the total population, $dem2$ is the old age dependency ratio, α is the time fixed effects and i refers to the country and t refers to the time. The regression results show a significant impact from economic and demographic factors on real house prices. The impact from real GDP per capita and total population is positive,

[10] Old age dependency ratio = the ratio of population over 65 years and the population between 20-64 years.

while that from the old age dependency ratio is negative. These results are consistent with the theoretical model developed by Takats (2012). A 1% increase in total population leads to a 1% increase in real house prices, while real house prices decrease by around 2/3% for a 1% increase in the age dependency ratio. Similarly, a 1% increase in real GDP per capita increases the real house prices by 1%. Further, Takats (2012) shows that the coefficient estimates are robust to various changes in the benchmark model. However, the estimates do not imply an asset price meltdown as argued by Mankiw and Weil (1989).

3.3.2 Financial Assets

While the earliest literature examining the relationships between demographic change and asset prices focused on the housing market, there is now a growing literature that explores the effect of demographics on financial assets. In a seminal work, Bakshi and Chen (1994) analyse the extent that variations in population age structure have an impact on stock price movements using U.S. data from 1900 to 1990. Bakshi and Chen (1994) formalise a life cycle investment hypothesis and a life cycle risk aversion hypothesis in an asset-pricing model. The life cycle investment hypothesis states the households' preferences regarding the types of assets they hold over the term of their life. Young households prefer to invest in housing, but as they get older they are likely to shift their preferences towards financial assets.

However, the authors do not conduct a formal empirical work to test the life cycle investment hypothesis. Instead, in support of their conclusion they use two approaches. The first is to cite existing empirical evidence supporting the hypothesis and the second is a graphical approach. Bakshi and Chen (1994) conclude that the empirical evidence of Mankiw and Weil (1989) and of Bossons (1973) is consistent with the life cycle hypothesis even though in both cases the analysis was cross sectional. In the graphical analysis of time series data, Bakshi and Chen (1994) divide the sample into four sub-periods: 1900-1945, 1946-1966, 1967-1980 and 1981-1990. These sub-periods exhibit certain unique demographic features of the U.S. population, which they link to the changes in investments. Based on these two approaches Bakshi and Chen (1994) demonstrate that the post-1945 period is supportive of the life cycle investment hypothesis and conclude that an ageing population drives an increase in stock market prices and declining housing prices.

Bakshi and Chen (1994) use a multi-period model with a representative agent to analyse the life cycle risk aversion hypothesis, which suggests that risk aversion increases with age. The authors apply Hansen's (1982) generalised methods of moments (GMM) to test the Euler Equation in the following form[11].

$$E_t\left[e^{-k\Delta t}\,\frac{C_{t+\Delta t}^{-(\gamma+\lambda.A_{t+\Delta t})}}{C_t^{-(\gamma+\lambda.A_t)}}.\frac{P_{n,t+\Delta t}}{P_{n,t}}\right]=1 \qquad (3.16)$$

In this form, the representative agent's intertemporal marginal rate of substitution (IMRS) is a function of both aggregate consumption and average age. The relative risk aversion is linear in average age and the coefficient of relative risk aversion is $\gamma+\lambda.A_t$, where A_t stands for the age of the representative agent at time *t*. The representative agent's age corresponds to the average age of the population. Further, λ and γ represent the effect of the age of the representative agent on the level of risk aversion and the constant level of risk aversion respectively. Bakshi and Chen (1994) expect the agent's relative risk aversion factor, $\gamma+\lambda.A_t$ should increase with age, according to the life cycle risk aversion hypothesis. Accordingly, they test the null hypothesis of $\lambda=0$. The estimation results in a statistically significant positive coefficient of λ and thus supporting the conclusion that the risk aversion increases with age.

The analysis of the subsamples shows the impact of the baby boom on the U.S. asset markets. Of the entire period, the sub-period of 1945-1990 supports the two hypotheses at the highest degree. This suggests that the U.S. demographic structure, which is substantially shaped by the baby boom, has a significant effect on the asset markets.

[11] In the Euler equation C_t refers to aggregate per capita consumption.

It is worth noting the authors' comments on the ability of life expectancy to explain asset prices. Although they use life expectancy at age 60 to explain asset price movements in their graphical analysis, they believe that it does not capture the fluctuations in the entire age distribution. Accordingly, Bakshi and Chen (1994) conclude that life expectancy cannot be used as a fully representative variable to measure the impact of demographic changes on aggregate asset demand. Moreover, the only variable that they use to explain demographic changes in their regression analysis is the average age, which is subsequently questioned by Yoo (1994a) and Poterba (1998). In contrast, many of the other studies employ proportion of the population at different ages as demographic variables which might better capture the lifetime asset accumulation profiles. We believe that including life expectancy along with some representative demographic variable/(s) would result in a strong model specification.

As with the Mankiw and Weil's (1989) predictions of the asset price meltdown, the validity of the Bakshi and Chen (1994) conclusions have been both supported and criticized. Poterba (1998) criticizes the substantive importance of demographic factors in the Euler equation, namely the fact that the age structure improves the fit of an Euler equation could simply reflect other failures of the Euler equation, rather than the substantive importance of demographic factors (Poterba, 1998, p. 7). Likewise, as Woodward (1991) argues for housing markets, since financial markets are forward looking asset values should account slow moving demographic changes.

In contrast to the tightly parameterized method of Bakshi and Chen (1994), Yoo (1994a) provides a more flexible time series regression analysis. Using data from 1926 to 1988, Yoo measures the relationship between real return on stocks, bonds, and Treasury bills in the United States with different age groups[12]. Based on the time series estimates, the author finds a statistically significant negative association between returns of assets and the proportion of the population aged 45-54 years. Yoo

[12] The returns on stocks, bond and Treasury bills are regressed on age groups of (25-34), (35-44), (45-54), (55-64), (65+).

(1994a) further analyses the sensitivity of the regression estimates by running a separate regression for the post-war period, 1948-1988 and finds a robust relationship between the age group of 45-54 with the return on assets during the post-war era.

While highlighting the difficulty of applying the ideas of Bakshi and Chen (1994) in an international context, Erb, Harvey and Viskanta (1997) reveal a weak relation between world average demographic measures and expected returns. On the other hand, the authors find a significant correlation between all demographic variables and risk indicators, particularly country specific equity market risk. It should be noted that the Erb et al. (1997) study is a cross sectional time series analyses based on 45 developed and emerging economies, where the use of average age in the regression casts doubt results particularly in the case of emerging economies[13]. It is not clear whether such demographic changes should be viewed as the driving force behind asset market movements, or whether they in turn reflect other factors at work in developing nations (Poterba, 2004, p. 14).

Contrary to the strong relationships between demographic structure and asset returns found in earlier studies, Poterba (1998) fails to find a robust relationship between demographic structure and the asset returns in the Unites States. Poterba (1998) focuses on the returns on Treasury bills, long term corporate bonds and corporate stocks over the period of 1926-1997 and 5 demographic variables, which include average age over 20 years, median age and population 40-64 years/population 65+, and population 40-64/population 20+ years. Poterba (1998, p. 24) mentions that 'what correlations do emerge are stronger between Treasury bill rates and long term government bond returns and the demographic variables than between stock returns and these demographic variables'. However, it is not clear whether author has made this statement based on a computation of correlation coefficients or based on the regression results. As the correlation coefficients do not imply cause and effect and also if the corresponding coefficient estimates from the regressions are not

[13] First 18 developed countries and then 45 developed and emerging economies.

statistically significant, this statement is ambiguous for the reader. In addition, Poterba finds a statistically significant negative coefficient for the proportion of population between ages 40-64 years in the regression with Treasury bill returns.

Bergantino (1998) criticises Poterba (1998) on three points as to why the latter does not find a significant relationship between demographics and financial asset returns. The first is that Bergantino (1998) uses analogous variables to those used by Poterba (1998), but he (Bergantino) does find a significant relationship between the financial asset returns and the level of demographic demand for financial assets. The second is that Poterba measures high frequency correlations between demographic variables and the asset returns. Thirdly, Poterba assumes a monotonic relationship between financial asset demand and age, as represented by the demographic variables he used in the analysis. Bergantino (1998) further criticises Poterba's finding of a statistically significant negative relationship between Treasury bill yields and the percentage of population between 40-64 years. Bergantino (1998) argues that this strong relation could be interpreted as evidence of a statistically significant positive correlation between the price of Treasury bills and the demographic demand for financial assets[14]. However, Poterba (1998, p. 25) argues that 'one possible interpretation of the findings presented here is that even though changes in age structure do affect asset demand, and thereby equilibrium asset returns, these effects are simply too small to be detected amongst other shocks to asset markets'. Thus, Poterba (1998) has already rejected the explanation proposed by Bergantino (1998).

In his doctoral dissertation Bergantino (1998) uses cross sectional data for the United States and extends the approach of Mankiw and Weil (1989) to investigate the relationship between demographics and asset prices[15]. He concludes that demographic factors explain a substantial share of the dynamic behaviour of financial asset prices in the United States in the post 1945 period. Also, Bergantino (1998) finds that approximately 77% and 81% of the annual increase in real stock

[14] see Doctoral Dissertation of Bergantino (1998) page 31-32.
[15] Housing asset section provides a detailed description of the methodology.

prices and de-trended real bond prices respectively are attributable to the demographically driven changes in the demand for financial assets.

Poterba (2001) re-examines the relationship between demographic structure and financial asset returns for the United States, and compares the results with Canada and the United Kingdom. The 2001 study examines the relationship between the population age structure and the real returns of three assets, the corporate stock, long term bonds, and Treasury bills. The findings do not suggest a robust relationship between asset returns and demographic structure in the Unites States. The results however contradict with the established link between age structure and asset returns as depicted by general equilibrium models for asset returns. Poterba's (2001) analysis uses data from 1926-1999 and uses two sub samples of 1926-1975 and 1947-1999 to examine the effect of low frequency demographics variation on asset returns.

Further, Poterba (2001) constructs a price-dividend ratio on the S&P500 to incorporate the long-run movements in stock prices which would better capture the life cycle consumption decisions as theory suggests. Thus, the author empirically investigates the relationship using the following regression equation.

$$\left(\frac{P}{D}\right)_t = \alpha + \beta * (Demographic\ variable)_t + \epsilon_t \qquad (3.17)$$

In contrast to previous results, the estimation exhibits a strong association between demographic variables with price-dividend ratio. However, the author establishes that these results suffer from the "spurious regression" problem and extends the analysis to construct the regression equation in first differences as given below.

$$\Delta\left(\frac{P}{D}\right)_t = \alpha' + \beta' * \Delta(Demographic\ variable)_t + \epsilon'_t \qquad (3.18)$$

The results from equation (3.17) suggests only two demographic variables (40-64 years/total population and 40-60/65+) have statistically significant positive relationships with price-dividend ratio. Poterba (2001, p. 578) interprets this result as '… even from differenced models that address the spurious regression problem, that the price-dividend ratio is higher when a larger share of population is between ages of 40 and 64'. In addition, Poterba's findings for Canada and U.K. further weaken the claim regarding the existence of a systematic link between demographic structure and asset returns.

The empirical results of Poterba (2001) described in the previous paragraphs do not utilise the age-wealth profiles of U.S. Surveys of Consumer Finances (CFS). Thus, Poterba constructs asset demand variables, which combine information on age structure of the population and age specific evolution of asset holdings using CFS data for the period 1925-2050. '… it offers a more formal link between household level data on the wealth-age profiles and aggregate analysis of asset demand' (Poterba, 2001, p. 579). He does not find a significant decline in asset demand with ageing of the Baby Boom generation. This result does not support the asset market meltdown hypothesis.

However, Abel (2001) criticises Poterba's conclusions for being based only on the projected asset demands on stock prices. He argues that Poterba focuses only on the demand for capital and does not consider the supply of capital in his forecast of price of capital. Abel (2001) develops a model which is consistent with Poterba's observations. That is, both Poterba (2001) and Abel (2001) observe that retired consumers continue to hold a substantial amount of assets at the time of death. Thus Abel (2001, p. 15-16) concludes that '… contrary to the Poterba's conclusion, there is an anticipated decline in the price of capital when baby boomer retire, and this decline is not attenuated at all by the introduction of a bequest motive'.

Poterba (2001) extends the analysis to test demographic structure and risk aversion using a parametric approach similar to Bakshi and Chen (1994). Poterba formalises the Euler equation as given in (3.19) and reports λ and γ for different demographic variables, $Z_{j,t}$[16,17]. The results are not consistent with the findings of Bakshi and Chen (1994) and suggest that the increase in percentage of population above 55 years leads to decline the risk aversion of the representative consumer.

[16]Three demographic variables, average age over 19 years, % of population 40-64 years, % of population 55+ years.
[17]λ and γ represent the effect of the age of the representative agent on the level of risk aversion and the constant level of risk aversion respectively.

$$E_t\left[\left({C_{t+1}}/{C_t}\right)^{-\gamma-\lambda * Z_{j,t}}(1+r_t)\right]=1 \qquad (3.19)$$

In an examination of the relationship between demographics and financial asset prices, Davis and Li (2003) use data from OECD countries for the period 1950-1999[18]. The studies mentioned so far only consider demographic variables as the explanatory variables of asset prices. This ignores the impact of economic forces on real asset prices. Davis and Li (2003) include both demographic and non-demographic variables in the econometric specification and use real share price and real bond yields as dependent variables. The empirical estimation consist two approaches. First, Davis and Li conduct a panel regression analysis for seven OECD countries, (say "panel") and a panel of six countries excluding the U.S. using GLS estimation techniques and fixed effects. Second, they use OLS estimation for the U.S. and for aggregate data for seven countries (say "international") separately. The results suggest a significant relationship between age distributions and real stock prices and real bond yields for all three data combinations of panel, U.S. and international. Also, they report a statistically significant larger positive coefficient of estimate associated with the demographic variable which represents the percentage of population age between 40-64 years even in the presence of non-demographic variables. This leads them to conclude that demographic changes, particularly the increase of the population in the age group of 40-64 can have a significant impact on stock prices and bond yields.

Davis and Li (2003) formulate the following regression model (equation 3.20) to examine the association between real stock price and demographic variables.

$$\Delta lnRSP=\alpha+\beta_1 AGE20+\beta_2 AGE40+\beta_3 DYHP+\beta_4 DDIFP+\beta_5 RLR+ \beta_6 VOL+\ \beta_7 DIVY(-1)^{19} \qquad (3.20)$$

[18] U.S., U.K., Germany, France, Italy, Spain and Japan.
[19] RSP – Real Share Price, AGE20 - % of population between 20-39 years, AGE40 - % of population between 40-64 years, DYHP – Trend GDP growth, RLR – Real Long Rate, VOL - Monthly average share price volatility, DIVY(-) – Dividend Yield.

The regression specification uses both first differences and levels of variables. It should be noted that taking differences may weaken the effect since the differenced variables do not contain the same information as in the variables in levels. Further, the dependent variable used is the first difference of log real share price, which actually gives the growth rate of real share price, not the real share price. Davis and Li (2003) do not consider this when they interpret results. Also, it is desirable to employ a standard test to test whether panel regression is more appropriate over country specific regressions before making conclusions, which cannot see in the analysis.

Geanakoplos et al. (2004) use a different form of empirical analysis to compare the results obtained from the theoretical model and use data from 1910-2002. They identify two variables namely, price-earnings (PE) ratio and rate of return on equity as the variables that most compatible with the model predictions. They define an MY ratio as the number of 40-49 year olds divided by the number of 20-29 year olds and use it to measure the demographic cycle. According to this measure, they find that the turning points of stock prices and price-earnings ratios synchronize with the demographic cycle. Further, the model predicts the behaviour in the price-earnings ratio in the U.S. equity market over the next twenty years. Contrary to the findings of Poterba (2001), they predict a decline in the price-earnings ratio with the predicted behaviour of the MY ratio.

The study offers some evidence for the relationship between equity markets and demographics in the United States. Geanakoplos et al. (2004) conclude that the demographic variable explains the 14% of the variability in the rates of return on S&P500 during 1945-2002. In addition, they examine whether there is a relationship between demographic structure and equity prices for France, Germany, Japan, and the United Kingdom. The mixed findings indicate a significant link between MY ratio and the real price of corporate equities for France and Japan. However, for Germany and the United Kingdom, the relationship is not significant.

Other than stock market returns, Goyal (2004) uses net outflow derived as dividends plus repurchases less net issues from stock market and for demographic variables (% of population between ages 25-44, 45-64 and 65+ years and average age of persons over 25 years) in the empirical analysis for the United States. However, Goyal's OLS specification looks slightly different from the previous studies' OLS specifications and uses next year net outflows as the dependent variable. Accordingly, Goyal (2004) tests the regression model (3.21) in several steps, including and not including demographic variables, and in levels and first differences.

$$LEAK_{t+1} = \beta_0 + \sum_{j=1}^{4} \beta_j \, DEMO_{j,t} + LEAK_t + ESRET_t + \varepsilon_t \qquad (3.21)$$

where $DEMO$ include for demographic variables; percentages of population between ages 25-44, 45-64 and 65+ years and average age of persons over 25 years, $LEAK$ is net outflow and $ESRET$ is the logged difference between stock returns of S&P 500 and risk free rate. The regression analyses give statistically significant positive and negative associations between net outflows from the stock market and the percentage of population over 65 years and the percentage of people between 45-64 years respectively. Thus the results support the traditional life cycle models. Goyal (2004) further concludes that average age alone is not an appropriate variable to capture demographic dynamics, which previous studies (Bakshi and Chen, 1994; Erb et al., 1997) used.

Goyal (2004) considers the case of stock market returns and conducts series of regressions, regressing excess stock returns on the dividend price ratio and demographic variables similar to the case of net outflows. He compares the results with the findings of Poterba (2001) and Bakshi and Chen (1994). As with Poterba (2001), Goyal (2004) is unable to find statistically significant associations with stock returns and demographic variables when the regression model proportions of populations for different age groups at levels as the demographic variables. However, Goyal (2004) finds results supportive of Bakshi and Chen (2004) and confirms that stock returns have a positive relationship with average age.

Next, Goyal (2004) uses a Vector Autoregressive (VAR) approach to forecast the outflows from the stock market. This paper is the first case in the literature where the VAR approach is used to investigate the impact of demographics on asset prices. However, Goyal (2004) formulates a slightly different VAR(1) from the traditional VAR(1); one that includes an additional set of explanatory variables. Goyal (2004) uses estimated coefficients from the VAR(1) model and Census Bureau of the United States projections for demographic variables and forecasts of net outflow from the stock market for 52 years (1999-2050).

The results predict an increase in outflows from the U.S. stock market for next 25 years, commencing from 1999 and also a high volume of outflows for nearly a decade. However, Goyal (2004, p. 131) concludes that 'outflows over the next 50 years are not expected to rise to levels that cause concern even with the retirement of Baby Boomers'. That is the projected changes in demographics in the U.S. are likely to have a modest impact on stock market returns at most.

Poterba (2004) presents a third study to examine the relationship between demographics and financial asset prices for the United States using data from 1926-2003. The econometric specification includes demographic variables and some control variables such as the real interest rate and the three year average of the GDP growth rate, which is different from his previous studies which included only demographic variables. Further, Poterba (2004) conducts the analysis with variables in levels and in first differences and demonstrates that the statistical significance of the results is weaker when the variables are in differences compared when the variables are in levels. However, Poterba (2004, p. 26) clearly mentions that '… the results of this price level analysis may be subject to "spurious regression bias" because the dependent and explanatory variables are all slowly trending time series'. Thus, conclusions made on level regression may not be sound from the point of view of correct econometric analysts.

However, based on the several analyses, Poterba (2004) does not conclude a strong correlation between asset returns on long-term government bonds, or Treasury bills and the age structure of the U.S. population. In summary, Poterba (2004, p. 1) concludes that ‘these empirical findings provide modest support, at best, for the view that asset prices could decline as the share of households over the age of 65 increases’.

The literature discussed so far have been empirical investigations of single equation models that link demographics and stock prices. Jamal and Quayes (2004) use a simultaneous equation model incorporating both demand and supply functions to explore the link between demographics and stock prices in the U.S. and the U.K. First, they model the price of stocks with proportion of population between ages 45-64 years, who are in prime earning age and then develop a similar model with return on stocks. Jamal and Quayes (2004) model is described by equations (3.22)-(3.25).

$$Demand\ equation: q_t = \alpha_0 + \alpha_1 y_t + \alpha_3 p_t + \alpha_3 demo_t + \epsilon_t \qquad (3.22)$$

$$Supply\ equation:\ q_t = \beta_0 + \beta_1 p_t + \varepsilon_t \qquad (3.23)$$

where, q_t is log of average volume of S&P500 traded daily, y_t is log of real GDP, p_t is price-dividend ratio for S&P500 and $demo_t$ is log of proportion of population between ages 45-64. The reduced form equations is derived from the above structural equations and estimated simultaneously.

$$q_t = \gamma_0 + \gamma_1 y_t + \gamma_2 demo_t + e_t \qquad (3.24)$$

$$p_t = \delta_0 + \delta_1 y_t + \delta_2 demo_t + u_t \qquad (3.25)$$

The authors expect δ_2 to be positive only if the demographic variable has a direct impact on stock prices. The estimated results for the United States using annual data from 1950-2000 indicates that a 1% increase in the proportion of the population in prime working age will lead to an increase of the price-dividend ratio of the S&P500 by approximately 5%. However, the results do not show a significant association between the proportion of the population between 40-60 years and the return on assets. Further, the U.S. Census Bureau predicts a decline in the proportion of the population aged between 40-64 years to 28% in 2030 from 30.4% in 2000. In this scenario, Jamal and Quayes (2004) compute approximately a 39% drop in the price-dividend ratio in the United States. Similar estimations for the U.K. indicate that stock prices are affected by demographic structure.

Even though Jamal and Quayes (2004) find that the variables they use to estimate the reduced form equations are non-stationary, they still use the OLS estimation procedure and make inferences using *t*-tests. Caballero (1994) points out that OLS estimates are valid only when the non-stationary regressors and error terms are exogenous and, if not, the subsequent finite sample bias leads to serious problems. In a later study Bae (2010) argues that OLS is not valid in such cases for non-stationary data and applies a cointegration approach to estimate the reduced form equation similar to them (Jamal and Quayes). Bae (2010) compares results from the Jamal and Quayes (2004) study and makes contrary conclusions. In contrast to the statistically significant relationship between stock prices and proportion of population in prime working age found by Jamal and Quayes (2004), Bae (2010) finds a statistically significant relationship between stock prices and the proportion of retired population (i.e. those over 65 years).

Ang and Maddaloni (2005) use two distinct datasets to examine the impact of demographic changes on future risk premiums. As with Geanakoplos et al. (2004), the first dataset comprises the five largest developed countries, (i.e. the G5 countries: France, Germany, Japan, the U.K. and the U.S.) covering a long span of 1900 to 2001[20]. Similar to Erb et al. (1997), the second dataset includes 15 countries covering a shorter time span (1970-2000)[21]. The empirical analysis takes place in three steps. Firstly, the authors estimate the following regression equation using GMM and examine the predictability of excess returns for three forecast horizons (k = 1, 2 and 5 years) for each of the five countries separately. They also estimate the regression equation with only one demographic variable in the first round and add non-demographic variables to the demographic variables in the second round[22].

[20] For Japan (1920-2001).
[21]Australia, Austria, Belgium, Denmark, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the U.K. and the U.S.
[22] Study uses three demographic variables; % over 65 years, % between 20-64 years and average age.

$$\widetilde{er}_{t+k} = \alpha + \beta' z_t + \varepsilon_{t+k,k} \qquad (3.26)$$

where, er is the log excess return, $\widetilde{er}_{t+k} = (\frac{1}{k})(er_{t+1} + er_{t+2} + \cdots + er_{t+k})$, z is the vector of explanatory variables. The error terms $\varepsilon_{t+k,k}$ have a *moving average* process with order *(k-1)*.

The results show a weak positive association between demographic variables and excess returns for the U.S. However, the percentage of population over 65 years has a significant impact on excess returns in the U.K. over all three horizons. At the one year horizon demographic coefficients are significant at the 5% level of significance for Japan, though with the opposite sign to that of the Unites States coefficient estimates. At the same time, results do not show significant relationships between demographics and excess returns for France and German at the 5% level of significance.

Second, Ang and Maddaloni (2005) pool cross sectional data of five countries and estimates a pooled version of the regression (3.26) while imposing cross sectional restrictions. The null hypothesis is that the demographic variables cannot predict the excess returns given that each country has different constant excess returns, but each country possesses the same coefficients for demographic variables. The results show that the percentage of population above 65 years has a significant negative impact on excess returns across all horizons and controlling for non-demographic variables of consumption growth and term spreads. This indicates that the change in the proportion of retired people has the most predictive power for excess returns across the G5 countries.

Third, Ang and Maddaloni (2005) re-estimate equation (3.26) using monthly data for the pool of all 15 countries. The estimated results demonstrate a negative relationship between the percentage of retired population and future excess equity returns. Thus, the authors' study using the much larger sample confirms that the international experience and the U.S. experience regarding demographic changes and excess returns are not the same. Ang and Maddaloni (2005) conclude that demographic changes indeed predict risk premiums internationally.

Huynh, Mallik and Hettihewa (2006) investigate the impact of the population in the 40-60 years age group in Australian share prices. The study uses cointegration analysis and annual data covering the period from 1965 to 2002. Huynh et al. (2006) conclude a significant positive effect on stock prices in Australia in the long run from the population in the 40-64 years cohort. Huynh et al. (2006, p. 695) further infer that '… it is possible that, when the baby boomers start to retire from the workforce, they will withdraw their money from their stock market investments… essentially the economy may be in crisis'. However, the cohort who was aged 40-64 years during 1965-2002 have already passed their retirement age and the Australian stock market does not show signs of a collapse due to high volume of withdrawals.

Shambora (2007) develops a a seminal semi-structural, four variable vector autoregressive model to quantify the effect of retiring Baby Boomers on the U.S. stock prices. She uses the S&P500 index to represent the stock price and the prime earner gap (the number of workers in the labour force in their prime earning years minus the number of non-institutionalized working-age people not in the labour force) as the demographic variable. Shambora (2007) posits that if the number in the prime earner gap decreases, it will have an impact on the domestic demand for U.S. equities and thus will exert a downward pressure on stock prices. He futher assumes that shocks to the demographic variable (prime earner gap) most likely impact on all variables directly. Thus he defines the prime earner gap as a function of its own current and past innovations and past innovations in other variables.

Shambora (2007, p. 1245) conludes that much of the variation in the S&P500 index is attributable to shocks to index itself. However, Shambora (2007) does not make a direct conclusion based on his results with respect to the potential impact of retiring Baby Boomers on the U.S. stock price. The impulse response analysis suggests that as the prime earner gap increases, the valuation of equity securities also increases (Shambora 2007, p. 1245). Accordingly instead of making a direct conclusion Shambora (2007, p. 1245) states that '… changes in prime earner gap can substantially alter stock prices… this appears to have the potential of creating a slow evaporation of stock prices rather than a meltdown'. This research further concludes that although there is potential for the impact on the S&P500 index of the Baby Boom bulge moving into retirement to be significant, other factors contribute much more to the short-run variance in the S&P500.

Brooks (2006) addresses the slow moving nature of the demographic changes and uses a long time series over the period 1900-2005 across 16 advanced economies to examine the link between demographic changes and financial asset prices[23].The empirical specification uses a panel regression and it controls for both country and year fixed effects. Brook's purpose in using a cross section dimension is to implicitly control for non-demographic fundamentals such as global long run business cycles. The country fixed effects control for the unobserved heterogeneity which affects the dependent variable at country level that is constant over time. As a results, country fixed effects remove the effect of those time invariant characteristics from the dependent variable and enables the measurement of the net effect. Similarly, the time fixed effects control for influences from unobserved factors on the dependent variable that vary for a year across countries. This approach is different from Davis and Li (2003) who include non-demographic variables (e.g. GDP growth and interest rates) into the model and explicitly control for the impact of economic forces.

Further, Brooks (2006) constructs demographic variables using a more agnostic approach while criticising the proportion of population in certain age ranges used in literature to define demographic variables. He argues that demographic variables used in previous studies '… arbitrarily partition the age distribution into net savers and net dis-savers…' (Brooks, 2006, p. 244). Brooks builds up the panel regression specification as shown in equation (3.27).

$$y_{it} = \alpha_i + \beta_t + \gamma_1 p_{1it} + \gamma_2 p_{2it} + \cdots + \gamma_j p_{jit} + u_{it} \qquad (3.27)$$

where i and t represent the country and time index respectively. α_i is the country dummy, β_t is the time dummy, y_{it} is the dependant variable (stock prices, real stock returns or equity premium) and p_{jit} is the share of population in the age j as a

[23]Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Sweden, Switzerland, the U.K. and the U.S.

proportion of the total population. Brooks (2006) then constructs the coefficients of the age shares to lie along a polynomial of order three and rewrites the regression specification (3.27) with three demographic variables. Thus,

$$\gamma_j = \delta_0 + \delta_1 j + \delta_2 j^2 + \delta_3 j^3 \quad (3.28)$$

$$y_{it} = \alpha_i + \beta_t + \delta_1 Z_{1it} + \delta_2 Z_{2it} + \delta_3 Z_{3it} \quad (3.29)$$

where;

$$Z_{kit} = \sum_{j=1}^{J} j^k p_{jit} - \frac{1}{J}\sum_{j=1}^{J} J^k \quad for\ k = 1,2,3$$

Brooks (2006, p. 244) makes the comment on the population coefficients as 'although these coefficients have no direct structural interpretation, the implicit age distribution coefficients can easily be recovered and will capture the sensitivity of asset prices, returns and equity premiums to the age distribution'.

Brooks (2006) estimates equation (3.29) on an unbalanced panel using OLS and compares the results to estimates where the same data is used but the demographic variables are replaced with conventional demographic variables[24]. The study uses both asset prices and asset returns. With asset prices, the results indicate significantly higher real stock, bond and Treasury bill prices occur when the middle age population cohort (40-44 and 60-64 years) is larger and an increasing share of old age groups leads to sharply lower real stock, bond and Treasury bill prices. In addition, Brooks (2006) does not find strong evidence to establish a significant association between demographics with equity premiums. However, the Brook's results indicate a positive and significant relationship between real stock returns and the percentage of population between ages 40-64, consistent with Davis and Li (2003).

The panel regression specification used by Brooks (2006) with country and time fixed effects for empirical analysis is questionable. With this specification Brooks

[24] Conventional demographic variables used; % of population (0-14), (15-39), (40-64), (65+) and % of adult population (40-64/20+), (65+/20+).

(2006) assumes that non-demographic fundamentals such as GDP accounts are implicitly in the model. It is reasonable to believe that in addition to the demographic factors, differences in non-demographic fundamentals across the countries have an influence on asset prices and asset returns. Further, the random effects model assumes that unobserved variations across the countries are random and distributed independently of the explanatory variables in the model. Therefore, it is appropriate to extend the empirical analysis to employ a panel regression with random effects and compare the results with fixed effects model.

Overall, the Brooks's (2006) study casts doubt on the previous finding for the relative importance of the middle age cohort's contribution to increases in the real stock and bond prices. Brooks (2006) concludes that this relationship does not hold for countries such as Australia, Canada, New Zealand, the U.K. and the U.S., where households' participation in equity market is strong. He demonstrates that increase in old age population affects to raise the real financial asset prices in those economies. In contrast, in countries such as Italy, Finland, Sweden, Norway and Japan where the households' participation in equity markets is limited, the older cohorts and the real stock prices are negatively related. Thus the findings are country specific.

The evidence of the study done by Brunetti and Torricelli (2010) also highlights the importance of country specific demographic dynamics in explaining the impact of demographics on financial markets. Italy has experienced rapid population ageing since the 1970s. Brunetti and Torricelli (2010) thus identify that Italy has a much steeper pronounced ageing and investigate the empirical connection between population ageing dynamics and financial markets using data from 1958-2004. Brunetti and Torricelli (2010) compare the results to the Unites States, particularly the findings of Poterba (2004). They employ OLS estimation for time series data to estimate equation (3.30).

$$R_t = \alpha + \beta D_t + \gamma F_t + \epsilon_t \qquad (3.30)$$

where R_t is the financial asset variable (real return on stocks, real yield on long term government bonds or real yield of one-year Treasury bills), D_t is the vector of demographic variables (20-40/total, 40-60/total, 65+/total, 40-64/20+, 65+/20+), F_t is the vector of non-demographic variables (lagged dividend yield, real long-term interest rate, share price volatility, GDP growth rate, output gap) and ϵ_t is the error term.

The results are sensitive to the model specifications. The first model includes only demographic variables as explanatory variables consistent with Poterba (2004). These results are similar to the findings for the United States by Poterba (2004) and do not show that demographic dynamics drive financial asset returns in Italy. However, Brunetti and Torricelli (2010) suggest that this could be due to omitted variable bias as demographic variables alone cannot explain the dynamics of financial asset returns. As a result, they extend the model to include set of explanatory control variables following Davis and Li (2003), which gives a different picture. In the extended model the signs of the coefficient estimates for demographic variables are in line with theoretical expectations. Hence authors conclude that demographics play a significant role on financial asset returns, particularly stock market returns in Italy. Also from the comparative analysis they further suggests that the degree of influence from demographics on financial markets is sensitive the specific ageing dynamics of a particular country.

The literature reveals a second study considering the effects of both demand and supply factors in determining the impact on stock prices from demographic structure. Bae (2010) estimates a reduced form equation derived from demand and supply structural equations similar to Jamal and Quayes (2004). The key difference between two estimation approaches is that Bae (2010) uses a cointegration method, but Jamal and Quayes (2010) use a standard OLS estimation. Accordingly, Bae (2010) employs the Dynamic Ordinary Least Square (DOLS) method to estimate equation (3.31) using annual data from 1949-2005 for the United States.

$$p_t = \alpha_0 + \alpha_1 y_t + \alpha_2 demo_t + \sum_{i=-p}^{p} \beta_{1i} \Delta y_{t-i} + \sum_{i=-p}^{p} \beta_{2i} \Delta demo_{t-i} + \varepsilon_t \quad (3.31)$$

As already discussed, Bae's (2010) results are different from that of Jamal and Quayes (2005) and he shows that an increase in the proportion of older (65+) population leads to decline in stock prices.

For the first time in literature Park (2010) uses a nonparametric approach to examine the predictions of the life cycle hypothesis empirically. The key feature of his approach is that it relates variations in stock prices to variations in the probability density function of the age distribution. This allows the measurement of impacts on asset prices from entire age distribution rather than a particular demographic measure. Brooks (2006) uses a similar approach however with a parametric method. Park (2010) conducts a misspecification test of the linear OLS regression using the data from 1900-2007 for the United States and criticises the previous literature. He tests for the problem of spurious regression using Augmented Dickey Fuller (ADF) test and the functional forms (linear or non-linear) of the regressions using the Ramsey Reset test. Based on the results, Park (2010, p. 1159) concludes that 'the linear regression in the existing studies appear to be either spurious, misspecified or both'.

However, readers should be cautious about Park's (2010) conclusion for several reasons. The first is that Park's (2010) misspecification analysis use only demographic variables and ignore the impact from non-demographic fundamentals leading to the problem of omitted variable bias. The second is that the model he used for misspecification test includes eight demographic variables leading to a multicollinearity problem. The third is that Park (2010) uses log of the price-dividend and price-earnings ratio as the dependent variables which does not directly match with the dependent variables used by the previous researchers.

Park (2010) uses the model (3.32) as the nonparametric econometric specification for empirical analysis.

$$y_t = \int f_t(s)\, g(s) ds + u_t \qquad (3.32)$$

where y_t is the log price-dividend ratio or price-earnings ratio of the stock price (i.e. normalised stock price), f_t is the density function of the age distribution at time *t* and

$g(s)$ is the age response function. In contrast to the mixed results found by Brooks (2006), Ang and Maddaloni (2005) and Geanakoplos et al. (2004) for G5 countries, Park (2010) concludes a significant impact from prime working age population on the stock prices for all G5 countries. He further computes the age response functions and shows that they are humped-shaped and significantly positive over prime working ages.

The existing literature on demographics and asset prices fails to accommodate both high and low frequency fluctuations in asset prices. Researchers concentrate either on low or high frequency fluctuations and ignore the different roles that asset price fluctuations possess at different frequencies. Favero, Gozluklu and Kotlikoff (2011) formulise this empirical framework to capture both high and low frequency fluctuations in a dynamic dividend growth model of asset prices and investigate how log dividend-price ratio relate to demographic trends as measured by MY, middle-aged to young ratio (40-49/20-29 years).

Favero et al. (2011) construct the empirical model based on Geanakoplos et al. (2004) theoretical model and combine it with dynamic dividend growth as per the derivation of Lettau and Nieuwerburgh (2008). This formulation allows the prediction of the log of the dividend-price ratio adjusted for demographics. Accordingly, they examine the statistical significance of the demographics and dividend-price ratio in a framework of long-run predictive regressions as given below. The variables in the system include real stock returns (h), dividend growth rate (Δd), real market returns adjusted for real dividend growth (h-Δd), stock price (p) and MY and the forecasting periods are from k =1, 2,…6.

$$\sum_{j=1}^{k} h_{t+j}^{s} = \beta_0 + \beta_1 p_t + \beta_2 d_t + \beta_3 MY_t + \varepsilon_{t,t+j} \quad (3.33)$$

$$\sum_{j=1}^{k} (\Delta d_{t+j}) = \beta_0 + \beta_1 p_t + \beta_2 d_t + \beta_3 MY_t + \varepsilon_{t,t+j} \quad (3.34)$$

$$\sum_{j=1}^{k} (h_{t+j}^{s} - \Delta d_{t+j}) = \beta_0 + \beta_1 p_t + \beta_2 d_t + \beta_3 MY_t + \varepsilon_{t,t+j} \quad (3.35)$$

The results indicate that the middle-aged to young ratio has a negative effect on the mean of the dividend-price ratio and hence a positive effect on the expected returns at all forecast horizons. Also, real market returns adjusted for real dividend growth rate have a significant positive relationship with the *MY* ratio. That is, the inclusion of demographic variables into the traditional dynamic dividend growth model gives significance evidence to conclude that the slowly evolving trend in the mean of log dividend-price ratio is related to demographics in the United States.

Favero et al. (2011, p. 1504) states that 'the evidence of forecasting power of a linear combination of dividend, price, and *MY* for forecasting long-term returns and long-run returns adjusted for dividend growth, provides indirect evidence of stationarity of such a combination'. Therefore, they test the validity of this hypothesis using a cointegration VAR similar to Johansen (1991, 1998). The results provide evidence for high persistence of the dividend-price ratio corresponding to high persistence of middle-aged to young ratio. Thus, it confirms the capability of the demographic trend as measured by the *MY* ratio of capturing the slowly evolving mean of dividend-price ratio in the long-run.

3.4 Conclusion

The evolution of research concerning the effect of demographic changes resulting from the Baby Boom on asset markets primarily focuses on the Unites States. The international studies mainly consider developed countries particularly the G5. Only one study includes emerging economies (Erb et al., 1997). The theoretical literature calibrates relevant variables based on inter-temporal general equilibrium or OLG models and then simulates the effects on asset markets of the changes in demographic structure, or provides analytical results. In contrast, empirical literature directly addresses the empirical question of whether there is a relationship between changing demographic structure and asset prices and/or asset returns.

The life cycle hypothesis (Modigliani and Brumberg, 1954; Ando and Modigliani, 1963) and overlapping generation models (Samuelson, 1958; Diamond, 1965) provide a theoretical foundation for the link between an individual's age, consumption and changing preferences over savings. In order to understand the link between demographic structure and asset prices, Yoo (1994a, 1997), Poterba (2001), Abel (2001, 2003), Brooks (2002), Geanakoplos et al. (2004), Goyal (2004), Brunetti and Torricelli (2010), Guest and Swift (2010) and Takats (2012) develop theoretical models primarily based on overlapping-generations models and produce simulation or analytical results. These theoretical models suggest that the working age population has a strong demand for assets and thereby raise asset prices. At the time of retirement individuals liquidate assets to finance their retirement and thereby exert a negative pressure on asset prices.

The seminal empirical research papers in the area of demographics and asset prices are those by Mankiw and Weil (1989) and Bakshi and Chen (1994). The former examines the relationship between demographics and housing asset prices and the latter concentrates on the link between demographics and financial asset prices, particularly stock and bond returns. Mankiw and Weil's (1989) startling result of fall in real house prices by 47% in the United States within 20 years from 1990s provoked a considerable criticism and raised concerns the validity of their forecast. Bakshi and Chen (1994) support the asset market meltdown hypothesis, which predicts a negative impact on stock prices when Baby Boomers retire. This paper was also subsequently both supported and criticised.

A notable number of empirical papers support the theoretical conclusion that demographic changes should have an impact on asset prices and asset returns. For instance, Yoo (1994a), Bergantino (1998), Davis and Li (2003), Geanakoplos et al. (2004), Goyal (2004), Jamal and Quayes (2004), Ang and Moddaloni (2005), Brooks (2006), Bae (2010), Guest and Swift (2010), Park (2011), Takats (2012) provide plausible arguments that demographic structure, specifically an ageing of population, could have a significant negative impact on housing and financial asset prices. Poterba conducted series of studies in 1998, 2001 and 2004 that do not support a robust relationship between asset prices and demographic structure. Although Poterba's (2001; 2004) studies find a statistically significant positive associations between stock returns as measured by price-dividend ratio and demographic variables, he concludes that it would not cause a decline in asset prices in the future as suggested by the asset market meltdown hypothesis. Poterba further argues that theoretical models that predicts asset market meltdown hypothesis assume that individuals would sell all their assets at the time of retirement, which is inconsistent with the data.

However, the empirical findings are sensitive to several factors and each empirical specification is open to questions. The first is whether the analysis uses recent data or historical data. The second is which demographic variables and which housing and financial asset variables are included into the model. The third is whether the model is purely demographic or not. And the fourth is whether it is a single country study or a cross country study. The fifth is whether the econometric model is parametric or non-parametric.

The econometric techniques used range from OLS (Mankiw and Weil, 1989; Engelhardt and Poterba, 1991; Yoo, 1994a; Green and Hendershott, 1996; Poterba, 1998; Poterba, 2001; *Geanakoplos*et al., 2004; Poterba, 2004; Goyal, 2004; Ang and Maddaloni, 2005), DOLS (Bae, 2010), panel regression (Davis and Li, 2003; Brooks, 2006; Takats, 2012), GMM (Bakshi and Chen, 1994), TSCS Regression (Erb et al., 1997) simultaneous equations (Jamal and Quayes, 2004; Bae, 2010), cointegrated VAR (Favero et al., 2011), semi-structural VAR (Shambora, 2007) and non-parametric regression (Park, 2010). A notable number of empirical studies use OLS, which ignores the non-stationary properties of time series data, leading spurious regressions and casts doubt about the findings. Further, OLS assumes that the association between the selected demographic variable and the asset price variable is linear in nature. In the case of cross country analyses, employing static panel regression ignores any lag effects of the dependent variable. The inclusion of lagged dependent variables as explanatory variables in dynamic panel could enhance controlling dynamics of the process. These factors may contribute to the mixed results and disjointed interpretations across the studies.

In summary, the existing literature however reveals that despite demography being a slow moving fundamental, the changing age structure has an impact on asset markets, which should not be neglected. Although the influence will not necessarily trigger an asset price meltdown as originally predicted by Mankiw and Weil (1989), it remains plausible that ageing will have a significant negative impact on housing and financial asset prices. Also, the literature provides evidence supporting the importance of country specific age dynamics to explain the relationship between demographics and financial asset prices.

CHAPTER 4 METHODOLOGY

4.1 Introduction

The review of literature in the previous chapter shows that the methodologies used to investigate the effects of demographics on asset prices are subject to a range of limitations and shortcomings. Consequently, this study uses a more rigorous approach and examines the dynamic relationships between demographic variables and asset prices using a structural vector autoregressive (SVAR) model. The advantages of this approach include taking into account the endogenous nature of the macroeconomic variables and modelling each variable as a function of all other variables. The effects of population ageing dynamics are addressed and the responses to ageing shocks on asset prices are quantified. In order to apply this methodology and interpret the results, a comprehensive understanding of vector autoregressive models is important.

This chapter provides a relatively non-technical survey of finite order vector autoregressive (VAR) models. It specifically focuses on the basic assumptions and properties of VAR and the fundamentals regarding interpretation of results. The chapter has a particular focus on structural VAR including various identification techniques. However, the chapter does not discuss VARs with cointegration relationships and proofs of theorems are not provided[25]. The primary references for this chapter are Lütkepohl (2005), Fry and Pagan (2011), Koop and Korobilis (2010), Lütkepohl (2011) and Kilian (2011).

Following the introduction section 4.2 provides an overview of VAR. The stability of VAR processes and the moving average representation are discussed in section 4.3. Standard estimation techniques such as least squares (LS) and maximum likelihood (ML) are commonly used in estimating VAR. These methods are discussed briefly in

[25]For theoretical details refer *Applied Econometric Time Series*, John Wily & Sons, 2008; *New Introduction to Multiple Time Series Analysis*, Helmut Lütkepohl, 2005, Springer

section 4.4. VAR model selection, that is choosing the appropriate lag-length, is imperative in VAR applications. Three basic lag-length selection criteria are described in section 4.5.

The reduced form VAR formulates the current value of a variable as a function of its own lagged values and the lagged values of other relevant variables. The recursive form, an extension of this approach, includes selected contemporaneous terms with lagged variables; however the contemporaneous terms were arbitrarily included. Cooley and Leroy (1985) criticised these two approaches because they don't have a strong theoretical basis. Cooley and Leroy (1985) further claimed that they cannot be interpreted as structural models. Subsequently macroeconomists have investigated non-recursive identifying restrictions on contemporaneous terms and the use of economic theory to determine the dynamic responses of macroeconomic variables to various shocks. Developments in this area lead to the introduction of the structural VAR framework which includes all contemporaneous and lagged variables in each equation of the model. However, to recover structural shocks additional identification restrictions are required. Section 4.6 provides an overview of the structural VAR. Three popular identification restrictions namely short-run, long-run and sign restrictions are described comprehensively in sections 4.6.1, 4.6.2 and 4.6.3 respectively.

Classical VAR estimation techniques suffer from the problem that large number of parameters to be estimated. However, many of these coefficients are not significantly different from zero leading to over-parameterization and poor quality estimates and forecasts. As a result, applied econometricians tend to formulate models with a limited number of variables and small lag-lengths to overcome the problem of over-parameterization.

The Bayesian VAR approach incorporates prior beliefs which enable a reduction in the number of parameters to be estimated (without necessarily imposing zero restrictions on coefficient estimates) while taking into account the uncertainty in the true population structure. Section 4.7 considers Bayesian VAR and four of the most common prior specifications are discussed. However, the chapter does not extend the basic Bayesian VAR model to time-varying coefficients, non-normal data and nonlinear relations.

Parameter estimates of VARs represent complex interactions between the variables. Therefore, researchers rarely use the estimates to explain the dynamic relationships between the variables. Instead, VAR models are used for forecasting, Granger causality and structural analysis. These three applications serve different purposes and the appropriate application has to be selected based on the problem at hand. Section 4.8 focuses on the applications of VAR models. Forecasting and Granger causality are discussed briefly. However, the section provides a comprehensive discussion of structural analysis, which covers impulse response functions, forecast error variance decomposition, historical decomposition and analysis of forecast scenarios. The conclusions drawn from the chapter are presented in section 4.9.

4.2 An Overview of Vector Autoregregressive (VAR) Model

VAR models were first proposed by Sims (1980a) as an alternative to large-scale dynamic simultaneous equations models (Kilian, 2011, p.1). In order to estimate a simultaneous equations model, each equation of the model has to satisfy the identification criteria. The question of whether an equation is identified or not depends on which variables are treated as exogenous and how many variables are included in each structural equation. In other words the identification relies on ad hoc dynamic exclusion restrictions in the regression model and empirically implausible exogeneity assumptions. In contrast, in formulating VAR models, the researcher does not dichotomise variables into endogenous and exogenous.

The development of VAR models were based on the concept of autoregression. An autoregressive process is a stochastic process where the current value is described by a weighted sum of its previous values and an error term. The equation (4.1) represents a univariate autoregressive process of order p, AR(p) assuming that data generation process is the same for each time period.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots + \alpha_p y_{t-p} + u_t \qquad (4.1)$$

where y_t, y_{t-1},…,y_{t-p} are random variables and u_t are homoscedastic and uncorrelated innovations (i.e. u_t and u_s are uncorrelated when $s \neq t$). The u_t are a white noise process with variance σ^2.

The framework of the VAR is an n-equation, n-variable linear model where the current value of each variable is described by its own lagged values plus the current and lagged values of remaining *n-1* variables. In the literature VARs have been used extensively to describe the dynamic behaviour of economic and financial time series data and it is considered to be the most successful and flexible model to analyse the rich dynamics of the data. The primary applications of VAR models are forecasting, structural inference and policy analysis. Impulse response functions and forecast error variance decompositions derived from VARs are well accepted and widely used in structural analysis. However, the success of VAR models depends on the extent to which we can evaluate shocks to the system as such shocks can reflect the effects of omitted variables. Structural interpretations based on impulse response analysis are worthless if important variables are omitted.

VARs have three forms; reduced, recursive and structural. A reduced form VAR represents current variable as a linear function of its own past values and the past values of all other variables. The error terms have zero mean and are serially uncorrelated. Each equation is estimated using ordinary least squares (OLS) as the values on the right hand side are predetermined or known at time *t*. Stock and Watson (2001, p. 6) note that in the reduced form 'the error terms in these regressions are the "surprise" movements in the variables, after taking its past values into account. If the different variables are correlated with each other – as they typically are in macroeconomic applications – then the error terms in the reduced form model will also be correlated across equations'. The specification and estimation of the reduced form VAR has a vast literature (for example see Watson, 1994; Lütkepohl (2005, 2011)).

In contrast to the reduced form, the recursive form VAR includes selected contemporaneous terms of the variables. The regressors and the model are constructed such that the error terms in each regression equation are uncorrelated with the error terms in the other equations. However, the selection of contemporaneous terms to be included in the model is arbitrary. Thus the estimation results depend on the recursive order of the variables.

Structural form VARs includes lagged variables plus contemporaneous terms. Unlike the reduced and recursive forms, structural VARs require additional identifying assumptions to define the contemporaneous links between the variables and thus impose appropriate restrictions on the variables in response to structural shocks. These assumptions are motivated by economic theory, institutional knowledge or other relevant constraints.

Table 4.1 shows the specifications of the three forms of VAR for a three variable (y_{1t}, y_{2t} and y_{3t}) model with lag 1.

Table 4.1: Three forms of VAR

Reduced form	$y_{1t} = \alpha_{10} + \alpha_{11} y_{1t-1} + \alpha_{12} y_{2t-1} + \alpha_{13} y_{3t-1} + u_{1t}$ $y_{2t} = \alpha_{20} + \alpha_{21} y_{1t-1} + \alpha_{22} y_{2t-1} + \alpha_{23} y_{3t-1} + u_{2t}$ $y_{3t} = \alpha_{30} + \alpha_{31} y_{1t-1} + \alpha_{32} y_{2t-1} + \alpha_{33} y_{3t-1} + u_{3t}$
Recursive form	$y_{1t} = \alpha_{10} + \alpha_{11} y_{1t-1} + \alpha_{12} y_{2t-1} + \alpha_{13} y_{3t-1} + u_{1t}$ $y_{2t} = \alpha_{20} + \alpha_{21} y_{1t-1} + \alpha_{22} y_{2t-1} + \alpha_{23} y_{3t-1} + \beta_{21} y_{1t} + u_{2t}$ $y_{3t} = \alpha_{30} + \alpha_{31} y_{1t-1} + \alpha_{32} y_{2t-1} + \alpha_{33} y_{3t-1} + \beta_{31} y_{1t} + \beta_{32} y_{2t} + u_{3t}$
Structural form	$y_{1t} = \alpha_{10} + \alpha_{11} y_{1t-1} + \alpha_{12} y_{2t-1} + \alpha_{13} y_{3t-1} + \beta_{12} y_{2t} + \beta_{13} y_{3t} + u_{1t}$ $y_{2t} = \alpha_{20} + \alpha_{21} y_{1t-1} + \alpha_{22} y_{2t-1} + \alpha_{23} y_{3t-1} + \beta_{21} y_{1t} + \beta_{23} y_{3t} + u_{2t}$ $y_{3t} = \alpha_{30} + \alpha_{31} y_{1t-1} + \alpha_{32} y_{2t-1} + \alpha_{33} y_{3t-1} + \beta_{31} y_{1t} + \beta_{32} y_{2t} + u_{3t}$

4.3 Basic Assumptions and Properties of VAR Processes

4.3.1 Stable VAR Processes

Consider the reduced form VAR model of order *p*, VAR(*p*) as given in equation 4.2 below.

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t \tag{4.2}$$

where, $y_t = (y_{1t}, \dots, y_{nt})'$ is a $(n \times 1)$ random vector of observable *n* time series for $(t = 1,2,\cdots,T)$; A_i are $(n \times n)$ coefficient matrices and $u_t = (u_{1t}, \dots, u_{nt})'$ is an *n*-dimensional white noise process.

$$E(u_t) = 0 \tag{4.3}$$

$$E(u_t u_t') = \Sigma_u \tag{4.4}$$

$$E(u_t u_s') = 0 \; for \; s \neq t \tag{4.5}$$

Σ_u is assumed to be non-singular.

The model in (4.2) is *reduced form* because all right hand side variables are lagged variables. Deterministic terms (constant/trend) have not been included for simplicity. The VAR(*p*) can be written as a corresponding *np*-dimensional VAR(1) process, which is given in equation (4.6).

$$Y_t = AY_{t-1} + U_t \tag{4.6}$$

where;

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \cdot \\ \cdot \\ \cdot \\ y_{t-p+1} \end{bmatrix}_{(np\times 1)} , \quad A = \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I_n & 0 & \cdots & 0 & 0 \\ 0 & I_n & \cdots & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ & & & \ddots & \\ 0 & 0 & . \; . \; . & I_n & 0 \end{bmatrix}_{(np\times np)} , \quad U_t = \begin{bmatrix} u_t \\ 0 \\ \cdot \\ \cdot \\ \cdot \\ 0 \end{bmatrix}_{(np\times 1)}$$

$$E(U_t) = 0 \tag{4.7}$$

$$E(U_t U_t') = \Sigma_U = \begin{bmatrix} \Omega & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & & \vdots \\ 0 & 0 & \dots & 0 \end{bmatrix}_{(np\times np)} \tag{4.8}$$

$$E(U_t U_s') = 0 \; for \; s \neq t \tag{4.9}$$

The stable VAR process generates time invariant means, variances and covariance structures. The time invariant mean and autocovariances of Y_t are given by (4.10) and (4.11).

$$E(Y_t) = 0 \quad (4.10)$$

$$\varphi_Y(h) = \sum_{i=0}^{\infty} A^{h+i}\, \Sigma_U (A^i)' \quad (4.11)$$

Accordingly, the mean and autocovariances of y_t are also time invariant and can be written as equations (4.12) and (4.13) respectively.

$$E(y_t) = 0 \quad (4.12)$$

(Note: If the VAR process considered in 4.2 had an intercept term (v), then $E(y_t) = \mu$ *where* $\mu = JE(Y_t) = J\left(I_{np} - A\right)^{-1} v$*)*

$$\varphi_y(h) = J\varphi_Y(h)J' = \sum_{i=1}^{\infty} A_1^{h+i}\, \Sigma_u A_i' \quad (4.13)$$

where *J* is defined as an $(n \times np)$ matrix, $J = [I_n : 0 : \ldots : 0]$.

As stated by Lütkepohl (2005, p. 16) if all the eigenvalues of matrix *A* have modules less than 1, then the VAR(*p*) process is stable[26]. That is

$$\det\left(I_{np} - Az\right) \neq 0 \text{ for } |z| \leq 1 \quad (4.14)$$

This is equivalent to the stability condition of (4.14) as follows.

$$\det\left(I_p - A_1 z - \cdots - A_p z^p\right) \neq 0 \text{ for } |z| \leq 1 \quad (4.15)$$

In other words, the roots of the characteristics equations (4.16) lie outside the unit circle which implies that the eigenvalues of the companion matrix *A* will be inside the unit circle.

$$\left|A - \lambda I_{np}\right| = (-1)^{np}\left|\lambda^p I_n - \lambda^{p-1} A_1 - \cdots - A_p\right| = 0 \text{ for } |z| > 1 \quad (4.16)$$

A stable VAR process has time invariant means, variances and covariance structure and is termed stationary.

[26]For the details of the derivation using VAR (1) and the definition for eigenvalue, refer Appendix A.

4.3.2 Moving Average (MA) Representation of VAR Processes

Under the stability assumption, the VAR processes can be written as a moving average decomposition. The moving average representation of a VAR(1) process (equation 4.6) can be expressed as equation (4.17).

$$Y_t = \sum_{i=0}^{\infty} A^i U_{t-i} \qquad (4.17)$$

Thus the MA representation of (4.2) can be found by pre-multiplying (4.17) by the matrix, J.

$$y_t = JY_t = \sum_{i=0}^{\infty} JA^i J' JU_{t-i} \qquad (4.18)$$

Let $\emptyset_i = JA^i J'$ and $u_t = JU_t$, then the MA(∞) of y_t is the accumulation of the effects of all past shocks as given by equation (4.19).

$$y_t = \emptyset_0 u_t + \emptyset_1 u_{t-1} + \emptyset_2 u_{t-2} + \cdots + \emptyset_p u_{t-p} + \cdots$$

$$y_t = \sum_{i=0}^{\infty} \emptyset_i u_{t-i} \qquad (4.19)$$

where $\emptyset_0 = I_n$ and $\emptyset_s = \sum_{j=1}^{s} \emptyset_{s-j} A_j$ for $j = 1, 2, \cdots$

4.4 Estimation of VAR Models

In this section it is assumed that an n variable multiple time series is generated by a stationary, stable VAR(p) process described in the equation (4.2). The coefficients, $(A_1, A_2, \cdots, A_p)$, and Σ_u are unknown and are to estimated using sample data. Least square and maximum likelihood estimation techniques based on chapter 3 of Lütkepohl (2005) are discussed briefly in sections 4.4.1 and 4.4.2 respectively. Bayesian methods for estimating VAR are discussed separately in section 4.7. Structural VAR models can be estimated using least square, maximum likelihood or Bayesian methods.

4.4.1 Least Square (LS) Estimation

Assume that we have the same sample size of T for each of the n variables and define an $(n \times T)$ observation matrix as $Y = (y_1, \cdots, y_T)$. We also assume that a p pre-sample of values for each variable $y_{-p+1}, \cdots, y_0$ are available.

Consider the VAR(p) model (4.2) in the more compact form shown in equation (4.20).

$$y_t = [A_1, A_2, \cdots, A_p] Z_{t-1} + u_t \tag{4.20}$$

where $Z_{t-1} = (y_{t-1}, \cdots, y_{t-p})'$

Accordingly, $Z_t = (y_t, \cdots, y_{t-p+1})'$

For a given sample size of T and p pre-sample vectors, the parameters of the VAR(p) can be estimated by applying OLS for each equation separately. Post-multiplying both sides in equation (4.20) by Z'_{t-1} then taking expectations and using the property of $E(u_t) = 0$ we obtain equation (4.21).

$$E(y_t Z'_{t-1}) = AE(Z_{t-1} Z'_{t-1}) \tag{4.21}$$

where $A = [A_1, A_2, \cdots, A_p]$.

$E(y_t Z'_{t-1})$ and $E(Z_t Z'_{t-1})$ can be estimated using equations (4.22) and (4.23) respectively.

$$E(y_t Z'_{t-1}) = \frac{1}{T} \sum_{t=1}^{T} y_t Z'_{t-1} = \frac{1}{T} YZ' \tag{4.22}$$

where $Z = (Z_0, \cdots, Z_{T-1})$

$$E(Z_t Z'_{t-1}) = \frac{1}{T} \sum_{t=1}^{T} Z_{t-1} Z'_{t-1} = \frac{1}{T} ZZ' \tag{4.23}$$

The normal equation is given in (4.24)

$$\frac{1}{T} YZ' = \hat{A} \frac{1}{T} ZZ' \tag{4.24}$$

Thus $\hat{A} = YZ'(ZZ')^{-1}$ (4.25)

Therefore, the LS estimator for sample size T is given in equation (4.26).

$$\hat{A} = [\hat{A}_1, \cdots, \hat{A}_p] = (\sum_{t=1}^{T} y_t Z'_{t-1})(\sum_{t=1}^{T} Z_t Z'_{t-1})^{-1} \tag{4.26}$$

This LS estimator is consistent and asymptotically normally distributed.

The estimator for variance-covariance matrix of Σ_u is;

$$\hat{\Sigma}_u = \frac{T}{T-np}\tilde{\Sigma}_u \tag{4.27}$$

where $\tilde{\Sigma}_u = \frac{1}{T}\sum_{t=1}^{T} \hat{u}_t \hat{u}_t'$

$$= \frac{1}{T} Y(I_T - Z'(ZZ')^{-1}Z)Y' \tag{4.28}$$

4.4.2 Maximum Likelihood (ML) Estimation

To derive the ML estimator, we assume that distribution of the VAR(*p*) process y_t is Gaussian. More specifically assume that

$$u = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_T \end{bmatrix} \sim N(0, I_T \otimes \Sigma_u) \tag{4.29}$$

where$\otimes$ denotes the *Kronecker product* of the two matrices. See Appendix A4 for the definition of the *Kronecker product.*

Thus, $u_t \sim N(0, \Sigma_u)$ (4.30)

The log likelihood function (*l*) for the full sample conditioning on the pre-sample values for each variable $y_{-p+1}, \cdots, y_0$ is given in equation (4.31).

$$l = -\frac{Tn}{2} log(2\pi) + \frac{T}{2} log\left|{\Sigma_u}^{-1}\right| - \frac{1}{2}\sum_{t=1}^{T}\left[(y_t - AZ_{t-1}')'{\Sigma_u}^{-1}(y_t - AZ_{t-1}')\right] \tag{4.31}$$

where $Z_{t-1} = \left(y_{t-1}, \cdots, y_{t-p}\right)'$ (4.32)

The ML estimator of *A* is given by equation (4.33).

$$\hat{A} = (\textstyle\sum_{t=1}^{T} y_t Z_{t-1}')(\sum_{t=1}^{T} Z_t Z_{t-1}')^{-1} \tag{4.33}$$

This ML estimator is identical to the LS estimator and it is a consistent estimator of the population parameter.

4.5 VAR Model Specification (Lag Length Selection)

In the previous sections we assumed that the order of the VAR model is *p*. However, we did not assume that all the coefficients (A_i) are nonzero. Choosing appropriate VAR order (or lag-length) is an important component of the VAR applications.

Lütkepohl (2005, p. 135) states that '... choosing p unnecessarily large will reduce the forecast precision of the corresponding estimated VAR(p) model. Also, the estimation precision of the impulse responses depends on the precision of the parameter estimates'.

The VAR order is typically determined by performing statistical tests or using model selection criteria. The most common statistical test is the likelihood-ratio test. The procedure first specifies a maximum reasonable lag length (say p_{max}) and then sequentially tests for shorter lags (i.e. $p_{max-1}, p_{max-2...}$). Accordingly, the corresponding null and alternative hypotheses are

$$H_0 : A_{p_{max}} = 0 \qquad \text{vs} \qquad H_1 : A_{p_{max-1}} = 0$$

If we denote the VAR model with order p_{max} as the unrestricted model and the model with order p_{max-1} as the restricted model, the corresponding estimators for $\Sigma_u$are $\hat{\Sigma}_u^U$ and $\hat{\Sigma}_u^R$ respectively. The test statistic (*TS*) for a given sample size of T is given in equation (4.34).

$$TS = T\left(ln\left|\hat{\Sigma}_u^R\right| - ln\left|\hat{\Sigma}_u^U\right|\right) \qquad (4.34)$$

This test statistic has a χ^2 distribution with degrees of freedom equals to the number of restrictions in the system.

Alternatively model selection criteria such as Akaike's information criterion (*AIC*), Hannan-Quinn criterion (*HQ*) and Schwarz criterion (*SC*) can be used. For a VAR(*m*) process the criteria is defined as in equations (4.35) to (4.37).

$$AIC(m) = ln\left|\hat{\Sigma}_u\right| + \frac{2}{T}mn^2 \qquad (4.35)$$

$$HQ(m) = ln\left|\hat{\Sigma}_u\right| + \frac{2lnlnT}{T}mn^2 \qquad (4.36)$$

$$SC(m) = ln\left|\hat{\Sigma}_u\right| + \frac{lnT}{T}mn^2 \qquad (4.37)$$

The optimum lag length is selected so as to minimize the value of the respective criterion over possible lag orders $m = 0, 1, \cdots, p_{max}$. As mentioned in the chapters 4 and 8 of Lütkepohl (2005), *AIC* suggests the largest lag length while *SC* usually chooses the smallest lag order. However, HQ suggests the lag order between the largest and the smallest.

4.6 Structural Vector Autoregressive (SVAR) Models

The VAR is a reduced form model and does not include the impact of contemporaneous variables. Cooley and LeRoy (1985) argue that the dynamic relations of the reduced form VAR are unrelated to economic theory and describe it as atheoretical. They further criticise the difficulty of reconciling economic theory with the dynamic characteristics implied by VAR models in the reduced form. As a result of this criticism the structural form of the VAR model was developed by Bernanke (1986), Blanchard and Watson (1986) and Sims (1986). As mentioned in section 4.2 the structural form of the VAR includes contemporaneous variables in the right hand side of the equations. This allows the researcher to use economic theory to transform the reduced form VAR model into a system of structural equations (Keating, 1992).

Consider the structural form model shown in equation (4.38).

$$B_0 y_t = B_1 y_{t-1} + \cdots + B_p y_{t-p} + \varepsilon_t \tag{4.38}$$

Using an autoregressive lag polynomial of order p, (4.38) can be written as equation (4.39).

$$B(L) y_t = \varepsilon_t \tag{4.39}$$

where $B(L) = B_0 - B_1 L - B_2 L^2 - \cdots - B_p L^p$

The matrix B_0 reflects the contemporaneous relationships among the variables. The error terms ε_t, are referred to as structural innovations/ shocks and have mean zero and are serially uncorrelated, that is $\varepsilon_t \sim (0, \Sigma_\varepsilon)$. It is also assumed that the errors are unconditionally homoskedastic following Killian (2011).

To apply standard estimation techniques as described in section (4.4), the structural form is first transformed to the reduced form VAR representation. Pre-multiplying (4.38) by B_0^{-1} gives

$$B_0^{-1}B_0y_t = B_0^{-1}B_1y_{t-1} + \cdots + B_0^{-1}B_py_{t-p} + B_0^{-1}\varepsilon_t \quad (4.40)$$

Denoting $A_i = B_0^{-1}B_i$ and $u_t = B_0^{-1}\varepsilon_t$ we can obtain reduced form VAR(p) model.

$$y_t = A_1y_{t-1} + \cdots + A_py_{t-p} + u_t \quad (4.41)$$

$$A(L)y_t = u_t \quad (4.42)$$

where $A(L) = I - A_1L - A_2L^2 - \cdots - A_pL^p$

The standard estimation methods provide consistent estimates for A_i $(i = 1, 2, \cdots, p)$, u_t and Σ_u. However, our goal is to investigate the response of y_t to the structural shocks, ε_t. From the previous construction of u_t $(i.e.\ u_t = B_0^{-1}\varepsilon_t)$ we can obtain

$$\varepsilon_t = B_0u_t \quad (4.43)$$

The structural shocks depending on B_i $(i = 1, 2, \cdots, p)$ can be derived using the reduced form parameters and B_0 since $B_i = B_0A_i$. Therefore, the central problem is to estimate B_0 from the reduced form parameters of A_i $(i = 1, 2, \cdots, p)$ and to learn about the structural responses. Thus imposing restrictions on B_0 and Σ_ε is the primary task of the analysis. From equation (4.43) we can derive the variance-covariance matrix of u_t.

$$E(u_tu_t') = B_0^{-1}E(\varepsilon_t\varepsilon_t')B_0^{-1\prime} \quad (4.44)$$

$$\Sigma_u = B_0^{-1}\Sigma_\varepsilon B_0^{-1\prime} \quad (4.45)$$

The diagonal elements of the variance-covariance matrix of the reduced form error terms (Σ_u in equation 4.45) can be normalised in three different ways. These three methods define three equivalent representations of structural VAR models. In this section these three representations are named as *Model 1*, *Model 2* and *Model 3*.

***Model 1*:**

In this model the variance of the structural innovations is normalised to one (i.e. $\varepsilon_t \sim (0, I_n)$).

Therefore, $\Sigma_\varepsilon = I_n$ (4.46)

This implies that structural shocks are mutually uncorrelated in addition to the variances of the structural shocks being equal to unity. Applying this condition to the equation (4.45), we can obtain the equation (4.47) for Σ_u as follows.

$$\Sigma_u = B_0^{-1}\Sigma_\varepsilon B_0^{-1'}$$

$$\Sigma_u = B_0^{-1}B_0^{-1'} \qquad (4.47)$$

Identification can be achieved by imposing restrictions on B_0^{-1}. There are n^2 elements in B_0^{-1} . Hence the identification requires to choosing a value for each element in B_0. The covariance matrix has $n(n+1)/2$ relations and therefore $n(n+1)/2$ parameters in B_0^{-1} can be uniquely identified. According to the order condition, to identify B_0^{-1} $n(n-1)/2$ further relations are needed, which is, however, just a necessary condition[27]. Choosing B_0^{-1} to be a lower triangular matrix provides sufficient restrictions.

***Model 2*:**

In this form, identification restrictions are imposed on the matrix B_0 such that the variance-covariance matrix of Σ_u is diagonal. The diagonal elements of B_0 are normalised to unity in $\varepsilon_t = B_0 u_t$ and the diagonal elements of Σ_ε are unconstrained. This representation also needs additional $n(n-1)/2$ restrictions to identify B_0^{-1} uniquely. Therefore when B_0 is restricted, $n(n-1)/2$ zeros are imposed above the main diagonal so that innovations are just identified. B_0 is a lower triangular matrix with unit diagonal elements.

$$B_0 = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ b_{21} & 1 & & 0 \\ \vdots & & \ddots & \vdots \\ b_{n1} & b_{n2} & & 1 \end{bmatrix} \qquad (4.48)$$

The lower triangular B_0 implies that B_0^{-1} is also lower triangular.

[27] The order condition is not sufficient, thus it does not identify the SVAR globally. The rank condition is a sufficient condition for global identification. See Rubio-Ramirez, Waggoner, & Zha (2010) for detailed information about local and global identification.

***Model 3*:**

This model specification combines both types of restrictions imposed in models 1 and 2.

$$B_0 u_t = C\varepsilon_t \tag{4.49}$$

with $\Sigma_\varepsilon = I_n$.

$$u_t = B_0^{-1} C\varepsilon_t \tag{4.50}$$

$$E(u_t u_t') = B_0^{-1} C \Sigma_\varepsilon C' B_0^{-1\prime}$$

$$\Sigma_u = B_0^{-1} C C' B_0^{-1\prime} \tag{4.51}$$

The two matrices B_0 and C together have $2n^2$ elements. Therefore, $[2n^2 - n(n+1)/2]$ restrictions are required to identify all $2n^2$ elements. However, this representation is flexible due to the alternative normalizations of $B_0 = I_n$ or $C = I_n$. For example, Blanchard and Perotti (1999) use this SVAR specification to investigate the dynamic effects of shocks to government spending and taxes on output. However, the literature reveals that it is difficult in practice to obtain suitable restrictions for matrices B_0 and C. As a result, any derived dynamic relationships among the variables would not be credible.

Each of the three model specifications require that additional identification assumptions are necessary to estimate the structural equation parameters and hence to recover structural shocks. As mentioned by Killian (2011, p. 1) the additional identifying restrictions must be based on institutional knowledge, economic theory or other extraneous constraints on the model responses. The following sections consider three alternative identification techniques to recover structural parameters/ shocks. The short run restrictions, long run restrictions and sign restrictions are discussed in sections 4.6.1, 4.6.2 and 4.6.3 respectively.

4.6.1 Identification by Short-Run Restrictions

The rationale of the short-run restrictions is to orthogonalize the error terms. The variance-covariance matrix of $\Sigma_u = B_0^{-1} \Sigma_\varepsilon B_0^{-1\prime}$ is decomposed by finding a lower triangular $(n \times n)$ matrix P which solves the equation (4.52). The orthogonalization produces uncorrelated errors.

$$\Sigma_u = PP' \tag{4.52}$$

where P is a lower triangular matrix with positive main diagonal elements. Equation (4.52) is called the *Choleski decomposition*.

$$P = \begin{bmatrix} \alpha_{11} & 0 & 0 & \cdots & 0 \\ \alpha_{21} & \alpha_{22} & 0 & \cdots & 0 \\ \vdots & & & & \vdots \\ \alpha_{n1} & \alpha_{n2} & \alpha_{n3} & \cdots & \alpha_{nn} \end{bmatrix} \tag{4.53}$$

From the *Choleski decomposition* of $\Sigma_u = B_0^{-1}\Sigma_\varepsilon B_0^{-1'}$,

$$chol(\Sigma_u) = \Sigma_\varepsilon{}^{1/2} B_0^{-1'} \tag{4.54}$$

$$B_0^{-1'} = \Sigma_\varepsilon{}^{-1/2} chol(\Sigma_u) \tag{4.55}$$

$$B_0^{-1} = chol(\Sigma_u)' \Sigma_\varepsilon{}^{-1/2} \tag{4.56}$$

According to equation (4.47) it follows that $B_0^{-1} = P$ is one possible solution to recover structural shocks of ε_t. However, since P is a lower triangular, a recursive contemporaneous structural model is created. Such a recursive system assumes that y_{1t} (the first variable of the vector of variables, y_t) is contemporaneously related to all other variables, y_{2t} (the second variable of the vector of variables, y_t) is contemporaneously related to all other variables except y_{1t} and so on (i. e. a triangular system). As a result, findings depend on the order of the variables. This implies that theoretical justifications for the selected recursive order of the variables are required. If there is not a convincing rationale for the selected recursive ordering the interpretations of the results may provide a misleading picture. This situation has led to interest in the alternative identifications methods discussed in the sections below.

4.6.2 Identification by Long-Run Restrictions

The concept of long-run restrictions was first discussed by Blanchard and Quah (1989). Long-run restrictions are based on the assumption that not all shocks have a permanent effect. For example, Blanchard and Quah (1989) assumed that aggregate demand shocks do not have long-run effects on output, but aggregate supply shocks do have long-run effects on output. Faust and Leeper (1997, p. 4) states that 'the long-run scheme rests on the view that if certain economically plausible long-run neutrality assumptions are imposed, then reliable inferences can be drawn about the short-run dynamics of behavioural disturbances in the economy'. The description of the identification by long-run restrictions outlined below is based on Killian (2011, p. 18-19).

First, consider the MA representation of the structural and corresponding reduced form VAR(p) models of (4.39) and (4.42). They are shown in equations (4.57) and (4.58) respectively.

$$B(L)y_t = \varepsilon_t \tag{4.39}$$

The MA representation of (4.39) is

$$y_t = B(L)^{-1}\varepsilon_t$$

$$y_t = \varphi(L)\varepsilon_t = \sum_{i=0}^{\infty} \varphi_i \varepsilon_{t-i} \tag{4.57}$$

$$A(L)y_t = u_t \tag{4.42}$$

The MA representation of (4.42) is

$$y_t = A(L)^{-1}u_t$$

$$y_t = \emptyset(L)u_t = \sum_{i=0}^{\infty} \emptyset_i u_{t-i} \tag{4.58}$$

where $\emptyset_0 = B_0^{-1}$, $\emptyset_1 = B_0^{-1}B_1$, …, $\emptyset_p = B_0^{-1}B_p$, …,

It was shown above that the reduced form errors (u_t) are a weighted average of structural shocks (ε_t) where $u_t = B_0^{-1}\varepsilon_t$.

With the assumption of $\Sigma_\varepsilon = I_n$, the variance-covariance matrix of the reduced-form innovations is

$$\Sigma_u = B_0^{-1} B_0^{-1'} \quad (4.59)$$

Using the relationship between coefficient matrices of the reduced-form VAR and structural VAR the relationship between $B(L)$ and $A(L)$ is derived (equation 4.60).

$$A(L) = B_0^{-1} B(L) \quad (4.60)$$

$$B_0^{-1} = A(L) B(L)^{-1} \quad (4.61)$$

For $p = 1$ (i.e. lag order of 1),

$$B_0^{-1} = A(1) B(1)^{-1} \quad (4.62)$$

Substituting for B_0^{-1} from (4.62) in (4.59), the variance-covariance matrix of reduced-form innovations can be written as follows.

$$\Sigma_u = [A(1)B(1)^{-1}][A(1)B(1)^{-1}]'$$

$$\Sigma_u = [A(1)B(1)^{-1}][B(1)^{-1}]'A(1)' \quad (4.63)$$

Pre-multiplying and post-multiplying equation (4.63) by $A(1)^{-1}$ and $[A(1)']^{-1}$, the right hand side of the equation (4.63) is simplified as shown in equation (4.64).

$$A(1)^{-1}\Sigma_u[A(1)']^{-1} = A(1)^{-1}A(1)B(1)^{-1}[B(1)^{-1}]'A(1)'[A(1)']^{-1}$$

$$A(1)^{-1}\Sigma_u[A(1)']^{-1} = B(1)^{-1}[B(1)^{-1}]' \quad (4.64)$$

Using the coefficient matrices of MA representations, equation (4.64) can be re-written

$$\emptyset(1)\Sigma_u\emptyset(1)' = \varphi(1)\varphi(1)' \quad (4.65)$$

Using the *vec* operator of the matrices, (4.65) can be stacked into column vectors such that[28]

$$vec(\emptyset(1)\Sigma_u\emptyset(1)') = vec(\varphi(1)\varphi(1)') \quad (4.66)$$

[28] Please see Appendix A for the definition of *vec* operator of the matrices.

The left-hand side components of equation (4.66) can be estimated using the reduced form model and sample data. Similar to the case of short-run restrictions, further $n(n-1)/2$ restrictions on $\varphi(1)$ must be imposed to satisfy the order condition for identification. Also, note that the elements of $\varphi(1) = B_1^{-1}$ represents the long-run cumulative effects of the each structural shock to each variable. For example, $\varphi_{ij}(1)$ measures the long-run impacts of structural shock *j* on variable *i*. It is important to keep in mind that the zero restrictions on selected elements of $\varphi(1)$ should only be on variables with a unit root (i.e. *I*(1) variables).

To illustrate the concept of long-run restrictions, consider a bivariate structural VAR(1) model where variable 1 is *I*(1) and variable 2 is *I*(0). Also assume that shocks on variable 2 do not have long-run effects on variable 1. The long-run cumulative impact of the structural shocks is captured by $\varphi(1) = B_1^{-1}$ as follows

$$\varphi(1) = \begin{bmatrix} \varphi_{11}(1) & \varphi_{12}(1) \\ \varphi_{21}(1) & \varphi_{22}(1) \end{bmatrix} = \begin{bmatrix} \sum_{s=0}^{\infty} \varphi_{11}^{s} & \sum_{s=0}^{\infty} \varphi_{12}^{s} \\ \sum_{s=0}^{\infty} \varphi_{21}^{s} & \sum_{s=0}^{\infty} \varphi_{22}^{s} \end{bmatrix} \quad (4.67)$$

Impose the restriction $\varphi_{12}(1) = \sum_{s=0}^{\infty} \varphi_{12}^{s} = 0$ (4.68)

This implies that the level of variable 2 is not affected in the long-run by the structural innovation that drives variable 2 to zero[29]. Therefore $\varphi(1)$ is rewritten as equation (4.69).

$$\varphi(1) = \begin{bmatrix} \varphi_{11}(1) & 0 \\ \varphi_{21}(1) & \varphi_{22}(1) \end{bmatrix} \quad (4.69)$$

Since $A(1)$ can be consistently estimated from the reduced-form model, B_0^{-1} can be estimated using formula (4.70).

$$B_0^{-1} = A(1)\varphi(1) \quad (4.70)$$

4.6.3 Identification by Sign Restrictions

The sign restrictions approach was first used in analysing the monetary policy shocks by Canova and Nicoló (2002) and Uhlig (2005). Both the short-run and long-run

29 Since the considered model has only 2 variables only one restriction is imposed.

identification restrictions impose parametric assumptions for recovering structural equation parameters. For instance, in the short run restrictions reduced form errors are orthogonalized to disentangle structural shocks from reduced form shocks while in the long-run restrictions some variables should have unit roots but not in other variables. In contrast, sign restrictions do not impose parametric assumptions. Instead, the sign restriction method involves restricting the sign of the responses of model variables to structural innovations and thereby identifies the structural parameters/shocks. In VAR application of the monetary policy, Uhlig (2005) replaced the conventional semi-structural model to identify monetary policy shocks on output by a model that uses only sign restrictions and obtained substantially different results.

The identification by sign restriction requires to restrict the signs of the coefficients in B_0^{-1}. Therefore, the task is to identify elements of B_0^{-1} which produce unique sign pattern and consistent with the set of *a priori* sign restrictions. The question arises as there will be many such combinations where some would provide postulated sign restrictions, while some would not.

Assuming, as above, that the structural shocks are uncorrelated and have unit variances (i.e. $\Sigma_\varepsilon = I_n$), then $\Sigma_u = B_0^{-1}B_0^{-1'}$. Let P be the lower triangular *Choleski decomposition* of Σ_u such that

$$\Sigma_u = PP' \qquad (4.71)$$

Finding an $(n \times n)$ orthogonal matrix Q (ie: $QQ' = Q'Q = I_n$), enables B_0^{-1} to be identified such that

$$B_0^{-1} = PQ \qquad (4.72)$$

$$P = B_0^{-1}Q^{-1} \qquad (4.73)$$

Substituting in (4.71) from (4.73), we obtain

$$\Sigma_u = B_0^{-1}Q^{-1}Q^{-1'}B_0^{-1'} = B_0^{-1}Q'QB_0^{-1'} = B_0^{-1}B_0^{-1'}$$

(*Note*: $Q^{-1} = Q'$ $because\ Q\ is\ orthogonal$)

That is, choosing $B_0^{-1} = PQ$ also satisfies the condition $\Sigma_u = B_0^{-1}B_0^{-1'}$ and using $\varepsilon_t = B_0 u_t$, we can show that $\Sigma_\varepsilon = I_n$.

Unlike P, PQ in general will be non-recursive. However, there are many possible Q's and the problem is then to find a unique Q. Fry and Pagan (2011, p. 944) describe the two most popular ways of forming the orthogonal matrix Q. They are using Givens matrices and Householder transformations.

Givens Matrices

In general, the Givens matrix is found as the product of $n(n-1)/2$ Givens rotation matrices. For example, for a 3 variable VAR, there are three possible Givens rotations which are named as Q_{12}, Q_{13} and Q_{23}. Each Q_{ij} depends on a separate parameter α_k and α lies between 0 and $\pi/2$.

$$Q_{12} = \begin{bmatrix} \cos\alpha & -sin\alpha & 0 \\ sin\alpha & cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4.74}$$

For any possible Givens rotation $Q_{ij}Q'_{ij} = I_n$ since $cos^2\alpha + sin^2\alpha = 1$.

For example, $Q_{12}Q'_{12} = \begin{bmatrix} cos\alpha & -sin\alpha & 0 \\ sin\alpha & cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} cos\alpha & sin\alpha & 0 \\ -sin\alpha & cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix}$

$$Q_{12}Q'_{12} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} = I_3 \tag{4.75}$$

Also, as discussed by Fry and Pagan (2011, p. 945), most users of the approach denote the multiples of the basic set of Givens matrices as Q. In the three variable case Q_G is given in equation (4.76) such that, $Q_G Q'_G = I_3$.

$$Q_G(\alpha) = Q_{12}(\alpha_1) \times Q_{13}(\alpha_2) \times Q_{23}(\alpha_3) \tag{4.76}$$

where

$$Q_{12} = \begin{bmatrix} cos\alpha_1 & -sin\alpha_1 & 0 \\ sin\alpha_1 & cos\alpha_1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, Q_{13} = \begin{bmatrix} cos\alpha_2 & 0 & sin\alpha_2 \\ 0 & 1 & 0 \\ -sin\alpha_2 & 0 & cos\alpha_2 \end{bmatrix} and\ Q_{23} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & cos\alpha_3 & sin\alpha_3 \\ 0 & -sin\alpha_3 & cos\alpha_3 \end{bmatrix}$$

Accordingly, many possible values for Q_G can be computed and, since $B_0^{-1} = PQ_G$, there are many possible solutions for estimated structural parameters/shocks[30]. However, the Q_G which are retained will be those that satisfy the postulated identifying restrictions. It should be noted that there are many different α values which will produce the requisite sign restrictions with the retained Q_G. That is with respect to each α there will be a new model in terms of new set of structural shocks and equations. Consequently, the procedure generates a number of impulse response functions that are consistent with the assumed signs[31]. Various methods have been suggested to establish a single set of impulse response functions (see Fry and Pagan, 2011; Killian, 2011).

Householder Transformations

In order to generate an orthogonal matrix *Q*, draw an $(n \times n)$ matrix *W* of $NID(0,1)$ and then derive the *QR* decomposition of *W* as shown in equation (4.77) with $QQ' = I_n$ and *R* a triangular matrix.

$$W = QR \tag{4.77}$$

There are many possible *Ws* and hence it is possible to find many *Qs*. Similar to the Givens approach retain *W* that satisfy the identifying restrictions and then compute $B_0^{-1} = PQ$. The resulting matrix B_0^{-1}, along with the estimated reduced-form errors, provides a set of acceptable structural parameters/shocks.

4.7 Bayesian VAR (BVAR)

The appropriate macroeconomic modelling of the dynamic relationships among the variables using VAR typically involves three or more variables. Often, however, the available time series are of moderate length because the data frequency is monthly, quarterly or annual. In addition, long lag lengths are sometimes necessary for the Wold MA representation of the VAR models. As a result, VAR involves estimating a

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[30] Canova and de Nicolo (2002) suggest to make a grid of M values for each of the values of α_k between 0 and $\pi/2$ and then compute all possible Q_G.

[31] Impulse response functions will be discussed in detail in section 4.8.

large number of parameters (over-parameterization). In some cases the number of parameters to be estimated exceeds the number of observations. The *n*-variable VAR(p) with intercept term has $(n + n^2p)$ parameters[32]. The BVAR approach addresses the problem of over-parameterization. The uncertainty of the population structure is taken into account and prior information in the form of prior probability distributions is utilised to estimate the VAR model parameters. Koop and Korobilis (2010, p. 7) describe the importance of priors, 'without prior information, it is hard to obtain precise estimates of so many coefficients and, thus, features such as responses and forecasts will tend to be imprecisely estimated'. The Bayesian VAR approach assumes that non-sample or prior information is available in the form of a *prior probability density function (pdf)* and sample information is summarised in the form of sample probability density function (sample *pdf*). Bayes' theorem is used to combine the two types of information.

Bayes' theorem, adopted from Lütkepohl (2005, p. 223), is given in equation (4.78).

$$g(\alpha|y) = \frac{f(y|\alpha)g(\alpha)}{f(y)} \tag{4.78}$$

where α is the vector of parameters of interest, $f(y)$ is the unconditional sample density for a given sample of y, $f(y|\alpha)$ is the conditional sample p.d.f. (identical to the likelihood function, $l(\alpha|y)$), $g(\alpha)$ is the *prior probability density function* and $g(\alpha|y)$ is the conditional distribution of α given y. The conditional density function of α, $g(\alpha|y)$ is the *posterior probability density function*, which contains all the information available on the parameter vector, α.

$$g(\alpha|y) \propto f(g|\alpha)g(\alpha) \tag{4.79}$$

The application of this general framework of Bayes' theorem to the VAR models is briefly discussed in subsequent sections. It is based on Ciccarelli and Rebucci (2003) and Koop and Korobilis (2010). Section 4.7.1 derives the likelihood function of a

[32] For example VAR (4) model with 5 variables involves 105 parameters

VAR and four alternative specifications of prior distributions are discussed in section 4.7.2.

4.7.1 Likelihood Function

The reduced form VAR(p) described in equation (4.2) can be written as equation (4.80) or (4.81). In these forms, the results will be expressed in terms of multivariate normal distribution[33].

First define $x_t = \left(y'_{t-1}, \cdots, y'_{t-p}\right)$ and denote $K = np$

$X = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_T \end{bmatrix}$ is a $(T \times K)$ matrix.

$A = \left(A_1, \cdots, A_p\right)'$ and $\alpha = vec(A)$ is a $Kn \times 1$ vector which stacks all the VAR coefficients into a vector.

The VAR(p) model can be written in one of the following forms denoted by (4.80) or (4.81).

$$Y = XA + U \qquad (4.80)$$

or

$$y = (I_n \otimes X)\alpha + u \qquad (4.81)$$

where $u \sim N(0, \Sigma_u \otimes I_T)$. That is $u_t \sim i.i.d.N(0, \Sigma_u)$

The sampling density function of the data conditional on α and Σ_u (in the form of the likelihood function $L(Y|\alpha, \Sigma_u)$ can be broken into two parts.

i. α given Σ_u has a normal distribution;

$$\alpha|\Sigma_u, y \sim N(\hat{\alpha}, \Sigma_u \otimes (X'X)^{-1}) \qquad (4.82)$$

ii. ${\Sigma_u}^{-1}$ given Y has a Wishart distribution;

[33] Depending on the matrix form of VAR representation, results can be expressed in terms of the multivariate normal or in terms of the matric-variate normal distribution.

$$\Sigma_u{}^{-1}|y \sim W(S^{-1}, T-K-n-1) \tag{4.83}$$

$$\hat{\alpha} = vec(\hat{A}) \tag{4.84}$$

$$S = (Y - X\hat{A})'(Y - X\hat{A}) \tag{4.85}$$

where $\hat{A} = (X'X)^{-1}X'Y$ is the OLS estimate of A. Thus, the likelihood function is the product of the normal density for α given Σ_u and the Wishart density of $\Sigma_u{}^{-1}$.

$$L(y|\alpha, \Sigma_u) \propto N(\hat{\alpha}, \Sigma_u \otimes (X'X)^{-1}) \times W(S^{-1}, T-K-n-1) \tag{4.86}$$

4.7.2 Prior Distributions for BVAR

The prior specifications that can be used for Bayesian analysis of VARs differ in relation to three issues (Koop and Korobilis, 2010). The first issue is related to the reduction of the number of parameters to be estimated. This is called shrinkage and it involves using non-sample or prior information. Shrinkage imposes restrictions on parameters in the VAR model that are to be estimated. The second issue depends on whether the priors lead directly to analytical results or whether Markov chain Monte Carlo (MCMC) methods are required to carry out inferences. The third relates to departures from the standard VAR model (e.g. time varying VAR coefficients, different explanatory variables in different equations, heteroskedastic errors etc.). Four alternative types of prior specifications commonly used in the literature are now discussed very briefly. They are the Minnesota prior, the natural conjugate prior, the independent Normal-Wishart prior and the diffuse prior.

The Minnesota Prior

The Minnesota prior is based on an approximation that involves replacing Σ_u by an estimate $\hat{\Sigma}_u$. Also, Σ_u is assumed to be fixed and diagonal. This enables the estimation of each equation in the VAR separately. Then a Normal prior for α is assumed such that $\alpha \sim N(\underline{\alpha}_{Mn}, \underline{V}_{Mn})$ where, $\underline{\alpha}_{Mn}$ and $\underline{V}_{Mn}$ are called the prior mean matrix and the prior covariance matrix of α respectively. Also $\underline{V}_{Mn}$ is assumed to be diagonal. To ensure the shrinkage of the VAR coefficients toward zero, most or all of the elements in $\underline{\alpha}_{Mn}$ is set to zero (i.e. $\underline{\alpha}_{Mn} = 0_{Kn}$). This is sensible when the data are expressed in terms of growth rates. However, when data are in levels the elements of the $\underline{\alpha}_{Mn}$ corresponding to the first own lag of the dependent variable in each equation are set equal to one (i.e. $\underline{\alpha}_{i1} = 1$ for $i = 1, \cdots, n$) and prior mean of the remaining parameters of $\underline{\alpha}_{Mn}$ is set to zero.

Let $\underline{V}_i$ be the block of $\underline{V}_{Mn}$ associated with the *n* coefficients in equation *i* and $\underline{V}_{i,jj}$ as its diagonal elements. Then three scalars of $\underline{a}_1$, $\underline{a}_2$, $\underline{a}_3$ can be chosen and $\underline{V}_{i,jj}$ is set as given in equation (4.87) for the common implementation of the Minnesota prior. The values of $\underline{a}_1$, $\underline{a}_2$, $\underline{a}_3$ depend on the research application of interest.

$$\underline{V}_{i,jj} = \begin{cases} \frac{\underline{a}_1}{r^2} \ for\ coefficients\ on\ own\ lags\ for\ r = 1, \cdots, p \\ \frac{\underline{a}_2 \sigma_{ii}}{r^2 \sigma_{jj}} \ for\ coefficients\ on\ r\ lag\ of\ variables\ j \neq i \\ \underline{a}_3 \sigma_{ii} \ \ for\ coefficients\ on\ exogenous\ variables \end{cases} \qquad (4.87)$$

where *r* is the lag length.

In empirical illustrations, it is reasonable to assume that the coefficients corresponding to higher lag order are shrunk toward zero. Also, selecting $\underline{a}_1 > \underline{a}_2$ gives an indication of the importance of own lags over the lags of other variables. A detailed discussion of and motivation for the prior beliefs is provided in Litterman (1986). A big advantage of the Minnesota prior is that it leads to simple posterior inference involving only the normal distribution (Koop and Korobilis, 2010, p. 10).

However, the two main shortcomings of the Minnesota prior are the diagonal and the fixed variance-covariance matrix. These assumptions are relaxed in the priors discussed below. These priors consider non-diagonal variance-covariance matrix for the residuals and take Σ_u as unknown.

The Diffuse Prior

The Diffuse prior specification consists of a constant prior for α and the Jeffreys (Diffuse) prior for Σ_u(see Geisser, 1965; Tiao and Zellner, 1964; Kadiyala and Karlsson, 1997). The joint density prior for (α, Σ_u) has the form

$$p(\alpha, \Sigma_u) \propto |\Sigma_u|^{-(n+1)/2} \qquad (4.88)$$

Then the joint posterior distribution is given by (4.89).

$$p(\alpha, \Sigma_u|y) = p(\alpha|\Sigma_u, y)p(\Sigma_u|y) \quad (4.89)$$

where; $p(\alpha|\Sigma_u, y) \propto N(\hat{\alpha}, \Sigma_u \otimes (X'X)^{-1})$ (4.90)

and

$$p(\Sigma_u|y) \sim iW\left(\left(Y - X\hat{A}\right)'\left(Y - X\hat{A}\right), T - K\right) \quad (4.91)$$

The marginal posterior distribution of A, $p(A|Y)$, has a generalized student-*t* distribution with degrees of freedom, $(T - K)$.

$$p(A|Y) \propto |\left(Y - X\hat{A}\right)'(Y - XA) + \left(A - \hat{A}\right)'X'X\left(A - \hat{A}\right)|^{-T/2} \quad (4.92)$$

The Natural Conjugate Prior

The conjugate prior distributions have the property that the posterior distribution follows the same parametric form as the prior distribution. The natural conjugate prior has the following forms for α and Σ_u.

$$\alpha|\Sigma_u \sim N\left(\underline{\alpha}, \Sigma_u \otimes \underline{V}\right) \quad (4.93)$$

and

$$\Sigma_u{}^{-1} \sim W\left(\underline{S}^{-1}, \underline{v}\right) \quad (4.94)$$

The prior hyper-parameters of $\underline{\alpha}$, $\underline{V}$, $\underline{S}$ and $\underline{v}$ are chosen by the researcher. The posterior distributions of α and Σ_u are given by equations (4.95) and (4.96) respectively.

$$\alpha|\Sigma_u, y \sim N(\bar{\alpha}, \Sigma_u \otimes \bar{V}) \quad (4.95)$$

and

$$\Sigma_u{}^{-1}|y \sim W(\bar{S}^{-1}, \bar{v}) \quad (4.96)$$

where; $\bar{V} = \left[\underline{V}^{-1} + X'X\right]^{-1}$ (4.97)

$$\bar{A} = \bar{V}\left[\underline{V}^{-1}\underline{A} + X'X\hat{A}\right] \quad (4.98)$$

$$\bar{\alpha} = vec(\bar{A}) \tag{4.99}$$

$$\bar{S} = S + \underline{S} + \hat{A}'X'X\hat{A} + \underline{A}'\underline{V}^{-1}\underline{A} - \bar{A}'\left(\underline{V}^{-1} + X'X\right)\bar{A} \tag{4.100}$$

$$\bar{v} = T + \underline{v} \tag{4.101}$$

The marginal posterior distribution for α is a multivariate t-distribution with degrees of freedom, $\bar{v}$.

The mean of the t-distribution is $\bar{\alpha}$ and the covariance matrix of α is given by (4.102).

$$var(\alpha|y) = \frac{1}{\bar{v}-n-1}\left(\bar{S} \otimes \underline{V}\right) \tag{4.102}$$

Using this information, the researcher can make posterior inferences about the VAR coefficients. Also, the non-informative prior can be obtained by setting the prior hyper-parameters of $\underline{v} = \underline{S} = \underline{V}^{-1} = cI$ and letting $c \rightarrow 0$. However, using the non-informative prior does not result in shrinkage. Shrinkage to overcome the problem of over-parameterization of the VAR model is one of the key functions of the priors discussed above.

The key advantage of the natural conjugate prior is that the analytical results are available for estimation and prediction. Hence the posterior simulation algorithms are not required except in special cases (see Koop, Steel and Osiewalski, 1992). However, two main undesirable properties of working with the natural conjugate prior have been identified (Koop and Korobilis, 2010, p. 12-13). First, it is necessary that every equation must have the same set of explanatory variables. Second, the form of the prior covariance matrix, ($\Sigma_u \otimes \underline{V}$) implies that the prior covariance of the coefficients in any two equations must be proportional to one another.

The Independent Normal-Wishart Prior

This prior specification overcomes the two main drawbacks identified in the natural conjugate prior. To allow for different explanatory variables for different equations, each equation of the VAR is written as shown in equation (4.103).

$$y_{kt} = z'_{kt}\beta_k + u_{kt} \tag{4.103}$$

where $t = 1, \cdots, T$ observations for $k = 1, \cdots, n$ variables. The z_{kt} vary across equations and are defined as $z_{kt} = \left(y'_{t-1}, \cdots, y'_{t-p}\right)'$ for $k = 1, \cdots, n$; a vector containing the *t*-th observation of the vector of explanatory variables relevant for *k*-th variable. y_{kt} is the *t*-th observation for the *k*-th variable. β_k is the corresponding vector of coefficients for the *k*-th equation with *m* explanatory variables.

Now denote

$y_t = (y_{1t}, \cdots, y_{nt})'$

$u_t = (u_{1t}, \cdots, u_{nt})'$ and define $K = \sum_{j=1}^{n} m_j$. Then

$\beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_n \end{pmatrix}$ is a $(K \times 1)$ vector and $Z_t = \begin{bmatrix} z'_{1t} & 0 & \cdots & 0 \\ 0 & z'_{2t} & \cdots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & z'_{nt} \end{bmatrix}$ is a $(n \times K)$ matrix.

As before assume that $u_t \sim iid. N(0, \Sigma_u)$.

Using the new notations, the VAR can be rewritten as given in (4.104) and (4.105).

$$y_t = Z_t \beta + u_t \qquad (4.104)$$

Staking the vectors for each observation we have

$$y = Z\beta + u \qquad (4.105)$$

where, $y = (y_1, \cdots, y_T)'$; $Z = (Z_1, \cdots, Z_T)'$ and $u = (u_1, \cdots, u_T)'$

The independent Normal-Wishart prior for the model is then given by equation (4.106).

$$p\left(\beta, {\Sigma_u}^{-1}\right) = p(\beta) p\left({\Sigma_u}^{-1}\right) \qquad (4.106)$$

where $\beta \sim N\left(\underline{\beta}, \underline{V_\beta}\right)$ and ${\Sigma_u}^{-1} \sim W\left(\underline{S}^{-1}, \underline{v}\right)$

The posterior covariance matrix $\underline{V_\beta}$ is chosen by the researcher. It does not have the restrictive form $(\Sigma_u \otimes \underline{V})$ seen in the natural conjugate prior. Note that the posterior mean and variance of β do not have analytical forms and thus the joint posterior $p\left(\beta, {\Sigma_u}^{-1} | y\right)$ does not have a convenient form. As a result, VAR models with the independent Normal-Wishart prior require posterior simulation algorithms such as the Gibbs sampler for Bayesian inferences.

However, the conditional posterior distributions of β and Σ_u have the convenient forms, which are given in equations (4.107) and (4.108) respectively.

$$\beta|y, {\Sigma_u}^{-1} \sim N\left(\bar{\beta}, \bar{V}_\beta\right) \tag{4.107}$$

$${\Sigma_u}^{-1}|y, \beta \sim W(\bar{S}^{-1}, \bar{v}) \tag{4.108}$$

where $\bar{V}_\beta = \left(\underline{V}_\beta^{-1} + \sum_{t=1}^{T} Z_t' {\Sigma_u}^{-1} Z_t\right)^{-1}$; $\bar{\beta} = \bar{V}_\beta\left(\underline{V}_\beta^{-1}\beta + \sum_{t=1}^{T} Z_t' {\Sigma_u}^{-1} y_t\right)$; $\bar{v} = T + \underline{v}$ and $\bar{S} = \underline{S} + \sum_{t=1}^{T}(y_t - Z_t\beta)(y_t - Z_t\beta)'$

4.8 Applications of VAR Models

In practice the parameter estimates of a VAR model are considered to be difficult to interpret as there are complex interactions among the variables, instead they are used to summarise forecasting, Granger causality and structural analysis. Forecasting is one of the main uses of VAR models. As Lütkepohl (2005, p. 41) notes the concepts of causality and predictions are interrelated such that '... a cause cannot come after the effect. Thus, if a variable *x* affects a variable *z*, the former should help improving the predictions of the latter variable'.

Forecasting and Granger causality from reduced VAR models are discussed briefly in sections 4.8.1 and 4.8.2 respectively. As with a univariate AR model, a reduced form VAR model also represents the conditional means of stochastic processes, which are available for forecasting. Granger causality is often investigated in VAR models with two variables. However, as discussed below, Granger causality analysis is problematic in models of more than three variables and various types of structural analysis are used to investigate the complex dynamic relationships (see Lütkepohl, 2005, section 2.3.1). The focus of this chapter is on structural VARs and how dynamic properties of the variables of interest are analysed through the effects of structural shocks in a system of equations. The related tools used for structural analysis are comprehensively discussed in section 8.3.

4.8.1 Forecasting

Consider the reduced form VAR(p) model described by equation (4.2). Also assume that the coefficient matrices are known, that is the data generation process (DGP) is known. The h step ahead forecast of y_t based on the information available at time T is

$$y_{T+h|T} = A_1 y_{t+h-1|T} + \cdots + A_p y_{T+h-p|T} \qquad (4.109)$$

Given that u_t is *iid*, $y_{T+h|T}$ is the best linear predictor based on the mean square error (MSE). The forecast error associated with (4.109) is given in equation (4.110) below.

$$y_{T+h} - y_{T+h|T} = u_{T+h} + \emptyset_1 u_{T+h-1} + \cdots + \emptyset_{h-1} u_{T+1} \qquad (4.110)$$

where $\emptyset_i = \sum_{j=1}^{i} \emptyset_{i-j} A_j$ for $i = 1,2,\cdots$ with $\emptyset_0 = I_n$ and $\emptyset_j = 0$ for $j > p$.

The mean of the forecast errors are zero, indicating that forecasts are unbiased. The forecast error covariance matrix is given by equation (4.111).

$$\Sigma_y(h) = E\left[\left(y_{T+h} - y_{T+h|T}\right)\left(y_{T+h} - y_{T+h|T}\right)'\right] = \sum_{j=0}^{h-1} \emptyset_j \Sigma_u \emptyset_j' \qquad (4.111)$$

If the DGP is unknown the parameters of the VAR(p) model provide an approximation of the true DGP. As a result, $y_{T+h|T}$ is not available and $y_{t+h|T}$ must be forecast based on a pre-specified VAR and the available data. Let $\hat{y}_{T+h|T}$ be the forecast based on estimated parameters and available data. Then the forecast error $(y_{T+h} - \hat{y}_{T+h|T})$ can be written as in equation (4.112).

$$\begin{aligned} y_{T+h} - \hat{y}_{T+h|T} &= (y_{T+h} - y_{T+h|T}) + (y_{T+h|T} - \hat{y}_{T+h|T}) \\ &= \sum_{i=0}^{h-1} \emptyset_i u_{T+h-i} + (y_{T+h|T} - \hat{y}_{T+h|T}) \qquad (4.112) \end{aligned}$$

The covariance matrix of the forecast error takes the form;

$$\begin{aligned} \Sigma_{\hat{y}}(h) &= E\left[\left(y_{T+h} - \hat{y}_{T+h|T}\right)\left(y_{T+h} - \hat{y}_{T+h|T}\right)'\right] \\ &= \Sigma_y(h) + MSE\left(y_{T+h} - \hat{y}_{T+h|T}\right) \qquad (4.113) \end{aligned}$$

As the sample size becomes large the second term approaches to zero given that the theoretical model properly represents the true DGP which implies that specification and estimation uncertainty are not important asymptotically.

4.8.2 Granger Causality

The concept of Granger causality was first defined by Granger (1969a) to investigate the causal relationships between two variables. Given two variables *x* and *y*, *x* Granger causes *y* if past values of *x* help predict the current value of *y*. The method is easily applied to the VAR framework. Let us consider a bivariate VAR model for $y_t = (y_{1t}\, , y_{2t})'$. If the coefficients of the lagged variables of y_1 is significant in the equation for y_2 then y_1 is said to Granger cause y_2, otherwise it is said $y_1$fails to Granger cause y_2.

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} a_{11}^{1} & 0 \\ a_{21}^{1} & a_{22}^{1} \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \cdots + \begin{bmatrix} a_{11}^{p} & 0 \\ a_{21}^{p} & a_{22}^{p} \end{bmatrix} \begin{bmatrix} y_{1t-p} \\ y_{2t-p} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix} \qquad (4.114)$$

As shown in equation (4.114), all the coefficient matrices are lower triangular. This implies that the coefficients of the lagged values of y_2 are zero in the equation for y_1 and thus there exists a unidirectional causality from y_{1t} to y_{2t}. In other words $y_{2t}$is not Granger causal for y_{1t}. The significance of the coefficients can be tested using Wald test for bivariate models with stationary data.

In the case of VAR models with more than two variables identification of causality or non-causality using the Granger approach is more complicated. Investigating the causality using two variables at a time ignores the possible effect from other variables and can lead to specification bias (see Lütkepohl, 1993; Gujarati, 1995 and Dufour and Renault, 1998). The apparent bivariate causal structure may disappear when a relevant third variable is added to the model. Similarly, if a third variable drives both the previous two variables, the first two variables might still show Granger causality even there is no actual causal relationship directly between the first two variables.

4.8.3 Structural Analysis with VAR

Investigation of the dynamic relationships among the variables in a VAR system should not be limited to simple causal relationships that can be identified using Granger causality. In applied research, it is imperative to explore the changes in variables induced by shocks or innovations that involve a system of variables. Structural analyses examine the relationships among the variables by tracing the effects of innovations in various ways. Structural analyses are carried out using four main methods. They are impulse response functions, forecast error variance decompositions, historical decompositions and construction of forecast scenarios (see Killian, 2011, p. 1). Such analyses provide useful information for policy analysis.

Impulse Response Functions (IRFs)

Impulse response functions are used in structural analysis to assess the response of current and future values of each of the variable to an impulse (exogenous shock or innovation) originating from another variable in a higher dimensional system. Lütkepohl (2005, p. 51) states that '… if there is reaction in one variable to an impulse in another variable we may call the latter causal for the former'. The non-orthogonal impulse responses consider shocks to one variable at a time while holding shocks to other variables constant in a system which contains a number of variables.

The elements of the $\emptyset_j$ matrices in the MA representation of the reduced form VAR(*p*) process contains the impulse responses. These are called forecast error impulse responses.

$$y_t = \sum_{i=0}^{\infty} \emptyset_i u_{t-i} \text{ with } \emptyset_0 = I_n \text{ and } \emptyset_s = \sum_{j=1}^{s} \emptyset_{s-j} A_j \qquad (4.115)$$

Analogous to this, the impulse response function of the variable *k* at time (*t*+*s*) to a unit shock of variable *j* with all other variables held constant for date *t* or earlier can be written as the change in $y_{k,t+s}$,which is given in equation (4.116).

$$\{\emptyset_s\}_{k,j} = \frac{\partial y_{k,t+s}}{\partial u_{j,t}} \qquad (4.116)$$

Further, the matrices $\emptyset_s$ have the form as given in (4.117).

$$\emptyset_s = \frac{\partial y_{t+s}}{\partial u_t'} = \begin{bmatrix} \frac{\partial y_{1,t+s}}{\partial u_{1t}} & \cdots & \frac{\partial y_{1,t+s}}{\partial u_{nt}} \\ \vdots & \ddots & \vdots \\ \frac{\partial y_{n,t+s}}{\partial u_{1t}} & \cdots & \frac{\partial y_{n,t+s}}{\partial u_{nt}} \end{bmatrix} \qquad (4.117)$$

Thus the plot of the sequence of the $[k, l]th$ entry of the matrix against s for ($s = 1,2,\cdots$) depicts the response of variable *k* to a unit shock of variable l (y_l).

However, Lütkepohl (2005, p. 53) mentions that 'if the variables have different scales, it is sometimes useful to consider innovations of one standard deviation rather than unit shocks ... this is just a matter of rescaling the impulse responses'.

Responses to Orthogonal Impulses

In reality isolated shocks in one variable at a time may be unlikely and hence the elements of the $\emptyset_s$ matrices would not properly describe by the impulse responses. In other words, the non-orthogonal impulse response functions assume that the shocks to different variables are independent and thus $\Sigma_u = I_n$. However, the correlations of the error terms indicate that the shock to a one variable may occur simultaneously with a shock to another variable. As a result, taking partial derivatives while holding all other variables constant may lead to an inaccurate picture of the impulse responses and the actual dynamic behaviour between the variables.

To overcome this problem, the errors are orthogonalized using the *Cholesky decomposition* as discussed in section 4.6.1.

Rewrite the MA representation of the VAR(p) as

$$y_t = \sum_{i=0}^{\infty} \emptyset_i P P^{-1} u_{t-i} \qquad (4.118)$$

Define $\theta_i = \emptyset_i P$ and $e_t = P^{-1} u_t$

Then equation (4.118) can be written as equation (4.119).

$$y_t = \sum_{i=0}^{\infty} \theta_i e_{t-i} \qquad (4.119)$$

Thus,

$$E(e_t e_t') = E(P^{-1} u_t u_t' (P^{-1})')$$

$$\Sigma_e = (P^{-1}\Sigma_u(P^{-1})') = P^{-1}PP'(P^{-1})' = I_n \tag{4.120}$$

This formulation implies that the variances of the innovations are now equal to one, which means that a unit shock is equivalent to an innovation of one standard deviation. Further, the $e_t = (e_{1t}\; e_{2t}\; \cdots\; e_{nt})'$ are uncorrelated (orthogonal) and hence the change in one component of e_t has no effects on the other components. Now the elements of θ_i are responses to shocks of one standard deviation in size and the $\theta_s = \frac{\partial y_{t+s}}{\partial e_t'}$ are the orthogonalized impulse response functions.

It should be noted that from the lower triangularity of the matrix *P* it follows that the shocks in the first equation of the VAR(*p*) process have an influence on all the other variables, the shocks in the second equation have influence on all other variables except the first variable and so no. This may produce different impulse response functions depending on the order of the variables.

Impulse Response Function in Structural VAR

The impulse responses of the structural VAR can be found from the MA representation, which is given by equation (4.121).

$$y_t = \sum_{i=0}^{\infty} \varphi_i \varepsilon_{t-i} \tag{4.121}$$

where $\varphi_i = \emptyset_i B_0^{-1}$ for $i = 1, 2, \cdots$

The responses to structural shocks (ε_t) are found from the elements of the φ_i matrices and it has the interpretation

$$\varphi_s = \frac{\partial y_{t+s}}{\partial \varepsilon_t'} \tag{4.122}$$

The impulse response of the variable *k* at time (*t*+*s*) to a unit shock of variable *j* is written as given by equation (4.123).

$$\{\varphi\}_{k,j} = \frac{\partial y_{k,t+s}}{\partial \varepsilon_{j,t}} \tag{4.123}$$

Forecast Error Variance Decomposition (FEVD)

The FEVD quantifies the importance of a structural shock to the variation in the left hand side variable for each equation in the system. That is, the idea is to decompose the total variance and then quantify the percentage contribution attributable to each structural shock for different forecast periods.

Consider a VAR(p) process that has a recursive identification scheme as described under "*Responses to Orthogonal Impulses"*. The MA representation with $\Sigma_e = I_n$ is

$$y_t = \sum_{i=0}^{\infty} \theta_i e_{t-i} \qquad (4.124)$$

Denote $y_t(h)$ as being the optimal *h*-step forecast at period *t* for y_t.

Then the *h*-step forecast error for the process is given in equation (4.125).

$$y_{t+h} - y_t(h) = \sum_{i=0}^{h-1} \theta_i e_{t+h-i} \qquad (4.125)$$

For a particular variable of y_k the forecast error has the form as shown in (4.125).

$$y_{k,t+h} - y_{k,t}(h) = \sum_{j=1}^{n} \left(\theta_{kj,0}\varepsilon_{j,t+h} + \cdots + \theta_{kj,h-1}\varepsilon_{j,t+1}\right) \qquad (4.125)$$

where θ_{kj} denotes the *kj*-th element of θ_i. Equation (4.125) implies that the forecast error of each component in y_t potentially consists of all the innovations in$(\varepsilon_{1t}, \cdots, \varepsilon_{nt})$.

Since the errors (ε_{jt}) are orthogonal, the forecast error variance of $y_{k,t}(h)$ can be written as shown in equation (4.126).

$$E\left(y_{k,t+h} - y_{k,t}(h)\right)^2 = \sum_{j=1}^{n} \left(\theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2\right) \qquad (4.126)$$

Thus,

$$var\left[y_{k,t}(h)\right] = \sum_{j=1}^{n} \left(\theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2\right) = \sum_{i=0}^{h-1} \sum_{j=1}^{n} \theta_{kj,i}^2 \qquad (4.127)$$

Therefore the contribution of the *j*-th shock to the *h*-step forecast error variance of the variable *k* of the process y_t is given by $\left(\theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2\right)$.

The relative contributions or the *FEVD* of the variable *k* is given by equation (4.128).

$$FEVD_k(h) = \left(\theta_{kj,0}^2 + \cdots + \theta_{kj,h-1}^2\right)/var\left[y_{k,t}(h)\right] \quad (4.128)$$

Further $var\left[y_{k,t}(h)\right]$ can be obtained from the diagonal elements of the *h*-step forecast MSE matrix of $\Sigma_y(h)$.

$$\Sigma_y(h) = \sum_{i=0}^{h-1} \emptyset_i \, \Sigma_u \emptyset_i' \quad (4.129)$$

FEVD in Structural VAR

The computation of the FEVD in structural VAR is similar to the reduced form VAR as described above. However, special caution should be made with the interpretation as the structural shocks are not uniquely associated with the variables in a system of structural equations. Lütkepohl (2005, p. 382) notes '… the forecast errors are not decomposed into contributions of the different variables but into contributions of the structural innovations'.

Using the MA representation of an identified SVAR, the *FEVD* of the variable *i* by the *k*-th structural shock is

$$FEDV_k(h) = \frac{\sum_{j=0}^{h} \varphi_{ik,j}^2}{\sum_{k=1}^{n} \sum_{j=1}^{h} \varphi_{ik,j}^2} \quad (4.130)$$

Historical Decomposition

Unlike measuring the timing and magnitude of the responses of variables in a VAR model to a one time shock using impulse response functions, historical decomposition enables measurement of the impact of a historically observed sequence of shocks on the evolution of variables over time. While the concept of historical decomposition was first developed by Sims (1980a), the first structural analysis based upon the method was by Burbidge and Harrison (1985).

The technical explanation of historical decomposition described below is based on Burbidge and Harrison (1985, p. 46). Equation (4.130) gives the historical decomposition of time series of y_{T+j} for some base period *T* and any *j* for $j = 1, 2, \cdots$ considering the MA representation of the SVAR.

$$y_{T+j} = \sum_{i=0}^{j-1} \varphi_i \varepsilon_{T+j-i} + \sum_{i=j}^{\infty} \varphi_i \varepsilon_{T+j-i} \quad (4.130)$$

The first term represents the part of y_{T+j} attributable to shocks in periods $T+1$ to $T+j$. The second term is defined as the base projection of the vector, y or the expectation of y_{T+j} based on the data available through time *T*. Fackler and McMillin (1998, p. 650) define the first term of the historical decomposition as the difference between the actual series and the base projection due to the structural innovation in the variables subsequent to period *T*.

Analysis of Forecast Scenarios

Another application of SVAR is analysing different forecast scenarios. This is also called conditional forecasting since it imposes restrictions on future structural shocks. Further, conditional forecasts can also be constructed assuming hypothetical sequence of future structural shocks.

The h-step ahead forecast of y_t based on the information available at time *T* conditional on the ε^*_{T+h} can be computed using the equation (4.131). The notation is same as above.

$$y^*_{T+h|T} = \sum_{i=1}^{h-1} \varphi_i \varepsilon^*_{T+h-1} + A_1^{(h)} y_T + \cdots + A_p^{(h)} y_{T-p+1} \qquad (4.131)$$

4.9 Conclusion

This chapter provides a review of finite order VAR models. The finite order VAR models, particularly structural VARs, have found widespread use in applied economics in the recent past. The stabilization conditions, MA representation, estimation, lag length selection, forecasting, Granger causality and structural analysis were discussed.

The original reduced form VAR models were a system of simultaneous equations which was proved a very flexible econometric tool. However, the main conceptual problem in their use is the inability to account for contemporaneous relationships among the variables. Further, VAR was often described as atheoretical and criticised heavily in the mid-1980s. Structural VAR was developed to give sensible solutions for these problems. Economic theory, institutional knowledge and/or other extraneous constraints are used to recover structural shocks from the VAR shocks. The structural parameters are estimated by imposing restrictions on the matrix which links contemporaneous relationships in the model. To do this, additional identification restrictions are required. Three methodologies have been used in the literature namely; short-run restrictions or *Cholesky decomposition*, long-run restrictions and sign restrictions for identification. The *Cholesky decomposition* can be used to orthogonolize the reduced form errors allowing structural shocks to be disentangled from the reduced form shocks. However, this generates a recursive structure. Therefore, the credibility of the results is assured only if the assumed recursive order has a plausible economic interpretation.

In empirical analysis certain economic shocks are neutral in the long-run whereas other shocks have permanent effects. Short-run identification restrictions ignore this fact and do not allow for the long-run responses of the variables to shocks. Alternatively, long-run identification restrictions take into account only the long-run properties of the time series. While the short-run and long-run identification methods impose exclusion restrictions on the coefficient matrix of the contemporaneous relationships, the sign restriction method involves restricting the sign of the responses of model variables to structural innovations. Sign restrictions were first applied in the context of monetary policy models. However, the method has found widespread use in various macroeconomic applications such as fiscal shocks, oil market shocks, technology shocks and labour market shocks. This thesis uses structural VAR with sign restrictions to study population ageing shocks on asset prices for the first time in the literature. The important feature of sign restrictions is that economic theories can often be used to restrict the sign of the responses to structural shocks. However, there should be a unique sign pattern associated with each identified shock.

In practice VAR models have a large number of parameters to estimate. Bayesian VAR is popular to overcome the over-parametrization problem encountered in VAR estimation. The vital component of Bayesian VAR specification is using non-sample or prior information in the form of prior probability distribution functions in addition to the data as the sources of information. The prior distributions proposed in the literature depend on the economic problem at hand, the sample data available and the method that can be applied to determine the parameters of the prior distribution.

VAR models have a wide range of uses. These are in three major categories namely forecasting, Granger causality and structural analysis. Forecasting with the reduced form VAR is based on the information available at a particular point of time. In contrast, conditional forecasting, which is particularly important in structural VAR, produces forecasts conditional on future values of some of the variables. Granger causality provides limited information about the causal relationships among the variables in a VAR system, but is generally limited to bivariate models. Thus structural analyses are carried out to examine the relationships among the variables by tracing the effects of innovations in various ways.

Forecast error impulse responses may not reflect the actual relationships between the variables since it is assumed that the variance-covariance matrix of the errors is diagonal and hence the instantaneous correlations among the residuals are ignored. One immediate solution for this is to derive orthogonal impulse responses from a *Cholesky decomposition* of the reduced-form error variance-covariance matrix. However, since the *Cholesky decomposition* is based on a lower triangular matrix the derived impulse responses may not be credible unless the recursive order of the variables is justified. Also, there will be more than one set of impulse response functions for various recursive orderings. In contrast, if the structure is identified and estimated, unique impulse response functions can be derived for structural VAR.

The reaction of each variable to innovations on the other variables in the model at different time horizons is important for policy analysis. The forecast error variance decomposition tool quantifies the contribution of a structural shock to the variance of each variable for different forecast periods. This enables a comparison of the role played by a structural shock to the variability of the each time series at different times.

Historical decomposition is a crucial tool to describe the relative importance over some sets of variables of the structural shocks to the time series during the sample period. This has an especial advantage over impulse response analysis and variance decomposition because it provides an understanding of the actual impact on the variables throughout the sample period in terms of the recovered structural shocks.

CHAPTER 5 THE EFFECTS OF POPULATION AGEING DYNAMICS ON HOUSE PRICES

5.1 Introduction

This chapter addresses the first research question of the study, namely, do the dynamics of population ageing affect house prices in Australia? The review of demographic statistics in chapter 2 shows that Baby Boomers comprise a demographic bulge. Conversely the Baby Bust generation (born 1966-1979) is a relatively smaller group. The significant differences in the Baby Boom and the Bust generations along with the increasing life expectancy create a demographic shift in Australia. This is evident in the rapidly increasing fraction of the population classed as old age (65+ years) and decreasing proportions of those young (0-19 years) and working age (20-64 years). The demographic shift is more pronounced since 2011 with the first Baby Boomers reaching retirement in 2011. A severe shift is projected for next two decades as a result of living Baby Boomers entering retirement during 2011-2031. Further, asset ownership statistics cited in chapter 2 reveal that housing equity is an important asset for many Australian households and around 50% of housing wealth is held by the Baby Boom generation, although it comprises 25% of the Australian population. Theoretical models such as the life cycle hypothesis (Modigliani and Brumberg, 1954; Ando and Modigliani, 1963) and overlapping generations models (Samuelson, 1958; Diamond, 1965) indicate that working age population buy assets to save for the old age and sell when they retire. These theoretical underpinnings, the observed demographic shift and housing asset ownership statistics raise a question of whether the ageing population is likely to trigger a pronounced downward pressure on real house prices in Australia?

The review of literature in chapter 3 provided a comprehensive discussion on the effects of population ageing on real house prices in general and in the specific case of Australia. These studies are subject to a range of limitations and shortcomings. The most important criticisms relate to the problems with the econometric methodologies used. These problems include factors such as the specification of the housing demand function, spurious regression, the dynamic adjustment process of the house price variable and the impact of ignoring the endogeneity component of the macroeconomic variables included in the models. This research uses a more rigorous econometric approach which resolves most of these problems, though there are limitations imposed by the available house price data. It is worth noting here that there is no well-developed theory connecting house prices to income, demographic factors, nominal interest rate and capital market innovations (Madsen, 2001).

The chapter is organised as follows. Section 5.2 reviews the measurement of house prices in Australia and associated problems of obtaining a consistent and representative time series for house prices. Section 5.3 is devoted to a detailed discussion of the variable selection. A fully structural VAR model is formulated for empirical analysis. Since this is the first time in the literature that a structural VAR methodology is used to examine the effect of population ageing on house prices, the rational for the econometric specification is discussed comprehensively in section 5.4. A brief technical description of the econometric model along with the identification restrictions applied is discussed in section 5.5.

Section 5.6 provides a detailed description of the data and its construction as the lack of availability of a long and accurate time series to assess the developments in house prices is one of the major challenges in this study. The steps involved in SVAR model estimation including transforming the time series into stationary series, lag length selection and adequacy of the estimated model are discussed in section 5.7. Following this, the dynamic relationships among the variables are examined by tracing the effects of structural innovations in various ways. Thus, the impulse response functions (IRF), historical decomposition and forecast error variance (FEVD) decomposition are generated after imposing the identification restrictions on the contemporaneous reaction of the variables to structural shocks. The important results are discussed in section 5.8. Robustness analysis is carried out in section 5.9, namely changing the identification method and the demographic variable used in the benchmark model. The conclusions of the chapter are presented in section 5.10.

5.2 Measuring House Prices in Australia

A number of different house price measures are published in Australia. Each of these measures has a different methodology, scope, data coverage and timing. There are three main primary sources and three secondary sources. The three main primary sources are Land Title Offices (LTOs), the Real Estate Institute of Australia (REIA) and the Commonwealth Bank of Australia (CBA). The Australian Bureau of Statistics (ABS) is the most important secondary source for house prices in Australia. The remaining two secondary sources are Residex and Australian Property Monitors (APM).

The REIA has estimated median house and unit prices since 1980 with prices published at the city level. However the REIA estimates before the second quarter of 1998 are based on the sales recorded by their members and reported to REIA offices. Since then, as noted by Abelson and Chung (2004, p. 3), the REIA obtains most of its data from the LTOs except for Victoria. LTOs also publish summary statistics on house prices, however not on a regular and timely basis. The Commonwealth Bank of Australia (CBA) publishes house prices based on sales for which they provide finance. Abelson and Chung (2004, p. 3) note about CBA prices as '… are unlikely to be a representative set of houses and … are often different from other price series'. The CBA's house price data include new houses and land prices.

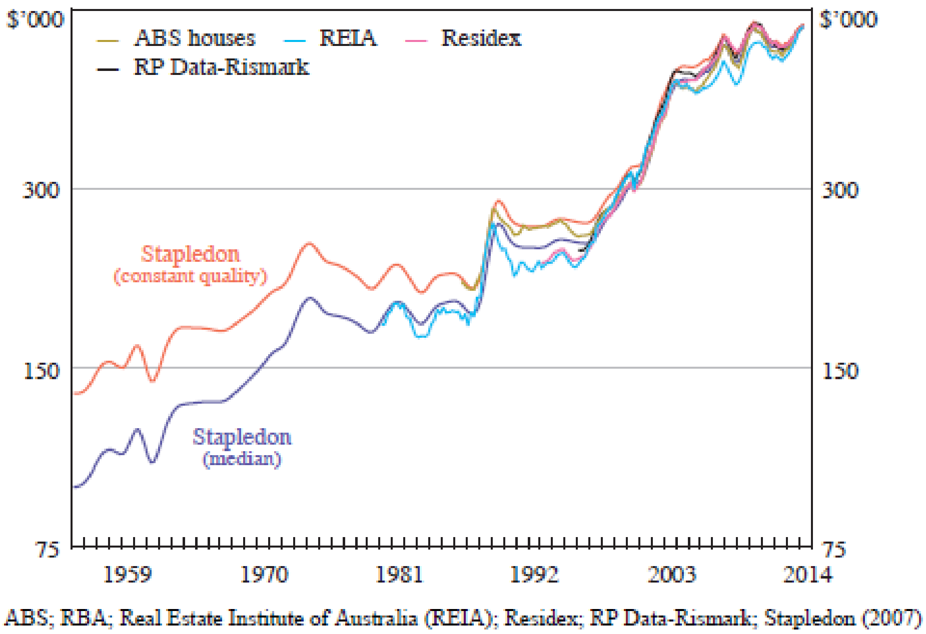
Among the secondary sources of house prices in Australia, Residex and APM provide house price information at the city level. Residex provides property price indices for Brisbane, Melbourne and Sydney from 1978. APM estimates prices for seven capital cities. Both of these secondary sources estimate prices based on the data from the LTOs.

The ABS compiles and publishes quarterly House Price Index (HPI) for the eight capital cities (Sydney, Melbourne, Brisbane, Adelaide, Perth, Hobart, Darwin, and Canberra) separately and a composite index at national level commencing from 1986. The national level index is a weighted average of the city level indexes (see *House Price Indexes, Eight Capital Cities, ABS cat. no. 6416.0*). Initially, the HPI was based on a median measure of price, with a partial attempt to control for compositional change made by stratifying houses within each capital city by region (Olczyk and Lane, 2008). The median price represents the price in a typical transaction and it is affected by compositional change and seasonality. Moreover, the ABS house price index has limited control for housing quality and does not account for alterations and extensions to the existing houses.

In 2004 a major revision was carried out in compilation of the HPI with the revised HPI commencing in the first quarter 2002. The revision includes the use of a stratification approach to compute the index. This approach controls for compositional changes. Furthermore, the 2004 revision expanded the coverage to include townhouses, units and apartments which minimises the effects of quality changes. The second and third reviews of the HPI took place in 2007 and 2012 respectively. The 2012 revision produced two new indexes. The first is an Attached Dwelling Price Index (ADPI) which covers the flats, units and apartments plus semi-detached raw and terrace houses. The second aggregates the HPI and ADPI in a new series called the Residential Property Price Index (RPPI).

In addition to the key primary and secondary sources mentioned above for house prices, Australian Treasury has estimated a national house price index since 1970 which is not published. However, Abelson and Chung (2004) have published the series in their research paper "Housing Prices in Australia: 1970 to 2003". The series is based on nominal median house prices for Australian capital cities. Abelson and Chung (2004) estimate their own house price index for Australia from 1970 and compare it to Treasury's national house price index. They first compute the median house and unit prices at the city level and then price indices for houses and units. Abelson and Chung (2004, p. 7) describe their house price index compilation procedure as 'we estimate our Australian price indices for houses and units by weighting the estimated real indices according to the number of houses or units in each city as shown in the 1991 Census'.

All the house price data described in the previous paragraphs are limited to the post 1970 period. Stapledon (2007) constructs a constant-quality house price series for a long time span from 1880-2006. RBA research discussion paper titled "Is Housing Overvalued?" by Fox and Tulip (2014) compares Stapledon's (2007) house price estimates with several other published house price series (see Figure 5.1). Fox and Tulip (2014, p. 28) state that 'Stapledon's constant-quality estimates provide a useful focal point – in part because they are more clearly consistent with other elements of the user cost than other house price measures'. Figure 5.1 clearly indicates that Stapledon's (2007) real constant-quality house price estimates are consistent with the ABS house prices.



Source: Adapted from Fox and Tulip (2014, p. 23)

Figure 5.1: Real (2014) dwelling prices (log scale)

5.3 Variable Selection for Empirical Models

A number of different models are used in the literature to investigate the effects of demographics on house prices. Some analyses consist only of demographic variables along with house price while others include both demographic variables and macroeconomic aggregates. Models which comprise demographic variables and house price only may suffer from omitted variable bias. For example, macroeconomic aggregates such as interest rate, real GDP per capita and unemployment may influence the demand and supply for housing and thus the house price. Moreover, housing assets have a dual purpose. They act as a mode of wealth storage and as a durable consumption good. According to the life cycle theory, the working age population accumulate assets as a mode of savings and de-cumulate those during the retirement life. Tobin's Q theory implies that a homogenous housing market creates profit margins when the marginal price for a house is higher than the marginal production cost. Thus house prices have an impact on construction activities and shocks to house prices may affect economic variables such as real output, unemployment and commodity prices.

In this analysis, both demographic and non-demographic variables are used. The old age ratio, which is defined as the proportion of population over 65 years divided by the population aged 0-64 years, is used to measure the impact of population ageing on house prices. From the life cycle theory we presume that old age population (65+ years) and adult population (20-64 years) are the relevant population of asset sellers and buyers. Children account for a low proportion of housing ownership though their impact is not negligible when we consider the reverse causality effect of demographics on house prices. In the literature of the impact of demographics on house prices the demographic variables most commonly used are the old age dependency ratio (65+/15-64 years), the old age population and the working age population, either individually or in combination. Such studies assume unidirectional causality from demographic variables to house prices.

When choosing an appropriate demographic variable possible changes to the fertility rate should also be considered. Excess demand for housing leads to upward pressure on house prices which would affect the purchasing decision of couples of child bearing age. The result could be to defer having a child which has an impact on the fertility rates. Dettling and Kearney (2014) find a negative relationship going from house prices to fertility rates in the United States. That is a causal relationship from house prices to demographic variables is evident. This relationship has been neglected in the previous studies. Dettling and Kearney (2015, p. 82) further conclude that changes in house prices exert a larger effect on birth rates than do in changes in unemployment rates. Further, the increasing proportion of old age population and lower labour market participation is projected to lead to a decrease in GDP per capita of 6.2% in Australia by 2050 (Kudrna et al., 2014, p. 120). If we assume that real disposable income affects fertility decisions, other things being equal, fertility rates will be depressed even further. Accordingly, a change in the fertility rates will affect the size of the young population and hence the proportion of old age population. Therefore, the old age ratio is used as the demographic variable to measure the effects of population ageing dynamics on house prices.

As described in the literature review chapter, using only demographic variables to examine the effect of population ageing on asset prices is subject to criticism. This study includes three non-demographic variables, namely an interest rate, real GDP per capita and the unemployment rate. Real GDP per capita captures the impact of economic forces, particularly the effect of income as the richer people may be willing to pay more their housing. However, it is worth noting that increasing house prices do not necessarily imply increased income for home buyers and/or home owners.

The majority of the home buyers utilise mortgage loans and the ability to service their debts is sensitive to their employment status. Louzis, Schelkle and Vogel (2012) find that unemployment has a significant impact on the quantity of non-performing loans in their study of the Greek banking sector. Increased risk of unemployment means a higher risk of default. Thus, unemployment is used as a variable in this study to capture two effects in the housing market. The first is the medium term effect of changes in consumer confidence over the business cycle. That is, if unemployment is high the demand for housing declines and hence it would have an impact on house prices and vice versa. The second effect is due to Baby Boomers entering into the labour market and increasing the size of the labour force. During the period from the mid-1970s to the 1980s the unemployment rate trended upwards in Australia. This upward trend in unemployment could have been partly a result of the high population growth during the Baby Boom period and their entry into the labour market[34]. Thus unemployment could be an important variable capturing the purchasing decision of houses by individuals, which will then have an impact on house prices.

The interest rate is widely regarded as an appropriate variable to include in a model of house prices. It is a common belief that low interest rates stimulate the housing market and there exists an inverse relationship between the house prices and interest rates. That is, an increase in interest rates puts downward pressure on house prices. On the other hand, studies pertaining to the relationship between house prices and interest rates, particularly the impact of monetary policy, have not established a stable relationship for Australia, instead they provide mixed evidence (Wadud, Bashar and Ahmed, 2012; Fry, Martin and Voukelatos, 2009; Abelson et al., 2005). Including interest rate as a variable into the model thus enables analysis of the effects of monetary policy shocks on house prices and contributes to the literature even though it is not the main objective of this thesis.

It is worth explicitly noting here that the focus of this research is not to establish the overvaluation or undervaluation of Australian housing markets. Also the main objective of this research is not to examine the underlying determinants of the house prices in Australia. Rather this study focuses on the effects of population ageing dynamics on house prices and specifically focuses whether the ageing population will exert a downward pressure on real house prices.

Similar studies in the literature do include variables such as GDP and an interest rate. For example, Guest and Swift's (2010) study of population ageing and house prices in Australia includes the variables the interest rate, the inflation rate, income per capita, the unemployment rate, population share and the house price. Takats (2012) who includes Australia in her cross country study examining the impact of demographics on house prices, includes population size, old age dependency ratio,

[34] Researchers have not concentrated on this aspect analysing the unemployment trends in Australia during this time.

real GDP per capita and real house price as variables (see chapter 3 for details). Thus following the relevant literature investigating the effects of population ageing on house prices, three macroeconomic variables, namely real GDP, the interest rate and the unemployment rate, are included along with real house price and the demographic variable in the following analysis.

5.4 Rationale for the Econometric Specification

Standard demand and supply theory suggests that an equilibrium market price is determined when the quantity demanded equals to the quantity supplied at a given point of time. Therefore, an appropriate starting point would be to model the quantity demanded and supplied as functions of price and other relevant variables and derive the reduced form model for the housing price as given below.

$$D = f(P, V_d) \tag{5.1}$$

$$S = f(P, V_s) \tag{5.2}$$

In equilibrium;

$$D = S \tag{5.3}$$

$$P = f(V_d, V_s) \tag{5.4}$$

where D and S are quantity of housing demanded and supplied respectively, P is the price and V_d and V_s are vectors of other demand and supply variables. This implies that price is a function of those variables influencing demand and supply. However, estimating a reduced form model for housing markets such as this, does not serve the purpose of this study. In reality shifts in demand do not necessarily have to be accompanied by shifts in supply and vice versa. Instead the change in price level could be due to the change in quantity demanded or supplied driven by factors outside the demand/supply fundamentals related to the housing market. For example, the change in price level could be due to exogenous shocks such as oil price shock. Furthermore, the traditional demand/supply equations assume that the variables which influence quantity demand and supply of housing are purely exogenous to the price. However, those variables may also be affected by price and there may be feedback from price to those variables (see Wadud et al., 2012). Further, DiPasquale and Wheaton (1994) showed that house prices themselves affect demand for houses. Therefore, estimating the reduced form model as given in (5.4) violates the key assumption of OLS estimation that the right hand side variables in the regression equation are purely exogenous will lead to incorrect inferences. Moreover, the realizations of the past values of those variables would also affect the house price.

Demand and supply fundamentals are affected by the information available to different participants of the housing market. Information asymmetry between real estate agents, sellers and buyers may shift the demand (supply) irrespective of the supply (demand). The “no-trade” theory of asymmetric information by Milgrom and Stokey (1982) says that uninformed agents will not trade with informed counterparts. As a result agents who are informationally disadvantaged have limited market participation. The housing market participants’ responses to these information disparities may create distortions in the equilibrium price.

Implicit in the literature investigating the response of demographic variables and macroeconomic aggregates to change in house price is the assumption that the impact of one variable on house prices can be isolated while holding other variables constant. Furthermore these studies assume that the variables of interest cause the house price to change and there is no relationship in the opposite direction. However, this assumption is empirically implausible since the macroeconomic variables such as house price, GDP per capita, unemployment and interest rate have a substantial endogeneity component as argued by Sims (1980). In addition, it can be argued that the demographic variable used in this study (the old age ratio) is also not purely exogenous with respect to other selected variables of the model (see section 5.3).

There are a number of ways in which economic conditions can affect the demographic variable used in this analysis. High income per capita countries are experiencing increasing longevity leading to increase the size of the old age population. An increase in the rate of unemployment can lead to a reduced standard of living and psychological stress which would then affect to the mortality and the population size. Also the studies related to the fertility scheduling states that the child bearing decisions of women are affected by the opportunity cost (see Ben-Porath, 1973; Becker, 1960). Further, Schaller (2016) examines this issue considering labour market conditions for both males and females and concludes that there exists a negative overall relationship between unemployment rate and birth rates.

Existing models which examine the demographic effects on house prices only take contemporaneous effects of the variables into account. However it is likely that there are lagged effects that should be considered. For example the dynamic version of Okun's law states that the current change in the unemployment rate is explained by the current and past values of GDP growth rates and past values of changes in unemployment rates. Further, economic conditions will not have a contemporaneous impact on immigrants, however, the effect may be seen in one or two years later. Thus a structural VAR model is appropriate to examine the effect of population ageing dynamics on house prices in this research. That is, each variable included in the model is described by its own lagged values plus the current and lagged values of the remaining variables.

5.5 Econometric Specification

A fully structural VAR model of lag p is formulated as given in equation (5.5) below (ignoring the deterministic terms).

$$B_0 z_t = \sum_{i=1}^{p} B_i z_{t-i} + \varepsilon_t \qquad (5.5)$$

where z_t consists of vector of variables, namely the first difference of the log of real house price (Δhp), first difference of the log of real GDP per capita (Δz), unemployment rate (u), interest rate (i) and de-trended old age ratio ($doar$); p is the lag order; B_0 is a (5×5) coefficient matrix representing the contemporaneous relationships among the variables; B_i are (5×5) coefficient matrices for lagged relationships and ε_t is a (5×1) vector of structural innovations. With a five variable VAR, we can identify five structural shocks. The two shocks that are of primary interest here are the shocks to house prices (ε_t^{PH}) and shocks to the old age ratio, namely "retirement shocks", (ε_t^R)[35]. Following standard practice in the VAR literature, the other three shocks are loosely identified as output shock (ε_t^Y), monetary policy shock (ε_t^{MP}) and unemployement shocks (ε_t^U)[36]. Then the order of the vector of structural shocks is as follows.

$$\varepsilon_t = [\varepsilon_t^R,\ \varepsilon_t^Y,\ \varepsilon_t^U, \varepsilon_t^{MP},\ \varepsilon_t^{HP}]$$

The structural innovations ε_t have mean zero and are mutually uncorrelated, that is, $\varepsilon_t \sim (0,\ \Sigma_\varepsilon)$ where Σ_ε is a diagonal matrix.

Using an autoregressive lag polynomial, the structural moving average, $MA(\infty)$ representation of (5.5) can be written as (ignoring any deterministic terms)

$$z_t = B(L)\varepsilon_t \tag{5.6}$$

Further, the variance-covariance matrix of structural errors (Σ_ε) is normalised such that the variances of the structural shocks to unity.

$$E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon = I_n \tag{5.7}$$

To apply the standard estimation technique as described in chapter 4 the structural form is first transformed to the reduced form VAR. Pre-multiplying (5.5) by B_0^{-1} gives

$$B_0^{-1} B_0 z_t = B_0^{-1} B_1 z_{t-1} + \cdots + B_0^{-1} B_p z_{t-p} + B_0^{-1}\varepsilon_t \tag{5.8}$$

Denoting $A_i = B_0^{-1} B_i$ (5.9)

and $u_t = B_0^{-1}\varepsilon_t$ (5.10)

$$z_t = A_1 z_{t-1} + \cdots + A_p z_{t-p} + u_t \tag{5.11}$$

The MA representation of the corresponding reduced form VAR is written as

$$z_t = A(L)u_t \tag{5.12}$$

[35] Bjørnland and Jacobsen (2010) identify the structural shock ε_t^{PH} as "shocks to house prices". We follow the same in this chapter.

[36] See Bjørnland and Jacobsen (2010).

$$E(u_t u_t') = \Sigma_u = B_0^{-1} B_0^{-1\prime} \quad \text{(because } \Sigma_\varepsilon = I_n\text{)} \tag{5.13}$$

The above construction implies that structural shocks depend on the coefficient estimates of the matrix, B_0 ($\varepsilon_t = B_0 u_t$). Therefore, when B_0 is known, structural coefficients and structural innovations can be calculated using the relationships in (5.9) and (5.10). To identify the parameters of the fully structural specification at least $n^2 = 25$ restrictions are required. Since Σ_ε is symmetric, $\frac{n(n+1)}{2} = 15$ parameters in B_0^{-1} can uniquely be identified. The additional identification restrictions of $\frac{n(n-1)}{2} = 10$ are required to fully determine B_0^{-1} and the structural equations and hence to recover the structural shocks (refer chapter 4 for details). Denote B_0^{-1} by S, where S is a (5×5) matrix. Reduced form errors are weighted averages of the selected structural innovations and the weights attached to the structural shocks are represented by the elements of s_{ij} for $i = 1, \cdots, 5$ and $j = 1, \cdots, 5$ in the S matrix.

5.5.1 Identification Restrictions on Contemporaneous Matrix

The identification described subsequently is contemporaneous restrictions on the coefficient matrix, which is a combination of short-run and long-run restrictions. It is unlikely that the old age ratio would be affected contemporaneously by shocks to house prices, monetary policy shocks, output shocks or unemployment shocks. However, the old age ratio may be affected by the past innovations of these variables as they have an impact on the fertility decisions of the households and immigrants as described in sections 5.3 and 5.4. Considering this, the old age ratio does not respond to shocks to house price, monetary policy shocks, output shocks or unemployment shocks instantaneously, but with lags. These assumptions allow placing the old age ratio at the top of the matrix, S.

Real GDP per capita is affected by the shocks to the old age ratio contemporaneously in addition to its own shocks. An increase in the retired population (over 65 years) may affect the number in the active labour force and it may slow down economic growth. Investments decisions both in physical and human capital are characterised by the different stages of an individual's life cycle. The Hviding and Mérette (1998) growth model with exogenous human capital suggests that the population ageing causes both the capital stock and the labour force to fall and as a result real output per capita also falls[37]. However, the simulation results with endogenous human capital of Fougere and Mérette, 1999 (1999, p. 422) finds that '… population ageing increases human capital investment, which leads to a greater reduction in effective labour supply in the short run… However, the increase in human capital investment eventually offsets this by raising effective labour supply, which in turn stimulates the economic growth'. Thus, the impact of population ageing still has a negative impact on GDP per capita in the short run however intensity of the impact is lower. Therefore shocks to the old age ratio have an impact on real GDP per capita contemporaneously. Unemployment shocks and shocks to house prices are assumed not to affect real GDP per capita in the same period though monetary policy shocks affect real GDP per capita contemporaneously.

It is assumed that unemployment responds to shocks to the old age ratio and output shocks at the same period along with its own shocks. Unemployment may not be a consequence of the shocks to house prices and monetary policy shocks instantaneously however there would be lagged effects. If increasing (decreasing) house prices are driven by the shortage (excess) in new house supply, it will have an impact on the employment opportunities in housing construction and influence the rate of unemployment in the subsequent periods. Okun's (1960) law points out a negative relationship between the unemployment rate and growth rate of real GDP. The change in the unemployment rate is modelled as a function of the growth rate of real GDP with a negative coefficient. Accordingly, we assume that the unemployment rate is contemporaneously affected by the output shocks. Thus output places above the unemployment of the identification matrix.

With regard to the contemporaneous reaction between unemployment and monetary policy shocks, it is assumed that unemployment responds with a lag to a monetary

[37] A study for seven OECD countries; Canada, Sweden, Japan, France, U.S.A., U.K. and Italy.

policy shock. However, unemployment shocks have an instantaneous effect on the interest rate. A justification for this assumption is that the Reserve Bank of Australian (RBA) uses its knowledge about the current state of the economy when it is setting interest rates. The RBA monetary policy stance states that ‘in determining monetary policy, the Bank has a duty to maintain price stability, full employment, and the economic prosperity and welfare of the Australian people’. To achieve these statutory objectives, the Bank has an ‘inflation target’ and seeks to keep consumer price inflation in the economy to 2–3 per cent, on average, over the medium term. Thus changes in unemployment rate are a factor in determining monetary policy decisions so that when unemployment rises the RBA may tend to lower the interest rate.

The zero contemporaneous restrictions in the fifth column of the *S* matrix imply that the old age ratio, real GDP per capita, unemployment and interest rate are treated as predetermined with respect to real house price. However, house prices are allowed to respond to shocks to these four variables contemporaneously. In this setting monetary policy does not respond contemporaneously to shocks in house prices. However, in the robustness analysis this restriction will be removed and it is assumed that shocks to house price have an instantaneous effect on interest rate.

In line with the above discussions, equation (5.14) summarises the zero restrictions on the *S* contemporaneous matrix.

$$\begin{bmatrix} doar_t \\ \Delta y_t \\ u_t \\ i_t \\ \Delta hp_t \end{bmatrix} = A(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & 0 & S_{24} & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^R \\ \varepsilon_t^Y \\ \varepsilon_t^U \\ \varepsilon_t^{MP} \\ \varepsilon_t^{HP} \end{bmatrix} \qquad (5.14)$$

The construction of the S matrix provides us with nine contemporaneous restrictions directly. However, it is still one restriction short for exact identification. The final restriction is that a monetary policy can have no long run effect on the level of real output[38]. Thus in the long-run, if real GDP is unaffected by a monetary policy shock, it must be the case that the cumulative effect of ε_t^{MP} on the Δy_t sequence must be equal to zero.

Hence, $\sum_{j=0}^{\infty} B_{23,j}\varepsilon_{t-j}^{MP} = 0$ (5.15)

Since this must be hold for any realization of the $\{\varepsilon_t^{MP}\}$ sequence, all the relevant lag coefficients in (5.6) are set to zero (see Blanchard and Quah, 1989). That is,

$$\sum_{j=0}^{\infty} B_{23,j} = 0 \quad (5.16)$$

The long-run expression of *B(L)* is now given in (5.17).

$$A(1)S = B(1) \quad (5.17)$$

In (5.17), $A(1) = \sum_{j=0}^{\infty} A_j$ and $B(1) = \sum_{j=0}^{\infty} B_j$ indicate the (5×5) long-run matrices of *A(L)* and *B(L)* respectively.

The long run restriction of $B_{23}(1) = 0$ implies that

$$A_{21}(1)S_{13} + A_{22}(1)S_{23} + A_{23}(1)S_{33} + A_{24}(1)S_{43} + A_{25}(1)S_{53} = 0 \quad (5.18)$$

The system is now just identifiable. *A(1)* is calculated from the estimation of reduced form of (5.12). The zero coefficients above the house price equation are identified by short-run restrictions. The imposed long-run restriction of $B_{23}(1) = 0$ uniquely identifies the remaining parameters.

5.6 Data Description and Construction

The structural VAR model described is estimated using annual data from 1950 to 2014, a total of 65 observations. Most of the previous empirical studies use data for the post World War II (WWII) period and, in particular, studies for Australia use data from the 1970s to investigate the effects of demographics on house prices (see chapter 3 for details). A longer time series is used in this study compared to the other

[38] See Bjørnland and Jacobsen (2010).

studies for Australia. This is an advantage as demographic change is a slow moving fundamental which is better captured with a longer time span.

However, constructing a longer and accurate time series to assess the developments in house prices in Australia is challenging. A continuous house price series is available for the post 1970 period though it possesses with a number of measurement problems such as effects from compositional change, seasonality and limited control for the changing quality of housing structures (see section 5.2). In addition, the revisions which took place in compilation of the HPI at several times make it difficult to rely on the consistency of the time series for analytical purposes. The impact of compositional and quality effects is significant as house prices evolve over a long period of time. Stapledon (2007) has constructed a constant quality real house price series for Australia covering the period 1880 to 2006. The significant improvements in this house price series include a stratification exercise which corrects the period to period volatility in the quality of the housing stock and estimations to measure the impacts of the compositional changes. This series forms the foundation for the house prices used in this study. To extend the series from 2007 to 2014, the real growth rates of the residential property price index of the ABS is applied to the constant quality house price of 2006 in the Stapledon's (2007, table 2.5) series[39]. This approach provides a consistent series to measure house price from 1950 to 2013.

The annual time series for the nominal mortgage interest rate is used to represent the effect of interest rates. For the period 1950-1959, the nominal mortgage interest rates were obtained from Table 3.21 (b) – *Interest Rates for Banks*, of the RBA Economic Statistics 1949-1950 to 1996-1997. The RBA statistics published in *Table F5: Indicator Lending Rates* were used to obtain the annual nominal mortgage interest rates for the period 1960-2014.

[39] ABS revised the HPI in 2004, which controls for compositional changes. Figure 5.1 of Fox and Tulip (2014) shows that Stapledon's (2007) real constant-quality house price estimates are consistent with the ABS house prices (see section 5.2 for details).

The annual time series for nominal GDP (for financial year) is obtained from Table 1: Key National Account Aggregates, 5206.0 - *Australian National Accounts: National Income, Expenditure and Product* for 1960 to 2013, published by the ABS. For the period from 1950 to 1959, nominal GDP (i.e. in current prices) figures were obtained from Table 5.1 (a) – *RBA Economic Statistics 1949-1950 to 1996-1997*. The current price GDP data were converted into constant prices using consumer price index published by the RBA in Table G02. The quarterly CPI series was first converted to annual average CPI series for the financial year. In order to be consistent with real house price data the current GDP series was converted to 2005 constant prices using the formula given in (5.19).

$$\text{year t value in year 2005 prices} = \text{year t value} \times \frac{\text{CPI}_{2005}}{\text{CPI}_{\text{t}}} \qquad (5.19)$$

An annual series for the unemployment rate was constructed using the ABS labour force historical time series commencing 1968. The annual averages of the quarterly figures published in the months of February, May, August and November were used to construct the unemployment series from 1968 to 1977. However, for the period of 1978 to 2014 the annual averages of monthly figures were obtained. The annual unemployment rates from 1950 to 1967 were obtained from the Table 4.3 – *Labour Force by Employment* of the RBA Economic Statistics 1949-1950 to 1996-1997.

The data for the demographic variables are based on ABS historical and projected population statistics. The data published in catalogue number 3105.0.65.001 was used in constructing required demographic variables from 1950 to 1970, while data from catalogue number 3101.0 was used for the period from 1971 to 2014.

Figure 5.2 shows the original level time series for the variables, namely log of real house price, log of real GDP per capita, the nominal mortgage interest rates, the unemployment rate and the old age ratio (population 65+ years /population 0-64 years).

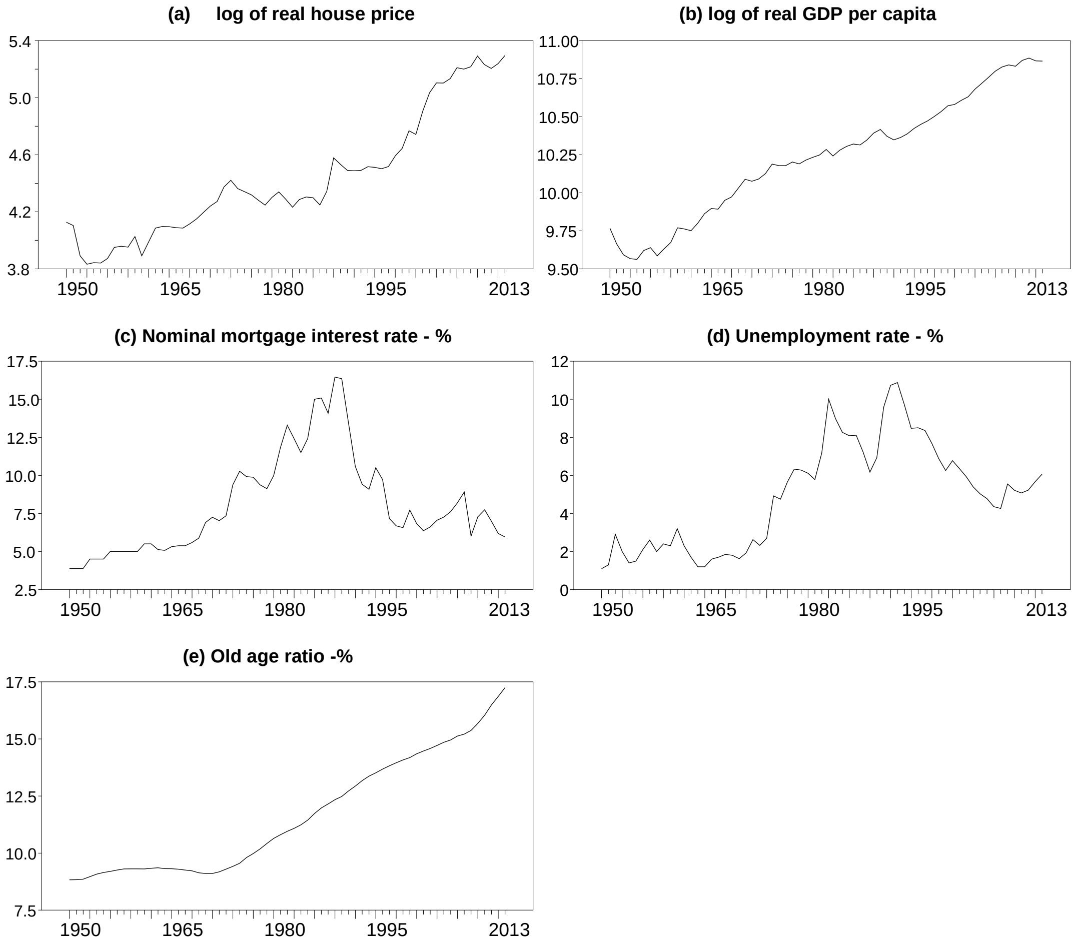


Figure 5.2: Time series original in levels, 1950-2014

5.7 Structural VAR Model Estimation

The OLS estimation method is used for the reduced form VAR (equation 5.8) derived from the structural VAR model (equation 5.5) since the structural parameters and residuals are not estimable directly. The structural parameters are then estimated from the reduced form estimates.

However, the formulation of the econometric model assumes that time series is generated by a stationary, stable and finite order VAR process. Thus as the first step, the time series shown in Figure 5.2 are visually inspected.

5.7.1 Visual Inspection of the Time Series

A visual inspection of the three time series, log of real house price, log of real GDP per capita and the old age ratio indicates likely non-stationarity. Therefore the standard unit root tests and stationary tests for the three variables are performed in section 5.7.2.

It is common in the VAR literature that the two time series, namely the interest rate and the unemployment rate, are considered to be stationary. However, Gustavsson and Osterholm (2001) note that there are mixed results in the literature on the hysteresis hypothesis and unemployment. While some researchers detect the existence of unemployment hysteresis (see Brunnello, 1990; Mitchell, 1993), other researchers reject the null hypothesis of hysteresis in unemployment time series (see Camarero and Tamarit, 2004; Lee, Wu and Lin, 2010 and Ener and Arica, 2001) and find the unemployment time series have mean-reversion properties. The study conducted by Furuoka (2014, p. 10) for Asia-Pacific countries using the Fourier ADF test concludes that '… unemployment rates in Australia and Hong-Kong could be considered as a stationary process …'. Also, considering the dynamics of unemployment rates in 29 OECD countries including Australia over the period 1980-2013, Khraief, Shahbaz, Heshmati and Azam (2015) concludes that the unemployment rate is a stationary process. Considering these results, the unemployment rate is treated as stationary in this research.

5.7.2 Stationary and Unit Root Tests

A number of unit root tests are available, however they sometimes yield conflicting results. Therefore, in order to produce robust results, five different unit root tests are performed. These tests are Augmented Dicky-Fuller (ADF), Phillips Perron (PP), Elliot Rothenberg Stock Dickey-Fuller GLS de-trended (DF-GLS), Ng Perron MZα (Ng-PP) and Kwiatkowski Phillips Schmidt Shin (KPSS).

The ADF test and the PP test are the most commonly used tests for unit roots, and they often give the same conclusions. However, Elliot, Rothenberg and Stock (1996) (hereafter ERS) and Ng and Perron (2001) (hereafter Ng-PP) criticise the ADF and PP tests due to their low power. ERS (1996) and Ng-PP (2001) introduced efficient unit root tests. They argue that the low power of the ADF and PP tests limits their ability to distinguish highly persistent stationary processes from non-stationary processes. The ERS test modifies the Dickey-Fuller test statistic using a generalised least squares (GLS) rationale. ERS (1996) find that this modified test (DF-GLS) has the best overall performance in terms of small sample size and power. In addition to the power, the sensitivity of unit root tests stems from the correct lag lengths being used for specifying the test regression. Ng and Perron (2001) proposed an efficient unit root test with solutions to two problems in the ADF and PP tests. The first is to enhance the power of several tests that have been shown to have small size distortions (see Ng and Perron (2001, p. 1520)). The second is to provide an improved procedure for selecting the lag length of the test regression. The null and alternative hypotheses for the ADF, PP, DF-GLS and Ng-PP tests are as follows.

H_0: Series y_t has a unit root *vs* H_1: Series y_t is stationary

It should be noted however, that Kwiatkowski, Phillips, Schmidt and Shin (1992, p. 160) argue that '… an alternative explanation for the common failure to reject a unit root is simply that most economic time series are not very informative about whether or not there is a unit root …'. A series of studies conducted by DeJong, Nankervis, Savin and Whiteman (1989), Diebold and Rudebusch (1990) and DeJong and Whiteman (1991) suggest that in deciding whether an economic data series is stationary or integrated, it would rather be useful to test a null hypothesis of stationarity (see Kwiatkowski, Phillips, Schmidt and Shin (1992, p. 160)). Accordingly in this research the KPSS test is performed to test the following null and alternative hypotheses.

H_0: Series y_t stationary *vs* H_1: Series y_t has a unit root

Table 5.1: Unit root and stationary test results for the old age ratio (oar_t)

Test	Test Statistic			Conclusion
	In levels	*In first differences*	*In second differences*	
ADF*	-0.78311 (1-AIC, maxlag=4)	-2.22774 (0, AIC, maxlag=4)	-8.40384 (0, AIC, maxlag=4)	oar_t is $I(2)$
DF-GLS*	-0.87075 (1-MAIC, maxlag=4) -0.87075 (1-AIC, maxlag=4)	-0.76533 (0, MAIC, maxlag=4) -0.76533 (0, AIC, maxlag=4)	-5.44860 (0, MAIC, maxlag=4) -8.39846 (0, AIC, maxlag=4)	oar_t is $I(2)$
PP test*	-0.72759	-1.25815	-8.40425	oar_t is $I(2)$
Ng-PP (MZα)**	-4.05670 (1-AIC, maxlag=4)	-3.37348 (0-AIC, maxlag=4)	-30.83420 (0-AIC, maxlag=4)	oar_t is $I(2)$
KPSS***	0.23572	0.64582	0.08661	oar_t is $I(2)$

Table 5.2: Unit root test results for the log of real GDP ($rgdp_t$)

Test	Test Statistic		Conclusion
	In levels	*In first differences*	
ADF*	-2.07134 (2-AIC, maxlag=4)	-3.17603 (1, AIC, maxlag=4)	$rgdp_t$ is $I(1)$
DF-GLS*	-1.83219 (2-MAIC, maxlag=4) -1.88826 (0-AIC, maxlag=4)	-0.29566 (4, MAIC, maxlag=4) -0.29566 (0, AIC, maxlag=4)	
PP test*	0.41277	-8.70795	$rgdp_t$ is $I(1)$
Ng-PP (MZα)**	-5.24473 (4-AIC, maxlag=4)	-0.23419 (4-AIC, maxlag=4)	
KPSS***	0.99821	0.20778	$rgdp_t$ is $I(1)$

Table 5.3: Unit root test results for the log of real house price (rhp_t)

Test	Test Statistic		Conclusion
	In levels	*In first differences*	
ADF*	-0.83392 (0-AIC, maxlag=4)	-6.56098 (1, AIC, maxlag=4)	rhp_t is $I(1)$
DF-GLS*	-0.79122 (2-MAIC, maxlag=4) -1.27601 (0-AIC, maxlag=4)	-2.57075 (4, MAIC, maxlag=4) -6.28233 (0, AIC, maxlag=4)	rhp_t is $I(1)$
PP test*	0.83392	-6.62296	rhp_t is $I(1)$
Ng-PP (MZα)**	-1.76682 (0-AIC, maxlag=4)	-29.95730 (0-AIC, maxlag=4)	rhp_t is $I(1)$
KPSS***	0.92285	0.31857	$rgdp_t$ is $I(1)$

*Test critical values are from MacKinnon (1996) one-sided p-values

**Test critical values are from Ng and Perron (2001, Table 1)

*** Test critical values are from Kwiatkowski, Phillips, Schmidt and Shin (1992, Table 1)

5.7.3 Transform Time Series into Stationary Processes

From a visual inspection and unit root and stationary tests it was concluded that three time series (old age ratio, real GDP, real house price) used in the empirical analysis are not stationary. Thus, as the first step of VAR estimation, these time series are transformed to the stationary series. The old age ratio time series is $I(2)$ and if it is differenced two times to make it stationary information is lost from the VAR estimation. Therefore the Hodrick-Prescott (HP) filter is used to remove the trend from the old age ratio time series before estimation of the VAR since the HP filter is optimal for $I(2)$ processes (see Mark, 2001).

It is worth noting that choosing the correct value for the smoothing parameter (λ) is imperative in order to extract the trend component from the time series when we use HP filter. The smoothing parameter is typically set to 1600 for quarterly data as suggested by Hodrick and Prescott (1997). However, the choice of correct smoothing parameter for different data frequencies such as annual and/or monthly is not clear. For example Backus and Kehoe (1992) and Correia, Neves and Rebelo (1992) suggest values of 100 and 400 respectively for annual data. By visually inspecting the transfer function of the HP filter and comparing the results from the bandpass filter, Baxter and King (1999) suggested a value of 10 for annual data. Subsequently these values were criticised by Ravn and Uhlig (2002) and de Jong and Sakarya (2016) and, using analytical approaches, they recommend a value of 6.25. However, the approaches used are different. The smoothing parameter for annual data is obtained using the formula $\lambda_A = 4^{-4}\lambda_Q$, where λ_A and λ_Q are smoothing parameters for annual and quarterly frequency respectively[40]. The value of 6.25 for the smoothing parameter is used in this research as the data are in annual frequency.

The remaining two non-stationary time series are transformed into stationary series by taking first differences. Figure 5.3 shows the transformed time series which are used in the VAR estimation. A visual inspection clearly shows that the HP filtered

[40] We emphasize annual frequency here since annual data is used in the analysis.

old age ratio and the fist difference of log real GDP and log of real house price are stationary.

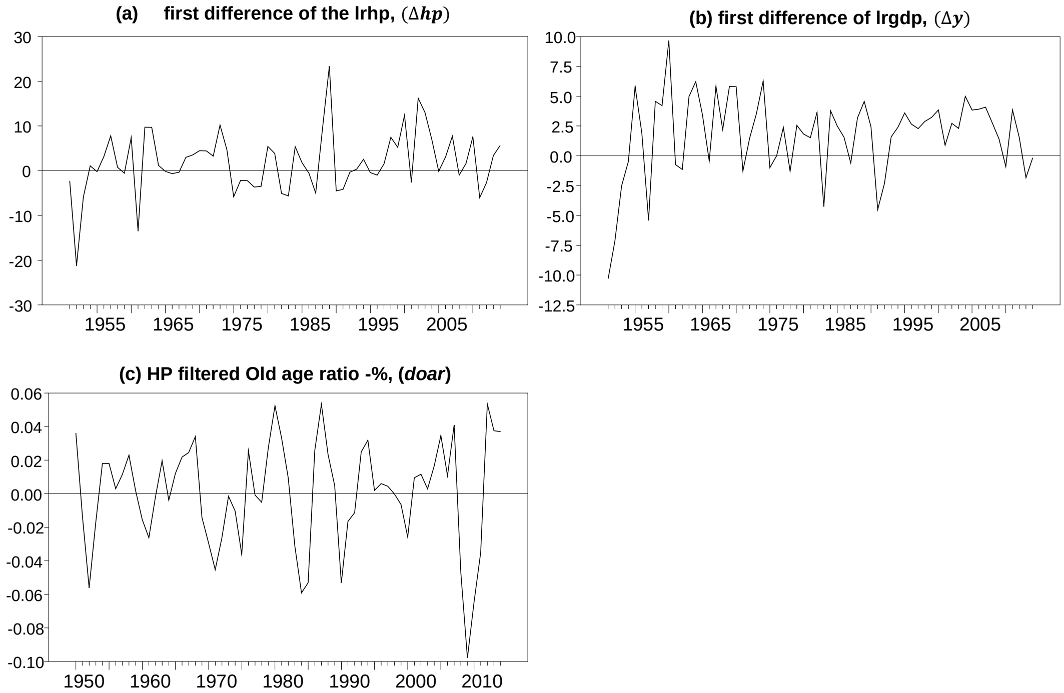


Figure 5.3: Transformed time series used for VAR estimation, 1950-2014

5.7.4 Lag Length Selection for Estimation

In VAR estimation of finite order, choosing the appropriate lag length is an important step. Different methods of lag length selection yield different results and both statistical tests and information criteria are used to select the optimal lag length (see section 4.5 in chapter 4 for details). The likelihood ratio test is performed starting with a lag of 6 (assuming that the upper bound for the VAR order is 6) through a sequence of null and alternative hypotheses, reducing the lag by 1 in each time. In addition two information criteria namely AIC and SC are used. The results are shown in table 5.4.

The LR test results suggest lag length of 2 while AIC and SC suggest 2 and 1 respectively. A lag length of 2 is selected as a shorter lag length would omit important dynamics with regard to the variables used in this research. For example, old age ratio is a slow moving variable and a longer the lag length would better capture the important population ageing dynamics. Also, the residuals produced from a VAR with too few lags may not have white-noise properties and the resulting model may not capture actual error process appropriately. At the same time, we are concerned not to include too many lags since a problem of over-parameterization would be created compared with sample size as discussed in chapter 4[41]. Thus the VAR order selection was based on the objective of the analysis as suggested by Lütkepohl (2005, p. 146). The white noise properties of the residuals are also satisfied for the selected lag order of 2, which is discussed in detail in the next section (section 5.7.3).

Table 5.4: VAR lag order selection, VAR(p) model, estimation period 1950-2014

Lags	AIC	SC	LR test statistic	p-value for LR test
1	11.7103	12.3637*	NA	NA
2	11.4369*	13.2130	50.9678	0.0016
3	12.5120	14.3319	34.5183	0.0973
4	13.4087	15.1615	65.5932	0.0000
5	15.0227	16.0803	61.1236	0.0001
6	17.9038	17.1879	51.1308	0.0015

* indicates lag order selected by the criteria

AIC: Akaike information criteria
SC: Schwarz information criteria
LR: Likelihood Ratio test statistic for the hypotheses $H_0 : A_p = 0 \quad Vs\ H_1 : A_{p-1} = 0$ for $p = 6, \cdots, 2$.
The $\boldsymbol{p}$-value represents the probability of calculated LR statistic greater than the observed value, assuming that the null hypothesis is true

5.7.3 Model Checking

After estimating the reduced form VAR model it is important to test whether the model adequately represents the data generation process (DGP) of the variables. Formal model checking tests, namely test for residual autocorrelation, non-normality and conditional heteroskedasticity, are performed on the reduced form estimations as the reduced form underlies every structural form.

[41] The n-variable VAR(p) process with constant term has $(n + n^2 p)$ parameters to be estimated.

Investigating the white noise (whiteness) assumptions of the reduced form residuals (i.e. the autocorrelation properties of the residuals) is particularly important in this case since different lag orders were suggested by different criteria as discussed in the previous section. Moreover Lütkepohl (2005, p. 157) states that '… the criteria for model choice may be regarded as criteria for deciding whether the residuals are close enough to white noise to satisfy the investigator'. Since the focus of this VAR estimation is not just forecasting but also on structural analyses, checking the whiteness of the residuals using residual autocorrelation tests is imperative.

Testing for Residual Autocorrelation

Table 5.5 shows the Portmanteau test results for the overall significance of residual autocorrelation up to lag h from the estimated VAR(2) process. The null hypothesis is : no residual autocorrelation up to lag h.

$H_0: R_h = (R_1, \cdots, R_h) = 0$ vs $H_1: R_h \neq 0$

Table 5.5: Portmanteau test for VAR(2) model, estimation period 1950-2014

H	**Q test statistic**	***p*-value**
1	11.8096	NA*
2	16.5130	NA*
3	27.9416	0.0321
4	54.0061	0.0088
5	70.2792	0.0197

* indicates test is valid only for lags larger than the VAR lag order

The ***p***-value represents the probability of calculated Q statistic greater than the observed value, assuming that the null hypothesis is true

None of the p-values exceeds 5% and therefore even at 5% level of significance, the null hypothesis of no residual autocorrelation is rejected for lag order higher than 2. That is at the lag lengths above 2, the estimated VAR model suffers from the problem of residual autocorrelation.

The Lagrange Multiplier (LM) test is also used to test for residual autocorrelation in the estimated VAR(2) process since Lütkepohl (2005, p. 173) suggests the LM test is more suitable for small values of h. This test assumes that a VAR model for the error vector can be written as; $u_t = C_1 u_{t-1} + \cdots + C_h u_{t-h} + e_t$, where e_t is white noise. If there is no residual autocorrelation, then $e_t = u_t$ should be satisfied (Lütkepohl, 2005, p. 171). Therefore, a test of

$$H_0: C_1 = \cdots = C_h = 0 \qquad \text{vs} \qquad H_1: C_j \neq 0 \text{ for at least one } j \in \{1, \cdots, h\}$$

is used for testing that residuals are white noise. The results are shown in Table 5.6. The null hypothesis of no residual autocorrelation cannot be rejected for the lag order 2. Thus both tests do not find evidence of residual autocorrelation for the estimated VAR(2) model, suggesting that the required whiteness property of the residuals is satisfied. Therefore, the selected lag order of 2 produces white noise residuals satisfying the first model checking criteria.

Table 5.6: LM test for VAR(2) model, estimation period 1950-2014

H	**LM test statistic**	***p*-value**
1	31.9997	0.0100
2	14.2137	0.5828
3	12.3888	0.7168
4	28.8044	0.0253
5	11.4184	0.3830

The ***p***-value represents the probability of calculated LM test statistic greater than the observed value, assuming that the null hypothesis is true

Testing for Non-normality

Normality of residuals is not a necessary condition for the validity of many statistical tests in VAR estimation though non-normal residuals can indicate that the model is not a good representation of the DGP. The multivariate normality tests to determine whether the third and fourth moments of the residuals (skewness and kurtosis respectively) are in line with a normal distribution are conducted using the least square residuals of the estimated VAR(2) model (see Lomnicki, 1961). The results of testing the null hypothesis that residuals are multivariate normal are shown in table 5.7. The asymptotic test results do not provide evidence to reject the null hypothesis that residuals are multivariate normal. Thus the data are generated from a Gaussian process.

Table 5.7: Normality test for residuals VAR(2) model, estimation period 1950-2014

Moment	Test statistic	*p*-value
Skewness	2.8593	0.5816
Kurtosis	0.1964	0.7772
Joint	3.0557	0.9308

Test statistics are calculated using OLS residuals of VAR(*2*) model and a *Choleski* decomposition of variance-covariance matrix of the residuals

The ***p***-value represents the probability of calculated test statistic greater than the observed value, assuming that the null hypothesis is true.

Testing for Conditional Heteroskedasticity

Testing for conditional heteroskedasticity is more important when the VAR model estimation is based on monthly or higher frequency data. This analysis uses annual data. Nevertheless conditional heteroskedasticity is checked to enhance the understanding of the underlying DGP and to improve inferences. In addition, the presence of heteroskedasticity may indicate structural changes, which will lead to produce time variant VAR parameters against the time invariant parameters throughout the sample period. The test of the null hypothesis of "no autoregressive conditional heteroskedasticity" produces a test statistic of 174.43 with a *p*-value of 0.2059. Therefore, the null hypothesis cannot be rejected at 5% level of significance and there is no evidence of conditional heteroskedasticity in the estimated VAR(2) process.

5.8 Analysis of Empirical Results

The tests of the model adequacy presented in the previous section confirm the validity of the assumptions underlying the estimated VAR(2) model with variables ordered old age ratio, real GDP per capita, unemployment, nominal mortgage interest rate and real house price. Thus the estimated model is appropriate to examine the dynamic effects of the old age ratio on real house prices in Australia. The dynamic relationships among the variables are examined by tracing the effects of structural innovations in various ways. The impulse response functions (IRF), historical decomposition and forecast error variance (FEVD) decomposition are generated after imposing short-run identification restrictions on the contemporaneous reaction of the variables to structural shocks for the unrestricted VAR(*2*) model.

The impulse response functions (IRFs) are generated to review the responses of each variable to a one standard deviation structural innovation at time *t* and for a period of 20 years from *t*. The impulse response confidence intervals are based on the Bayesian Monte Carlo integration method with 10,000 replications using the method for just-identified systems (see Doan 2004)[42]. The IRF only models an initial period shock. However, in general, structural shocks are not limited to a one-off shock. Rather they involve a vector sequence of shocks, often with different signs at different points in time[43]. The cumulative effect of such a sequence of shocks on the evolution of variables over time is examined using historical decomposition. Whilst the FEVD uses the same information as the IRF, it decomposes the forecast error variance into components due to each structural innovation. Accordingly, the FEVD quantifies the percentage contribution of the total variation in a variable attributable to each structural shock including its own shocks for different forecast periods.

5.8.1 The Dynamics of Real House Prices

Figure 5.4 (a-e) shows the plots of the impulse responses of real house price to positive shocks to old age ratio, output, unemployment, monetary policy and real house price itself. One-standard error confidence bands are indicated by dotted lines. All impulse responses approach zero quickly and the effects of shocks after 6 years are negligible. The responses of the real house prices are more pronounced to its own shocks compared to other three shocks considered. A positive shock to house price causes an immediate increase in the real house price by 5% though the increase is not persistent.

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[42] In IR analysis estimation uncertainty is typically displayed by constructing error bands around estimated IRFs.
[43]See Kilian and Park (2009, p. 1272).

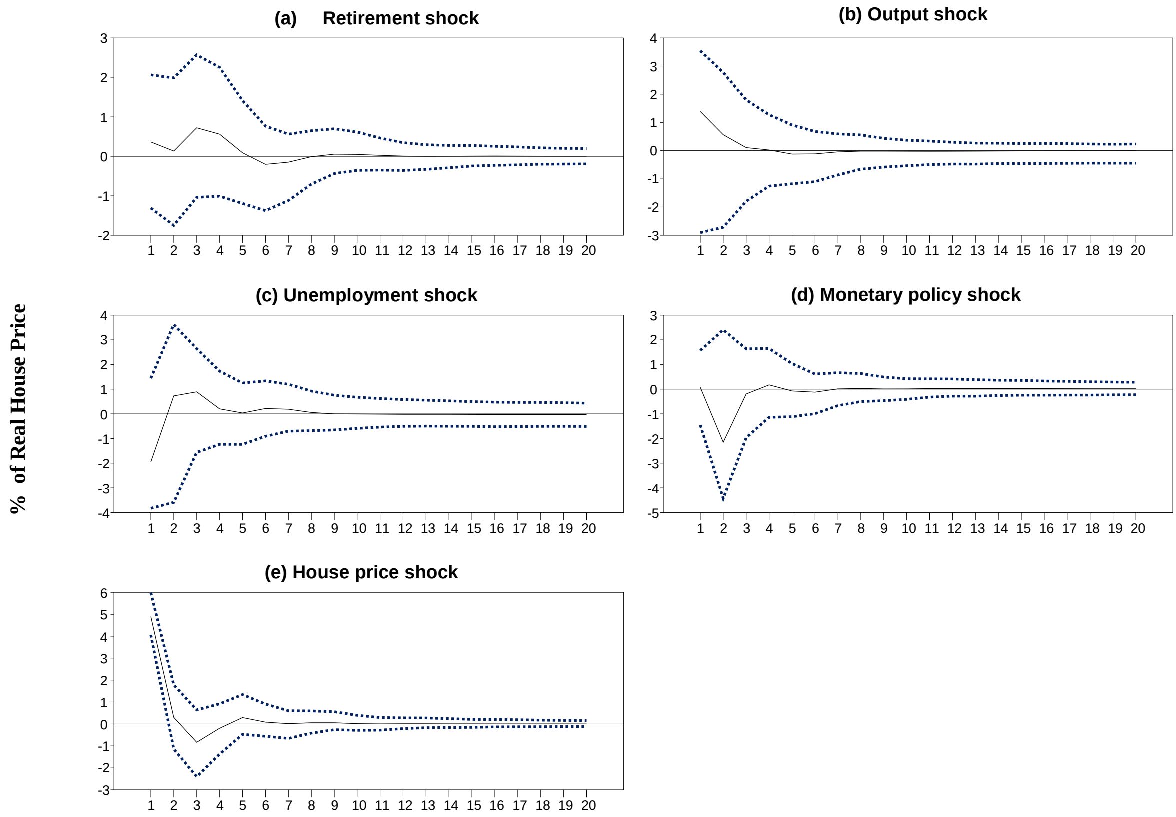

Figure 5.4: IRF of real house price: Point estimates with error bands

The central item of interest in Figure 5.4 is the effect of a positive retirement shock or shock to the old age ratio (plot a). The IRF does not suggest a decrease in the real house price in response to an increase in the old age ratio as a result of a positive retirement shock. Instead it shows an increase in the real house price for the first five years after a shock with a peak increase of 0.5% in the third year. However, the wider error bands at these points show that the effects of retirement shocks on house prices are statistically insignificant or uncertainty in the responses[44]. A potential explanation for this increase is that rather than housing consumption falling after age

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[44] See Bjørnland and Jacobsen (2010) and Fry et al. (2010). The large standard errors of the of the impulse response coefficients reflect the substantial estimation uncertainty in the VAR coefficients (Lütkepohl, 2005, p. 119).

40 as Mankiw and Weil (1989) assumed, housing consumption continues to increase even after retirement. A similar result was found by Pitkin and Myers (1994) for the United States using a cohort-linked cross section analysis and they conclude that housing consumption actually continues to increase past age 70. As a result the ageing Baby Boomers would not be expected to cause a decrease in housing demand.

The output and unemployment shocks have different effects on real house prices. A positive output shock causes an instantaneous increase in real house prices while a similar shock to unemployment causes a decrease. This result is consistent with the discussion of the rationale of variable selection. The negative impact from unemployment is higher than the positive impact from real GDP per capita. A positive unemployment shock decreases the real house price by 2% immediately. Although a positive shock to output increases real house price instantaneously, it reverses back to zero in three years. This is a plausible result since the policymakers attempt to mitigate the effects of economic booms and increasing unemployment on other sectors of the economy. Also the responses are consistent with economic theories. The positive shocks to output induce higher demand for consumption and investment (e.g. spending on houses) while increase in unemployment induce lower demand.

A contractionary monetary policy (a positive shock to interest rate) leads to a decrease in real house prices with the peak decline of 2% in the second year after the shock. The effect gradually declines and dissipates three years after the shock. As argued by Wadud et al. (2012), changes in monetary policy do not always pass through mortgage lending rates in Australia. This could be attributable to the observed temporary decline in real house price in response to a contractionary monetary policy shock. Thus the impulse response analysis suggests there is not a strong and prolonged effect from monetary policy shock on house prices.

The historical decomposition depicting the cumulative effects of current and past shocks on the real house price is shown in Figure 5.5.

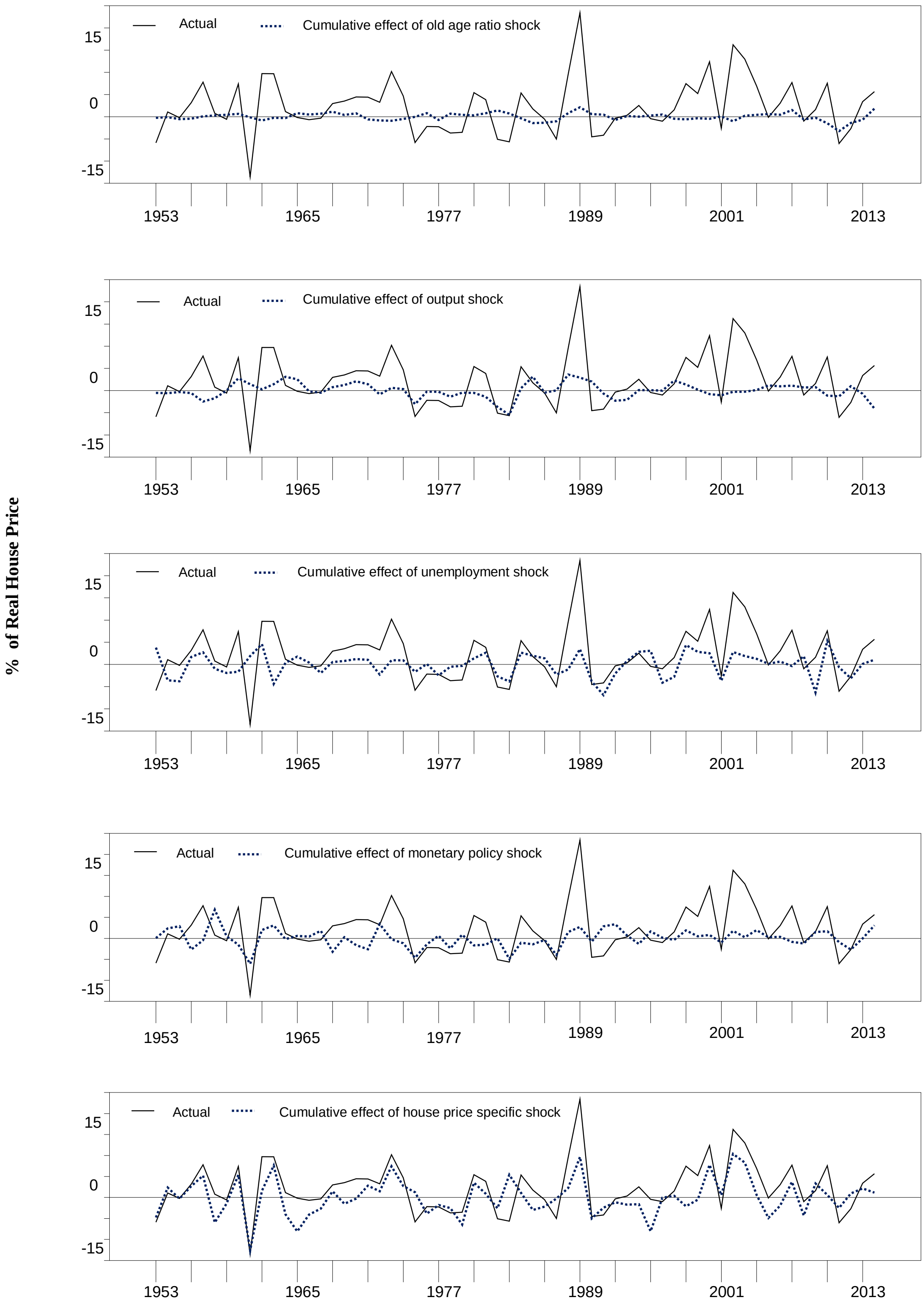


Figure 5.5: Historical decomposition of real house price

The figure clearly suggests that the historical fluctuations of the real house prices are mainly attributable to shocks to the real house price itself and unemployment shocks. The cumulative effect from monetary policy shocks is more noticeable during the period before 1990. The fluctuations in real house price between 1955 and 1975 were driven to some extent by shocks to output though after this period its impact has been decaying. The contribution from shocks to the old age ratio is minor for historical fluctuations in the real house price. The fluctuations in real house price after 2011 do not show a systematic downwards movement associated with the cumulative effect of old age ratio shock required to support the view that the retirement of large number of Baby Boomers since 2001 would cause a downward pressure on house prices.

The FEVD presented in Table 5.8 quantifies the importance of each structural shock ($\varepsilon_t^{OR}, \varepsilon_t^{Y}, \varepsilon_t^{U},\ \varepsilon_t^{MP}, \varepsilon_t^{HP}$) to the forecast error variance of the real house price for different forecast horizons. For example, about 77% of the 1-step forecast error variance of the real house price is accounted for by its own innovations. The statistically insignificant effect of the shocks to the old age ratio as revealed in the impulse response analysis is supported by the forecast error variance decomposition. The contribution of old age shocks is small, less than 2.5%, both in the short and long runs.

In contrast, the relative contribution of unemployment is around 15% even in the 1-step forecast error variance of the real house price. In the long-run, more than 18% of the error variance is attributable to the unemployment shocks. The importance of real GDP per capita is almost constant over the forecast horizons starting from 2-step forecast error. Less than 10% of the variation in real house price is explained by the output shocks in the medium and long runs. The contribution from monetary policy shocks is minor in the 1-step forecast error variance decomposition of the real house price. However, its contribution is substantially increased in the 2-step forecast error variance and in the long-run the contribution is around 14%.

Table 5.8: Forecast Error Variance Decomposition of Real House Price

Horizon	Shock to old age ratio	Output shock	Unemployment shock	Monetary policy shock	Shock to house price
1	0.402	7.371	14.852	0.017	77.358
2	0.348	9.716	15.962	14.287	59.688
3	1.440	9.163	18.388	13.346	57.663
4	2.113	9.060	18.240	13.579	57.008
5	2.116	9.082	18.189	13.599	57.014
10	2.314	9.051	18.459	13.594	56.584
15	2.316	9.054	18.466	13.598	56.566
∞	2.316	9.054	18.481	13.601	56.548

5.9 Robustness Analysis

The robustness of the above results is tested by using plausible alternative models. First, robustness to the structural identification system is analysed. In section 5.5.1, an assumption was made that monetary policy does not respond contemporaneously to the shocks to house prices. Following a similar argument to Bjørnland and Jacobsen (2010) we do not restrict monetary policy from responding contemporaneously shocks to house prices (in equation 5.14, set $S_{45} \neq 0$). However, it is assumed that monetary policy shocks do not have long-run effects on the level of the real house price. Thus the identifiaction restrictions now consist of two long-run restrictions. The impulse response function of real house price is shown in Figure 5.6.

The responses of the real house price to a positive shock to the old age ratio (a positive retirement shock) is very much similar to the plot (a) of the Figure 5.4, suggesting that the changing of the identification does not affect to the main result. However, the real house price increases by about 0.75% instantaneously responding to a contractionary monetary policy shock. This is in contrast to the negative response of real house price to a contractionary monetary policy shock where the instantaneous reaction of monetary policy was restricted the shocks to house prices. However, the error bands are wider at this point, emphasizing the uncertainty in the response. The response turns negative from the second year, but not significantly and tapers off to zero after three years.

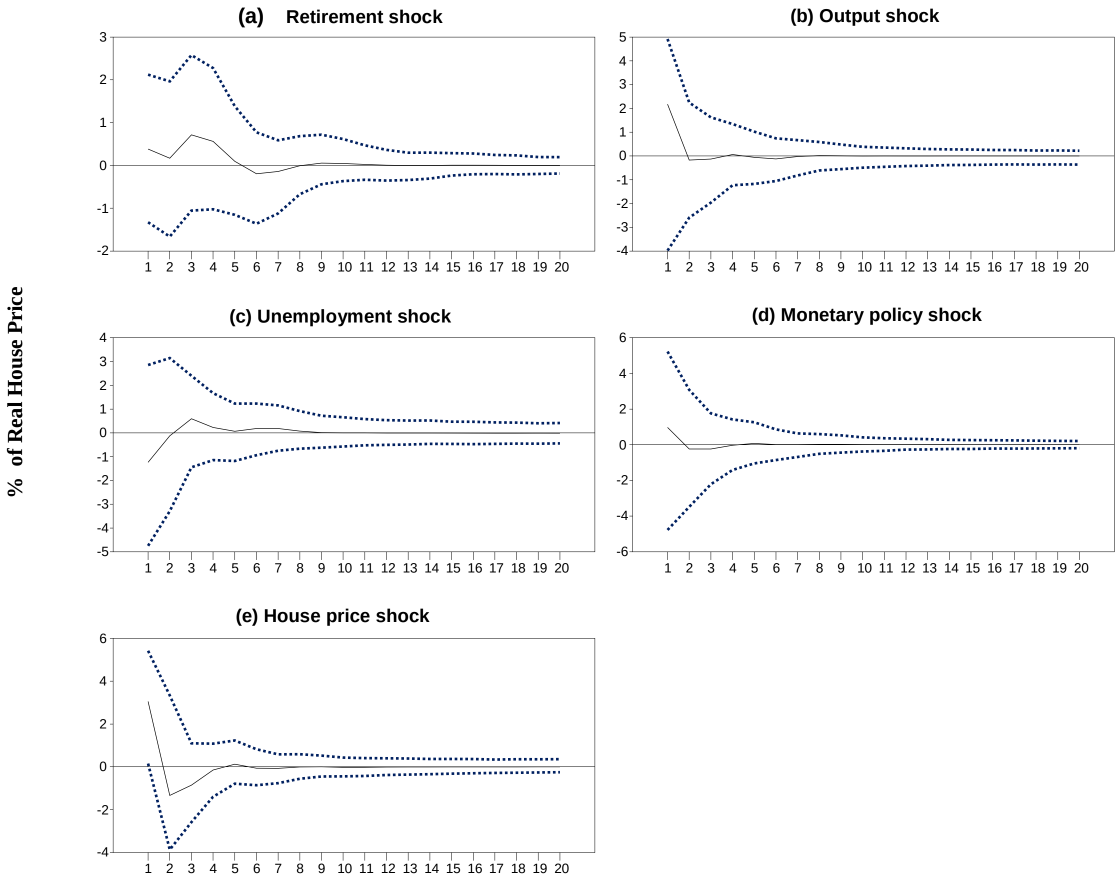


Figure 5.6: IRF of real house price (monetary policy responds contemporaneously to the shocks to house price)

Second, the robustness analysis uses a stylised model that incorporates the major features of the "life cycle" behaviour of households in the housing market. The analysis directly applies the life cycle theory and assumes that demographic changes affect real house prices through the channel of asset accumulation and the portfolio decisions of the individuals at different ages of their lives. Consequentially, changes in the populations' age distribution may influence the aggregate demand for housing assets. Applying the life cycle theory to the housing market, we see that the young population are net borrowers and they generate a high demand for housing assets, while the old population de-accumulate wealth by selling assets and thus lower the demand for housing assets. This variation in demand may produce a relationship between house prices and the demographic structure. Therefore old age ratio is replaced by the number in the old population (population 65 years and above) in the benchmark model. That is the absolute importance of population ageing on real house price is measured rather than the relative importance as measured using the old age ratio in the previous analysis.

The impulse response functions are shown in Figure 5.7. The responses of the real house price to a positive retirement shock is very much similar to plot (a) of figure 5.4 though the peak increase is nearly 1%. A possible explanation for this is that as even after retirement Australians continue to hold and/or accumulate housing assets rather than de-accumulate as predicted by life cycle theory (see chapter 2 for details). However, the wider error bands associated with the increase in the real house price responding to a positive retirement shock in old population emphasize that responses are insignificant. This is supported by the forecast error variance decomposition. The contribution of the retirement shock to the variation of real house price is small, less than 3%, both in the short and long runs.

Moreover, the analysis using the old age population was extended by having the identification similar to the case of the old age ratio. The impulse responses of real house price have a similar shape in response to a positive retirement shock.

Overall, the robustness analysis strengthened the main conclusion namely that the increase in the old population associated with the retirement of the Baby Boom cohort would not cause a downward pressure on real house prices.

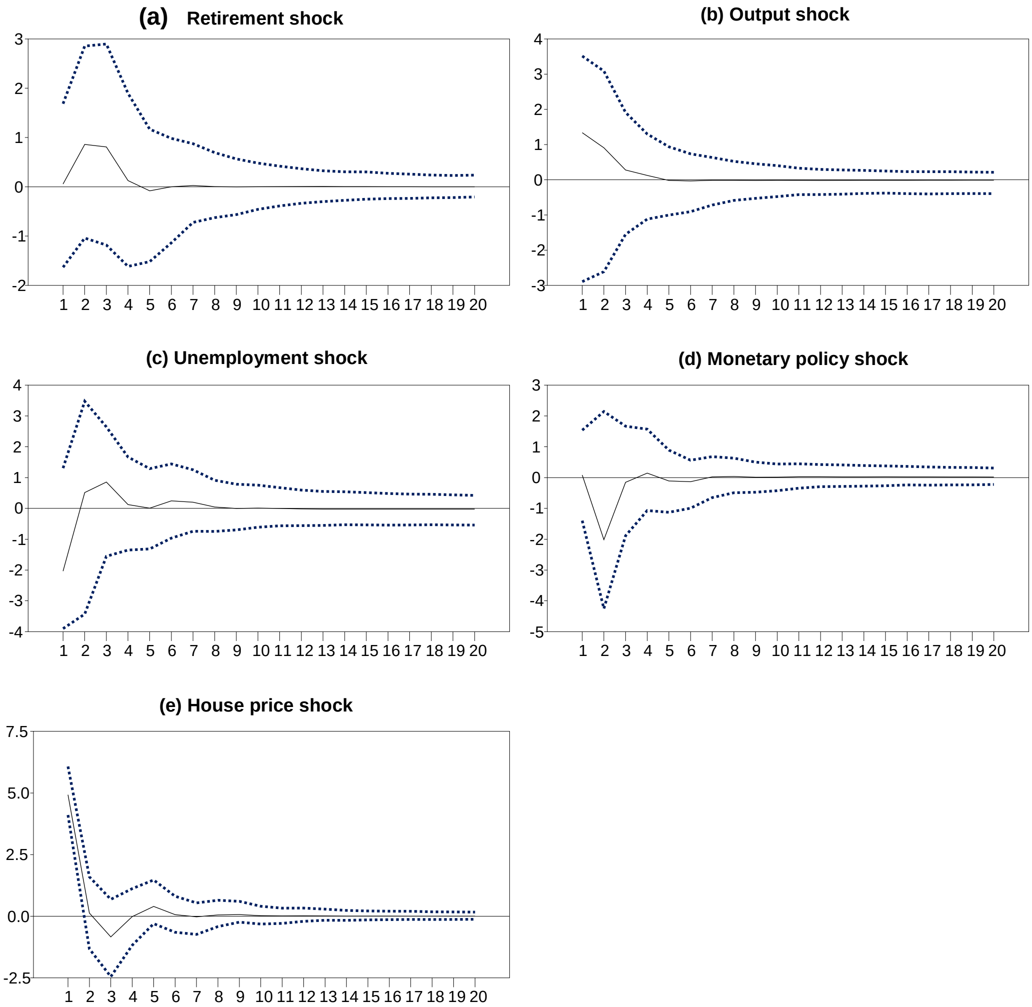


Figure 5.7: IRF of real house price (replaced old age ratio by old population in the benchmark model)

5.10 Conclusion

This chapter provides a detailed description of the econometric model used to examine the effects of population ageing dynamics on real house prices in Australia and the results of the analysis. The analysis is more rigorous than previous studies. The Structural VAR model takes into account the endogenous nature and the dynamic adjustment process of the macroeconomic variables in contrast to the existing literature which focuses on the average effect of the old age population on real house prices in a single equation model.

In summary, the findings do not predict a downward pressure on real house prices in Australia due to the retirement of the Baby Boom cohort. The findings are in contrast to earlier predictions of a downward pressure on real house prices in Australia due to the effect of population ageing. Such predictions are made by Guest and Swift (2010) for Australia and Takats (2012) considering 22 OECD countries including Australia. The former predict that real house prices would be 27.1% lower in 2050 than they would be if the population share of the 35-59 years cohort remains constant. The latter estimates a fall in real house price by 2/3% for 1% increase in old age dependency ratio. However, similar to our conclusions, Chen et al. (2012) conclude that population ageing, or more generally changes in age structures, is not likely to be a main determinant of house prices in Scotland, which has an ageing population problem more severe than in Australia.

The impulse response analyses, measuring both absolute and relative effects of population ageing, support the conclusion that population ageing or more generally the changing age structure does not exert a significant downward pressure on real house prices. Also, historical decomposition of the fluctuations in the real house price suggests that real house price shocks historically have been driven mainly by a combination of its own shocks and unemployment and monetary policy shocks. A possible explanation for this is that despite the fact that housing demand is influenced by the population age structure, these effects could be simply too small to be detected among the other shocks to house prices. In the short-run, more than 75% of the variation in real house prices is accounted for by its own shocks. These housing market specific shocks could include shocks to material cost, shocks to land prices, credit channel shocks and behavioural shocks such as change of peoples' attitude to live surrounding major cities.

The life cycle hypothesis suggests that when the Baby Boomers retire, many are likely to sell their assets to finance their retirement exerting downward pressure on house prices. The failure to find any potential house price meltdown postulates that process of selling houses by the retired population is gradual, thus it is unlikely to produce a significant sudden negative impact. Moreover, asset ownership statistics for Australia (2011-2012 survey) presented in chapter 2 reveal that a significant portion of population over 65 years have an owner occupied dwelling. In an international comparison of home ownership statistics, Bradbury (2010, p. vi) concludes that ‘among the elderly, own home ownership wealth is much greater proportion of disposable income in Australia than in all other countries’. These evidences imply that the retired population do not have a tendency to sell their houses immediately. If the same attitude adopted by retiring Baby Boomers there will not be a significant and sudden negative impact on real house prices, which supports the findings of the empirical analysis.

One of the important findings of the analysis is that unemployment has a significant impact on the fluctuations in real house prices in Australia. Most of the previous studies related to the housing sector in Australia (Abelson et al. 2005; Otto 2007; Fry et al. 2009; Wadud et al. 2012) do not include unemployment as a variable. Even though Guest and Swift (2010) include unemployment in their analysis they do not find a statistically significant coefficient. This finding makes a significant contribution to the literature and highlights that unemployment is an important macroeconomic variable in determining real house prices in Australia in the short-run. Moreover, the cumulative effect of shocks to unemployment is higher than that of shocks to output in driving real house prices historically. This effect of unemployment on real house price is an expected outcome, since higher unemployment affects the ability to obtain mortgage loans and people’s confidence over the business cycles. The combined effect then turns to a lower demand for housing.

Financial innovations available in Australia such as equity withdrawal facilities provide an alternative for retired people to trading down their homes to finance consumption needs during the retirement. Also reverse mortgage loans allows people 65 years and over to borrow against the home equity or asset value of the property.

This delays selling homes by the retired people. As long as financial innovations persist and there are no major shocks to unemployment, adverse shocks to real economic activities and/or adverse housing market specific shocks population ageing does not necessarily constitute a reason for real house prices to fall or for it to exert a dampening effect. Even in the long-run less than 3% of the variation in real house prices is accounted for by the population ageing effect. This finding is in contrast to the Guest and Swift (2010, p. 249) conclusion of a dampening effect of ageing on house prices in Australia. Moreover, a report published by the RBA (Schwartz Hampton, Lewis and Norman, 2007) indicates that old people are home equity withdrawers suggesting that there is a reduced pressure to sell their homes to finance consumption. Also, increasing longevity delays the time of selling or trading down the existing house.

The Intergenerational Report (2015) forecasts an increase in the workforce participation rate of the Australian population above age 65 years from 12.9% in 2014-15 to 17.3% in 2054-55. This also has an influence on decisions to defer the de-cumulation of wealth by the people over 65 years. Therefore, it is reasonable to expect age-specific housing wealth ownership rates at older ages will not decrease over the current rates. In summary, the combination of the empirical findings of this chapter, projected workforce participation rates and asset ownership statistics refute predictions that population ageing will lead to pronounced downward pressure on real house prices in Australia.

CHAPTER 6 THE EFFECTS OF POPULATION AGEING DYNAMICS ON STOCK PRICES

6.1 Introduction

The theoretical basis of the asset meltdown hypothesis (AMH) is the assumption that the performance of the American stock market in the 1990s was influenced by demographics as Baby Boomers saved for retirement. It is argued that this led to an increase in the demand for financial assets and a dramatic rise in financial asset prices. However, on retirement, Baby Boomers will be selling their assets to a relatively smaller number of young investors[45]. Other things equal, this would exert a downward pressure on stock prices. Pessimists, those who believe in the AMH, presume that this sell-off will cause asset prices to plummet. In contrast, optimists hold an opposing view, namely that forward looking market participants will anticipate the impact of the retirement of Baby Boomers, so that it would be softened or even perhaps be totally offset.

For example, Poterba (2001) rejects the AMH based on the empirical evidence for the United States. He finds that the individuals in the peak saving age have a strong tendency to accumulate assets while retired individuals de-accumulate assets slowly. However, Abel's (2001) results contradict Poterba (2001) and support the AMH despite that both (Poterba and Abel) having consistent observations about the asset holdings of retired people. Abel (2001) predicts that equilibrium price of assets may fall when the Baby Boomers retire.

Financial assets are one of the principal saving vehicles for rational economic agents. Therefore changes in savings at different stages in life affect demand for such assets and thereby asset prices. Incorporating the permanent income hypothesis, the life cycle hypothesis posits that individuals save for their retirement during their working

[45] This was an assumption at that time.

age. This is the crucial assumption underlying the asset meltdown hypothesis. A substantial number of theoretical and empirical studies applied this concept to the changing demographic structures associated with the ageing of Baby Boomers though the studies are subject to several important caveats (see chapter 3 for details). Moreover, most of the existing studies focused primarily on the United States and international studies mainly consider G5 countries (France, Germany, Japan, the U.K. and the U.S.).

Three studies (Brooks, 2006; Ang and Maddaloni, 2005; Erb et al., 1997) include Australia in their cross country studies of examining the relationship between demographics and financial asset prices/returns. The results predict mixed outcomes. Whilst Ang and Maddaloni (2005) demonstrate a negative relationship between proportion of the retired population and equity premium using monthly data for the pool of 15 countries, Erb et al. (1997) reveal a weak relation between world average demographic measures and expected returns considering 45 developed and emerging economies. On the other hand Brooks (2006, p. 1) states that '… in countries where stock market participation is greatest, including Australia, Canada, New Zealand, the United Kingdom and the United States, evidence suggests that real financial asset prices may continue to rise as population age…'. Using cointegration analysis and annual data covering the period from 1965 to 2002, Huynh et al. (2006) conclude a significant positive effect on stock prices in Australia in the long run from the population in the 40-64 years cohort. Huynh et al. (2006, p. 695) further infer that '… it is possible that, when the baby boomers start to retire from the workforce, they will withdraw their money from their stock market investments… essentially the economy may be in crisis'. However, the cohort who was aged 40-64 years during 1965-2002 have already passed their retirement age and the Australian stock market does not show signs of a collapse due to a high volume of withdrawals.

Moreover, in contrast to the experiences of population ageing in developed countries, developing countries are still experiencing rapid population growth with low average ages. These divergent demographic trends along with the increasing globalization of financial markets may exert changes in savings patterns and on asset markets.

Further, the closed economy models do not capture the influence of international capital flows on domestic asset prices. In addition, the asset ownership statistics reveals an anomaly in the behaviour of the older populations savings as they continue accumulating savings rather than dis-saving as originally predicted by the life cycle theory (see chapter 2 for details).

The factors discussed in the previous paragraphs raise the questions whether the increasing number of population over 65 years in Australia dis-save and sell their financial assets to fund the retirement and whether that will cause a fall in stock prices? These questions are the foundation for this chapter as it is an issue of great debate among the academics and retirement policy planners.

The analysis presented below makes an important advance over the existing literature. Even though the existing theoretical and empirical models suggest a link between population age structure, particularly the effect of old population on financial asset prices, it is a challenge to step beyond this simple intuition. It is necessary to develop an insight into the potential magnitude of demographic shocks, particularly retirement shocks and quantifying the responses in financial asset prices to those shocks. The structural VAR methodology approach enables the reactions of stock price to demographic shocks to be quantified. Measuring the presence of stock price responses to demographic shocks in actual data is an important improvement over measuring the average effect of demographic variables on stock prices using a single equation model as has been commonly done in the literature.

Following the chapter introduction, in section 6.2 we “eyeball” the data associated with the meltdown scenario. A brief review of share market ownership statistics is presented in section 6.3 to indicate which population segment invests most heavily in capital markets, particularly share markets. The selection of the demographic variable for empirical analysis is supported by the findings of this section. A theoretical link between demographics and asset prices following Poterba (2001) is developed in section 6.4 as a starting point of analysing why population ageing shocks would affect stock prices. This provides some insight for the empirical analysis which is the main focus of the chapter.

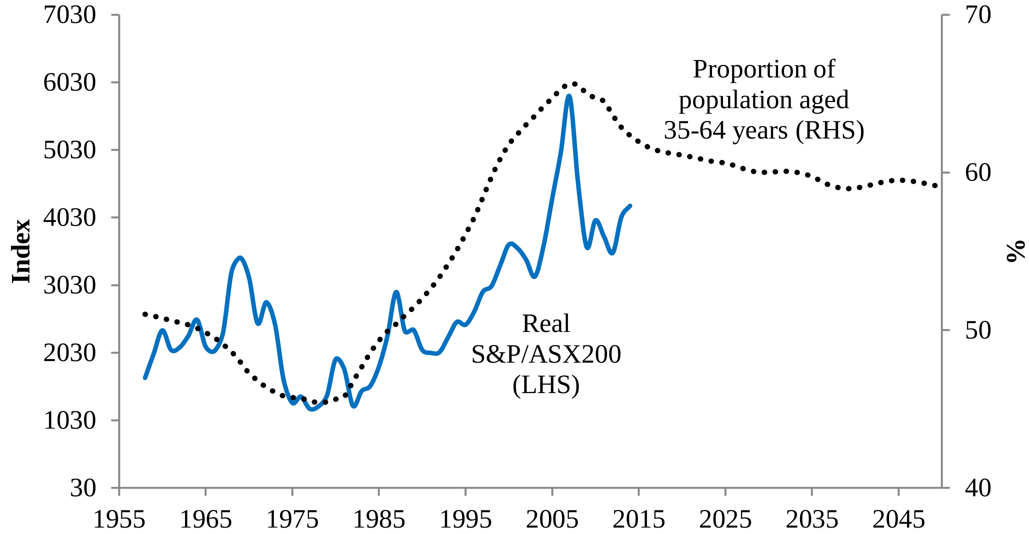
The structural VAR model formulated for empirical analysis is based on a strong conceptual framework which is described in section 6.5 and which produces a detailed description of the notion of relative stock market efficiency. The effects of economic forces on stock prices, along with the prevailing relative market efficiency in the stock market, form the foundation for variable selection for the empirical model. Section 6.6 provides a detailed description of the empirical model. This section presents the identification scheme which constitutes a combination of short-run and long-run restrictions.

The model estimation is based on annual data from 1969 to 2014 on a Bayesian framework. Section 6.7 briefly describes data sources and variable construction. Following this, section 6.8 presents and discusses the model estimation and empirical results. A robustness analysis is carried out in section 6.9 and the conclusions drawn from the chapter are provided in section 6.10.

6.2 Eyeballing the Data on the Meltdown Scenario

Eyeballing the data provides preliminary support for the meltdown scenario. Figure 6.1 plots the real S&P/ASX200 and the ratio of population aged 35-64 years to the remaining population (those aged 0-34 years and 65+ years). This indicates that the decline in real stock price from 1970s to the mid-1980s coincides with a comparatively low proportion of prime earners (35-64 years). Proponents of the AMH linked this decline in real stock prices to Baby Boomers. They assumed that the parents of the Baby Boomers switched from investing in the stock market to housing market and raising children. Furthermore, the story was extended to establish a link between population age structures and the increased stock prices in the 1990s. Thus the proponents of the AMH argued that Baby Boomers (born between 1946 and 1964) who reached in the prime saving years during the 1990s contributed to an increase in demand for stocks and thus increased the stock prices.

The result of this interpretation was a prediction of an asset price meltdown when the Baby Boomers began to retire 20 years from the 1990s.



Source(s): DataStream (AUYSP001F), ABS Australian Historical Population Statistics, 2008 (cat. no. 3105.0.65.001), ABS Australian Demographic Statistics, 2013 (cat. no. 2101.0), ABS Population Projections (cat. no. 3222.0)

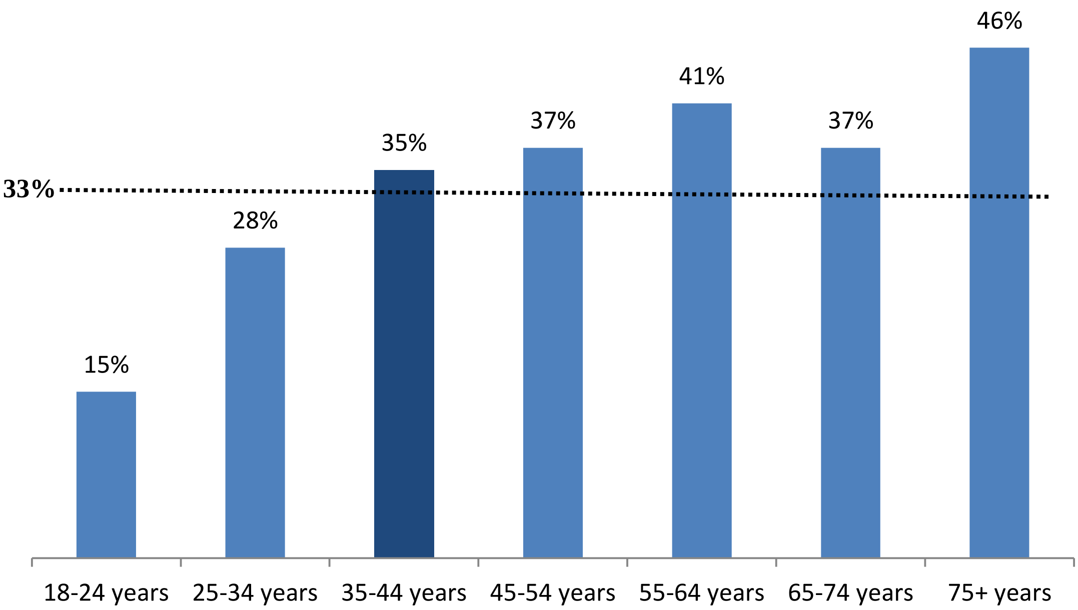
Figure 6.1: Meltdown scenario of stock prices

However, caution should be exercised when predicting a meltdown scenario for Australia based on eyeballing the data in the Figure 6.1. It is well known that correlation does not imply causation and the relationship between demographics and stock prices apparently evident in figure 6.1 may be deceptive. With the benefit of hindsight the movements in the stock prices in the 1990s are attributable to at least three other factors[46]. The first is the deregulation of Australian financial markets in the 1980s. The second is the introduction of compulsory superannuation in the early 1990s. The large superannuation funds invest in the ASX. The third is the privatization of government business during the 1990s. These transactions lead to increase the number of shareholders during the 1990s. However the majority of those shareholders were Baby Boomers as they were then in their prime earning years. Thus, while recognising the multiple causes of changes to stock prices, it is

[46] The three factors were summarised based on the information from Eslake (2007).

reasonable to leave open the possibility that when the Baby Boomers retire, it will have a negative impact on financial asset prices. Against this background more sophisticated analysis than “eyeballing the data” or simple regression analysis is required to disentangle the relationships and examine the effects of population ageing dynamics on stock prices.

6.3 Share Market Ownership by Age



Source: Australian Share Ownership Study, 2014

Note: 33% = Overall incidence of direct share market ownership (shares and other listed investments)

Figure 6.2: Incidence of share ownership by Age (%)

A change in population age distribution leading to a change the ratio of people belonging to prime savers and dis-savers may have an impact on share market ownership. According to the 2014 Australian share ownership study conducted by the Australian Stock Exchange (ASX), the likelihood of share ownership increases with age. Among direct share investors, there was a 46% incidence in the 75+ years age group[47]. As revealed in the Figure 6.2, the age at which investing normalises is around 35 years. Among the investors in 35 to 44 years, 35% directly own shares.

[47] The data by age was available only for direct investors.

The ASX share ownership study (2015) notes that the 35% share ownership among 35 to 44 years is a significant increase from the 28% held by 25 to 34 year olds who are direct owners.

6.4 Theoretical Analysis of Population Age Structure and Asset Prices

As a motivation for empirical analysis, a simple theoretical model of the link between asset prices and demographics is formalised following Poterba (2001). This gives a starting point for understanding why demographic shocks would affect asset prices. The model is based on the intuition that a rapid rise in stock prices in the United States stemmed from the increase in savings in the stock market by the Baby Boomers in their prime earning years.

Assume a closed economy with overlapping generations of individuals who live for two periods and work when young (y) and retire when old (o). In any given period, N_y number of young individuals are working and produce one unit of good (provide one unit of labour) each. Normalise their production to one unit of numeraire good[48]. Also assume that there is a fixed supply of a durable capital good which does not depreciate. The saving rate (s) out of labour income is assumed as fixed for young workers. Then the demand for assets in any period will be, $N_y \times s$. If K is the fixed supply of durable assets, the relative price of these assets in terms of numeraire good (p) will satisfy the following equation.

$$K \times p = N_y \times s \qquad (6.1)$$

Equation (6.1) can be interpreted as the demand for capital and since the quantity of capital is assumed fixed the price of capital can directly be derived from this demand curve. Therefore, it can be asserted that price of capital is proportional to N_y. An increase in the size of the young working cohort bids up asset prices in order to meet greater demand of the fixed capital supply. Thus a Baby Boom which creates large cohort in the prime earning age in their way through life cycle purchase assets at

[48] Numeraire is an economic term that usually applies to a single good. This becomes the base good and all other prices can be expressed in terms of a numeraire good

higher prices. If this large cohort is followed by a smaller cohort, then when the large cohort of workers retires demand will decrease and the Baby Boom cohort will have to sell their financial assets at a lower price. This simple model implicitly assumes that the Baby Boomers generate a large cohort in the prime working age which will be followed by a smaller cohort in the next generation.

However, as stated by Poterba (2001), this model is simple and it neglects many important realities of asset pricing. The important over-simplifications include a fixed saving rate for young workers, a fixed supply of capital, a closed economy without international capital flows and other economic effects of population ageing. In this research, we develop an econometric model based on a strong conceptual framework which overcomes most of the drawbacks in the simple theoretical analysis produced above.

6.5 Conceptual Framework for Empirical Analysis

The efficient market hypothesis (EMH) introduced by Fama (1970) created an important debate among the academics and stock market investors. The EMH posits that stock prices should reflect all available information at any point in time which would then leads to postulate that investors will integrate all relevant information into prices when making the buying and selling decisions. The EMH takes three forms which are based on the term “all available information”. The weak form asserts that the current stock prices fully incorporate historical price data. Therefore, if a market is weakly efficient the current price reflects all past market data. The correct implication of weak form efficient market is that the past history of price information is of no value in assessing future changes in price (Jones, 2007, p. 325). The semi-strong form is a more comprehensive form of market efficiency and suggests that current price incorporates not only historical price data, but also all other publicly known and available information. This public information includes earnings, dividends, new product developments, accounting changes, etc. The third form of the EMH is the strong form, which states that stock prices fully reflect all existing information, both public and private. Strong form efficiency represents the highest level of market efficiency and if an individual believes in strong form efficiency, both the weak and semi-strong forms are encompassed. In summary, as stated by Malkeil (2003, p. 1) the EMH is associated with the idea of a "random walk", which is a term widely used in the finance literature to characterise a price series where all subsequent price changes represent random departures from previous prices.

However, the validity of the EMH is currently under debate. The controversy is summarised in three books, '*A random walk down wall street*' by Malkiel (1999), '*A non-random walk down wall street*' by Lo and MacKinlay (2002) and '*Beyond the random walk*' by Singal (2006). Further, Campbell, Lo and MacKinlay (1997) made an analogy with physical systems to provide insight into the controversy of the efficiency in stock markets as implied by the EMH. They compare the efficiency in stock markets with the function of a piston engine. A piston engine never rate as 100% efficient because they cannot convert 100% of its fuel to turn the crankshaft. On average, a piston engine has 60% efficiency rating, meaning that the remaining 40% of energy is lost to generate heat, light and noise, thus it is partially efficient. Applying the same concept to the stock markets, they must be regarded as partially efficient because stock markets may be affected by many other factors in addition to the fundamental factors. These fundamental factors are at the basic level a combination of the earning base (e.g. earnings per share) and valuation multiple (e.g. Price/Earnings ratio). If stock prices respond only to fundamentals then we can expect that average growth in stock prices would be same as the average dividend growth over time. However, this is not true for the stock price behaviour, which suggests that further explanations are required.

Technical factors and market sentiment are the two other main non-fundamental forces that drive stock prices. Technical factors constitute a mix of external conditions such as economic growth, demographics, interest rate and inflation which alter the demand and supply in the stock markets. Some of the technical factors have an indirect impact on fundamentals. For example, economic growth indirectly contributes to growth in earnings. Market sentiment relates to the psychology of stock market participants, which is often considered to be subjective, biased and obstinate. Behavioural finance explores the inefficiencies in financial markets that result from market sentiment, that is, when market participants do not act perfectly rationally as assumed in the EMH.

The notion that partial efficiency prevails in the stock market forms the basis of the conceptual model used in this chapter. Also, the emphasis is given to the technical forces, especially demographic variables since the focus of this study is to examine the effects of demographics on stock prices. Intuitively, an increase in the size of the middle-aged population, who are peak earners, leads to an increase in overall investment in the stock market. Similarly, an increase in the size of the old population who tend to dis-save from the stock market to finance their retirement consumption leads to decrease in the overall investments. The hypothesis is that a larger the proportion of middle-aged population among the investor population drives up the stock prices through greater demands leading to higher valuation multiples. The opposite result is posited when proportion of the old population is larger.

Internal developments that occur within companies such as earnings reports, dividend growth, mergers and acquisitions, development of innovative products affect the stock prices. These internal developments and the psychology of stock market participants (market sentiment or investor sentiment) are considered as ‘inside’ demand forces which are distinguished from ‘outside’ demand. The change in the number of potential stock market participants which has a close relation with the changing demographics is a source of ‘outside’ demand. In this research it is not essential to disentangle sources of ‘inside’ demand and thus innovations to ‘inside’ demand factors are modelled as direct innovations to the level of stock prices. However a direct innovation to outside demand, which is represented by the innovations to demographic change, is modelled separately since this creates the basis of the asset meltdown hypothesis.

In addition, the effects of economic forces have direct and indirect influence on equity demand and equity supply, which in turn has an impact on stock prices[49]. General equilibrium models indicate that the income structure of the macro economy should be related to asset returns (Huynh et al., 2006, p. 689). Therefore, the empirical model is embedded the analysis in a broader model including control macroeconomic variables. The inclusions of control variables are enriched with economic theories and the studies related to stock markets.

Economic theories such as *Keynesian hypothesis*, *real activity hypothesis*, Fama's *proxy hypothesis*, *risk premium hypothesis* suggest several reasons why there is an interaction between monetary policy and stock prices[50]. As Bjørnland and Leitemo (2009, p. 276) note 'since stock prices are determined in a forward-looking manner, monetary policy, and in particular surprise policy moves, is likely to influence stock prices through the interest rate (discount) channel and indirectly through its influence on the determinants of dividends and stock return premium by influencing the degree of uncertainty faced by agents'. Even though earlier studies (e.g. Millard and Wells, 2003; Patelis, 1997; Lee, 1992; Kaul, 1987) find that only a small variation in stock returns are accounted for by monetary policy shocks, Bjørnland and Leitemo (2009) find a strong ineteraction between stock market and interest rate setting using data for the United States.

In principle, economic growth may accelerate stock market activity by providing avenues for growing companies to raise capital at lower cost. In addition, firm's fundamental values respond to developments in the real economy and thus economic booms/recessions may have an impact on the stock market (see Fama, 1990; Ritter, 2005; Oksooe, 2010). Supply side models that have been developed to explain stock market fluctuations based on macroeconomic performance assume that GDP growth of the underlying economy has three steps when it transfers to the shareholders. In the first step, the GDP growth transforms into corporate profit growth. Then this

[49] The relationship between stock prices and macroeconomic variables is well established in the United States (Fama, 1970, 1990).
[50] See Sellin (2010).

aggregate level growth translates into earnings per share (EPS) growth in the second step. The growth in EPS translates into increase in stock prices in the third step.

6.6 Empirical Model

A structural VAR model is used to test empirically whether the evolution of the population ageing entails a downward pressure on stock prices. The conceptual framework presented in the previous section creates the basis for the structural VAR model, which includes variables representing stock prices, macroeconomic forces and the demographic factors. In line with the discussion in the previous section, two variables, namely interest rate and real GDP, are used to represent the effects of monetary policy and economic developments respectively. However, the selection of an appropriate demographic variable is important to correctly address the issue of any population ageing effect on stock prices. Therefore, a selection of an appropriate demographic variable is presented in section 6.6.1.

The structural VAR model allows the analysis of the movements in stock prices in relation to shocks to demographic and non-demographic variables introduced in the model. The model is estimated in a Bayesian framework (see section 4.7 of the chapter 4 for details). The contemporaneous links between the variables are identified by imposing specific restrictions on the variables in response to structural shocks. The identification assumptions are described in detail in section 6.6.2.

6.6.1 Construction of an Appropriate Demographic Variable

Although changes in population age structure are considered as an important factor for understanding current and expected future fluctuations in stock prices, the empirical evidence is mixed for the effects of population ageing on stock prices. These mixed results are partly due to the selection of different demographic variables to represent the ageing effect in the econometric specification. Some studies use cross-sectional age-wealth profiles to construct asset demand profiles and combine those with the age distribution of the country's population data to construct time series data (e.g. Bergantino, 1998; Yoo, 1994). However, Poterba (2001) criticises this method and he argues that it distorts the evolution of asset demand in the changing population structures over time. The asset ownership statistics show that there are different underlying patterns of asset accumulation over the life cycle resulting from changing combinations of cohort and time effects.

Use of average age as a demographic variable is less complex though it has limited usefulness in capturing the profile of lifetime asset accumulation. Bakshi and Chen (1994) and Erb et al. (1997) use average age whereas more recent studies use aggregate age groups as a proportion of the total population or some other population group. For example, Poterba (2001) uses demographic variables such as (40-64) years/total population and (40-64)/65+ years; Geanakoplos et al. (2004) define a MY ratio as the number of 40-49 year olds divided by the number of 20-29 year olds and use it to represent the demographic cycle; Brunetti and Torricelli (2010) include a vector of demographic variables (20-40 years/total, 40-60 years/total, 65+/total, 40-64years/20+, 65+/20+). However, Brooks (2006) criticises the proportion of population in certain age ranges and constructs demographic variables using a more agnostic approach, though such demographic coefficients suffer from the lack of direct structural interpretation.

In this chapter, we use a different approach at the selection of an appropriate demographic variable to represent the shocks to population ageing in the econometric model. The approach takes into account the important and related question of the effects of the retired large Baby Boomer cohort. The asset meltdown hypothesis is based on the assumption that a large number of retired Baby Boomers will induce a downward pressure on stock prices since this large number will have to sell their financial assets to a much smaller number of young investors[51]. Accordingly the demographic variable is defined as the age 65 years and above cohort (henceforth "old population") and is measured in person-units (1 unit per person)[52]. The intuition is that a shock to the old population (henceforth "retirement shock") will lead to an

[51] Old age dependency ratio is 24% in 2014 and it is projected to increase to 33% in 2030 (see chapter 2, Figure 2.12).
[52] Huynh et al. (2006) use the number of people in the 40-64 age cohort.

increase in the size of the old age population. A large number of the retired population would start to withdraw their savings from the stock market which will place supply side pressure on stock prices as summarises by Siegal (1998). If the asset meltdown hypothesis (AMH) holds for Australia we can expect a decline in real stock prices as a result of a positive retirement shock. In addition, a different demographic variable, namely the OY ratio which is defined as the number aged 65 years and above divided by the number of 35-64 year olds (prime earners), is used to measure the demographic cycle in section 6.9 (robustness analysis). The purpose of this demographic variable is to take into account the effects of both outflow and inflow from the stock market as discussed in the conceptual framework. A positive shock to OY ratio leads to increase the OY ratio and, if the AMH holds, there would be downward pressure on stock prices.

6.6.2 The Structural VAR Model and Identification

In order to present the structural VAR model, the variables included in the system are first introduced. The model is comprised of annual data for the de-trended log of old population (*dold*), the first difference of the log of real GDP per capita (Δy_t), the interest rate (i_t), and the log of the S&P/ASX200 stock price index (s_t). The stock price index is first deflated by the CPI to obtain a measure in real terms and then the first difference is taken so that it denotes the annual change (Δs_t). The old population series is integrated of order 2 (i.e. $I(2)$) and thus a HP filter is used to remove the trend[53].

Thus, four endogenous variables discussed above are modelled in the structural VAR and define

$$z_t = [dold_t, \Delta y_t, i_t, \Delta s_t]' \qquad (6.2)$$

where z_t is a (4×1) vector of variables ordered as $dold_t, \Delta y_t, i_t \; and \; \Delta s_t$.

A structural VAR for the vector of variables, z_t is given by

[53] The HP filter is optimal for processes integrated of order two.

$$A_0 z_t = A_1 z_{t-1} + \cdots + A_q z_{t-q} + \varepsilon_t \quad (6.3)$$

Here, q is a non-negative integer and ε_t is a (4×1) vector of structural shocks. A_j is a (4×4) matrix of constants, $j = 1, \cdots, q$ and A_0 is an invertible square matrix.

The moving average (MA) representation of the structural VAR model (ignoring any deterministic terms) is written as

$$z_t = A(L)\varepsilon_t \quad (6.4)$$

where $A(L) = \sum_{j=0}^{\infty} A_j L^j$ and $A(L)$ is the (4×4) convergent matrix polynomial in the lag operator L. The vector of uncorrelated structural shocks are ordered as- $\varepsilon_t = [\varepsilon_t^R, \varepsilon_t^Y, \varepsilon_t^{MP}, \varepsilon_t^{SP}]'$, where ε_t^R is the "retirement shock", ε_t^Y is the "output shock", ε_t^{MP} is the "monetary policy shock" and ε_t^{SP} is the "stock price shock". The shock to stock price (or "stock price shock") is designed to capture stock price specific shocks which are not accounted for by monetary policy, output or retirement shocks. These specific shocks could include fundamental and behavioural shocks.

The MA representation of the corresponding reduced form VAR is written as

$$z_t = B(L)u_t \quad (6.5)$$

where u_t is a (4×1) vector of reduced form errors assumed to be identically and independently distributed, i.e. $u_t \sim iid(0, \sum_u)$ with positive-definite covariance matrix of $\sum_u$.

$$B(L) = \sum_{j=0}^{\infty} B_j L^j \quad (6.6)$$

The B_j's and u_t's can be estimated, but it is still not possible to compute the dynamic response function of z_t to the structural shocks. However, the underlying structural innovations can be written as linear combinations of reduced form errors as

$$u_t = S\varepsilon_t \quad (6.7)$$

where S is the (4×4) contemporaneous matrix. Then the relationship between *B(L)* and *A(L)* can be written as

$$B(L)S = A(L) \quad (6.8)$$

Now the important step is to estimate the elements in *S*. To identify *S*, assume that ε_t have unit variances. Thus

$$\textstyle\sum_{\varepsilon} = I_n \qquad (6.9)$$

$$\textstyle\sum_{u} = SE(\varepsilon_t \varepsilon_t')S' \qquad (6.10)$$

$$\textstyle\sum_{u} = S\sum_{\varepsilon}S' \qquad (6.11)$$

Since, $\sum_{\varepsilon} = I_n$

$$\textstyle\sum_{u} = SS' \qquad (6.12)$$

S has n^2 parameters while the symmetric matrix, $\sum_u$ has at most $\frac{n(n+1)}{2}$ distinct elements. As long as $n>1$, there is an identification problem. Identification is achieved by imposing restrictions on *S*. Since there are $n^2=16$ elements in *S*, identification requires choosing *16* elements in *S*. The covariance matrix has $\frac{n(n+1)}{2} = 10$ distinct elements and therefore 10 parameters in *S* can be uniquely identified and hence 6 identification restrictions should be imposed for exact identification.

Identification Restrictions on Contemporaneous Matrix (S)[54]

The model imposes a combination of short-run and long-run identification restrictions. A contemporaneous reaction from the old population to the other three variables is most likely, however, shocks to those variables do not contemporaneously affect the old population. This assumption allows placing the old population at the top of the matrix *S*. Monetary policy and output shocks are identified assuming instantaneous effects from real GDP to the interest rate and vice versa. It is worth noting that Christiano, Eichenbaum and Evans (2005) identify the monetary policy shock by assuming that economic growth does not instantaneously react to the interest rate; on the other hand, there is an instantaneous effect from economic growth to the interest rate. However, this assumption is based on quarterly

[54] Robustness analysis is carried out in section 6.9 while changing identification restrictions

data. Since our study is based on annual data it is reasonable to assume contemporaneous effects from monetary policy shocks to economic growth and from output shocks to interest rates. With regard to the contemporaneous reaction between stock price shocks and monetary policy shocks, following the standard practice in the VAR literature it is assumed that monetary policy responds with a lag to a stock price shock, hence, $S_{34} = 0$. Accordingly, zero restrictions are imposed on the second, third and fourth columns of the *S* matrix, as follows.

$$\begin{bmatrix} dold_t \\ \Delta y_t \\ i_t \\ \Delta s_t \end{bmatrix} = B(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 \\ S_{21} & S_{22} & S_{23} & 0 \\ S_{31} & S_{32} & S_{33} & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^R \\ \varepsilon_t^Y \\ \varepsilon_t^{MP} \\ \varepsilon_t^{SP} \end{bmatrix} \qquad (6.13)$$

The construction of the *S* matrix in (6.13) provides us with five contemporaneous restrictions directly. However it is still one restriction short for exact identification. The final restriction is that a monetary policy shock can have no long-run effects on the level of real output[55]. In line with this, it is important to note that the level of the real output variable is integrated of order 1. In the long-run, if real GDP is unaffected by a monetary policy shock, it must be the case that the cumulative effect of an ε_t^{MP} on the Δy_t sequence must be equal to zero.

Hence, $\sum_{j=0}^{\infty} A_{23,j}\, \varepsilon_{t-j}^{MP} = 0$ (6.14)

Since this must be hold for any realization of the $\{\varepsilon_t^{MP}\}$ sequence, all the relevant lag coefficients in (6.4) are set to zero (see Blanchard and Quah, 1989). That is

$$\sum_{j=0}^{\infty} A_{23,j} = 0 \qquad (6.15)$$

The long-run expression of *A(L)* is now given in (6.16).

$$B(1)S = A(1) \qquad (6.16)$$

In (6.16), $B(1) = \sum_{j=0}^{\infty} B_j$ and $A(1) = \sum_{j=0}^{\infty} A_j$ indicate the (4×4) long-run matrices of *B(L)* and *A(L)* respectively.

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[55] See Bjørnland and Jecobsen (2010)

$$B(1)=\begin{bmatrix}\sum_{j=0}^{\infty}B_{11,j} & \sum_{j=0}^{\infty}B_{12,j} & \sum_{j=0}^{\infty}B_{13,j} & \sum_{j=0}^{\infty}B_{14,j}\\ \vdots & \vdots & \vdots & \vdots\\ \sum_{j=0}^{\infty}B_{41,j} & \sum_{j=0}^{\infty}B_{42,j} & \sum_{j=0}^{\infty}B_{43,j} & \sum_{j=0}^{\infty}B_{44,j}\end{bmatrix} \tag{6.17}$$

$$A(1)=\begin{bmatrix}\sum_{j=0}^{\infty}A_{11,j} & \sum_{j=0}^{\infty}A_{12,j} & \sum_{j=0}^{\infty}A_{13,j} & \sum_{j=0}^{\infty}A_{14,j}\\ \vdots & \vdots & \vdots & \vdots\\ \sum_{j=0}^{\infty}A_{41,j} & \sum_{j=0}^{\infty}A_{42,j} & \sum_{j=0}^{\infty}A_{43,j} & \sum_{j=0}^{\infty}A_{44,j}\end{bmatrix} \tag{6.18}$$

From (6.16)

$$S = B(1)^{-1}A(1) \tag{6.19}$$

Thus, substituting in (6.12)

$$\textstyle\sum_u = [B(1)A(1)^{-1}][B(1)A(1)^{-1}]' \tag{6.20}$$

$$\textstyle\sum_u = B(1)A(1)^{-1}[A(1)^{-1}]'B(1)' \tag{6.21}$$

Pre-multiplying and post-multiplying equation (6.21) by $B(1)^{-1}$ and $[A(1)^{-1}]'$

$$B(1)^{-1}\textstyle\sum_u[A(1)']^{-1} = B(1)^{-1}[B(1)^{-1}]' \tag{6.22}$$

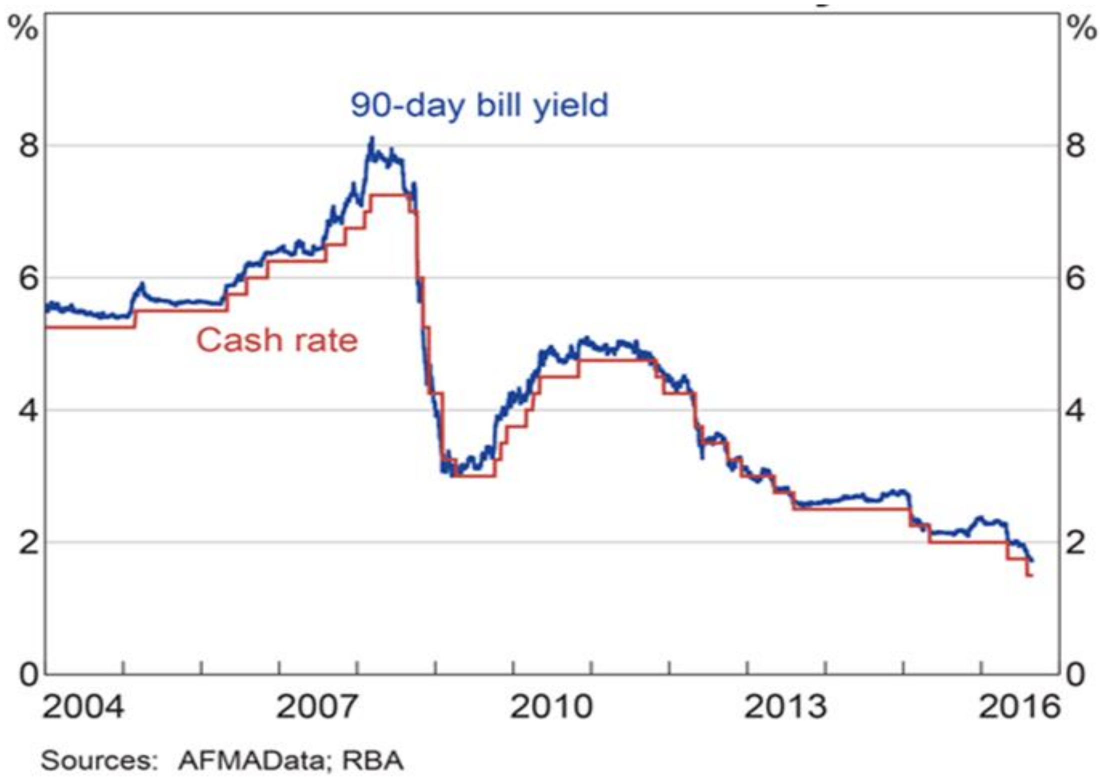
The long-run restriction of $A_{23}(1) = 0$ implies that

$$B_{21}(1)S_{13} + B_{22}(1)S_{23} + B_{23}(1)S_{33} + B_{24}(1)S_{43} = 0 \tag{6.22}$$

In this setting, the system is now just identifiable. Note that $B(1)$ is calculated from the estimation of the reduced form of (6.5). The non-zero coefficients above the stock price equation are identified by short-run restrictions. The imposed long-run restriction of $A_{23}(1) = 0$ uniquely identifies the remaining parameters.

6.7 Data Sources, Description and Variable Construction

The Australian S&P/ASX200 index is used to represent stock prices. The S&P/ASX200 is recognised as the investable benchmark for the Australian equity market and it is comprised of the S&P/ASX100 plus an additional 100 stocks. The leading 200 companies by market capitalization and covers approximately 80% of Australian equity market capitalization. The annual series for S&P/ASX200 is obtained from the DataStream (AUYSP001F). The 90-day bank accepted bill rate is used to represent the interest rate. The ASX's 90 Day Bank Bill Futures and Options product is Australia's benchmark indicator for short-rem interest rates (AFMA, 2013). The benchmark 90-day bill rate captures the monetary policy shocks virtually instantaneously as shown in Figure 6.3.



Adapted from: The Australian Economy and Financial Markets Chart Pack, RBA (September, 2016)

Figure 6.3: Australian cash rate and 90-day bill rate

The 90-day bank accepted bill rates in *Table F1.1-Interest Rates and Yields (Money Market)* published by the RBA is originally at monthly frequency. These are transformed to annual observations by averageing over 12 months. However, a consistent series is available only from 1969.

The nominal GDP data are based on the ABS *Key National Account* aggregates[56]. The nominal GDP series is converted to a real series using the consumer price index (CPI) and divided by total population to convert them to real GDP per capita. The CPI data is obtained from the *Table G1*of the RBA. The Δy_t series is constructed first taking the log and then taking the first difference.

The data for computing the old population and population aged 35-64 years is based on the ABS catalogue numbers 3105.0.65.001 and 3101.0.

6.8 Model Estimation and Results

The model described in section 6.6 is estimated using annual data from 1969 to 2014. The reduced form coefficients are first estimated using a Bayesian framework[57]. Since the length of the time series is moderate (45 data points) and the model includes 4 variables, a Bayesian framework is more appropriate to handle the problem of over-parameterization. The symmetric *Minnesota* prior distribution for the coefficient vector is specified as a function of a parameter vector. The parameter vector controls for the unknown aspects of the prior such as mean, the own lag tightness and the relative tightness on the other lags (see section 4.7 of chapter 4 for details). Following Stock and Watson (2008) and many other authors, the variables included in the VAR model are stationary as shown in Figure 6.4 (see Koop, 2013).

The identification restrictions on the contemporaneous matrix of the structural VAR model are a combination of the long-run and short-run restrictions described in detail in section 6.6.2. In this setting confirmation is required that the log level of real GDP (y_t) is $I(1)$. The results from the unit root tests are summarised in Table 6.1. The test results from each test confirm that the log level of real GDP is $I(1)$ as required for the structural identification employed. This is despite the fact that various lag length selection criteria give different lag lengths.

[56] The detailed description of the source is provided in Chapter 5.
[57] RATS software is used.

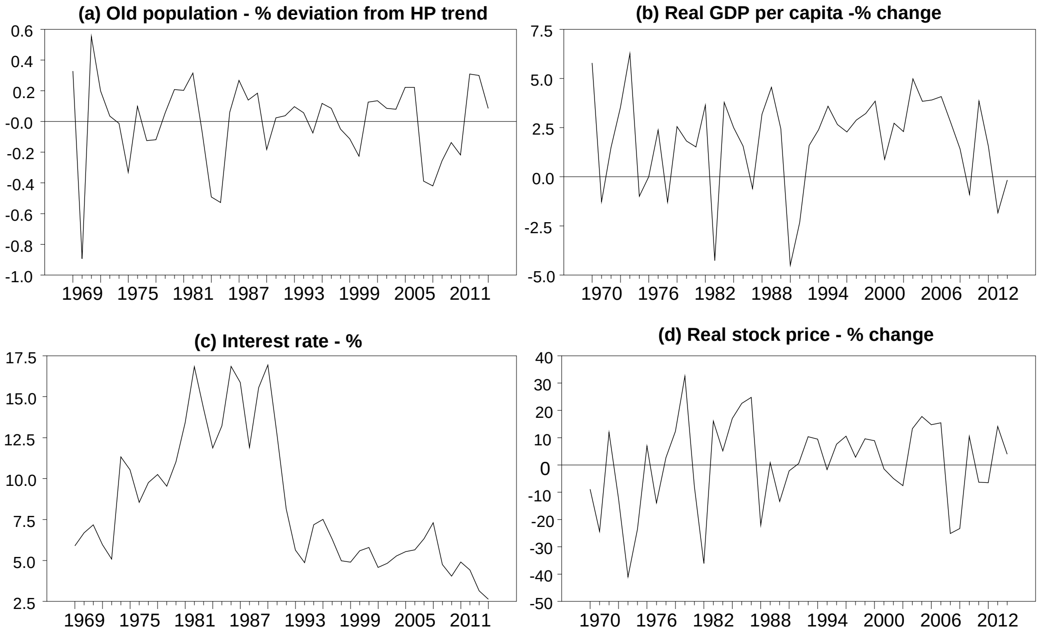


Figure 6.4: Variables used in the VAR model described

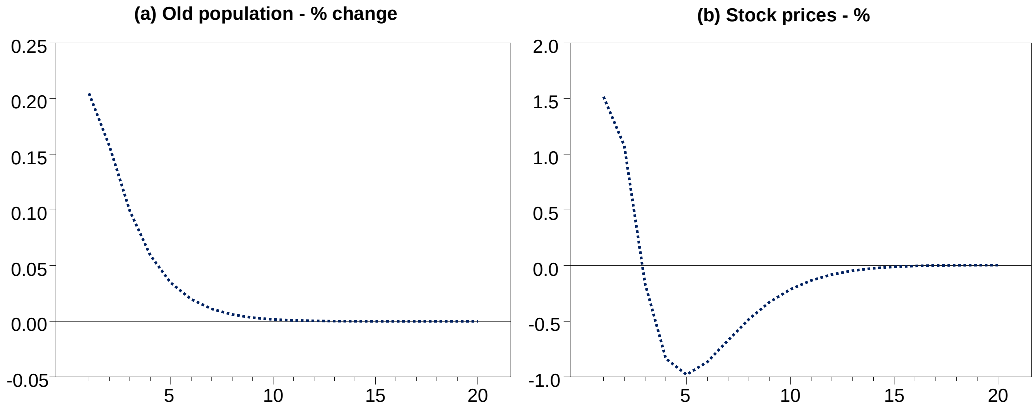
Table 6.1: Unit root test results for the log of real GDP (y_t)

Test	Test Statistic		Conclusion
	In levels	*In first differences*	
ADF*	-1.6551 (1-AIC, maxlag=4)	-6.0962 (0, AIC, maxlag=4)	y_t is $I(1)$
DF-GLS*	-1.6720 (2-MAIC, maxlag=4) -1.3967 (1-AIC, maxlag=4)	-5.5629 (0, MAIC, maxlag=4) -5.1278 (0, AIC, maxlag=4)	y_t is $I(1)$
PP test*	-1.7676	-6.0954	y_t is $I(1)$
Ng-PP (MZα)**	-5.0206 (0-AIC, maxlag=4)	-20.1152 (0-AIC, maxlag=4)	y_t is $I(1)$
KPSS***	0.1746	0.0329	y_t is $I(1)$

*Test critical values are from MacKinnon (1996) one-sided p-values
**Test critical values are from Ng and Perron (2001, Table 1)
*** Test critical values are from Kwiatkowski, Phillips, Schmidt and Shin (1992, Table 1)
Notes: Lag lengths are in parenthesis with lag selection criteria. Lag selection is based on Akaike Information Criterion (AIC), modified Akaike Information Criterion (MAIC). The maximum lag length was set at 4.

6.8.1 Results

The objective of this chapter is to examine the effects of population ageing on stock prices. Thus the impulse response analysis is mainly focused on the responses of real stock prices to retirement shocks. Figures 6.5 (a) and (b) plot the response in the old population and in real stock prices following a positive retirement shock.



Notes: Estimates are based on the VAR model described in section 6.6 of the text.

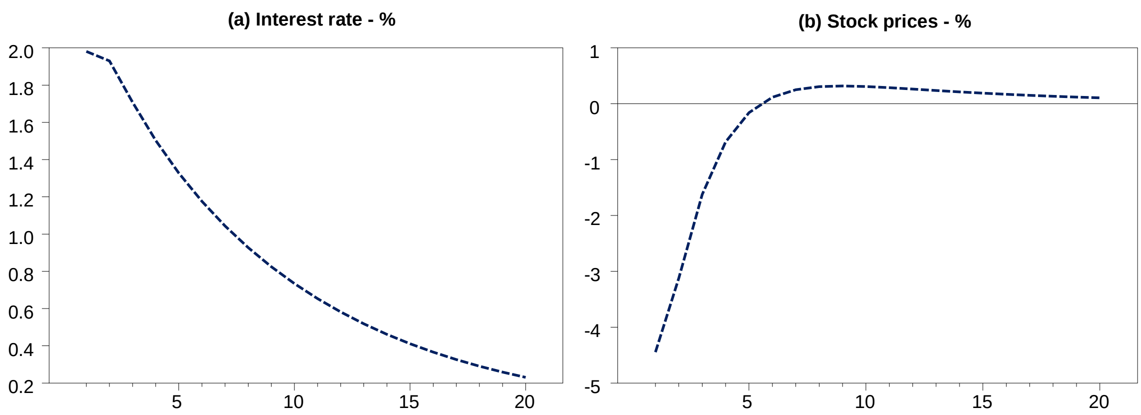
Figure 6.5: IRF of old population and real stock price to a positive retirement shock[58]

Plot (b) of Figure 6.5 shows that a positive retirement shock temporarily increases real stock prices by about 1.6% in the first year and then the effect gradually decreases and crosses zero in fourth year after the shock. From four years after the shock, the real stock prices have a negative impact, creating an inverse hump-shaped from the medium to the long run. The peak decline of around 0.6% occurs in the fifth year after the retirement shock though the effect thereafter dies out gradually. A potential explanation for this is that stock market investors entering their prime saving years continue to invest for some years even after reaching retirement age. Also individuals receive lump sum payments at retirement which they may invest in the stock market. The impulse response function does not suggest a downward

[58] The confidence intervals for impulse response functions are not produced here. The Bayesian estimation method employed for the VAR coefficients use prior information in the form of probability distribution functions. This information shrinks the unrestricted model towards a parsimonious naïve benchmark, thereby reducing parameter uncertainty in the VAR coefficients.

pressure on stock prices caused by an increase in the size of the old age cohort as a result of a retirement shock in the short run. An increase in the old population does not substantially alter stock prices even in the medium or long run. This is consistent with the survey data which shows that 37% of individuals between 65-74 years and 46% of individuals 75 years and above still have investments in the share market (see Figure 6.2).

As shown in the Figure 6.6 (b), a monetary policy shock has a strong impact on stock prices, with a contractionary monetary policy shock of around 2% increase in interest rates leading to a fall of about 4.5% in stock prices in the first year. The effect gradually declines and dissipates after 5 years. This is consistent with the results of Bjørnland and Leitemo (2009) and the results found in Rigobon and Sack (2004). A possible explanation for this, similar to the explanation in Bjørnland and Leitemo (2009, p. 279), is that the monetry policy shock causes to increase the interest rate immediately and then gradually falls (Figure 6.6 (a)), the discounted value of expected future dividends increases while output and profits build up, leading to a normalisation of real stock prices.



Notes: Estimates are based on the VAR model described in section 6.6 of the text.

Figure 6.6: IRF of interest rate and real stock price to a contractionary monetary policy shock

Stock price specific shocks, which include primarily a combination of fundamental shocks and behavioural shocks, cause an immediate increase in real stock prices by

16 per cent within the first year though the effect gradually decreases (see Figure 6.7). Compared to the response of stock price specific shocks, the response of stock prices to the impact of the Baby Boom bulge moving into retirement appears to be insignificant.

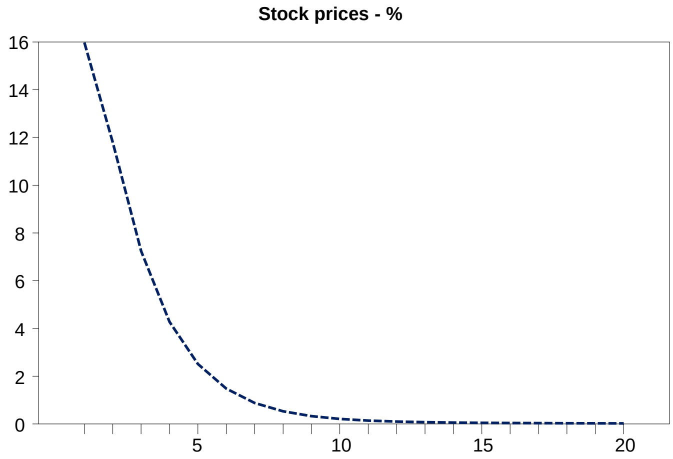


Figure 6.7: IRF of stock prices to a positive stock price shock

Historical episodes of real stock price shocks involve a vector of sequence of shocks often with different signs at different points of time (Kilian and Park, 2009, p. 1272), in contrast to the one-off shocks analysed above. Thus, to understand the historical evolution of the real stock prices, it is more useful to measure the cumulative effect of each individual shock on the real stock price at each point in time as graphed in Figure 6.8. The figure suggests that real stock prices historically have been mainly driven by the stock price specific shocks and monetary policy shocks.

There is no evidence to suggest that there is an effect from the old population for the fluctuations of real stock price historically. There has been no systematic downward movement in the real stock price after 2011 associated with retirement shocks to support the view that the retirement of the Baby Boom bulge would cause a downward pressure on stock prices.

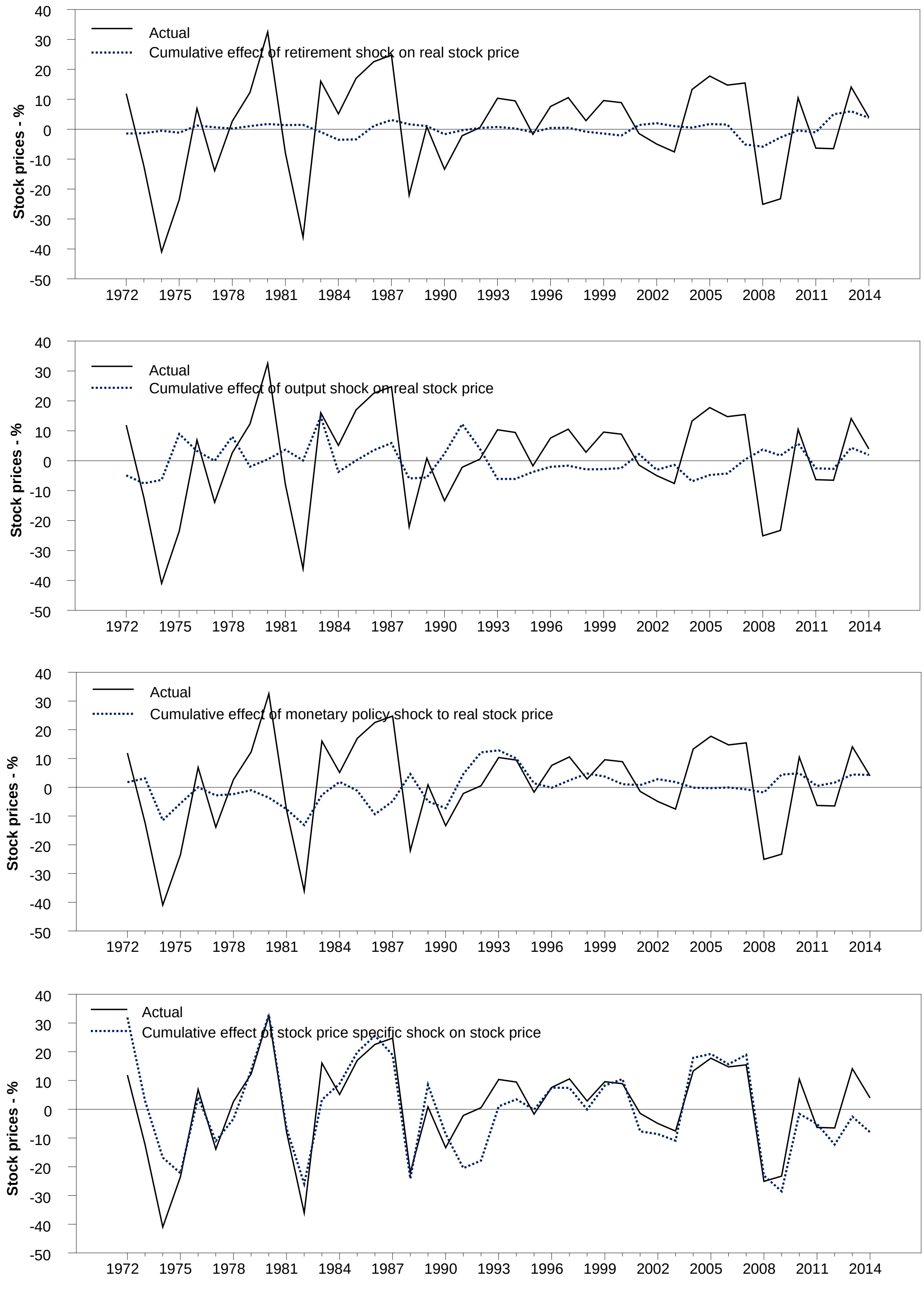


Figure 6.8: Historical decomposition of real stock price

The contributions of each structural shock to the variation of real stock prices can be quantitatively gauged using forecast error variance decomposition (FEVD). Both in the short and long-run less than 1% of the variation in real stock price is driven by retirement shocks. The explanatory power of monetary policy shocks and output shocks together stand at around 17% and 15% in the short-run and in the long-run respectively. The FEVD indicates that the stock price specific shock is the most important source of stock price variation.

6.9 Robustness Analysis

Two questions that may immediately arise from the analysis presented in the previous sections can be identified. The first is related to the demographic variable used to assess the impact of population ageing. The second is whether the results are sensitive to different identification restrictions. This section addresses these two questions. However, it is worth noting that since the objective of this research is to examine the effects of changes in the old population (65+ years) on stock prices, the robustness analysis is limited to investigating the impulse response functions of stock prices to the demographic variable.

6.9.1 Response of Real Stock Prices using the OY Ratio

In the analysis presented in section 6.8, we used the size of the old population as the demographic variable to determine the impact of population ageing on stock prices. However, in the literature some studies have focused the proportion of the old population with respect to various other age groups as described in section 6.6.2 and the literature review chapter (chapter 3). To compare the present results with the results in the literature, the OY (Old Young) ratio, which is defined as the population aged 65 and above divided by the population between 35-64 years of age, is used in the econometric specification of the baseline model[59]. If the economy is ageing, the proportion of prime savers in the stock market will be relatively smaller compared to

[59] Figure 6.2 indicates that the age at which investing normalises is around 35 years.

the prime dis-savers and thus would impose a downward pressure on stock prices. In other words, in contrast to the absolute importance, the relative importance of dis-savers in the stock market is taken into account using the OY ratio as the demographic variable.

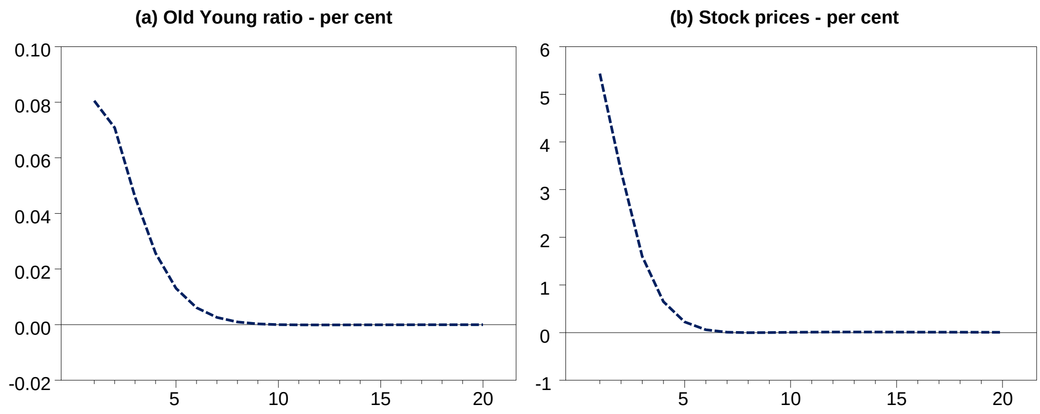


Figure 6.9: IRF of OY ratio and real stock price to a positive retirement shock

Plot (a) of the Figure 6.9 shows that a positive shock to the OY ratio (i.e. a positive retirement shock) temporarily increases the real stock prices by about 5.5% in the first year and then the effect gradually decreases and tapers off to zero after five years. The results emphasize that the increasing number of the population aged 65 and above, particularly due to the retired Baby Boomers, does not exert downward pressure on stock prices immediately, which is a similar outcome found when we considered the absolute effect of old population on stock prices in the econometric specification.

6.9.2 Response of Real Stock Prices for Shock to Demographic Variable Using Different Identification

The structural VAR model identification described in section 6.6.2 followed the standard practice in the VAR literature, in which it was assumed that monetary policy responds with a lag to stock price shock. Robustness with regard to identification is tested by adopting an alternative approach specified by Bjørnland and Leitemo (2009) with regard to the contemporaneous reaction between stock price shocks and monetary policy shocks. Here it is assumed that monetary policy shocks do not have long-run effects on the level of the real stock price. This is in addition to the long-run identification with regard to the contemporanous reaction between output shocks and monetary policy shocks. Thus the new identification comprises of two long-run restrictions. The impulse response functions of real stock prices remain robust to shock to both demographic variables (the old population and the OY ratio) with this alternative identification.

6.10 Conclusion

The theoretical models widely used to study the relationship between demography and financial asset prices predict that the retirement of a large proportion of individuals would be associated with a liquidation of their financial assets to fund consumption, leading to lower stock prices. However, the empirical results of this research do not show a downward pressure on stock prices in Australia as a result of an increase in the proportion of retired people. An increase in the size of the old population or the OY ratio does not lead to a slowdown in the growth in stock prices or a persistent slow liquidation in the stock market. This result is contrary to the AMH.

Despite the fact that a large number of individuals became shareholders during the 1990s, analysis of cumulative effect of shock to prime earners (i.e. the population aged 35-64 years) does not support the conclusion that the increase in stock prices in the 1990s was driven by the increase number of prime earners (see Figure D.1 in Appendix D). The positive growth rates in stock prices in the 1990s were mainly driven by monetary policy shocks and stock price specific shocks. The rise in stock prices is consistent with the fall in interest rates during the 1990s. This finding shows that simple correlation analysis such as represented in Figure 6.1 gives a false prediction of an asset price meltdown in Australia.

The empirical findings above support Poterba's argument as stated by Abel (2001, p. 5), '… since consumers continue to hold assets throughout old age, the aggregate demand for capital does not fall when the Baby Boomers age, and hence, contrary to the asset meltdown hypothesis, the price of capital will not plunge when the Baby

Boomers are retired'. Moreover, the conclusion from the empirical analysis is consistent with the conclusion drawn in Brooks (2006) for Australia using his cross-section study of developed countries. Survey evidence also indicates that households continue to accumulate financial wealth during their retirement and run down a little from their savings in the retirement. The recent ABC news item (12 January 2016) mentions that '… many people still die with significant superannuation funds'[60]. This also indicates that the retirees run down their accumulated financial wealth at a slower rate than predicted by the life-cycle theory.

Taking all these factors into consideration, it may not be so surprising that this research does not support the prediction of a downward pressure on stock prices resulting from the retirement of a large number of Baby Boomers. While the literature has established that the link between the size of the prime saver cohort and high stock prices is relatively important, the findings of this research do not indicate a strong historical link between demographics and stock prices for Australia.

[60] Based on CSIRO research.

CHAPTER 7 THE EFFECTS OF POPULATION AGEING DYNAMICS ON HOUSE PRICES AND STOCK PRICES IN CONJUNCTION WITH THE JOINT DYNAMICS OF THE TWO CLASSES OF ASSETS

7.1 Introduction

The literature since 1989 has explored the relationship between changing demographic structures, more specifically the ageing population due to the Baby Boom and asset prices, both in housing and financial markets. However, the results are mixed and there is a lack of clear consensus on whether population ageing significantly affects house prices and financial asset prices. A key issue that researchers have faced, due to the difficulty in controlling for various economic factors, is the difficulty in formulating accurate and reliable models that isolate the influence of population ageing on asset prices. Chapters 5 and 6 contribute to this debate on the effects of population ageing on house price and on stock price variables in Australia separately in terms of the dynamic responses to population ageing shocks in a structural VAR framework. Following the literature, the models developed in these two chapters did not consider the interaction between house prices and stock prices in a unified framework. Instead two separate models were developed. However, if the financial assets markets and housing markets are in equilibrium, the possibility of interaction should be considered. Further, the dynamic relationship between house and stock prices has been the subject of considerable debate in the literature (see Quan and Titman, 1999; Piazzesi, Schneider and Tuzel, 2007). Thus, each of the models developed in the preceding chapters can be extended to incorporate the interaction between house prices and stock prices. However the process is not straightforward.

Individuals accumulate wealth in the form of housing, stocks (equities) and other assets. In general, housing and stocks are considered as investment alternatives, but the former can also be viewed as consumption good. It can be asserted that price inflation or deflation in one form of asset will influence the overall investments decisions of individuals. If the individuals respond to price changes in one class of assets the resulting reallocation of portfolios will influence the price of the other class of asset. The effects of stock prices on house prices are controversial due to the presence of substitution effects and wealth effects which work in opposite directions (see Algieri, 2013). The substitution effect suggests that house prices and equity prices should move in opposite directions. As Shiller (2014) explains, both housing and stocks are speculative assets and they can be considered as investment alternatives and thus the higher returns in one asset markets will shift investment away from the other market and cause prices in the latter market to decline. In contrast, the wealth effect suggests that an increase in stock (or house) prices leads to increase the household wealth and thus enables an increase the investments in both markets. For example, increase in stock prices, reflecting greater share of stocks in the investment portfolio and wealth will have an impact of households' decision to rebalance or reallocate investment portfolios by investing in or consuming more of housing. Thus stock and house prices move in the same direction.

The dynamic relationships between house prices and stock prices is extensively examined in the literature (see for example, Warzala and Vandell, 1993; Quan and Titman, 1999; Sutton, 2002; Stock and Watson, 2003; Ayuso, Blanco and Restoy, 2006; Sim and Chang, 2006; Ibrahim, Padli and Baharom, 2009; Algieri, 2013; Lean and Smyth, 2014; Shiller, 2014). However, the objectives of these studies were to examine the comovement of house and stock prices in terms of correlation analysis and/or computing long-run and short-run coefficients. None of these studies concerned the effects of demographics, in particular whether the population age structure will have an impact on the joint relationship between house and stock prices. On the other hand, Sutton (2002) finds a positive response of house prices to stock price changes using a four variable VAR model for six advanced economies including Australia. Against this background it is interesting to further examine whether the effect of population ageing on house prices and stock prices, already examined for Australia, will attenuate or intensify when the joint dynamics of two assets are included in a unified structural VAR model. This is the first research in the literature to examine the effect of population ageing on asset prices which simultaneously study the population ageing, house price and stock price dynamics.

The remainder of the chapter is organised as follows. Section 7.2 describes the two extended models based on the benchmark models developed in chapter 5 and chapter 6. These extended models examine the dynamic relationships among population ageing, real house and stock prices in a unified framework. A detailed discussion of the main results forms section 7.2 and further analysis is provided in section 7.3. Following a brief discussion between the differences in housing and financial assets in section 7.4, the main concluding remarks provided in section 7.5.

7.2 Dynamics of House and Stock Prices in Response to Population Ageing Shocks

Two econometric model specifications in a structural VAR framework are used to examine the dynamic relationships among the population ageing, house prices and stock prices.

1. The benchmark specification developed in section 5.5 of the chapter 5 is extended to include the real stock prices. This model is called the extended house price model.
2. The benchmark model developed in section 6.6 of the chapter 6 is extended to incorporate real house prices. This model is called the extended stock market model.

The data sources, description and variable construction for the relevant time series in each model are described in sections 5.6 and 6.7 of chapter 5 and chapter 6 respectively.

7.2.1 Extended House Price Model

In this extended model, real stock price is added to the model (5.5) in chapter 5. The structural representation of this VAR model is

$$B_0 z_t = \alpha + \sum_{i=1}^{p} B_i z_{t-i} + \varepsilon_t \qquad (7.1)$$

The vector of variables, y_t now consists of the first difference of the log of real house price (Δhp), the log of real GDP per capita (Δy), the unemployment rate (u), the de-trended old age ratio ($doar$), interest rate (i) and the log of real stock price (Δs). The order of the vector of variables (y_t) and the structural shocks (ε_t) is as follows.

$$z_t = [doar, \Delta y, u, \Delta hp, i, \Delta s]'$$

$$\varepsilon_t = [\varepsilon_t^R,\ \varepsilon_t^Y,\ \varepsilon_t^U, \varepsilon_t^{MP}\ \varepsilon_t^{HP}, \varepsilon_t^{SP}]'$$

Recalling the structural shocks, the three shocks that are of primary interest here are the shocks to house prices (ε_t^{HP}) and shocks to old age ratio (or retirement shock) (ε_t^R) and shocks to stock prices (ε_t^{SP})[61]. Following standard practice in the VAR literature, the other three shocks are only loosely identified as output shocks (ε_t^Y), unemployement shocks (ε_t^U) and monetary policy shocks (ε_t^{MP}). Similar to the section 5.5.1 the stuctural identification is based on a combination of short-run and long-run restrictions. Equation (7.2) summarises the zero restrictions based on the contemporaneous matrix.

Ordering the stock price at the bottom of the vector of variables reflects that the stock price is the most response variable in the system. Accordingly, stock prices are allowed to react simultaneously to the shocks to the other five variables. In this setting it is assumed that stock prices are more flexible than house prices. Thus, there is a lag for stock price innovations to affect the house price, but the house price

[61] Bjørnland and Jacobsen (2010) identify the structural shock ε_t^{PH} as "shocks to house prices". We follow the same in this chapter.

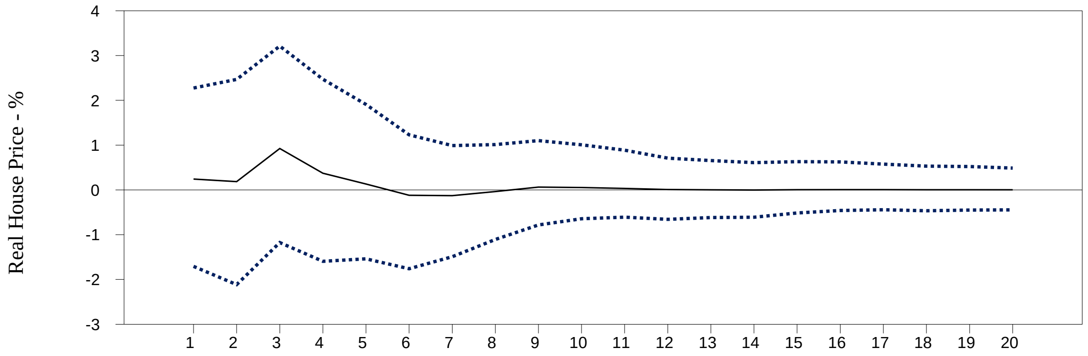
reacts contemporaneously to the shocks to old age ratio, output, unemployment and interest rates.

$$\begin{bmatrix} doar \\ \Delta y_t \\ u_t \\ i_t \\ \Delta hp_t \\ \Delta s_t \end{bmatrix} = A(L) \begin{bmatrix} s_{11} & 0 & 0 & 0 & 0 & 0 \\ s_{21} & s_{22} & 0 & s_{24} & 0 & 0 \\ s_{31} & s_{32} & s_{33} & 0 & 0 & 0 \\ s_{41} & s_{42} & s_{43} & s_{44} & 0 & 0 \\ s_{51} & s_{42} & s_{53} & s_{54} & s_{55} & 0 \\ s_{61} & s_{62} & s_{63} & s_{64} & s_{65} & s_{66} \end{bmatrix} \begin{bmatrix} \varepsilon_t^R \\ \varepsilon_t^Y \\ \varepsilon_t^U \\ \varepsilon_t^{MP} \\ \varepsilon_t^{HP} \\ \varepsilon_t^{SP} \end{bmatrix} \tag{7.2}$$

OLS estimation is used for the reduced form VAR derived from the structural VAR model (7.1) for the period of 1958 to 2014. In chapter 5, the sample period was from 1950 to 2014. Since a continuous time series for S&P/ASX200 was available only from 1958, the sample period is changed to 1958 to 2014. Thus the impulse response functions for the real house prices based on the model used in chapter 5 (i.e. the model without stock prices) is reproduced here for the reduced sample period to directly compare the results with the extended model discussed above. Figure 7.1 plots (a) and (b) shows the impulse response functions of real house prices to a positive shock to old age ratio based on model (5.5) and model (7.1) respectively.

A positive retirement shock has similar effects on real house prices in both cases though the magnitudes are slightly different. In particular, the response in third year based on the extended model shows about 0.2% increase than that of based on the model without stock prices (model 5.5, see Figure 7.1 (a)). Thus, the impulse response analysis shows that the effect of real house prices to a positive retirement shock has slightly intensified when both asset prices are considered simultaneously. However, as discussed in chapter 5 the wider error bands in both cases indicates that responses are statistically insignificant.

(a) Responses to a positive retirement shock (model 5.5)



(b) Response to a positive retirement shock (extended house price model)

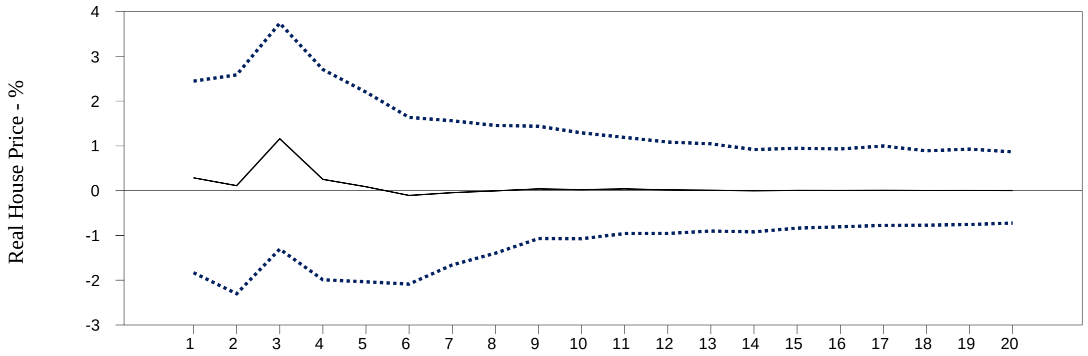


Figure 7.1: Responses of the real house prices to a positive shock to old age ratio

7.2.2 Extended Stock Price Model

In this extended model the real house price is included in the structural VAR model specification of (6.6) in addition to the four endogenous variables (real stock price, real GDP per capita, old population and interest rate). Following a similar argument to section 7.2.1, the real house price is placed before the real stock price. Thus, the model is comprised of annual data for the log of the de-trended old population (*dold*), the first difference of the log of real GDP per capita (Δy_t), the interest rate (i_t), the first difference of log of the real house price (Δph_t) and the first difference of the log of the S&P/ASX200 stock price index (Δs_t).

In this setting five structural shocks are identified but the three shocks that are of primary interest are the shocks to house prices (ε_t^{HP}), shocks to stock prices (ε_t^{SP}) and retirement shocks (ε_t^{R}). The identification restrictions are based on a combination of short-run and long-run restrictions, which are similar to those in section 6.6.2. The S matrix described in (7.3) provides nine contemporaneous restrictions directly though is still one restriction short of identification[62]. Thus, the final restriction is that a monetary policy shock can have no long-run effects on the level of real output[63]. It is important to note that the interest rate is placed above the asset prices because monetary policy reacts to asset price movements, if they are prolonged, whereas asset prices reacts immediately to changes in monetary policy (see Assemacher-Wesche and Gerlach, 2008).

$$\begin{bmatrix} dold_t \\ \Delta y_t \\ i_t \\ \Delta hp_t \\ \Delta s_t \end{bmatrix} = B(L) \begin{bmatrix} S_{11} & 0 & 0 & 0 & 0 \\ S_{21} & S_{22} & S_{23} & 0 & 0 \\ S_{31} & S_{32} & S_{33} & 0 & 0 \\ S_{41} & S_{42} & S_{43} & S_{44} & 0 \\ S_{51} & S_{52} & S_{53} & S_{54} & S_{55} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{R} \\ \varepsilon_t^{Y} \\ \varepsilon_t^{MP} \\ \varepsilon_t^{HP} \\ \varepsilon_t^{SP} \end{bmatrix} \qquad (7.3)$$

The extended stock price model is estimated using annual data from 1969 to 2014[64]. The reduced form coefficients are first estimated using a Bayesian framework[65]. The symmetric *Minnesota* prior distribution for the coefficient vector is specified as a function of a parameter vector. The responses of real stock prices for a positive shock to old population are shown in Figure 7.2.

A positive retirement shock temporarily increases real stock prices by about 1.4% in the first year and then the effect gradually decreases and crosses zero in fourth year after the shock. From four years after the shock, the real stock prices have a negative impact, creating an inverse hump-shape from the medium to the long run. The peak decline of around 0.6% occurs in the fifth year after the retirement shock though the effect thereafter dies out gradually. The behaviour of the impulse response function is similar to the responses of a positive shock to old age population observed in

[62] Since S has 25 parameters, 10 restrictions are required for exact identification.
[63] See Bjørnland and Jecobsen (2010).
[64] A continuous series of 90 day bill rate representing the interest rate is available only from 1969. See section 6.7 for details.
[65] Since the number of observations (45) are low, the Bayesian framework is more appropriate to overcome the problem of over-parameterization.

chapter 6 (plot 6.2 (b)) where the interaction between house prices and stock prices were not considered in a unified framework. However, in the benchmark model real stock prices increased by 1.6% in the first year responding to a positive shock to old population compared to the 1.4% increase in this extended model. That is, the net effect has been attenuated by 0.2%, despite the increase in real stock prices in response to a consequent positive shock to house prices (see Figure 7.3 plot (b)). A possible explanation for this would be that the interactions between house prices and stock prices have lowered the demand for stocks and hence the reduced pressure on real stock prices in response to the increase in the old population. In this scenario it could be considered that retired people invest primarily in the housing market as a source of profitable investment and so there is reduced interest in investing in the stock market, reducing demand and lowering prices.

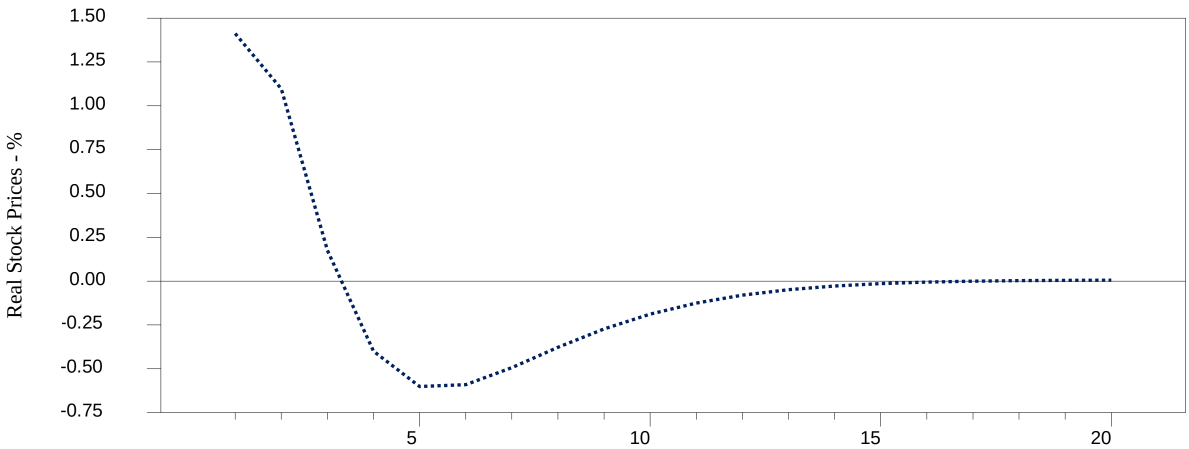


Figure 7.2: Responses of real stock prices to a positive retirement shock

Figure 7.3 shows that the two classes of asset prices have positive co-movement meaning that positive shock to house price drives stock prices up and vice versa. In particular, a positive shock to house prices, which leads to increase real house prices by about 6.5% drives stock prices up by 3.8% in the first year and then the effect gradually decreases. The maximum response of real house prices to a positive shock to stock price is about 0.15% and the impulse response functions show a humped shape. The positive effects can be explained in two ways. First, an increase in house price (stock price) raises the wealth of households and thereby pushes up the demand in the stock market (housing market) investments. Second, an increase in house price (stock price) might trigger the expectations that stock prices (house prices) might also increase leading to expectations driven movements in stock prices. In addition, Ibrahim (2010) describes a credit-price effect such that increase in house prices would be favourable especially for credit-constrained firms since real estate acts as collateral and thus such firms may get access to lower cost of borrowing. This will lead to an increase firms' value through expanded investments and hence firms' stock prices.

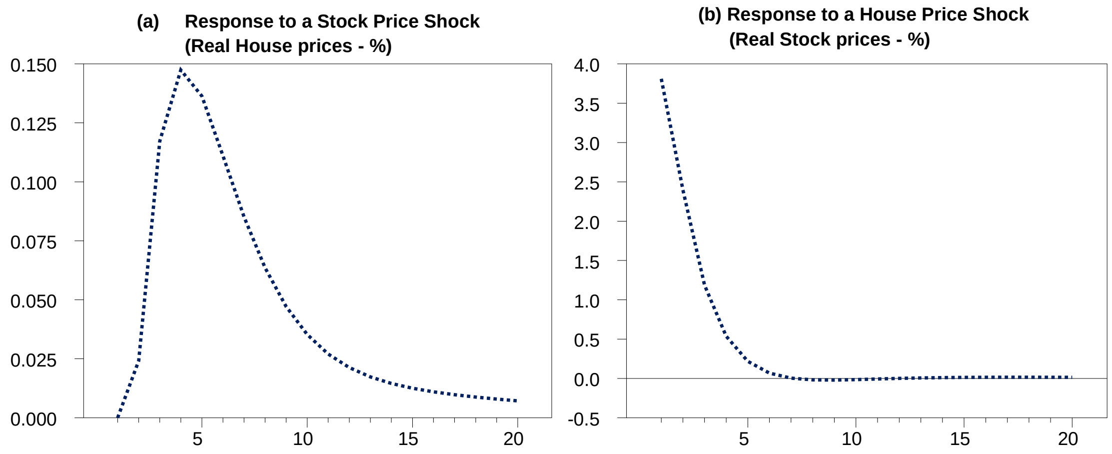


Figure 7.3: Responses of real house and stock prices

To determine the impact of population ageing on stock prices when the house price is also included into the model, robustness analysis is carried out. The demographic variable is replaced by the OY (Old Young) ratio, which is defined as the population aged 65 and above divided by the population between 35-64 years of age. That is, in contrast to the absolute importance, the relative importance of the old population in the stock market is taken into account using OY ratio as the demographic variable. Therefore, the model (7.2) now consists of the de-trended OY ratio along with the four other variables namely, the first difference of the log of real GDP per capita (Δy_t), the interest rate (i_t), the first difference of log of the real house price (Δph_t) and the first difference of the log of the real S&P/ASX200 stock price index (Δs_t). A positive shock to the OY ratio increases the real stock price by about 5.2% (see

Figure 7.4) in the first year which is attenuated slightly compared to the 5.5% when real house price was not included into the model (see Figure 6.9, plot (b) in chapter 6). The effect gradually decreases and tapers off to zero after 5 years in both cases.

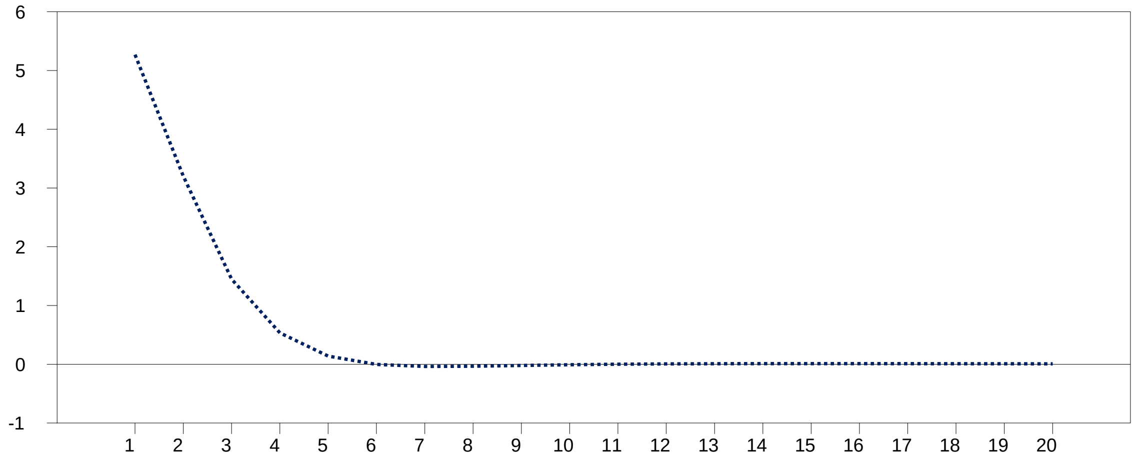


Figure 7.4: Responses of real stock prices to a positive shock to OY ratio

7.3 Discussion of the Results from the Two Extended Models

The analyses in chapter 5 and chapter 6 conclude that population ageing does not exert significant downward pressures on real house prices and real stock prices in Australia. However, the analyses in sections 7.2.1 and 7.2.2 above produce slightly different results in terms of attenuating or intensifying the already observed impacts on two asset prices when the interaction of two asset markets considered simultaneously. The responses of a positive shock to the old age ratio (65+/0-64) on real house prices are slightly intensified when the benchmark house price model considered in chapter 5, (model 5.5) is extended by including the stock prices. However, when the benchmark model developed in chapter 6, (model 6.6) is extended with the real house prices, the responses of real stock prices to a positive shock to old population (65+) are attenuated slightly. The different sample sizes, impact of distinct variables used in the econometric specifications, two different demographic variables used and two different methods followed to estimate the reduced form VAR estimates may have contributed to the distinct results. These results provide the motivation for further investigation of the effect of population ageing dynamics on real house and stock prices in conjunction with joint interactions of the two classes of assets.

In order to perform a direct comparison an econometric model is formulated while keeping only the common variables in two models used in the sections 7.2.1 and 7.2.2[66]. That is a small model with four variables which includes a demographic variable to represent the population ageing effect, a variable to represent the real economic forces, real house price and real stock price is used. The number of retired people (population aged 65 and above) is used as the demographic variable with a view to measure the absolute importance of the population ageing effect. Real GDP per capita can be considered as a natural and straightforward measure to represent the effects from real economic factors. Accordingly, the following structural VAR model is formulated to include four endogenous variables namely, de-trended old population (*dold*)[67], the first difference of the log of real GDP per capita (Δy_t), the first difference of the log of the real house price (Δhp_t) and the first difference of log of the real S&P/ASX200 stock price index (Δs_t). The literature which examines the demographics and asset prices typically uses small models that include one asset price variable (either housing or financial) and the demographic variables or the one asset price variable along with the demographic variables and GDP to measure the economic factors (see chapter 3 for details). Accordingly, the small model considered in this section provides an opportunity to compare results directly to some extent.

Define the vector of endogenous variables ordered as $z_t = [dold_t, \Delta y_t, \Delta hp_t, \Delta s_t]'$

$$A_0 z_t = A_1 z_{t-1} + \cdots + A_q z_{t-q} + \varepsilon_t \quad (7.5)$$

[66] Even though interest rate is a common variable for both benchmark models in section 5.5 and section 6.6, the mortgage interest rate and 90-day bill rates were used in former and latter models respectively. The rationale for using two different variables to represent the effect of interest rate was discussed in detail in chapters 5 and 6.

[67] Used HP filter because *old* is $I(2)$.

Here, q is a non-negative integer and ε_t is a (4×1) vector of structural shocks. A_j is a (4×4) matrix of constants, $j = 1, \cdots, q$ and A_0 is an invertible square matrix. The vector of uncorrelated structural shocks are ordered as $\varepsilon_t = [\varepsilon_t^R, \varepsilon_t^Y, \varepsilon_t^{HP}, \varepsilon_t^{SP}]'$, where ε_t^R is the "retirement shock", ε_t^Y is the "output shock", ε_t^{HP} is the "shock to house prices" and ε_t^{SP} is the "shock to stock prices". Let e_t denote the reduced form errors such that $e_t = A_0^{-1}\varepsilon_t$ and then the structural innovations are derived from reduced form errors by imposing exclusion restrictions on A_0^{-1}.

$$\begin{bmatrix} e_t^R \\ e_t^Y \\ e_t^{HP} \\ e_t^{SP} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{bmatrix} \varepsilon_t^R \\ \varepsilon_t^Y \\ \varepsilon_t^{HP} \\ \varepsilon_t^{SP} \end{bmatrix} \qquad (7.6)^{68}$$

The reduced form VAR coefficients are estimated in a Bayesian framework using data from 1958 to 2014. The short-run identification (exclusion) restrictions on the contemporaneous reactions of the variables to structural shocks for the unrestricted VAR model corresponding to the order of the variables, old population, real GDP per capita, real house price and real stock price. The dynamic relationships among the variables are examined using the impulse response functions to a positive shock at time *t* and for a period of 20 years.

A positive retirement shock leads to an increase in real house prices with a peak increase of 0.33% in the fourth year after the shock and then the effect gradually decreases (Figure 7.5, plot (a)). The corresponding impulse response function for the real house price without considering the interaction between the two asset prices are shown in Figure 7.6, plot (a)[69]. The behaviour of the two impulse response functions are similar although the effect is slightly attenuated when the interaction of the real

[68] See Kilian and Park (2009, p. 1271).
[69] Using three variables (old population, real GDP per capita and real house price) and short run-exclusion restrictions.

house and stock prices are considered in a unified model. A similar result can be seen with regard to the real stock prices (see plot (b) of the Figures 7.5 and 7.6)[70].

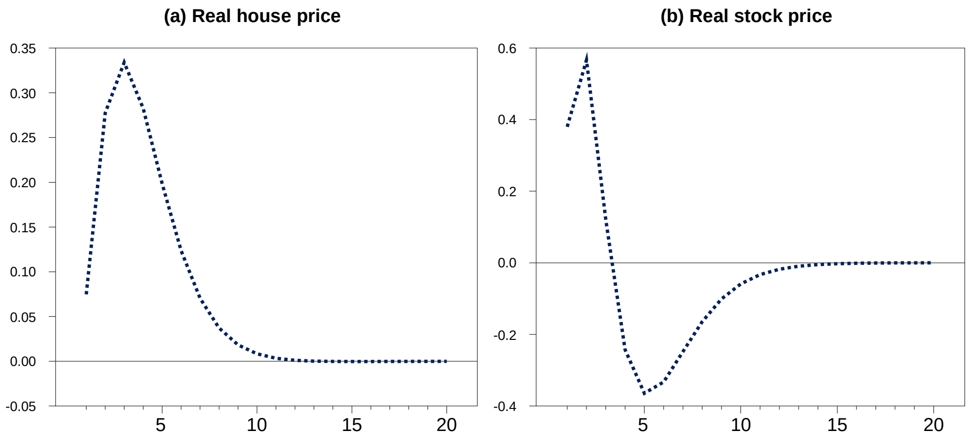


Figure 7.5: Responses of real house and stock prices to a retirement shock (with interaction of house and stock prices)

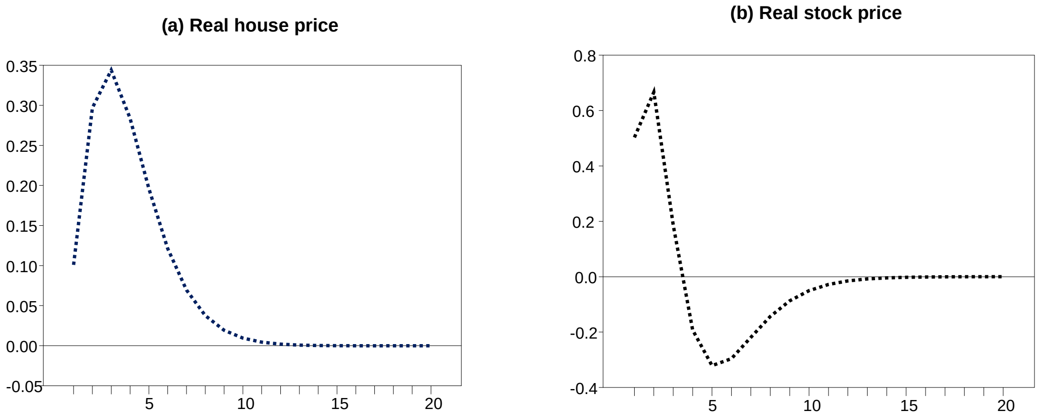


Figure 7.6: Responses of real house and stock prices to a retirement shock (without interaction of house and stock prices)

7.4 A Brief Discussion on the Differences between Housing Assets and Financial Assets

The analyses presented in sections 7.2 and 7.3 indicate that the shapes of the impulse response functions for housing prices and for stock prices are not same subsequent to a positive retirement shock. This could be attributable to the structural differences of

[70] Again plot (b) of the Figure 7.6 is based on three variables (old population, real GDP per capita and real stock price) and short-run exclusion restrictions

the two classes of assets (see Yang, 2009; Davies et al., 2011). The differences between housing and financial assets are now outlined with the aid of relevant statistics from Australia.

An asymmetric distribution of wealth may have an impact on the run-down of asset holdings in order to finance retirement consumption. The mean household net worth of all households in Australia in 2011-2012 was $728,000 while median was substantially lower of $434,000 (*Household Wealth and Wealth Distribution Australia*, 2011-2012). Thus, more specifically, a relatively small number of households have high net worth and a relatively large number of households have low net worth. Moreover, in general, the distribution of financial asset ownership is more right skewed (i.e. left tailed) compared to the housing asset ownership with respect to household wealth. That is, financial asset holdings such as stocks and bonds are mainly concentrated on the richest households. In Australia, 58% of the direct share owners have annual income over $200,000 and 40% of direct share owners have annual income of $100,000-200,000 (*Australian Share Ownership Study*, 2013). In this context, the richest individuals have much less pressure to run down their asset holdings to finance the consumption needs when they are old compared with the less affluent individuals. This will lead to differences in the response rates as well as the direction of the population ageing effect on real house and stock prices.

The timing of housing and financial assets purchases and sales are different. Financial assets such as shares in the stock markets are purchased later in life and sold earlier than housing assets. In contrast, housing assets are purchased earlier in life and sold later. Individuals buy houses the early part of their lives because of borrowing constraints on mortgages and the role of housing as collateral. In Australia, critical ages for entry into home ownership are between 24 and 44 years and for each age cohort (45-54; 55-64; 65-74; 75+) the increase in home purchase/ownership rise only slightly beyond the age of 45 years (*AHURI Positioning Paper No. 79,* June 2014). However, selling houses involves high transaction costs which prevent trading down houses quickly later in life. As a result, home ownership rates continue to be high late in life. Three studies done by NATSEM (Kelly and Harding, 2003; Kelly, 2003b; Harding, King and Kelly, 2002) discuss the significance of home ownership as a source of private wealth for older Australians. Moreover, Dvornak and Kohler (2003) state that housing wealth tends to be viewed as less liquid than financial wealth. This discussion also sheds light why the responses of real house prices and real stock prices to the population ageing shocks are not similar irrespective of the main finding that the population ageing does not exert a pronounced downward pressure on two asset markets.

The extent to which households view their current wealth as temporary or uncertain may differ between housing and share market wealth. Households view changes in housing wealth as more permanent than changes in financial wealth (Pichette and Tremblay, 2003). Also, the emotional impact of accumulating the two forms of wealth may not be the same, especially for owner occupied housing. Knowledge about the changes in real housing wealth in the short-run is limited compared to the stock market wealth since the stock market changes can be tracked daily (see Dvornak and Kohler, 2003; Case et al., 2005). However, at the same time the indirect owners in the stock market might be less aware of the current value of their portfolio than that of direct share owners. Also the bequest motives for housing assets and stock market assets are distinct. Each of these suggests a distinction between the effects of using housing wealth and stock market wealth for old age consumption and hence the ageing related pressure on the two forms of assets.

Differences in financial and housing assets such as liquidity, permanence of shocks, tractability and perceived opportunities of financing consumption might affect the propensity to dis-save (see Seirminska and Takhtamanova, 2007). Population age structures also have an impact on the rate of financing consumption out of these two forms of assets. Both standard economic theories (Gourinches and Parker, 2002) and empirical evidence (Hurd and Rohwedder, 2005; Lehnert, 2004) support the assertion that the marginal propensity to consume of older individuals is more sensitive to change than that of young individuals in response to wealth shocks. Given these lifecycle differences with regard to the marginal propensity to consume out of wealth would have distinct effects from the changing demographic structure on house and stock prices.

7.5 Conclusion

In the existing literature on the effects of population ageing on house prices and stock prices the interaction between house prices and stock prices is not considered in a unified framework. Chapters 5 and 6 of this thesis contribute to the literature using a more rigorous approach. The results support the conclusion that there will not be a pronounced downward pressure on real house prices or real stock prices in Australia due to the effects of population ageing. However in market economies asset prices are jointly determined and hence, through substitution and wealth effects, changes in house prices have implications on stock prices and vice versa. Thus this chapter investigates the effects of population ageing dynamics on real house prices and real stock prices using models in which the interactions are taken into account. Overall the main conclusions from chapters 5 and 6 remain unchanged and there is no evidence of a significant downward pressure on real house prices and stock prices as a result of increase in the size of old population or the proportion of old population. Thus the analysis in this chapter supports for the main findings made above on the population ageing effects on real house prices and real stock prices.

CHAPTER 8 CONCLUSIONS AND POLICY IMPLICATIONS

8.1 Introduction

The main objective of this thesis is to contribute to the asset meltdown debate by examining whether demographic transitions, particularly the increasing proportion of the population in the old age cohort due to the retirement of Baby Boomers, will precipitate a dramatic decline in asset prices in Australia. Thus, the study investigates the effects of population ageing shocks on real house prices and real stock prices using two approaches in a structural vector autoregressive framework. In the first approach, the interaction between house prices and stock prices were not taken into account and two separate models were developed for house prices and stock prices as described in Chapters 5 and 6 respectively. In the second approach, as discussed in Chapter 7, the interaction of house and stock prices were considered in a unified framework. This latter approach is new to the literature and it contributes by clarifying any ambiguity as to whether the key findings are sensitive to interaction effects between house prices and stock prices.

The motivation for the present study was the analysis of demographic transitions and asset ownership statistics along with a comprehensive review of the existing literature, and most importantly the ongoing discussions about the effects of retiring Baby Boomers on the Australian housing market. Instead of focusing on the average effect of the old population on asset prices, the structural VAR approach analyses impact of a shock to demographic variables, namely the large cohort entering retirement age since 2011. This is an important improvement over the methodologies used in the existing literature investigating the effects of demographics on asset prices. The thesis findings are significant not only in terms of expanding the body of literature but they also provide important insights for policy makers, real estate professionals, financial planners and other market participants regarding the potential impact of an ageing population on asset markets.

The remainder of the chapter is organised as follows. Section 8.2 summarises the main conclusions of the research and a discussion of the results. Following a discussion of the policy implications and recommendations in section 8.3, the limitations of the study are provided in section 8.4. The directions for further research are presented briefly in the final section.

8.2 Main Conclusions of the Research and Discussion

The effects of population ageing on asset markets are complex. Recent literature has raised concerns of significant downward pressure on asset prices, housing and financial, due to the rapid demographic transition associated with retiring Baby Boomers. Awareness of this demographic transition and speculation over the possible consequent effects on asset markets prompted the asset meltdown debate. The findings of this thesis support the optimists' view of the asset meltdown debate. Predictions that population ageing, or more generally changes in age structure particularly due to retiring Baby Boomers, will lead to pronounced downward pressure on real house or real stock price in Australia are rejected. The results suggest that the de-accumulation of wealth by the old age population is more complex than predicted by the life-cycle theory. This result appears to violate the rational agent model. Further, the fact that people do not always behave as economic models assume has been increasingly discussed in the literature (see for example Canzoneri, Cumby, Diba, 2006 or Kueng, 2016)

During retirement, old people de-accumulate wealth much less rapidly than what the life-cycle theory suggests and there is only modest dissaving at older ages. Moreover the growth in asset ownership among the older populations during last two decades , as revealed by ABS asset ownership statistics (ABS Household Wealth and Wealth Distribution, 2011-12), is difficult to reconcile with the age related hump-shaped pattern of asset ownership predicted by the life-cycle theory. This observation also confirms that the rapid dissaving that underlies most predictions of an asset meltdown may be incorrect.

Neither findings on real house prices, nor the findings on real stock prices, are consistent with the view that asset prices in Australia will decline sharply due to the retiring Baby Boomers. This is in contrast to the predictions of the life cycle hypothesis, the findings of Guest and Swift (2010) and Takats (2012) in relation to the house prices and the inferences of Huynh et al. (2006) in relation to the stock prices. However, the findings for the house prices are similar to those by Chen et al. (2012) for the Scotland which has a population ageing problem more severe than in Australia. Similarly, with respect to stock prices the conclusion is consistent with Brooks' (2006) conclusion for Australia from his cross country study and the Poterba's (1998, 2001, 2004) conclusions for the United States. Further a report published by the United States Government Accountability Office [GAO] (2006) states that '… retiring boomers are not likely to sell financial assets in such a way as to cause a sharp and sudden decline in financial asset prices'.

The analyses suggest that traditional approaches measuring the impact of population ageing on asset markets must be rethought. Findings from this research illustrate the dangers of incorrectly invoking the ceteris paribus assumption in linking the increasing size of the old age population due to retiring Baby Boomers to a decline in asset prices. The structural VAR methodology is superior by analysing the dynamic relationships among the variables by tracing the effects of structural innovations in various ways. The impulse response analyses suggest that increase in the size of the old age cohort as a result of positive retirement shock does not induce a decline in real house or stock price. The historical decomposition measure the cumulative effect of each individual shock to demographic variables on the real house and stock prices at each point in time. The effects are not capable of explaining a substantial part of the fluctuations in real house or stock prices historically. There has been no systematic downward pressure in the real house or stock price after 2011 associated with the cumulative effect of retirement shock to support the view that retirement of the Baby Boom bulge since 2011 would cause a downward pressure on stock or house prices. Macroeconomic shocks and asset price specific shocks explain more of the variation in historical house and stock prices than the shifts in the population age structure, suggesting that such factors could outweigh any effects of future demographic shifts on asset prices. These findings are contrary to the life cycle theory and results from general equilibrium models for asset prices, which suggest a direct link between demographic structure and asset prices. Poterba (2001) provides a possible explanation for these findings, namely, even though changes in age structure affect asset demand, these affects are simply too small to be detected among the other shocks to asset prices. Moreover, the anomaly, as revealed by asset ownership statistics (ABS Household Wealth and Wealth Distribution, 2011-12), that the older population cohort continues to hold or accumulate assets rather than de-accumulate as originally predicted by the life cycle hypothesis sheds light on why population ageing does not exert a pronounced downward pressure on real house and stock prices in Australia.

The main conclusion of the thesis is supported in various ways. Australian retirees have range of options apart from selling their houses or immediately withdrawing from the stock market investments to finance retirement consumption. These include the aged pension and superannuation, equity withdrawal facilities and reverse mortgage loans. For example, Schwartz et al. (2006) indicates that old people are home equity withdrawers. In an international comparison of home ownership statistics, Bradbury (2010) concludes that among elderly, own home ownership wealth is a much greater proportion of disposable income in Australia than in all other countries. Also, the MLC Quarterly Survey (2014) reveals that only one in ten Australians currently intend to sell the family home to fund their retirement. Moreover, the exemption of the principal residence from the age pension asset test discourage older population physically downsizing to a smaller home as evident in some empirical studies (see Judd et al., 2014; Sane and Piggott, 2011). Research conducted by the Productivity Commission in 2015 indicates that about 80% of older Australians are home owners. All these findings suggest that Australian elderly people do not face pressure to sell their homes to finance consumption and thus it is likely that housing ownership rates for older ages will not decrease over the current rates.

At present, Australia exempts owner-occupied housing from the capital gains tax (CGT). This is reinforced by the exclusion of owner occupied housing from the age pension test. A Treasury White Paper issued in 2015 also identifies these tax incentives as one of the underlying causes of house price inflation (Treasury, 2015, p. 59). Cowan and Taylor (2015) estimates the total value of pensioner home equity at $625 billion. These tax incentives encourage the retired retain and live in their homes during retirement.

The Australian Share Ownership Study (2014) reveals that 37% of individuals between 65-74 years and 46% of individuals 75 years and above have investments in the share market. Thus an increase in the old population would not substantially affect stock prices through high volume of withdrawals from stock market investments as inferred by Huynh et al. (2006). Also, Baby Boomers gradually transit into the retirement, suggesting that their withdrawals from the stock market would be spread over a long period of time. This mitigates the risk of shocks to the stock prices.

The Intergenerational Report (2015) forecasts an increase in the workforce participation rate of the Australian population above age 65 years from 12.9% in 2014-2015 to 17.3% in 2054-55. GAO (2006) notes that '…continuing to work for pay in retirement, often called partial or phased retirement, would reduce the need to sell assets to provide income'. Also, increasing expected longevity after retirement as a result of increasing life expectancy encourages the retired population to invest in housing and stock markets as a precautionary saving. These have an influence on decisions to defer the de-accumulation of wealth by people over 65 years.

8.3 Implications of the Study and Recommendations

Had this study found significant downward pressure on asset prices, or indeed the possibility of an asset meltdown, due to population ageing, then monetary policy and/or fiscal policy are possible instruments that could be used to offset the impact. However, this study does not predict a significant negative impact on asset prices as a result of ageing of Baby Boomers. As previously discussed these findings are mainly driven by two factors. The first is the anomaly revealed in the asset ownership statistics and the second is that the effects from changing age structure were too small amongst the other shocks that drive asset prices. This implies that policy makers do not have to develop policies on how to respond to any severe falls in house and stock prices due to changing age structure. However, caution must be exercised because of the indirect effects of any policy actions. For example, since older people continue to invest in housing and the stock market after retirement, price stability (i.e. low and stable inflation) would be an important monetary policy outcome so as to ensure that the real value of houses and financial stocks are maintained. At the same time it is worth noting that the inflation targeting monetary policy framework in Australia has to date prevented any substantial fluctuations in inflation. The impact of population ageing on fiscal policy has attracted greater attention, however this has largely been discussed in terms of the impacts on GDP and the fiscal deficit rather than the consequences for asset prices.

Against this background the policy implications discussed in this section are not directly related to monetary and fiscal policy. However, these research findings are relevant for wider range of policy makers, individuals, real estate professionals, and financial planners. Such stakeholders can usefully incorporate the findings of this study into their policies, plans and strategies.

The most important implication from this thesis in practical terms is to reduce the fear among retired people that the value of their houses or stocks will fall sharply as a result of retiring Baby Boomers. About 80% of the older Australians are home owners (Productivity Commission, 2015). The results give a measure of reassurance to older people that their stock of wealth may benefit from house price growth in the coming years. Even though financial products such as equity withdrawal facilities exist to access increasing housing wealth as a retirement income stream, Ralston (2015) states that current policy settings do not provide significant incentives to draw on housing equity. Such financial products need to be developed to contribute to the provision of aged care services and with the provisions of public and private health insurance to assist older Australians manageing their health-associated financial risks.

At present the principal residence is excluded in the means test calculation for the age pension. As indicated in research report of the Productivity Commission (2015) a significant majority of older Australians rely primarily on means tested age pensions. The rapidly increasing size of the retired population will impose an increasing fiscal burden due to age pension expenditure. The way in which housing is treated for age pension eligibility will affect choices on whether older households remain in current residence or face pressure on selling their houses to finance the retirement consumption. This will have an impact on releasing housing stock into the market. If the government revisits the exclusion of the owner-occupied housing from the age pension asset test it may induce a supply shock in the housing market as a result of retirees being encouraged to sell their houses. This may lead to change the results if the retirees sell their houses immediately and the effect of this supply shock is large enough to be detected among the other shocks to house prices.

The analyses suggest that the housing-release equity market remains small. There is a lack of suitable housing options for retirees to downsizing their existing homes. Australian Financial Review article titled *Elderly Home Owners Can't Afford to Move*, states that 'downsizing, typically be selling the large family home and buying a smaller one is unrealistic for most ageing Baby Boomers as their home is not worth enough to buy a new home and leave them with enough cash to live' (Australian Financial Review, 14 August 2014, para 2). Without quality and suitable houses in areas where ageing Australians want to live and can afford to buy, there will be an impact of health and well-being of older people. The World Health Organization [WHO] (2012) finds a causal link between housing quality and long-term health conditions. The report further indicates that housing characteristics have a significant correlation with risks of falls for older people. Supporting these findings, the Housing and Ageing Alliance [HAA] (2014) argues that suitable housing for older people leads to reduced health care costs. The rising cost of health care for the increasing number of older people puts unsustainable pressure on public spending in Australia (see Productivity Commission, 2015). This has become one of the key drivers of the Australian government fiscal deficit (Intergenerational Report, 2010). Therefore designing and building affordable homes for older people and improving existing homes will be an important policy issue to contribute to reducing health care expenditure on ageing population and thus to reduce the fiscal deficit. In addition, this would have a range of economic benefits including creation of jobs in the construction industry.

Zhu, Sneddon, Stephenson and Minney (2016) indicate that the number of Self-Managed-Superannuation-Funds (SMSFs) has increased substantially from 270,000 in 2004 to more than 534,000 in 2014 in Australia. During the same time, the number of SMSF members has increased from 523,000 to more than 1,000,000. The research findings do not predict a slow down the growth in stock price or induce a persistent slow evaporation in the stock market due to retiring Baby Boomers. Considering the substantially increasing number of SMSFs, this thesis' finding is informative for retirees to determine whether superannuation fund balances should be invested in a life annuity or in the share market. Furthermore, introducing devices such as cash payout dividends for older investors coupled with long-term care insurance products will be an innovative policy measure to mitigate any negative effect on stock markets if retired people decide to withdraw their investments immediately after retirement.

Whilst the retiring Baby Boomers are not likely to cause a sharp decline in stock prices, the retirement security of elderly population will likely to depend on individual savings and returns on these savings. The 2010 Intergenerational Report projected that expenditure on age related pension payments would increase from around 2.7% to 3.9% of GDP by 2050. This raises a fear that tax paying workers will not be able to support a growing proportion of age pensioners. Considering other fiscal uncertainties, lowering the government old age benefits for certain age groups and income levels seems to be inevitable. Further, a report published by the National Commission of Audit (2014) states that '… from 2017 the Age Pension age will be increased by half a year every two years and will reach 67 by 2023'. This would place more responsibility for saving on individuals. In addition, adequate rates of return on financial assets are required to ensure retirees are provided with sufficient income from their assets. Thus, it is imperative for individuals to efficiently manage the accumulation of funds and their spending of assets and savings. That said, enhancing the financial literacy among the individuals will likely to be an important policy role in the retirement security of the older population. This could include increased knowledge about financial issues such as accumulating assets and the ability to effectively draw down on them to meet the needs of a potentially long retirement.

The analysis of asset holdings of elderly households and empirical results suggest that current retirees draw down on savings at a slow rate.[71]. A possible explanation is that retirees are taking increasing longevity into account. Private annuities which could act as a hedge against longevity are not widely held by Australian retirees. Increased awareness about the effectiveness of private annuities among the elderly people and formulating attractive private annuities would be useful for insurance companies.

8.4 Limitations of the Study

The main limitation of this study is related to the various issues with data. There were several methodological changes in the construction of a house price index over the period in which the HPI was compiled, which may have influenced the trends in house prices. This makes it difficult to be entirely confident of the consistency of the time series for analytical purposes. A constant quality house price series was not developed by the ABS until the 2004 major revision.

As described in chapter 6, the benchmark 90-day bill rate captures monetary policy shocks virtually instantaneously though a consistent time series is available only from 1969. Thus the analysis presented in chapter 6 was based on data from 1969.

[71] 37% of individuals between 65-74 years and 46% of individuals 75 years and above still have investments in the share market (Australian share market study, 2014).

However, since demographic change is a slow moving fundamental a longer time series may have better captured the impact of demographic changes.

In addition to the length and the quality of the time series used, the analysis was restricted to annual data. This is because the demographic variables are available only on annual frequency. In general, the SVAR methodology is more appropriate higher frequency data, such as quarterly and monthly, than annual data. Thus the structural identification restrictions may be vulnerable to criticism some times. However, to avoid this problem a combination of short and long run restrictions is used in identification.

8.5 Directions for Future Research

This thesis has focused on the effects of population ageing, or more specifically the changing age structure due to Baby Boomers, on real house and stock prices in Australia. However, this is just one component of the effects of population ageing and future research should be extended to examine the wider implications of a changing population age structure on macroeconomic aggregates and individual welfare. As noted by Ludwig et al. (2012) the changing population structure will lead to a scarcity of labour relative to physical capital and hence a decline in real returns on physical capital and increases in gross wages. The working age population ratio is projected to decrease and the old age dependency ratio is projected to increase in Australia (see Chapter 2). Thus, future research should focus on the effects of the endogenous human capital accumulation to mitigate the effects of demographic change on macroeconomic aggregates and individual welfare. With this in mind and given the findings of this thesis, future research on the impact of population ageing on asset prices will not be discussed extensively though a few avenues for future research are as follows.

- The present study uses a constant quality national house price index to examine the effects of population ageing on real house prices. Since Australia has six states, the analysis can be extended to include unobserved state-specific heterogeneity that may be correlated with variables used to explain the house prices. A dynamic panel model with generalised methods of moments (GMM) at state level data would be an interesting area to investigate in relation to demographics and house prices.

- Increasing life expectancy suggests that retirees will take longer to run down their assets throughout their retirement. Therefore including a variable to measure the longevity would partially counteract the effect of that the ageing population would have on house and stock prices.
- An age response function that represents the entire age distribution could be estimated so that different impacts on the asset price determination from different ages can be analysed. Thus a relationship can be built up to measure the link between stock price and variations in the probability density function of the age distribution.

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APPENDICES

Appendix A – Matrix Notations and Definitions used in Chapter 4

A.1 Basic Matrix Notations

Suppose that $(m \times n)$ matrix A is given. Then the following notations were used throughout chapter 4.

Description	Notation
Transpose	A'
Inverse	A^{-1}
Determinant	*det* (A) or $\|A\|$
Rank	*rk* (A)
Trace	*tr* (A)

A.2 Definitions

Eigenvalue

λ is an eigenvalue of a square matrix A if and only if $|A - \lambda I_n| = 0$

Orthogonal Matrix

$(m \times m)$ square matrix A is orthogonal if $AA' = I_m$

The Kronecker Product

Let A be an $(m \times n)$ matrix and B be an $(p \times q)$ matrix.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}$$

Then the Kronecker Product of A and B ($A \otimes B$) is defined as;

$$A \otimes B = \begin{bmatrix} a_{11}B & \cdots & a_{1n}B \\ \vdots & & \vdots \\ a_{m1}B & \cdots & a_{mn}B \end{bmatrix}_{(mp \times nq)}$$

The *vec* Operator

Let A be an $(m \times n)$ matrix with $(m \times 1)$ columns a_i.

$A = [a_1, \cdots a_n]$

The *vec* operator stacks the columns and transforms A into an $(mn \times 1)$ vector.

$$vec(A) = \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}$$

Derivation of the Stability Condition for VAR (1) Process

Consider the VAR (1) process as given by A.1

$$y_t = A_1 y_{t-1} + u_t \tag{A.1}$$

Now let us consider the generation mechanism which starts at some time *t=1*.

$$\begin{aligned} y_1 &= A_1 y_0 + u_1 \\ y_2 &= A_1 y_1 + u_2 = A_1(A_1 y_0 + u_1) + u_2 \\ &= A_1^2 y_0 + A_1 u_1 + u_2 \\ &\vdots \\ y_t &= A_1^t y_0 + \sum_{i=1}^{t-1} A_1^i \, u_{t-i} \\ &\vdots \end{aligned} \tag{A.2}$$

If the process started in the infinite past, then using A.1 can be written using A.2 as given in IV.3.

$$y_t = A_1^{j+1} y_{t-j-1} + \sum_{i=0}^{j} A_1^i \, u_{t-i} \tag{A.3}$$

VAR (1) process is stable if the modulus of all eigenvalues of A_1 less than 1. This condition is equivalent to

$$|I_n - A_1 z| \neq 0 \text{ for } |z| \leq 1 \tag{A.4}$$

Appendix B – RATS Programme Codes for Chapter 5

Programme B.1: IRF for the Model Described in Section 5.6

```
* Rats codes (Old age ratio, real GDP, unemployment, mortgage interest rate,
house price)
* Short-run restrictions and one long-run restriction. The codes are based
on the replication file for: Bjørnland, Hilde C. and Kai Leitemo (2009)


OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 5\Final RATS Oct 2016\OAR 2014.xls"
DATA(FORMAT=XLS,ORG=COLUMNS) 1950:01 2014:01 rhp rgdp unem oar int

* Transform to log

set lrhp = log(rhp)
*
set lrgdp = log(rgdp)
*
* Plot variables in levels
spgraph(vfields=3,hfields=2)
     graph(row=1,col=1,header="log of real house price") 1
     # lrhp

graph(row=1,col=2,header="log of real GDP per capita") 1
     # lrgdp

graph(row=2,col=1,header="Nominal mortgage interest rate - %") 1
     # int

graph(row=2,col=2,header="Unemployment rate - %") 1
     # unem

graph(row=3,col=1,header="Old age ratio -%") 1
     # oar
spgraph(done)

*
* Transform variables
* HP filter for old age ratio

FILTER(TYPE=HP,TUNING=6.25) oar /oart
set doar = oar-oart

* log first difference for GDP and HP
set drgdp = 100*(log(rgdp/rgdp{1}))
set drhp = 100*(log(rhp/rhp{1}))

* Plot transformed series

spgraph(vfields=2,hfields=2)
     graph(row=1,col=1,header="first difference of the lrhp") 1
     # drhp

graph(row=1,col=2,header="first difference of lrgdp") 1
     # drgdp
```

```
graph(row=3,col=1,header="HP filtered Old age ratio -%") 1
     # doar
spgraph(done)

*
*
* set-up VAR
compute lags=2
compute nvar=5
compute nstep=20
*compute ndraws=10000
*
system(model=model1)
var doar drgdp unem int drhp
lags 1 to lags
det constant
end(system)
estimate(resids=resids)
compute vsigma=%sigma
*
* Identification
dec rect lr(5,5) sr(5,5)
input lr
. . . . .
. . . 0 .
. . . . .
. . . . .
. . . . .
input sr
. 0 0 0 0
. . 0 . 0
. . . 0 0
. . . . 0
. . . . .

* Define variable names and shock lables
dec vect[strings] shocklabels varlabels
compute shocklabels=||"oar shock", "output","unemployment", "monetary
policy","House price"||
compute varlabels=||"old age ratio","GDP", "Unemployment", "Interest Rate",
"House price"||
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f
* Point estimates
@varirf(model=model1, steps=nstep, factor=f,
page=byvariable,shocks=shocklabels, $
varlabels=varlabels)

* Monte Carlo integration
*
procedure SRLRDoDraws
*
option model     model
option integer   draws   10000
option integer   steps   40
option vect[int] accum
option rect      lr
option rect      sr
*
local integer nvar
```

```
local rect    fxx fwish fsigmad factor
local integer wishdof
local rect    betaols betau betadraw
local vect    ix
local symm    sigmad
local integer i j draw
*
if .not.%defined(model) {
   disp "###SRLRDoDraws(MODEL=model name,other options)"
   return
}
compute nvar=%modelsize(model)
*
* Standard setup for drawing from an OLS VAR
*
compute fxx    =%decomp(%xx)
compute fwish  =%decomp(inv(%nobs*%sigma))
compute wishdof=%nobs-%nreg
compute betaols=%modelgetcoeffs(model)
*
local rect[series] impulses(nvar,nvar)
*
* These are global variables
*
declare vect[rect]   %%responses(draws)
*
infobox(action=define,progress,lower=1,upper=draws) "Monte Carlo
Integration"
do draw=1,draws
   if %clock(draw,2)==1 {
      compute sigmad  =%ranwisharti(fwish,wishdof)
      compute fsigmad =%decomp(sigmad)
      compute betau   =%ranmvkron(fsigmad,fxx)
      compute betadraw=betaols+betau
   }
   else
      compute betadraw=betaols-betau
   compute %modelsetcoeffs(model,betadraw)
   *
   * Compute the short-and-long-run factor using the recalculated lag
   * sums of the model.
   *
   @ShortAndLong(lr=lr,sr=sr,masum=inv(%modellagsums(model))) sigmad factor
   *
   *
   impulse(noprint,model=model,factor=factor,results=impulses,steps=steps)

 * Store the impulse responses
   *
   dim %%responses(draw)(nvar*nvar,steps)
   ewise %%responses(draw)(i,j)=ix=%vec(%xt(impulses,j)),ix(i)
   infobox(current=draw)
end do draw
infobox(action=remove)
*
* Restore the original coefficients
*
compute %modelsetcoeffs(model,betaols)
*
end SRLRDoDraws
*
```

```
@SRLRDoDraws(steps=20,model=model1,lr=lr,sr=sr)
@MCProcessIRF(model=model1,percent=||.025,.975||,center=median,lower=lower,u
pper=upper,irf=irf)

* Graph impulse response functions

* Responses to real house price
spgraph(vfields=3,hfields=2)
     graph(row=1,col=1,header=varlabels(1),nodates) 3
     # irf(5,1)   / 1
     # lower(5,1) / 2
     # upper(5,1) / 2

graph(row=1,col=2,header=varlabels(2),nodates) 3
     # irf(5,2)   / 1
     # lower(5,2) / 2
     # upper(5,2) / 2

graph(row=2,col=1,header=varlabels(3),nodates) 3
     # irf(5,3)   / 1
     # lower(5,3) / 2
     # upper(5,3) / 2

graph(row=2,col=2,header=varlabels(4),nodates) 3
     # irf(5,4)   / 1
     # lower(5,4) / 2
     # upper(5,4) / 2

graph(row=3,col=1,header=varlabels(5),nodates) 3
     # irf(5,5)   / 1
     # lower(5,5) / 2
     # upper(5,5) / 2
spgraph(done)
```

Programme B.2: HD and FEVD for the model described in section 5.6

```
* Rats codes (Old age ratio, real GDP, unemployment, mortgage interest rate,
house price)
* Short-run restrictions and one long-run restriction.


* Historical decomposition and variance decomposition
OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 5\Final RATS Oct 2016\OAR 2014.xls"
DATA(FORMAT=XLS,ORG=COLUMNS) 1950:01 2014:01 rhp rgdp unem oar int

* Tranform to log

set lrhp = log(rhp)
*
set lrgdp = log(rgdp)
*
*
* Transform variables
* HP filter for old age ratio

FILTER(TYPE=HP,TUNING=6.25) oar /oart
set doar = oar-oart

* log first difference for GDP and HP
set drgdp = 100*(log(rgdp/rgdp{1}))
set drhp = 100*(log(rhp/rhp{1}))
*
* set-up VAR
compute lags=2
compute nvar=5
compute nstep=20
*
system(model=model1)
var doar drgdp unem int drhp
lags 1 to lags
det constant
end(system)
estimate(resids=resids)
compute vsigma=%sigma
*
* Identification
dec rect lr(5,5) sr(5,5)
input lr
. . . . .
. . . 0 .
. . . . .
. . . . .
. . . . .
input sr
. 0 0 0 0
. . 0 . 0
. . . 0 0
. . . . 0
. . . . .
```

```
dec vect[strings] shocklabels varlabels
compute shocklabels=||"oar shock", "output shock","unemployment shock",
"monetary policy shock",$
"House price shock"||
compute varlabels=||"old age ratio","GDP", "Unemployment", "Interest Rate",
"House price"||
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f
*
* Historical Decomposition
*
compute hstart=1953:01
compute hend=2014:01
history(model=model1, factor=f, from=1953:01, to=2014:01,
results=histdecomp, print)
*
* Graph HD

spgraph(vfields=5,hfields=1)
graph(row=1,col=1,key=upleft, nokbox, style=line, overlay=line, ovsamescale,
$
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of old age ratio shock'||) 2
     # drhp 1953:1 2014:1
     # histdecomp(2,5) / 2

graph(row=2,col=1,key=upleft, nokbox, style=line, overlay=line, ovsamescale,
$
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of output shock'||) 2
     # drhp 1953:1 2014:1
     # histdecomp(3,5) / 2

graph(row=3,col=1,key=upleft, nokbox, style=line, overlay=line, ovsamescale,
$
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of unemployment shock'||) 2
     # drhp 1953:1 2014:1
     # histdecomp(4,5) / 2

graph(row=4,col=1,key=upleft, nokbox, style=line, overlay=line, ovsamescale,
$
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of monetary policy shock'||) 2
     # drhp 1953:1 2014:1
     # histdecomp(5,5) / 2

graph(row=5,col=1,key=upleft, nokbox, style=line, overlay=line, ovsamescale,
$
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of house price specific
shock'||) 2
     # drhp 1953:1 2014:1
     # histdecomp(6,5) / 2
spgraph(done)


* Variance Error Decomposition
errors(model=model1, factor=f,steps=nstep, results=fevd, print)
```

Programme B.3: IRF for the model with two long-run restrictions

```
* Rats codes (Old age ratio, real GDP, unemployment, mortgage interest rate,
house price)
* Short-run restrictions and
* 2 long-run restrictions

OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 5\Final RATS Oct 2016\OAR 2014.xls"
DATA(FORMAT=XLS,ORG=COLUMNS) 1950:01 2014:01 rhp rgdp unem oar int

* Tranform to log

set lrhp = log(rhp)
*
set lrgdp = log(rgdp)
*
* Plot variables in levels
spgraph(vfields=3,hfields=2)
     graph(row=1,col=1,header="log of real house price") 1
     # lrhp

graph(row=1,col=2,header="log of real GDP per capita") 1
     # lrgdp

graph(row=2,col=1,header="Nominal mortgage interest rate - %") 1
     # int

graph(row=2,col=2,header="Unemployment rate - %") 1
     # unem

graph(row=3,col=1,header="Old age ratio -%") 1
     # oar
spgraph(done)

*
* Transform variables
* HP filter for old age ratio

FILTER(TYPE=HP,TUNING=6.25) oar /oart
set doar = oar-oart

* log first difference for GDP and HP
set drgdp = 100*(log(rgdp/rgdp{1}))
set drhp = 100*(log(rhp/rhp{1}))

* Plot transformed series

spgraph(vfields=2,hfields=2)
     graph(row=1,col=1,header="first difference of the lrhp") 1
     # drhp

graph(row=1,col=2,header="first difference of lrgdp") 1
     # drgdp

graph(row=3,col=1,header="HP filtered Old age ratio -%") 1
     # doar
spgraph(done)
*
```

```
*
*
compute lags=2
compute nvar=5
compute nstep=20
*
* Set up the system
*

* Set up the VAR
system(model=model1)
var doar drgdp unem int drhp
lags 1 to lags
det constant
end(system)
estimate(resids=resids)
compute vsigma=%sigma
*display vsigma
*
dec rect lr(5,5) sr(5,5)
input lr
. . . . .
. . . 0 .
. . . . .
. . . . .
. . . . 0
input sr
. 0 0 0 0
. . 0 . 0
. . . 0 0
. . . . .
. . . . .

dec vect[strings] shocklabels varlabels
compute shocklabels=||"oar shock", "output shock","unemployment shock",
"monetary policy shock",$
"House price shock"||
compute varlabels=||"old age ratio","GDP", "Unemployment", "Interest Rate",
"House price"||
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f
*
* Point estimates
@varirf(model=model1, steps=nstep, factor=f,
page=byvariable,shocks=shocklabels, $
varlabels=varlabels)


* Monte Carlo integration
*
procedure SRLRDoDraws
*
option model     model
option integer   draws   10000
option integer   steps   40
option vect[int] accum
option rect      lr
option rect      sr
*
local integer nvar
local rect    fxx fwish fsigmad factor
```

```
local integer wishdof
local rect    betaols betau betadraw
local vect    ix
local symm    sigmad
local integer i j draw
*
if .not.%defined(model) {
   disp "###SRLRDoDraws(MODEL=model name,other options)"
   return
}
compute nvar=%modelsize(model)
*
* Standard setup for drawing from an OLS VAR
*
compute fxx    =%decomp(%xx)
compute fwish  =%decomp(inv(%nobs*%sigma))
compute wishdof=%nobs-%nreg
compute betaols=%modelgetcoeffs(model)
*
local rect[series] impulses(nvar,nvar)
*
* These are global variables
*
declare vect[rect]   %%responses(draws)
*
infobox(action=define,progress,lower=1,upper=draws) "Monte Carlo
Integration"
do draw=1,draws
   if %clock(draw,2)==1 {
      compute sigmad  =%ranwisharti(fwish,wishdof)
      compute fsigmad =%decomp(sigmad)
      compute betau   =%ranmvkron(fsigmad,fxx)
      compute betadraw=betaols+betau
   }
   else
      compute betadraw=betaols-betau
   compute %modelsetcoeffs(model,betadraw)
   *
   * Compute the short-and-long-run factor using the recalculated lag
   * sums of the model.
   *
   @ShortAndLong(lr=lr,sr=sr,masum=inv(%modellagsums(model))) sigmad factor
   *
   *
   impulse(noprint,model=model,factor=factor,results=impulses,steps=steps)
*

 * Store the impulse responses
   *
   dim %%responses(draw)(nvar*nvar,steps)
   ewise %%responses(draw)(i,j)=ix=%vec(%xt(impulses,j)),ix(i)
   infobox(current=draw)
end do draw
infobox(action=remove)
*
* Restore the original coefficients
*
compute %modelsetcoeffs(model,betaols)
*
end SRLRDoDraws
*
```

```
@SRLRDoDraws(steps=20,model=model1,lr=lr,sr=sr)
@MCProcessIRF(model=model1,percent=||.025,.975||,center=median,lower=lower,u
pper=upper,irf=irf)

* Graph impulse response functions

* Responses to real house price
spgraph(vfields=3,hfields=2)
     graph(row=1,col=1,header=varlabels(1),nodates) 3
     # irf(5,1)   / 1
     # lower(5,1) / 2
     # upper(5,1) / 2

graph(row=1,col=2,header=varlabels(2),nodates) 3
     # irf(5,2)   / 1
     # lower(5,2) / 2
     # upper(5,2) / 2

graph(row=2,col=1,header=varlabels(3),nodates) 3
     # irf(5,3)   / 1
     # lower(5,3) / 2
     # upper(5,3) / 2

graph(row=2,col=2,header=varlabels(4),nodates) 3
     # irf(5,4)   / 1
     # lower(5,4) / 2
     # upper(5,4) / 2

graph(row=3,col=1,header=varlabels(5),nodates) 3
     # irf(5,5)   / 1
     # lower(5,5) / 2
     # upper(5,5) / 2
spgraph(done)
```

Appendix C – RATS Programme Codes for Chapter 6

Programme C.1: Codes for the Model Described in Section 6.6.2

```
*
* Rats codes (old population, real GDP, 90-day bill rate, stock price)
* Short-run restrictions and one long-run restriction

OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 6\Rats Prg\data15.xls"
CALENDAR(A) 1969:1
DATA(FORMAT=XLS,ORG=COLUMNS) 1969:01 2014:01 rsp rgdp old int
*
set lrsp = log(rsp)
*
set lrgdp = log(rgdp)
*
*
set drgdp = 100*(log(rgdp/rgdp{1}))
*
set lold = log(old)
FILTER(TYPE=HP,TUNING=6.25) lold /loldt
set dold = (lold-loldt)*100
set drsp = 100*(log(rsp/rsp{1}))
*
*
* Plot variables - trend removed

spgraph(vfields=2, hfields=2)
GRAPH(STYLE=LINE, row=1, col=1, header="(a) Old population - % deviation
from HP trend") 1
# dold
GRAPH(STYLE=LINE, row=1, col=2, header="(b) Real GDP per capita - % change")
1
# drgdp
GRAPH(STYLE=LINE, row=2, col=1, header="(c) Interest rate - %") 1
# int
GRAPH(STYLE=LINE, row=2, col=2, header="(d) Real stock price- % change") 1
# drsp
spgraph(done)
*
* Set up the system
*
compute lags=2
compute nvar=4
compute nstep=20
compute tight =0.1
compute other =0.5

* Set up the VAR
system(model=model1)
variables dold drgdp int drsp
lags 1 to lags
specify(type=symmetric, tight=tight) other
det constant
end(system)
estimate(resids=resids)
```

```
compute vsigma=%sigma
display vsigma

*
*
dec rect lr(4,4) sr(4,4)
input lr
. . . .
. . 0 .
. . . .
. . . .
input sr
. 0 0 0
. . . 0
. . . 0
. . . .

dec vect[strings] shocklabels varlabels
compute shocklabels=||"retirement", "output","monetary policy","stock
price"||
compute varlabels=||"old population","GDP", "Interest Rate", "Stock price"||
*
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f
display f
compute shock=%xcol(f,1)~%xcol(f,2)~%xcol(f,3)~%xcol(f,4)
*
* Point estimates
*
impulse(print, model=model1, steps=nstep, factor=shock, results=impulses)
@varirf(model=model1, steps=nstep, factor=shock,page=byvariable,$
         shocks=shocklabels, varlabels=varlabels)
@varirf(model=model1, steps=nstep, factor=shock,$
         shocks=shocklabels, varlabels=varlabels)
@varirf(model=model1, steps=nstep, factor=shock,page=byshock,$
         shocks=shocklabels, varlabels=varlabels)

GRAPH(nodates, STYLE=LINE) 1
# impulses(1,1)

GRAPH(nodates, STYLE=LINE) 1
# impulses(4,1)

GRAPH(nodates, STYLE=LINE, key=upleft, klabel=||'Stock prices - %'||) 1
# impulses(4,4)

spgraph(vfields=1, hfields=2, xlabels=||"(a) Old population - %",$
"(b) Stock prices - per cent"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(1,1)
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(4,1)
spgraph(done)

spgraph(vfields=1, hfields=2, xlabels=||"(a) Interest rate - per cent",$
"(b) Stock prices - per cent"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(3,3)
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(4,3)
spgraph(done)
```

```
*
* Historical Decomposition
*
compute hstart=1972:01
compute hend=2014:01
history(model=model1, factor=shock, from=1972:01, to=2014:01,
results=histdecomp, print)
graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of retirement shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(2,4) / 2

graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of output shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(3,4) / 2

graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of stock price shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(5,4) / 2

graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of monetary policy shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(4,4) / 2


* Variance Error Decomposition

errors(model=model1, factor=shock,steps=nstep, results=fevd, print)
```

Program C.2: Codes for the model described in section 6.9 (with two long-run restrictions)

```
* Rats codes (old population, real GDP, 90-day bill arte, stock price)
* Short-run restrictions and two long-run restrictions

OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 6\Rats Prg\data15.xls"
CALENDAR(A) 1969:1
DATA(FORMAT=XLS,ORG=COLUMNS) 1969:01 2014:01 rsp rgdp old int

set lrsp = log(rsp)
set lrgdp = log(rgdp)
*
set drgdp = 100*(log(rgdp/rgdp{1}))
*
set lold = log(old)
FILTER(TYPE=HP,TUNING=6.25) lold /loldt
set dold = (lold-loldt)*100
*
set drsp = 100*(log(rsp/rsp{1}))
*
*
compute lags=2
compute nvar=4
compute nstep=20

*
* Set up the system
*
compute tight =0.1
compute other =0.5

* Set up the VAR
system(model=model1)
variables dold drgdp drsp int
lags 1 to lags
specify(type=symmetric, tight=tight) other
det constant
end(system)
estimate(resids=resids)
compute vsigma=%sigma
display vsigma
*
dec rect lr(4,4) sr(4,4)
input lr
. . . .
. . 0 .
. . . .
. . . 0
input sr
. 0 0 0
. . . 0
. . . .
. . . .

dec vect[strings] shocklabels varlabels
compute shocklabels=||"retirement", "output", "stock price", "monetary
policy"||
compute varlabels=||"old population","GDP", "Stock price", "Interest rate"||
```

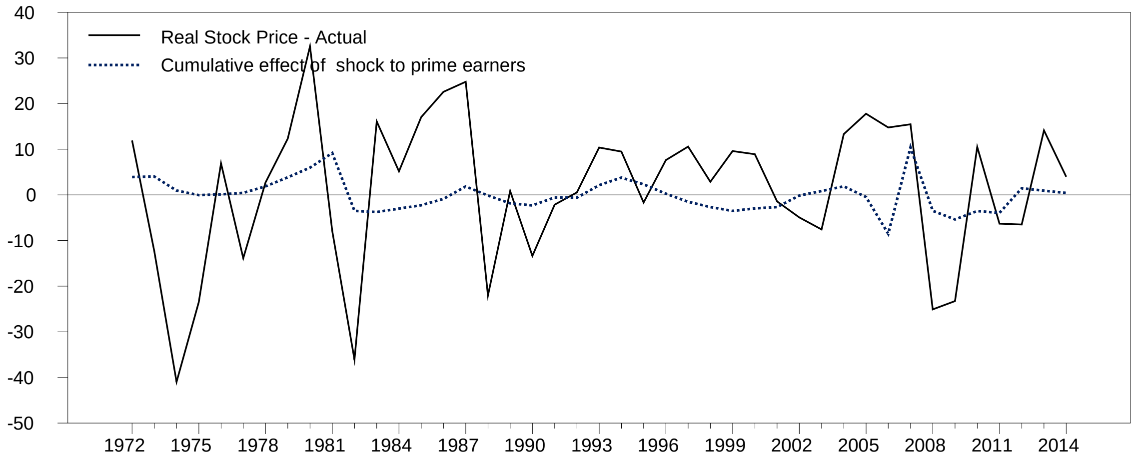
```
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f
display f

compute shock=%xcol(f,1)~%xcol(f,2)~%xcol(f,3)~%xcol(f,4)
*
* Point estimates
*
impulse(print, model=model1, steps=nstep, factor=shock, results=impulses)
@varirf(model=model1, steps=nstep, factor=shock,page=byvariable,$
         shocks=shocklabels, varlabels=varlabels)
@varirf(model=model1, steps=nstep, factor=shock,$
         shocks=shocklabels, varlabels=varlabels)
@varirf(model=model1, steps=nstep, factor=shock,page=byshock,$
         shocks=shocklabels, varlabels=varlabels)

spgraph(vfields=1, hfields=2, xlabels=||"(a) Old population - %",$
"(b) Stock prices - per cent"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(1,1)
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(3,1)
spgraph(done)

*
```

Appendix D: Cumulative Effect of Real Stock Price to Shock to Prime Earners



Notes: Estimates are based on the VAR model described in section 6.5 of the text (the old population variable is replaced by the prime earners).

Figure D.1: Cumulative effect of shock to prime earners (i.e. population aged 35-64 years) on real stock price

Appendix E – RATS Programme Codes for Chapter 7

Programme E.1: IRF for the model described in section 7.2.1 (Extended House Price Model)

```
* Rats codes (Old age ratio, real GDP, unemployment, mortgage interest rate,
house price)
* Short-run restrictions and one long-run restriction.

OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 7\Rats Prg\HP extended data 2014.xls"
CALENDAR(A) 1958:1
DATA(FORMAT=XLS,ORG=COLUMNS) 1958:01 2014:01 rhp rgdp unem oar int rsp


set lrhp = log(rhp)
*
set lrgdp = log(rgdp)
set lrsp = log(rsp)
*
*
* Plot variables in levels
spgraph(vfields=3,hfields=2)
     graph(row=1,col=1,header="log of real house price") 1
     # lrhp

graph(row=1,col=2,header="log of real GDP per capita") 1
     # lrgdp

graph(row=2,col=1,header="Nominal mortgage interest rate - %") 1
     # int

graph(row=2,col=2,header="Unemployment rate - %") 1
     # unem

graph(row=3,col=1,header="Old age ratio -%") 1
     # oar
graph(row=3,col=2,header="log of real stock price") 1
     # lrsp
spgraph(done)

*
* Transform variables
set drgdp = 100*(log(rgdp/rgdp{1}))

FILTER(TYPE=HP,TUNING=6.25) oar /oart
set doar = oar-oart
set drhp = 100*(log(rhp/rhp{1}))
set drsp = 100*(log(rsp/rsp{1}))

* Plot transformed series

spgraph(vfields=2,hfields=2)
     graph(row=1,col=1,header="first difference of the lrhp") 1
     # drhp
```

```
graph(row=1,col=2,header="first difference of lrgdp") 1
     # drgdp

graph(row=3,col=1,header="HP filtered Old age ratio -%") 1
     # doar
graph(row=3,col=2,header="first difference of lrsp") 1
     # drsp
spgraph(done)

*
*
*
compute lags=2
compute nvar=6
compute nstep=20
compute ndraws=10000
*
* Set up the system
*

* Set up the VAR
system(model=model1)
var doar drgdp unem int drhp drsp
lags 1 to lags
det constant
end(system)
estimate(resids=resids)
compute vsigma=%sigma
*display vsigma
*
dec rect lr(6,6) sr(6,6)
input lr
. . . . . .
. . . 0 . .
. . . . . .
. . . . . .
. . . . . .
. . . . . .
input sr
. 0 0 0 0 0
. . 0 . 0 0
. . . 0 0 0
. . . . 0 0
. . . . . 0
. . . . . .

dec vect[strings] shocklabels varlabels
compute shocklabels=||"oar shock", "output","unemployment", "monetary
policy","House price", $
"Stock price"||
compute varlabels=||"old age ratio","GDP", "Unemployment", "Interest Rate",
"House price", $
"stock price"||
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f

*
* Point estimates
@varirf(model=model1, steps=nstep, factor=f,
page=byvariable,shocks=shocklabels, $
varlabels=varlabels)
```

```
*
*
procedure SRLRDoDraws
*
option model     model
option integer   draws   10000
option integer   steps   40
option vect[int] accum
option rect      lr
option rect      sr
*
local integer nvar
local rect    fxx fwish fsigmad factor
local integer wishdof
local rect    betaols betau betadraw
local vect    ix
local symm    sigmad
local integer i j draw
*
if .not.%defined(model) {
   disp "###SRLRDoDraws(MODEL=model name,other options)"
   return
}
compute nvar=%modelsize(model)
*
* Standard setup for drawing from an OLS VAR
*
compute fxx    =%decomp(%xx)
compute fwish  =%decomp(inv(%nobs*%sigma))
compute wishdof=%nobs-%nreg
compute betaols=%modelgetcoeffs(model)
*
local rect[series] impulses(nvar,nvar)
*
* These are global variables
*
declare vect[rect]   %%responses(draws)
*
infobox(action=define,progress,lower=1,upper=draws) "Monte Carlo
Integration"
do draw=1,draws
   if %clock(draw,2)==1 {
      compute sigmad  =%ranwisharti(fwish,wishdof)
      compute fsigmad =%decomp(sigmad)
      compute betau   =%ranmvkron(fsigmad,fxx)
      compute betadraw=betaols+betau
   }
   else
      compute betadraw=betaols-betau
   compute %modelsetcoeffs(model,betadraw)
   *
   * Compute the short-and-long-run factor using the recalculated lag
   * sums of the model.
   *
   @ShortAndLong(lr=lr,sr=sr,masum=inv(%modellagsums(model))) sigmad factor
   *
   impulse(noprint,model=model,factor=factor,results=impulses,steps=steps)
*
```

```
 * Store the impulse responses
   *
   dim %%responses(draw)(nvar*nvar,steps)
   ewise %%responses(draw)(i,j)=ix=%vec(%xt(impulses,j)),ix(i)
   infobox(current=draw)
end do draw
infobox(action=remove)
*
* Restore the original coefficients
*
compute %modelsetcoeffs(model,betaols)
*
end SRLRDoDraws
*
@SRLRDoDraws(steps=20,model=model1,lr=lr,sr=sr)
@MCProcessIRF(model=model1,percent=||.025,.975||,center=median,lower=lower,u
pper=upper,irf=irf)

* Graph impulse response functions

* Responses to real house price
spgraph(vfields=3,hfields=2)
     graph(row=1,col=1,header=varlabels(1),nodates) 3
     # irf(5,1)   / 1
     # lower(5,1) / 2
     # upper(5,1) / 2

graph(row=1,col=2,header=varlabels(2),nodates) 3
     # irf(5,2)   / 1
     # lower(5,2) / 2
     # upper(5,2) / 2

graph(row=2,col=1,header=varlabels(3),nodates) 3
     # irf(5,3)   / 1
     # lower(5,3) / 2
     # upper(5,3) / 2

graph(row=2,col=2,header=varlabels(4),nodates) 3
     # irf(5,4)   / 1
     # lower(5,4) / 2
     # upper(5,4) / 2

graph(row=3,col=1,header=varlabels(5),nodates) 3
     # irf(5,5)   / 1
     # lower(5,5) / 2
     # upper(5,5) / 2
graph(row=3,col=2,header=varlabels(6),nodates) 3
     # irf(5,6)   / 1
     # lower(5,6) / 2
     # upper(5,6) / 2
spgraph(done)

spgraph(vfields=1,hfields=1)
     graph(row=1,col=1,header=varlabels(1),nodates) 3
     # irf(5,1)   / 1
     # lower(5,1) / 2
     # upper(5,1) / 2
spgraph(done)
```

Programme E.2: IRF for the Model Described in Section 7.2.2 (Extended Stock Price Model)

```
OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 7\Data\SPextended.xls"
DATA(FORMAT=XLS,ORG=COLUMNS) 1969:01 2014:01 rsp rgdp old int rhp

set lrsp = log(rsp)

set lrgdp = log(rgdp)
*set rsp1 = rsp - rsp{1}

*
set drgdp = 100*(log(rgdp/rgdp{1}))
*set drgdp = log(rgdp/rgdp{1})

*set lold = log(old)
*FILTER(TYPE=HP,TUNING=6.25) lold /loldt
*set dold = lold-loldt

FILTER(TYPE=HP,TUNING=6.25) old /oldt
set dold = old-oldt
set drsp = 100*(log(rsp/rsp{1}))
set drhp = 100*(log(rhp/rhp{1}))
*set drsp = log(rsp/rsp{1})
*
*
compute lags=2
compute nvar=5
compute nstep=20
compute ndraws=10000
*

*
* Set up the system
*
compute tight =0.1
compute other =0.5

* Set up the VAR
system(model=model1)
variables dold drgdp int drhp drsp
lags 1 to lags
specify(type=symmetric, tight=tight) other
det constant
end(system)
estimate(resids=resids)
compute vsigma=%sigma
display vsigma
*
dec rect lr(5,5) sr(5,5)
input lr
. . . . .
. . 0 . .
. . . . .
. . . . .
. . . . .
input sr
. 0 0 0 0
```

```
. . . 0 0
. . . 0 0
. . . . 0
. . . . .

dec vect[strings] shocklabels varlabels
compute shocklabels=||"retirement", "output","monetary policy","house
price", "stock price"||
compute varlabels=||"old population","GDP", "Interest Rate", "house price",
"Stock price"||
*
@ShortAndLong(lr=lr, sr=sr, masum=inv(%varlagsums)) %sigma f

display f
compute nshock=5

compute shock=%xcol(f,1)~%xcol(f,2)~%xcol(f,3)~%xcol(f,4)~%xcol(f,5)

*compute shock=%sqrt(%diag(%sigma))
*
* Point estimates
*
impulse(print, model=model1, steps=nstep, factor=shock, results=impulses)
@varirf(model=model1, steps=nstep, factor=shock,page=byvariable,$
         shocks=shocklabels, varlabels=varlabels)
@varirf(model=model1, steps=nstep, factor=shock,$
         shocks=shocklabels, varlabels=varlabels)

GRAPH(nodates, STYLE=LINE) 1
# impulses(5,1)

GRAPH(nodates, STYLE=LINE) 1
# impulses(4,1)

GRAPH(nodates, STYLE=LINE, key=upleft, klabel=||'Stock prices - %'||) 1
# impulses(4,4)


spgraph(vfields=1, hfields=2, xlabels=||"(a) Response old age shock",$
"(b) Response to house price shock"||, ylabels=||"stock price - %"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(5,1)
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(5,4)
spgraph(done)


spgraph(vfields=1, hfields=2, xlabels=||"(a) House prices - %",$
"(b) Stock prices - %"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(4,5)
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(5,4)
spgraph(done)



spgraph(vfields=1, hfields=2, xlabels=||"(a) Response old age shock",$
"(b) Response to stock price shock"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(4,1)
```

```
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(4,5)
spgraph(done)


*
* Historical Decomposition
*
compute hstart=1972:01
compute hend=2014:01
history(model=model1, factor=shock, from=1972:01, to=2014:01,
results=histdecomp, print)
graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of retirement shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(2,5) / 2

graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of output shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(3,5) / 2

graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of monetary policy shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(4,5) / 2

graph(key=upleft, nokbox, style=line, overlay=line, ovsamescale, $
      ovcount=2, $
      klabel=||'Actual', 'Cumulative effect of house price shock'||) 2
# drsp 1972:1 2014:1
# histdecomp(5,5) / 2
```

Program E.3: IRF for the Model Described in Section 7.3

```
OPEN DATA "C:\Users\wthenuwa\Documents\Aug 2015\Aug
28\Wasanthi\Thesis\Chapter 7\Data\SPHPextended Old.xls"
CALENDAR(A) 1958:1
DATA(FORMAT=XLS,ORG=COLUMNS) 1958:01 2014:01 rsp rgdp old rhp

*
compute lags=2
compute nvar=4
compute nstep=20

*
set lrhp = log(rhp)
set lrgdp = log(rgdp)
set lrsp = log(rsp)

* variables are detrended using hp filter

*
set drhp = 100*(log(rhp/rhp{1}))
*
set drgdp = 100*(log(rgdp/rgdp{1}))
*
*statistics rgdp
*
*
FILTER(TYPE=HP,TUNING=6.25) old /oldt
set dold = old-oldt

set drsp = 100*(log(rsp/rsp{1}))
*
* Set up the system
*

* Set up the VAR
compute tight =0.1
compute other =0.5

system(model=model1)
variables dold drgdp drhp drsp
lags 1 to lags
specify(type=symmetric, tight=tight) other
det constant
end(system)
estimate(resids=resids)
*compute vsigma=%sigma
*display vsigma

*

compute implabel=||"Retirement shock",$
                   "Output shock",$
                   "Shock to house price ", "Shock to stock price"||

compute varlabels=||"old population", "real GDP per capita",$
                    "real house price", "real stock price"||

*
*Identification of structural VAR
```

```
*
nonlin(parmset=svar) a21 a31 a32 a41 a42 a43
compute nfree=6

*
dec frml[rect] afrml
frml afrml = ||1.0,    0.0,   0.0, 0.0|$
               a21,    1.0,   0.0, 0.0|$
               a31,    a32,   1.0, 0.0|$
               a41,    a42,   a43, 1.0||

compute a21=a31=a32=a41=a42=a43=0

cvmodel(a=afrml, parmset=svar, method=bfgs, factor=fsvar) %sigma
impulse(print, model=model1, steps=nstep, factor=fsvar, results=impulses)
@varirf(model=model1, steps=nstep, page=byvariable, shocks=implabel,
var=varlabels)
*
*
* Response of real house and stock price
spgraph(vfields=1, hfields=2, xlabels=||"(a) Real house price",$
"(b) Real Stock price"||, ylabels=||"stock price - %"||)
GRAPH(nodates, STYLE=LINE, row=1, col=1) 1
# impulses(3,1)
GRAPH(nodates, STYLE=LINE, row=1, col=2) 1
# impulses(4,1)
spgraph(done)
```

Appendix F – Journal Articles Submitted

Appendix F.1 Will Population Ageing Cause a House Price Meltdown in Australia?

Wasanthi Thenuwara[ab] , Nam Hoang[c] and Mahinda Siriwardana[d]

[a] UNE Business School, University of New England, Armidale, NSW 2351, Australia
wthenuw2@une.edu.au

[b] Corresponding author
Telephone: +61 2 6773 5037

[c] UNE Business School, University of New England, Armidale, NSW 2351, Australia
nam.hoang@une.edu.au
Telephone: +61 2 6773 2682

[d] UNE Business School, University of New England, Armidale, NSW 2351, Australia
asiriwar@une.edu.au
Telephone: +61 2 6773 2501

This appendix has been removed as it has been submitted for publication elsewhere.

Appendix F.2 Rethinking the Asset Meltdown Debate: New Evidence from Australia

Wasanthi Thenuwara[ab] , Nam Hoang[c] and Mahinda Siriwardana[d]

[a] UNE Business School, University of New England, Armidale, NSW 2351, Australia
wthenuw2@une.edu.au

[b] Corresponding author
Telephone: +61 2 6773 5037

[c] UNE Business School, University of New England, Armidale, NSW 2351, Australia
nam.hoang@une.edu.au

[d] UNE Business School, University of New England, Armidale, NSW 2351, Australia
asiriwar@une.edu.au

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