Age Structure and Consumer Price Inflation in Australia

MRES Thesis

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List of Abbreviations

ABS Australian Bureau of Statistics

ADF Augmented Dickey Fuller test

AIC Akaike information criterion

ARCH Autoregressive Conditional Heteroscedasticity

AS & S Productivity is Administrative Services and Support Gross Value Added in constant prices divided by Real Capital Stock

BGLM Breusch-Godfrey test for autocorrelation

BIC Bayesian Information Criteria

CPI Consumer Price Index

DOLS Dynamic Ordinary Least Squares

DW Durban Watson test

GDP Gross Domestic Product

GST Goods and Services Tax

HAC Heteroscedasticity and autocorrelation consistent standard errors

IPD Implicit Price Deflator

KPSS Kwiatkowski-Phillips-Schmidt-Shin test for stationarity

OLS Ordinary Least Squares

PP Phillips Peron unit root test

RBA Reserve Bank of Australia

SE Standard Error

VIF Variance Inflation Factor

YOY Year on year change

Abstract

This thesis assesses the links between age structure and inflation in Australia. This is the first study, to our knowledge, to use disaggregated data to clarify the links between age structure and inflation. The aim is to shed light on some of the contentious issues in the research to date and to quantify the likely impact of Australia's aging population.

Faust and Wright (2013), in their comprehensive review of inflation forecasting, concluded that attention must be paid to improving the modelling of low frequency changes in inflation to reduce forecast errors. Age structure models have the potential to deliver this improvement and contribute to inflation forecasting.

This thesis assesses the effect of different parts of the age structure on the common factors driving inflation and on disaggregated price inflation. It also estimates the relative impact of the young, middle and early old age cohorts on aggregate inflation, and uses these estimates to project inflation forward.

The main finding is that age structure is important for inflation in Australia. All the analysis points to a consistent picture: younger age cohorts add to inflation, while late middle age and older cohorts reduce inflation. The mechanism of action is likely to be through changing relative demand and thus prices. The results suggest that the aging of the population will subtract from inflation significantly over the next ten years.

Statement of Originality

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made in the thesis itself.

(Signed) Date: 17 October 2019

David Corby

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Chapter 1: Introduction

This thesis assesses the links between age structure and inflation in Australia. A growing body of research strongly supports using age structure to model low frequency changes in inflation. To date this body of research has focussed on aggregate price measures (Andrews, Oberoi, Wirjanto and Zhou, 2018, Broniatowska, 2017, Faik, 2012, Gajewski, 2014, Lindh, 2004, Lindh and Malmberg, 1998, Takats, 2016, Yoon, Kim and Lee, 2018).

This is the first study, to our knowledge, to use disaggregated data to clarify the links between age structure and inflation. The aim is to shed light on some of the contentious issues in the research to date – particularly the mechanisms by which age structure impacts inflation and the impact the early old cohort (65 years to 79 years) has on inflation.

Inflation has both low and high frequency waves or cycles. This is illustrated in Figure 1 where the year on year percentage changes in the Consumer Price Index for Australia (ABS-6401) are displayed together with its centred moving average. Since 1949 inflation has moved through one wave down, up and then down – with these low frequency moves taking a decade or longer. Around this moving average is a great deal of cyclical volatility of much shorter duration. In more recent times inflation has trended down below the RBA's target band, remaining below the target band of 2 to 3% for 17 of the last 19 quarters to March 2019.

Monetary authorities target inflation in 70 countries, including Australia (Nielsen, 2019). The Reserve Bank of Australia's target of 'maintaining inflation in a 2-3% band on average *over the course of the business cycle*' (emphasis added) (RBA, 2016) confirms that lower frequency movements of inflation are important to inflation targeting in Australia.

Faust and Wright (2013), in their comprehensive review of inflation forecasting, conclude that inflation forecasting methods need to be changed because subjective inflation forecasts outperform model-based forecasts, often by a wide margin, in contrast to GDP forecasts where the opposite is true. They argue that attention must be paid to trend inflation to reduce forecast errors – particularly over longer time horizons.

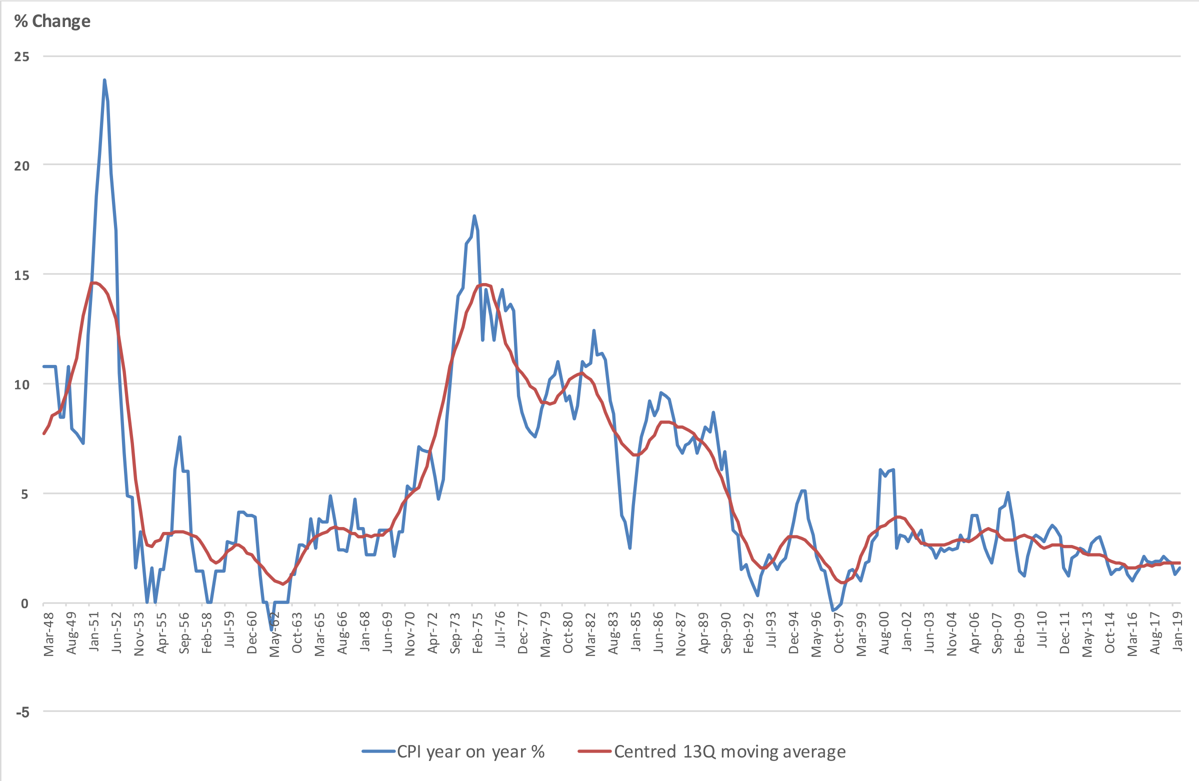

Figure 1: Australia Consumer Price Index Inflation (ABS-6401)

Current inflation modelling research predominantly has a shorter term perspective with univariate approaches prevailing and with past inflation or inflationary expectations as the focus of the models (Clark and Doh, 2014, Stock and Watson, 2010). These models generally divide inflation into a trend and a deviation from trend. The best performing models assume trend inflation is a stochastic process that slowly evolves over time (Faust and Wright, 2013).

The Fischer (1996) study of the last 700 years of price history showed that long periods of price stability alternate with periods of rising inflation. One of the factors common to all periods of inflation was rising population growth. Times of price stability tended to be preceded by declining population growth. Other factors played roles at times, for example monetary growth, but Fischer (1996) argued these tended to be more endogenous to the wave rather than preceding it.

It is possible that the low frequency changes in inflation in Australia are driven by the equally low frequency changes in demographics. This is consistent with a number of recent studies producing evidence of the importance of age structure for inflation (Andrews, Oberoi, Wirjanto and Zhou, 2018, Broniatowska, 2017, Faik, 2012, Gajewski, 2014, Lindh, 2004, Lindh and Malmberg, 1998, Takats, 2016, Yoon, Kim and Lee, 2018).

This thesis examines the impact of age structure on inflation in Australia by answering three key questions:

1. Which of the common factors driving inflation are affected by age structure?
2. What impact do different parts of the age structure have on disaggregated prices?
3. What is the relative impact of the young, middle and early old age cohorts on aggregate inflation, and what does this imply for inflation projecting forward?

The first question is addressed by using factor analysis to determine how many factors drive the disaggregated components of Australian inflation and which, if any, of these factors are affected by demographic variables (Chapter 5).

The second question is addressed by regressing 58 disaggregated inflation series against each part of the age structure, looking for patterns in the coefficients of the age structure variables (Chapter 6). The results from this disaggregated analysis are then compared with demand profiles of young and early old households.

The third question is answered by applying a cointegration analysis to age structure and inflation using dynamic ordinary least squares and Johansen maximum likelihood estimations (Chapter 7). The results are then used to project the potential impact of demographic changes on inflation using ABS population projections assuming all other things are equal.

This thesis clarifies the impact of the early old (65-79 years) by carefully selecting age ratios that enable inferences to be made about the relative effect of an increase in the early old on aggregate inflation, without being invalidated by multicollinearity.

The main finding is that age structure is important for inflation in Australia. All the analysis points to a consistent picture: younger age cohorts add to inflation, while late middle and older cohorts reduce inflation. The mechanism of action is likely to be through changing relative demand and thus prices.

An important finding is that the early old cohort is generally disinflationary. The results here suggest that the aging of Australia's population over the next ten years will subtract from inflation significantly. This is in stark contrast to Takats (2015) study, which found that recent retirees are inflationary and predicted that age structure would add to Australian inflation over the period 2010 to 2050.

The rest of the thesis is organised as follows: Chapter 2 reviews the relevant inflation literature; Chapter 3 considers recent trends in inflation and age structure; the framework for the research and analysis, the data and general methodology are summarised in Chapter 4; Chapter 5 sets out the methodology and results specific to the factor analysis and factor regressions; Chapter 6 details the methodology and results specific to the disaggregated price inflation regressions; Chapter 7 details the methodology and results for estimations of the relative impact of late young, late middle and early old cohorts on aggregate inflation; and the conclusions are set out in Chapter 8.

Chapter 2: Literature Review

2.1 Current Inflation Research

Current inflation research focuses on univariate approaches to modelling trend inflation using past inflation or inflationary expectations (Clark and Doh, 2014, RBA, 2016, Stock and Watson, 2007). Approaches that assume inflation has a stochastic trend outperform those assuming a stationary trend (Clark and Doh, 2014, Faust and Wright, 2013, Stock and Watson, 2007). This type of specification is very common – for example, Garnier, Mertens and Nelson (2013), Manopimoke and Limjaroenrat (2017), Quah and Vahey (1995), Sbrana, Silvestrini and Venditti (2017), Stella and Stock (2012), Stock and Watson (2015), Tallman and Zaman (2017) all use a stochastic trend.

This assumption of a stochastic trend suggests inflation is not a stationary series. It may be a matter of time-span – over long enough periods of time it is stationary, as Altissimo, Mojon and Zaffaroni (2009) argue. However, at a disaggregated level, the persistence of some prices is very long (Altissimo, Mojon and Zaffaroni, 2009), (Boivin, Giannoni and Mihov, 2009). Inflation in certain situations is clearly non-stationary, such as in the hyperinflation period in Germany in the 1930s.

Fuhrer (2010)'s comprehensive analysis of inflation persistence demonstrates that it is difficult to conclude whether inflation does or does not have a unit root even during periods in which central banks set inflation targets. Persistence has declined in the US in many inflation measures, but not all (Fuhrer, 2010).

Persistence has also declined in many other countries in the inflation targeting era (Stock and Watson, 2007), (Mumtaz and Surico, 2012) and the decline appears largely to be due to a decline in the persistence of services sector inflation (Altissimo, Mojon and Zaffaroni, 2009), (Choi and O'Sullivan, 2013). This may relate to the successful anchoring of inflationary expectations due to inflation targeting, or it may be an outcome of other factors like declining wage inflation in some countries due to a move towards decentralised bargaining (Kügler, Schönberg and Schreiner, 2019).

Despite the common assumption of a stochastic trend, detailed modelling of factors that determine this trend is difficult to find in the literature. The most common explanation is changing inflationary expectations – see for example Stock and Watson (2007). What drives this trend in inflationary expectations is usually argued to be changing monetary rules – see for example Choi and O'Sullivan (2013) and Bratsiotis, Madsen and Martin (2016).

A model that explains long-term dynamics more fully would potentially improve inflation forecasting performance and enable a more precise evaluation of the impact of changing monetary regimes on trend inflation (Faust and Wright, 2013).

2.2 Population

This need to find slowly evolving factors that affect inflation has spurred interest in the impact of demographic change on inflation. Numerous studies show that demographic change has a marked impact on inflation (Andrews, Oberoi, Wirjanto and Zhou, 2018, Broniatowska, 2017, Faik, 2012, Gajewski, 2014, Lindh, 2004, Lindh and Malmberg, 1998, Takats, 2016, Yoon, Kim and Lee, 2018). These studies look at the effect of different age groups on aggregate inflation rates, within countries and/or across countries.

What is clear from the studies is that demographics impact inflation. What is less clear is which parts of the age structure are pro-inflationary and which are disinflationary. There is general agreement in the literature that the early years are inflationary, and that years from 30 to 65 and above 80 years (late old) are disinflationary. There is widespread disagreement on the impact of the early old (65-79 years) cohort. Table 1 below summarises the results from these studies.

To avoid confusion, this thesis will refer consistently to 0-14 years as being the early young, 15-29 years as being the late young, 30-39 years as the early middle, 40-54 years as the late middle, 65-79 as the early old and 80+ as the late old.

Table 1: Summary of Results for Age Structure Inflation Studies

Author	Method	Countries	Results Inflationary Age Cohorts	Results Disinflationary Age Cohorts
Lindh and Malmberg (1998)	5 age ratios used in each estimation equation	20 OECD countries	15-29/population 65-74/population	30-49/population 50-64/population* 75+/population
Lindh (2004)	6 age ratios used in an estimation equation with no intercept	Sweden	0-14/population* 65-74/population	15-29/population* 30-49/population* 50-64/population 75+/population
Faik (2012)	1 age ratio used in estimation equation	Germany		65+/20-64
Gajewski (2014)	4 estimation methods: 1. Two ratios used; [1] 2. Two ratios used; [1] 3. One ratio used; [1] 4. One ratio used. [1]	34 OECD countries	1. 0-14/15-64[1] 2. 0-20/20-64[1]	1. 65+/15-64*[1] 2. 65+/20-64*[1] 3. 65+/15-64*[1] 4. 80+/population[1]
Takats (2016)	Coefficients restricted to lie on a 4th degree polynomial	22 OECD countries	10-14/population 15-19/population 20-24/population 25-29/population 65-69/population 70-74/population 75-79/population	35-39/population 40-44/population 45-49/population 50-54/population 55/59/population
Broniatowska (2017)	2 estimation methods: 1. 1 age ratio (the ratio adds young and old and divides by working age population); 2. 2 age ratios.	32 OECD countries	1. (0-14 & 65+)/ 15-64 2. 0-14/15-64	2. 65+/15-64
Yoon, Kim and Lee (2018)	2 estimation methods: 1. 1 age ratio; 2. 2 age ratios.	30 Countries		1. 65+/population 2. 65+/population 15-64/population
Andrews, Oberoi, Wirjanto and Zhou (2018)	2 estimation methods: 1. Coefficients restricted to lie on a 4th degree polynomial; 2. 4 age ratios used in one estimation regression.	22 countries	1. 0-4/population 5-9/population 10-14/population 15-19/population 20-24/population 60-64/population 65-69/population 70-74/population 2. 0-19/pop. 65-74/population	1. 30-34/population 35-39/population 40-44/population 45-49/population 50-54/population 80+/population 2.20-64/population 75+/population
*insignificant at 5%				

[1] 1. Refers here to equation 1 in the study, 2. refers to equation 2, 3. to equation 3 and 4. to equation 4

The early old cohort (65-79 years) is becoming important because in many countries, including Australia, there is an increasing share of the population entering retirement years. The estimates of Lindh and Malmberg (1998), Takats (2016), Lindh (2004), and Andrews, Oberoi, Wirjanto and Zhou (2018) show that these early retirement years are inflationary, while those of Gajewski (2014), Faik (2012), Yoon, Kim and Lee (2018), and Broniatowska (2017) show that they are disinflationary.

These contrasting results appear largely to be due to differences in methodology. The studies that utilise no more than two ratios in a single regression equation show early old (65-79) to be disinflationary. Studies that utilise more ratios in a regression or constrain ratios to lie on a 4th degree polynomial find these early old years are inflationary.

These differences could reflect the impact of collinearity between age cohorts. While, as Lindh (2004) argues, collinearity between cohorts does not affect the overall conclusion that age structure affects inflation, it potentially does affect conclusions about the impact of particular cohorts in equations that contain more than one cohort. If the equations have only a few cohorts then there will potentially be a missing variable problem as other cohorts may be important for inflation as well. However, if two highly correlated cohorts are included in the estimation then the reliability of each parameter will be affected.

Two major approaches have been taken to reduce this problem. One uses a limited number of cohorts – Yoon, Kim and Lee (2018), Broniatowska (2017), Lindh and Malmberg (1998) – and the other restricts the coefficients of the age structure variables to lie on a polynomial – Andrews, Oberoi, Wirjanto and Zhou (2018) and Takats (2016). This enables a smooth transition from one age cohort to another; however, it also restricts the estimated coefficients significantly at times of life when situations change significantly – such as retirement. The degree of restriction can be adjusted somewhat by changing the order of the polynomial.

Lindh and Malmberg (1999) argue that the population polynomials approach encounters estimation problems when behaviour shifts abruptly at certain ages. It may be appropriate when economic behaviours evolve smoothly, but there are at least three major times in life when life cycle theory suggests behaviour could be expected to change considerably: when first forming a household, when saving for retirement after children have grown up, and retirement.

Using population polynomials to estimate age structure coefficients does not eliminate multicollinearity issues. The 4th degree polynomial estimations of Andrews, Oberoi, Wirjanto and Zhou (2018) and Takats (2016) require four polynomial coefficients to be estimated. Lindh and Malmberg (1999) show these coefficients are highly correlated in their cross-country sample. This would significantly limit the reliability of estimates of the effect of certain parts of the age structure on inflation.

There is also debate over the transmission mechanism from changing demographics to inflation. Demographics impact both supply and demand. The life cycle hypothesis (Ando and Modigliani, 1963) predicts that saving rates rise in middle years, dampening inflation, and then fall in retirement years when retirees fund their consumption from savings and do not add to production. In that model recent retirees are expected to reduce supply more than demand, leading to an increase in inflationary pressure (Gajewski, 2014). In addition, retirement shrinks the labour force, potentially reducing the total number of workers and potentially shifting the balance between younger lower paid workers and older higher paid workers. Faik (2012) argues that this may, on balance, place upward pressure on wages.

Lindh and Malmberg (1998) develop a Wicksellian model of a closed economy that explains the transmission as occurring predominantly through changing savings and investment rates and aggregate demand. Their model has similar implications to the life cycle hypothesis.

Fedotenkov (2018) develops an overlapping generations model that explains the transmission mechanism as the effect of aging on endogenous credit growth. His model predicts that aging will reduce inflation. He includes a figure of the proportion of credit held by different age cohorts in Lithuania. It shows that the people in young working years have the highest proportion of credit (more than 70% being held by persons under 40) and this rapidly declines through later working years. A reduction in the size of the young cohort reduces borrowings and credit creation. An increase in longevity increases the savings of the cohort in the middle and later working years.

Analysis of the effect of aging on consumption demand in West Germany shows that aging affects relative demand, particularly for furniture, clothing, transport, education and leisure items (Luhrmann, 2005). Demand for these items, and overall demand, increases as the average age of the head of the household rises from 20 to around 40-45 years of age, and then falls consistently from that age onwards. This peak and then fall in spending is consistent with Fedotenkov (2018) model's rise in endogenous credit growth in young working years, peak in early middle years and then fall from then onwards. Together these results suggest that demand rises in early years and then falls from mid-life onwards.

Katagiri (2018) uses a multisector new Keynesian model to explain Japan's experience of disinflation and aging. In his model, aging reduces aggregate demand and prices and affects relative demand and relative prices – manufactured goods demand and prices fall relative to service demand and prices (Katagiri, 2018).

Anderson, Botman and Hunt (2014) use the IMF's Global Integrated Fiscal and Monetary Model to show that aging is disinflationary. Aging reduces growth, asset prices and causes a repatriation of overseas assets by retirees, which leads to an increase in the exchange rate when the home country ages more quickly than other countries. They present evidence showing that aging leads to shifts in consumption patterns, with the elderly decreasing expenditure on housing, education, communication and transportation, and increasing expenditure on medical services and utilities. The disinflation effect is further amplified by the need for greater fiscal spending which prompts fiscal consolidation, higher taxes and below average growth rates.

Bullard (2012) argues that aging changes the socio-political landscape because an aging population prefers lower inflation as older people seek to increase their return on capital. In his model inflation shifts investment away from money towards capital, increasing wages and reducing capital returns for savers. Thus, older populations prefer lower inflation as it increases the demand for money relative to capital, increasing returns to capital from savings. This drives a political environment that encourages the central bank to target lower inflation as the population ages. Takats (2016) finds evidence that the age structure affects inflation even after allowing for the impact of real interest rates. This result argues against the political economy view being the link between age structure and inflation (Takats, 2016).

2.3 Relative Prices and Disaggregated Inflation

The effect of aging on relative demand and potentially on relative prices, and the effect it may have on aggregate prices, has not been explored in the literature. Reis and Watson (2010) use a three factor unobserved components model of disaggregated US consumer price data to show that, at business cycle frequencies, 76% of the change in aggregate prices in the US over the period 1959-2006 came from changes in relative prices. 15% of the change came from factors that affect all prices equally (they term this ‘pure inflation’ – factors like changes in the supply of money or other macro-shocks).

Reis and Watson (2010) results point to low frequency moves in inflation being driven more by changes in relative prices than by aggregate factors. They also considered whether particular categories of relative prices were responsible for these relative price shifts and found that movements in food and energy, services, durables and non-durables were all well correlated with the relative price factor.

In the last 750 years, consumer inflation in England has averaged 1% per annum (Fischer, 1996). During that period there have been four distinct inflationary cycles – the first from the late 12th century to the early 14th century, the second from the 15th to the mid 17th century, and the third from around 1730 to around 1810, while the fourth began in 1896 and is still continuing. Between these inflationary cycles were extended periods of flat or declining trend inflation.

Similar cycles exist in the history of other countries in Europe and also the United States. Fischer (1996) considers price data from numerous countries and cities in Europe as well as the United states and argues that they all have common properties:

- they begin with economic stability and increasing optimism that leads to higher population growth;
- agriculture, energy and raw material production increases, but not sufficiently to prevent a growth in prices, particularly for energy, food and shelter;
- real wages start to rise, there is pressure on money supply and novel ways of increasing the supply of currency are introduced;

- towards the end of the wave real wages fall, and income inequality, poverty and crime rise;
- population growth starts to decline in response, as pessimism prevails. During this late period, real returns to capital are maintained so the distribution of income shifts towards landowners/business.

The end of each inflationary epoch tends to coincide with major shocks – poor agricultural seasons, banking instability, and war.

Fischer's analysis points to the importance of food, energy and housing prices in each inflationary wave. This is driven largely by the rise in population growth which precedes rises in money supply. His data shows manufactured goods prices are relatively stable compared with those of food, energy, shelter and raw materials. Together this argues for a disaggregated approach to modelling inflation.

Empirical evidence as to how firms actually price points to variations in the pricing models used by firms in different sectors – see Means (as reported in Lee and Downward (1999)), Andrews, Hall and Hitch (as reviewed in Lee (1984)) and more recently Blinder (1991) and Fabiani, Loupias, Martins and Sabbatini (2007). Overall, this research points towards a majority of firms pricing on a mark-up model with prices adjusting infrequently, and a minority of firms adjusting prices frequently.

Pricing approaches across industries do appear to vary, with the more heterogeneous industrialised products priced on a different basis to the more homogeneous commodities (Lee and Downward, 1999). Means' analysis categorised products into administered prices – where price changes are irregular – and market prices – where price changes are regular. The Lee and Downward (1999) review of Means' data suggests that:

- administered prices respond less to changes in demand than market prices do;
- the type of good, rather than market concentration, determines what sort of pricing is used;
- durable goods, finished goods and unique goods were more likely to use administrative prices;

- non-durable goods, raw materials and homogeneous goods are more likely to use market prices.

A large proportion of GDP uses administrative prices – for example, Means' data, which covered the period 1926-1933, suggested that more than 53.8% were administered prices (changed prices three times a year or less) and only 21.2% were market based prices (changed 73 or more times in 96 months). A more recent study of sticky/flexible prices showed that for disaggregated US CPI data, 70% of components changed prices less than once every 4.3 months (Bryan and Meyer, 2010). The goods that changed prices frequently were predominantly food and energy. Services tend to be in the sticky category. Similarly, Blinder (1991) data suggest that more than 50% of US firms in the non-farm sector change prices once every 12 months or longer.

This has important implications for modelling inflation. Different pricing models imply different inflation dynamics. Modelling sticky and flexible priced goods and services separately and then aggregating would potentially improve aggregate inflation model performance, as Bryan and Meyer (2010) demonstrate. Also, sector weights for services and industrial products have risen relative to food and energy and hence the ratio of administered/market prices is likely to be evolving over time. Modelling on a disaggregated basis may be one way of taking this into account.

There is considerable support for a disaggregated approach to forecasting inflation. Bermingham and D'Agostino (2013) review concludes that a disaggregated approach is always better so long as the data is sufficiently disaggregated to generate a gain and the timespan is sufficient to model the data. Hubrich (2005) is one of only a few researchers who do not find a benefit from a disaggregated approach, but Bermingham and D'Agostino (2013) argue this is probably due to the short timespan (10 years of data).

Stock and Watson (2015), Potter (2009), Cristadoro, Forni, Reichlin and Veronese (2005), Ibarra (2012), Manopimoke and Limjaroenrat (2017), and Carlo and Marçal (2016) use disaggregated price series to calculate core inflation series that improve on standard core inflation measures, and produce more accurate forecasts.

Tallman and Zaman (2017) use a composite approach to modelling US inflation in which goods and services inflation rates are modelled separately using different models and then aggregated to compare against other forecasting models. They find that the composite approach improves both point and density forecast performance compared with common benchmark univariate aggregate models.

Sbrana, Silvestrini and Venditti (2017) use disaggregated European price series to model core goods and services inflation separately and then aggregate up and compare with other forecasting methods. Their results compare well with benchmark forecasting methods as well as with the surveys of experts.

Together, all of these studies support a disaggregated approach to modelling inflation.

2.4 Australian Inflation Research

There has been limited research in Australia using disaggregated prices. Gillitzer (2006) constructs an underlying inflation measure using disaggregated prices adjusted for their volatility. Kirker (2011) uses disaggregated consumer prices in Australian and New Zealand to construct core inflation measures using dynamic factor analysis. He allocates price series to traded and non-traded factors based on their Australian Bureau of Statistics (ABS) classification. Using Bayesian criteria to determine the optimal number of factors, he calculates the optimal number of factors for Australia to be four tradeable and one non-tradable.

Saha and Zhang (2016) disaggregate data into manufacturing, mining and agriculture, to compare the flow-through of exchange rate and other shocks to Australia, China and India. They find that Australia is responsive to oil price changes and that the exchange rate impact is not strong for bilateral China and India exchange rates.

The predominant approach to modelling inflation in Australia has been to use mark-up models – Brouwer and Ericsson (1998), Dwyer and Leong (2001), Francis and Sugema (1995), Valadkhani and Mitchell (2002), Norman and Richards (2012) – with the focus generally being on supply considerations such as wages, unit labour costs, import price inflation, oil price inflation.

Makin, Robson and Ratnasiri (2017) find a cointegrated relationship between currency growth and inflation, with a structural break in 1991.

Norman and Richards (2012), Abbas and Sgro (2011), and Abbas (2012) model inflation using New Keynesian Phillips curve models, with the latter two including real exchange rate and real terms of trade variables. Paradiso and Rao (2012) use an unobserved components framework to estimate a Phillips curve style model with oil price inflation. They find oil price inflation to be significant for Australia.

Shepherd and Driver (2003) use survey based measures of supply and demand to model inflation. They conclude that scarcity of plant, rather than labour, drove inflation from 1972 to 2001.

Chapter 3: Recent Consumer Price and Population Ratio Trends

3.1 CPI Trends

The most detailed source of consumer price data in Australia comes from the Consumer Price Index (CPI) (ABS-6401). This will be the source of the detailed disaggregated inflation data used in the factor analysis and regression analysis in later chapters. The other measure of consumer prices is the household consumption implicit price deflator from the National Accounts (ABS-5206). Figure 2 shows that the year on year (YOY) changes in both measures have moved closely together and that consumer price inflation has been trending down since 1975 in Australia. The household consumption implicit price deflator (Cons IPD YOY) inflation has a smoother profile than CPI inflation (CPI YOY). This is probably because the chain weighting used for the deflator allows for the weighting of each price component to shift as volume shifts.

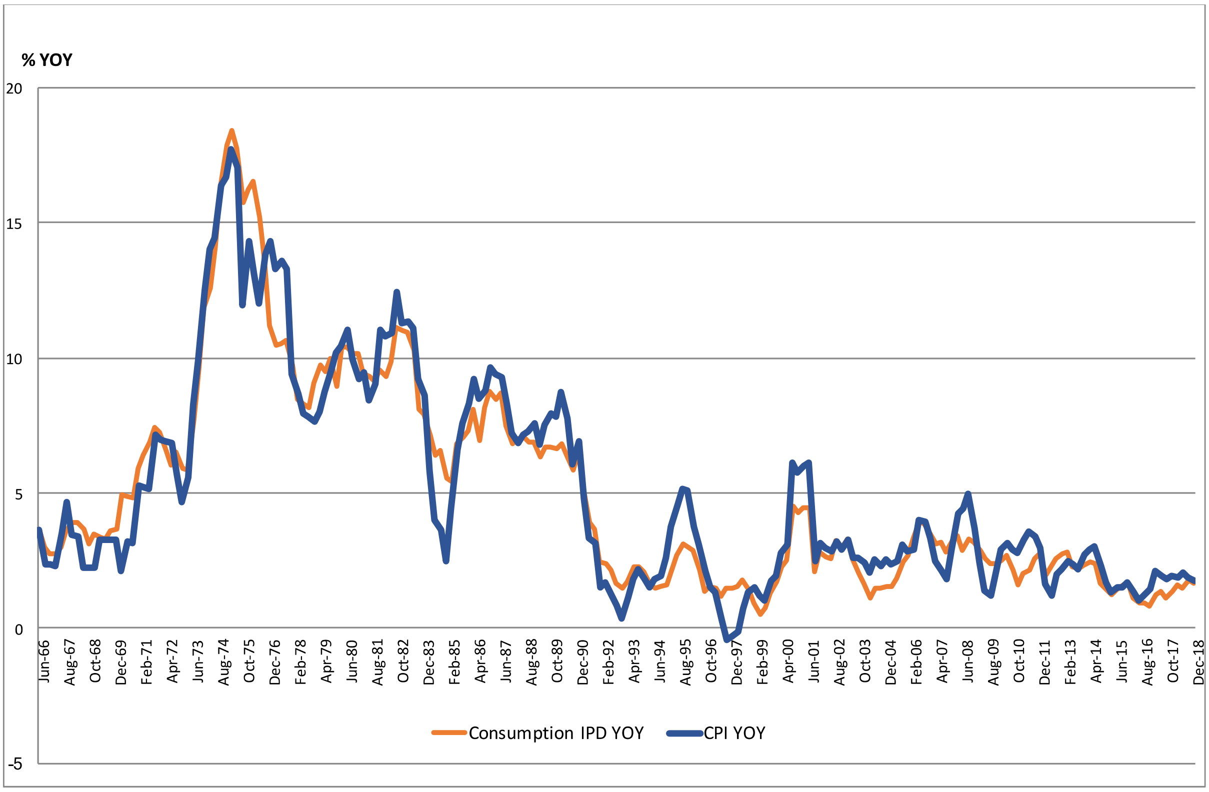

Figure 2: Measures of Consumer Prices in Australia (ABS-6401)

Inflation varies considerably between tradeable and non-tradeable expenditure items, as is apparent in Figure 3 (data from RBA (2019)). 53 of the 87 expenditure items in the CPI are classified as tradeable, contributing around 35% of the CPI (ABS-6401). The expenditure items included as tradeable and non-tradeable are listed in Table 2. Generally, a price is classified as non-tradeable when Australia is not a significant exporter or importer of that good or service. Where taxes and subsidies comprise a large component of the final price paid for a good or service, it is classified as non-tradeable. This is the case for alcohol and tobacco.

Tradeable inflation has been consistently lower and more volatile than non-tradeable since 1988 (Figure 3). There also seems to have been a decoupling of the cycles in tradeable inflation and non-tradeable inflation over the past 20 years.

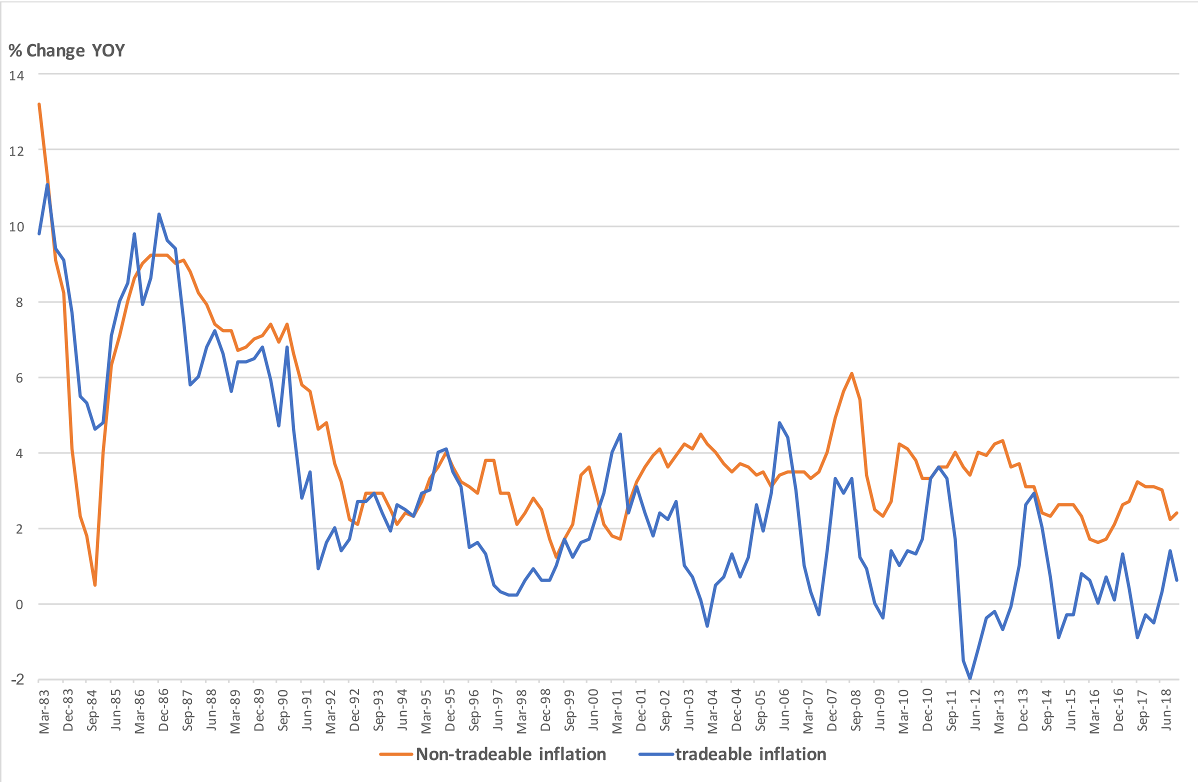

Figure 3: Tradeable and Non-tradeable CPI Inflation in Australia (RBA Statistical Tables June 2019)

Table 2 Tradeable and Non-tradeable Expenditure Items (ABS-6401)

Tradeable component	Non-tradeable component
Food and non-alcoholic beverages	
Breakfast cereals; Waters, soft drinks and juices; Cakes and biscuits; Other cereal products; Beef and veal; Pork; Lamb and goat; Other meats; Fish and other seafood; Cheese; Ice cream and other dairy products; Fruit; Vegetables; Jams, honey and spreads; Food additives and condiments; Oils and fats; Snacks and confectionery; Other food products not elsewhere classified; Coffee, tea and cocoa.	Bread; Poultry; Milk; Eggs; Restaurant meals; Take away and fast foods.
Alcohol and tobacco	
Wine.	Spirits; Beer; Tobacco.
Clothing and footwear	
Garments for men; Garments for women; Garments for infants and children; Footwear for men; Footwear for women; Footwear for infants and children; Accessories.	Cleaning, repair and hire of clothing and footwear.
Housing	
Gas and other household fuels.	Rents; New dwelling purchase by owner-occupiers; Maintenance and repair of the dwelling; Property rates and charges; Water and sewerage; Electricity.
Furnishings, household equipment and services	
Furniture; Carpets and other floor coverings; Household textiles; Major household appliances; Small electric household appliances; Glassware, tableware and household utensils; Tools and equipment for house and garden; Cleaning and maintenance products; Personal care products; Other non-durable household products.	Child care; Hairdressing and personal grooming services; Other household services.
Health	
Therapeutic appliances and equipment.	Medical and hospital services; Dental services; Pharmaceutical products.
Transport	
Motor vehicles; Spare parts and accessories for motor vehicles; Automotive fuel.	Maintenance and repair of motor vehicles; Other services in respect of motor vehicles; Urban transport fares.
Communication	
	Postal services; Telecommunication equipment and services.

Recreation and culture	
Newspapers, magazines and stationery; Audio, visual and computing equipment; Audio, visual and computing media and services; Books; International holiday travel and accommodation; Equipment for sports, camping and open-air recreation; Games, toys and hobbies.	Domestic holiday travel and accommodation; Veterinary and other services for pets; Sports participation; Other recreational, sporting and cultural services; Pets and related products.
Education	
	Preschool and primary education; Secondary education; Tertiary education.
Insurance and financial services	
	Insurance; Deposit and loan facilities (direct charges); Other financial services.

The heterogeneity of price changes becomes even more apparent on a CPI expenditure group basis. Price changes have been uneven between groups over the last decade. From March 2009 to December 2018, six of the eleven CPI Groups had smaller changes in prices than the overall CPI, one group (insurance and financial) had similar changes and four groups had substantially faster changes in prices – see Table 3 (ABS-6401).

Table 3: Percentage Change from March 2009 to December 2018

CPI Group	% Change
Communication	-17%
Clothing and footwear	-6%
Recreation and culture	6%
Furnishings, household equipment and services	6%
Food and non-alcoholic beverages	12%
Transport	16%
CPI total	23%
Insurance and financial	24%
Housing	39%
Health	50%
Education	53%
Alcohol and Tobacco	77%

Two groups contributed 57.3% of the change (13.5 percentage points out of 23.4) in inflation over the 11 years to December 2018[2] (see Table 4 (ABS-6401)). These two groups were alcohol

[2] Calculated by multiplying the changes in price for each group by their weight in the CPI (allowing for changes in weights with each rebase).

and tobacco, and housing. This impact is far greater than their weight in the CPI of 29.8% (ABS-6431).

Table 4: Percentage Point Contribution of Groups in the CPI from March 2009 to December 2018

CPI Group	**% Change**
Communication	-0.4%
Clothing and footwear	-0.2%
Furnishings, household equipment and services	0.6
Recreation and culture	0.7
Insurance and financial	1.4
Education	1.7
Transport	1.7
Food and non-alcoholic beverages	1.8
Health	2.6
Alcohol and tobacco	5.4
Housing	8.1
CPI total pp change	23.4

Most items in the CPI are subject to the Goods and Services Tax (GST) but some are also subject to additional excise taxes and duties, most notably alcohol, tobacco, and automotive fuels. Alcohol and tobacco have contributed significantly to the CPI, as can be seen by the detailed breakdown of the largest positive and negative contributors to the CPI from March 2009 to March 2019 (Table 5[3]). Tobacco by itself contributed 5 percentage points (pp), and this mostly reflects the rapid rise in tobacco excise rates. Housing also contributed significantly, new dwelling purchases and rents contributing 2.6 and 1.8 percentage points respectively.

Government policy and regulation have also affected another item significantly – electricity. In the past decade electricity has added 1.8 pp to the CPI as the pricing mechanism changed to include a component for recouping the cost of capital investment during a time when capital investment rose significantly (Plumb and Davis, 2010).

The largest contributors to the CPI increase all came from the non-tradeable sector. Most of the largest negative contributors come from the tradeable sector (Table 5).

[3] Shows the percentage point contribution to the change in the CPI between March 2009 and March 2019 (data sourced from ABS-6401).

Table 5: Largest Positive and Negative Percentage Point Contributions for 85 Series in CPI March 09 to March 19[4]

Audio, visual & computing equipment	-1.3	Tobacco	5.0
Telecommunication equipment and services	-0.9	New dwelling purchase by owner-occupiers	2.6
Garments for women	-0.3	Medical and hospital services	2.5
Motor vehicles	-0.3	Rents	1.8
Personal care products	-0.2	Electricity	1.8
Games, toys and hobbies	-0.1	Insurance and financial services	1.2
Household textiles	-0.1	Secondary education	0.8
Major household appliances	-0.1	Domestic holiday travel and accommodation	0.7
Milk	-0.1	Other services in respect of motor vehicles	0.7
Footwear for women	-0.1	Beer	0.7
Total	-3.5		17.8

Figure 4 expands from Table 5 and displays the percentage point contribution of all 85 expenditure components from March 2009 to March 2019, ordered from the largest negative contribution to the largest positive contribution. It illustrates how the vast majority of series in the CPI have made little contribution to the change in the CPI over the last decade. Only a relatively few components (largely those displayed in Table 5) are adding significantly or detracting significantly from the CPI.

[4] Calculated by multiplying the changes in price for each item by their weight in the CPI (allowing for changes in weights with each rebase).

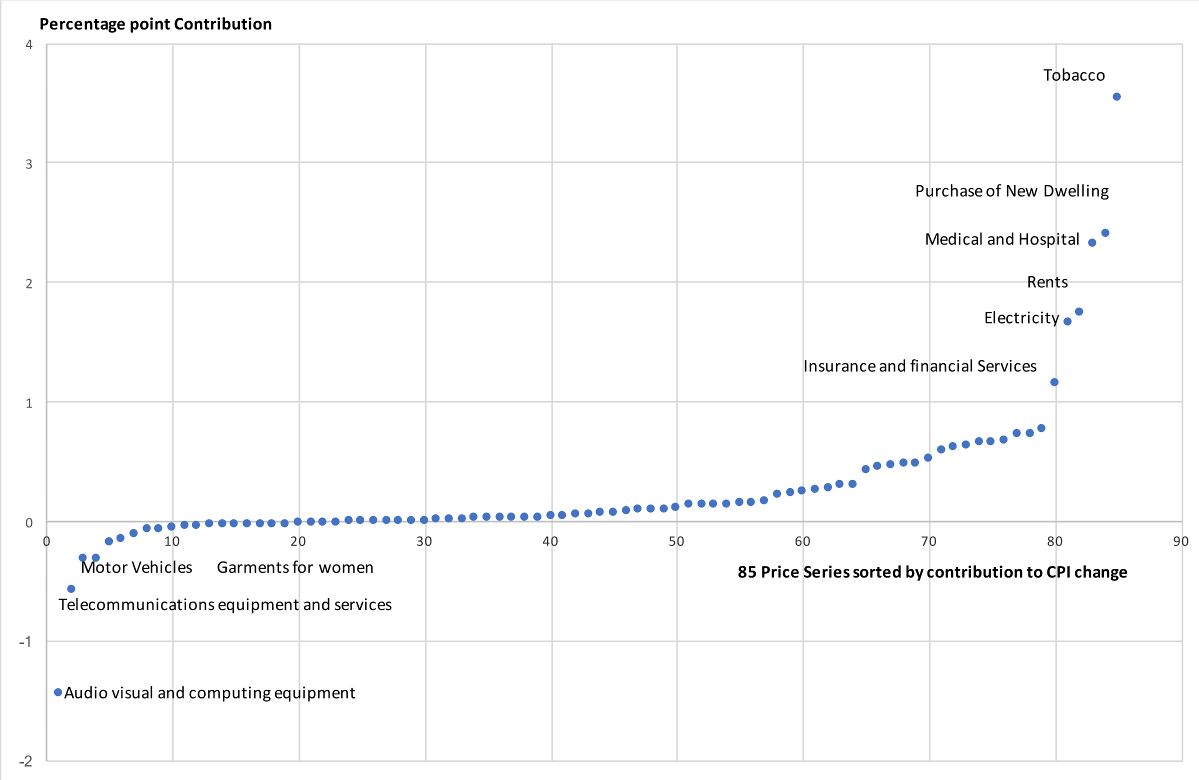

Figure 4: Percentage Point Contributions from March 09 to March 19 of the 85 CPI Components (ABS 6401)

3.2 Population Trends

Figures 5 and 6 below show that the young and middle population cohorts are the largest as a percentage of the population (source: ABS-3105.0.65.001, ABS-3101). The size of the youngest cohorts has been declining for most of the last 40 years while those in the later middle years and in their 60s and 70s have begun to rise as a share of the population.

The ratios that are used throughout the thesis are the late young to late middle ratio and the early old to late middle ratio. These ratios are shown in Figure 7. The late young ratio rose significantly from 1960, peaked in the late 1970s and then fell significantly over the next two decades. The early old ratio has been rising steadily, and more recently the rate of increase has picked up further.

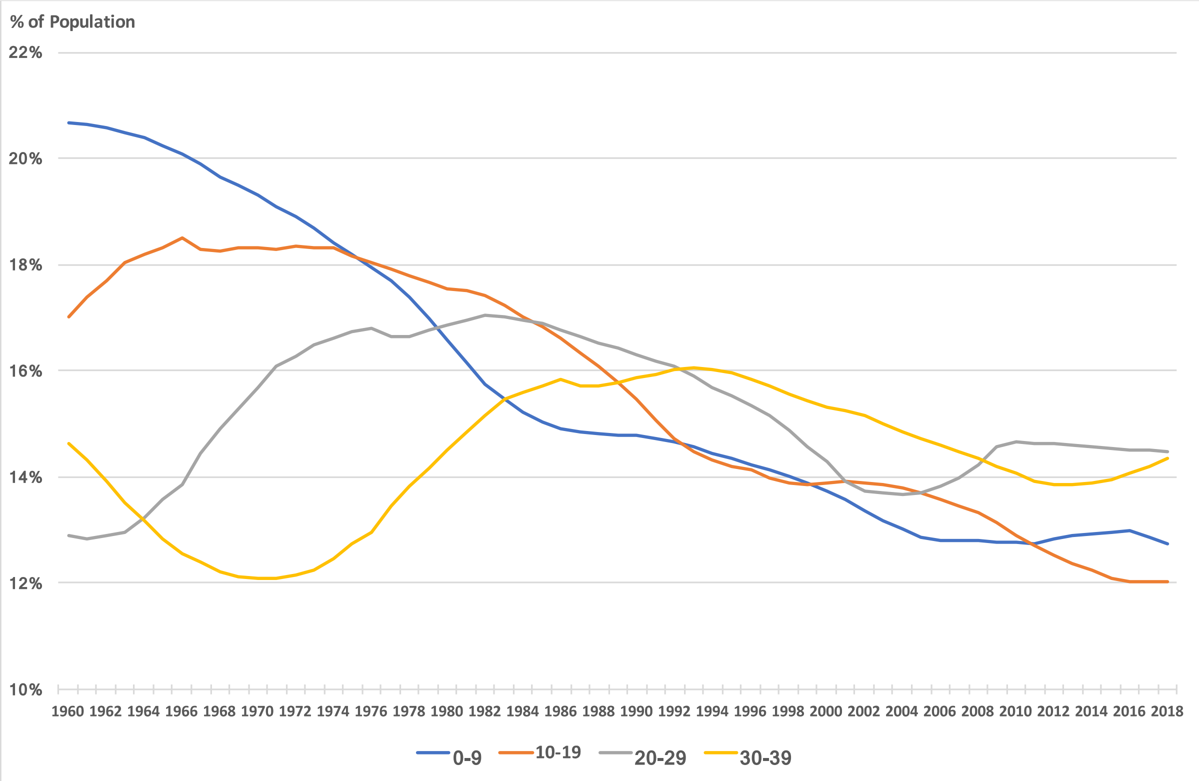

Figure 5: Population Ratios since 1960 – Younger Cohorts Relative to Total Population

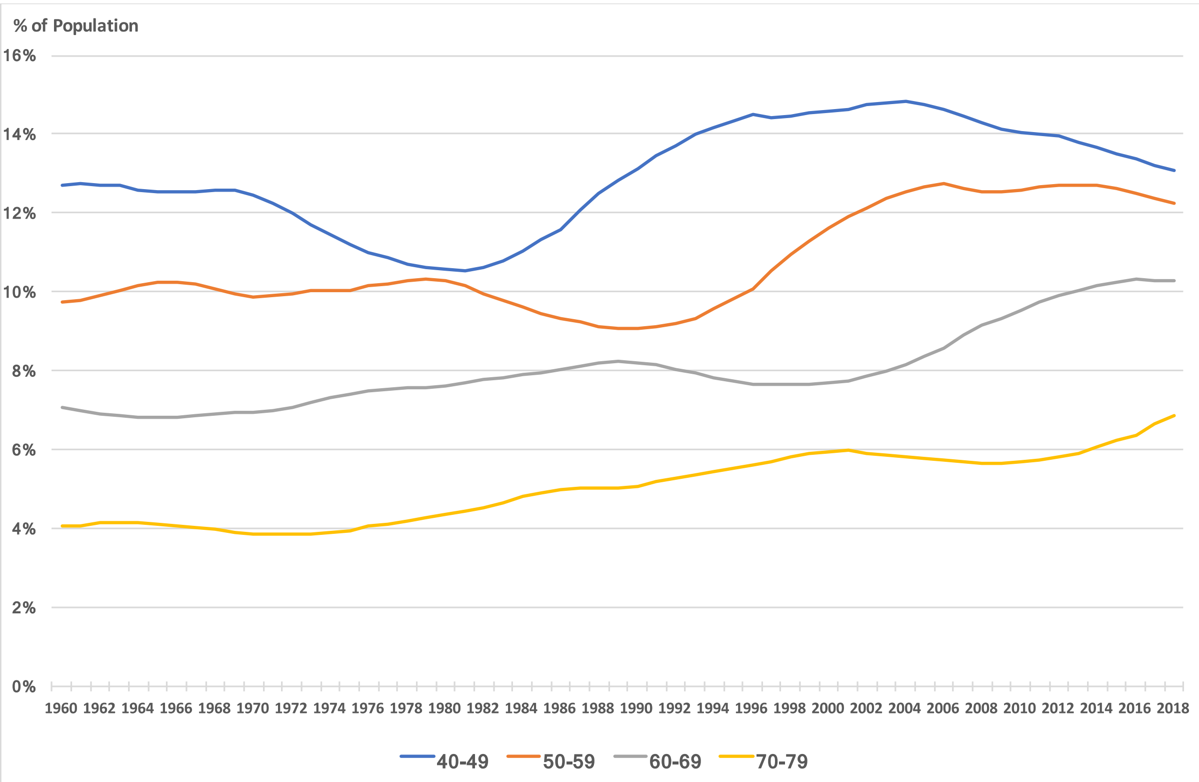

Figure 6: Population Ratios since 1960 – Older Cohorts Relative to Total Population

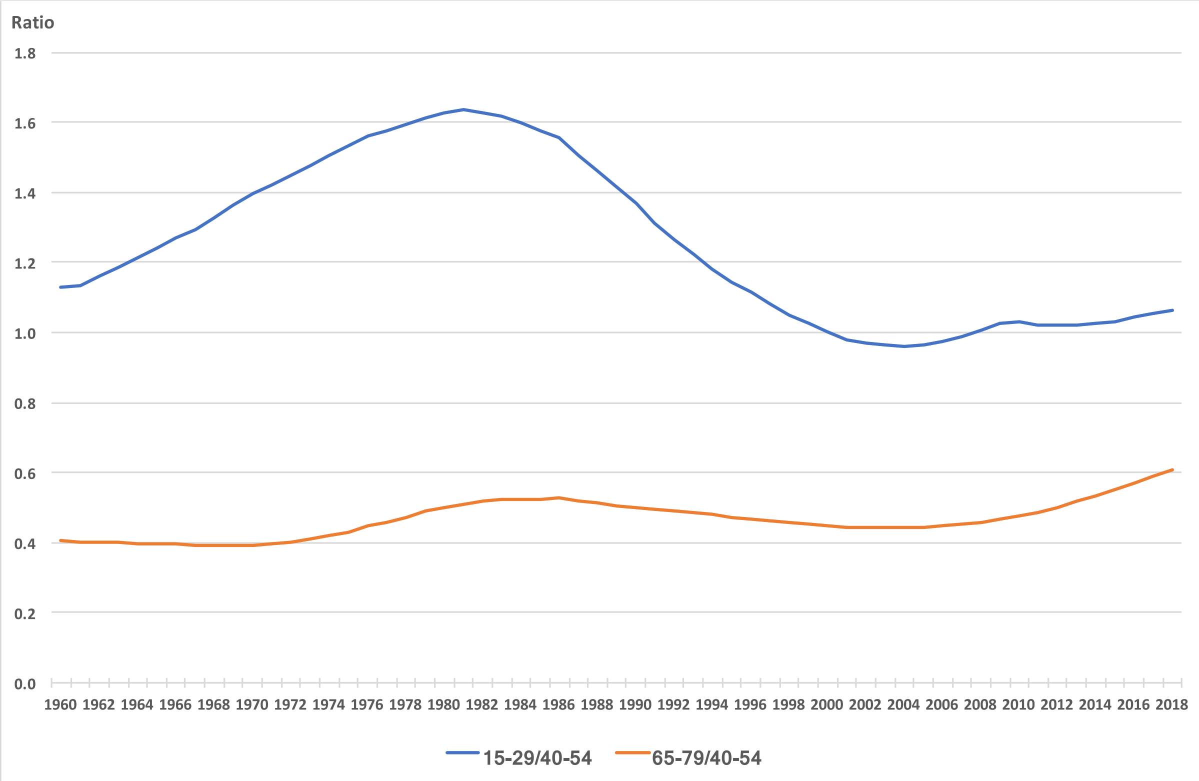

Figure 7: The Late Young to Late Middle Ratio and Early Old to Late Middle Ratio

Chapter 4: Research Framework and Data Issues

This chapter summarises the research framework, data and methodology used throughout the thesis. Methodology specific to Chapters 5, 6 and 7 is described at the beginning of each of those chapters.

4.1 Framework

Faust and Wright (2013) have highlighted the importance of improving inflation modelling through a better understanding of what drives low frequency changes in inflation. Age structure can potentially provide some of this understanding.

There are two key challenges to be confronted in applying age structure models. The first is to explain the contrasting results from studies to date regarding the impact of the early old (65-79 years) on inflation. This demographic is growing in most OECD countries and will be very important in the next two decades. The second challenge is to resolve the debate about the transmission mechanism between age structure and inflation. Greater clarity about the transmission mechanism will allow for better assessments of the likely stability of age structure and inflation links going forward.

This thesis will focus on analysing three questions:

1. Which of the common factors driving inflation are affected by age structure?
2. What impact do different parts of the age structure have on disaggregated prices?
3. What is the relative impact of the late young, late middle and early old age cohorts on aggregate inflation?

The first question is answered in Chapter 5 using dynamic factor analysis to model disaggregated inflation data. The optimal number of factors is analysed and rotated to maximise interpretability. Then correlation analysis is undertaken for each rotated factor assessing how many factors age structure ratios are correlated with. The impact of age structure ratios is estimated using dynamic regressions.

The second question is answered in Chapter 6 where each individual disaggregated inflation series is modelled against ratios covering each part of the age structure and control variables using multiple dynamic regressions. The coefficients of each part of the age structure are analysed looking for patterns. This process is repeated for a longer time span with a lower level of disaggregation as a check on the robustness of the results. The results are compared with known expenditure patterns for the opposite ends of the age structure.

This analysis of disaggregated price patterns helps to shed light on one of the mechanisms that may link demographic change to aggregate inflation. Anderson, Botman and Hunt (2014) and Katagiri (2018) suggest that demographic change affects relative demand for goods and services. This thesis addresses whether this translates into a link with relative price inflation. If demographic change affects relative price inflation then Reis and Watson (2010) results would suggest that demographic change is likely to impact aggregate inflation.

The third question will be answered in Chapter 7 where the relative importance and impact of the late young, late middle and early old cohorts on aggregate inflation will be analysed. The results will be used to project ahead the impact of demographics on aggregate inflation.

4.2 Modelling Structure

Inflation series are persistent – having a relatively long memory – and slowly evolving (as discussed in Chapter 2). A dynamic model (with a lagged dependent variable) is a common method for modelling this type of series. However, if the series is non-stationary a dynamic model can produce biased and unstable estimates and a cointegration framework should be used (Keele and Kelly, 2006).

Whether inflation series are stationary or not is a matter of considerable debate, as discussed in Chapter 2. It is likely to depend on the inflation series being modelled and the timespan. This thesis chooses the appropriate modelling structure based on whether the inflation series being modelled is stationary or non-stationary. In Chapter 5 the factors are stationary and are modelled using a dynamic lagged dependent variable structure.

For the disaggregated analysis in Chapter 6, over 500 equations are to be estimated and results compared. Thus, a consistent modelling structure is required. 53 out of 58 of the disaggregated inflation series reject the unit root null at 5% and 57 out of 58 at 10% – Augmented Dickey Fuller test (ADF) (Dickey and Fuller, 1979). Thus, a dynamic structure is applied in these disaggregated estimations.

In Chapter 7 aggregate inflation is found to be integrated of order one for Australia and is modelled using a cointegration framework.

A strength of using both dynamic lagged dependent variable and cointegration modelling methods in this thesis is that the results of both can be compared to determine whether the modelling method impacts conclusions about age structure variables.

4.3 Data

The demographic ratios used in this thesis are constructed from combining Australian Bureau of Statistics (ABS) current demographic statistics Table 59 (ABS-3101.0) with the historical population statistics (ABS-3105.0.65). Australian population statistics are available only on an annual basis. Inflation regressions in Chapters 6 and 7 thus use annual data.

In Chapter 5 factor analysis uses quarterly data to allow for the full dynamics of inflation to be extracted. In these models the population ratios are interpolated into quarterly ratios using a centred moving average. The slow movement of age ratios limits the disadvantage of interpolation and the use of annual data for the inflation regressions limits the reliance on interpolation.

For Australian price series there is a trade-off between the level of disaggregation available and the length of the time period. There are relatively few price series available in the early 1970s at the expenditure class level (the most disaggregated level published by the ABS). A significant number (44) were added from March 1980 to March 1982. It was thus decided to use all available expenditure classes from March 1982.

The yearly changes in the log of 58 quarterly price series from the ABS Consumer price index (ABS-6401) are used in both the factor analysis (Chapter 5) and the inflation regressions (Chapter 6). The year on year change in quarterly data is available from March 1983 and is calculated from June 1983 for annual data (consistent with other annual series from the ABS). The annual price data are calculated as an average of the four quarters' index levels. Where annual regressions use a lagged dependent variable, the regressions are run from 1984 to 2018.

Chapter 6 inflation regressions also use the yearly changes in the log of 12 National Accounts (ABS-5204) household expenditure price components (calculated as current price value divided by chain weighted constant value). This acts as a robustness check as it allows for longer time-span regressions – from June 1961 to June 2018.

Real GDP, import prices, and the household consumption implicit price deflator were sourced from the National Accounts (ABS-5204), and the exchange rate against the USD from the Balance of Payments data (ABS 5302). Oil prices in $US were sourced from the FRED database (WTISPLC).

The regressions in Chapters 5 and 6 use an output gap variable lagged four quarters and import prices with lagged two quarters. The lags were chosen using Akaike Information Criteria (AIC) to compare model performance with different lags (Akaike, 1974). Lags of the output gap are usually used in inflation models as prices are sticky and econometric models often show lags of at least four quarters between output gap and inflation (Black, Macklem and Rose, 1997, Druant, Fabiani, Kezdi, Lamo, Martins and Sabbatini, 2012, Fisher, Mahadeva and Whitley, 1996). Similarly the flow through from import prices to consumer prices takes time (see for example Lam (1994)).

Capital productivity variables were added as independent variables in Chapter 5 regressions – the capital productivity measures are calculated as the annual change in the log of real gross value added divided by the log of real value of capital stock for each industry (ABS-5204). The descriptive statistics for the independent variables in the regressions can be found in Appendix 1.

4.4 Limiting the Impact of Multicollinearity

It is clear from the literature review that multicollinearity is one of the key problems in age structure estimations. This will need to be addressed if the impact of the early old and aging in general is to be estimated reliably.

The degree of the potential problem is shown by the correlation between age structure ratios. Table 6 below shows the correlation between the various age cohorts. The age cohorts were calculated as a share of total population for the following cohorts: 0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, and above 80 years (80+) and the last row shows correlations for 65-74 years. Each row shows the correlation of each cohort with other cohorts where 1 represents 100% correlation and 0 represents 0% correlation.

Table 6: Correlation between Age Cohort Ratios 1960:2018

	0-9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
0-9	1.00	0.90	0.00	-0.61	-0.57	-0.61	-0.80	-0.92	-0.90
10-19	0.90	1.00	0.35	-0.46	-0.76	-0.74	-0.84	-0.97	-0.97
20-29	0.00	0.35	1.00	0.14	-0.65	-0.54	-0.10	-0.30	-0.33
30-39	-0.61	-0.46	0.14	1.00	0.31	-0.10	0.23	0.55	0.31
40-49	-0.57	-0.76	-0.65	0.31	1.00	0.57	0.37	0.72	0.70
50-59	-0.61	-0.74	-0.54	-0.10	0.57	1.00	0.70	0.69	0.85
60-69	-0.80	-0.84	-0.10	0.23	0.37	0.70	1.00	0.80	0.88
70-79	-0.92	-0.97	-0.30	0.55	0.72	0.69	0.80	1.00	0.94
80+	-0.90	-0.97	-0.33	0.31	0.70	0.85	0.88	0.94	1.00
65-74	-0.80	-0.87	-0.08	0.35	0.39	0.59	0.96	0.84	0.85

The older cohorts 60-69, 65-74, 70-79, and 80+ are highly inversely correlated (greater than 80%) with the young (0-9 and 10-19) and positively correlated with 50-59 years. The only age category with which they are not all strongly correlated is 20-29 years.

Methods that model multiple age structure variables against inflation will have the greatest potential multicollinearity issues. The more of the age structure that is modelled the greater the potential for multicollinearity. This issue needs to be weighed against the advantage of covering more of the age structure – that is, reducing potential missing variable risk.

Multiple regressions were estimated to assess how much of the age structure is relevant for inflation and whether each part of the age structure has the same impact on inflation. The regressions used the following structure:

$$\pi = \alpha_i + \beta_i Age_i + \varepsilon_i \qquad (1)$$

Where π denotes the annual change in log of CPI, α_i is an intercept for equation *i*, β_i is the coefficient of age cohort *i*, and ε_i is an error term for equation *i*. Age_i denotes the age cohort *i*, with *i* being an integer between 1 and 16. Each cohort is calculated as the number of people in the cohort as a proportion of the population. The 16 cohorts used are 0–4, 5–9, 10–14, 15–19, 20–24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–59, 60–64, 65–69, 70–74, and 75–79.

The R^2 of each equation was used to assess the degree of variance in inflation that is explained by each cohort. The equations were estimated over two time-periods: 1960 to 2018 and 1980 to 2018. The R^2 of each of the equations for each time-period and age cohort is shown in Figure 8.

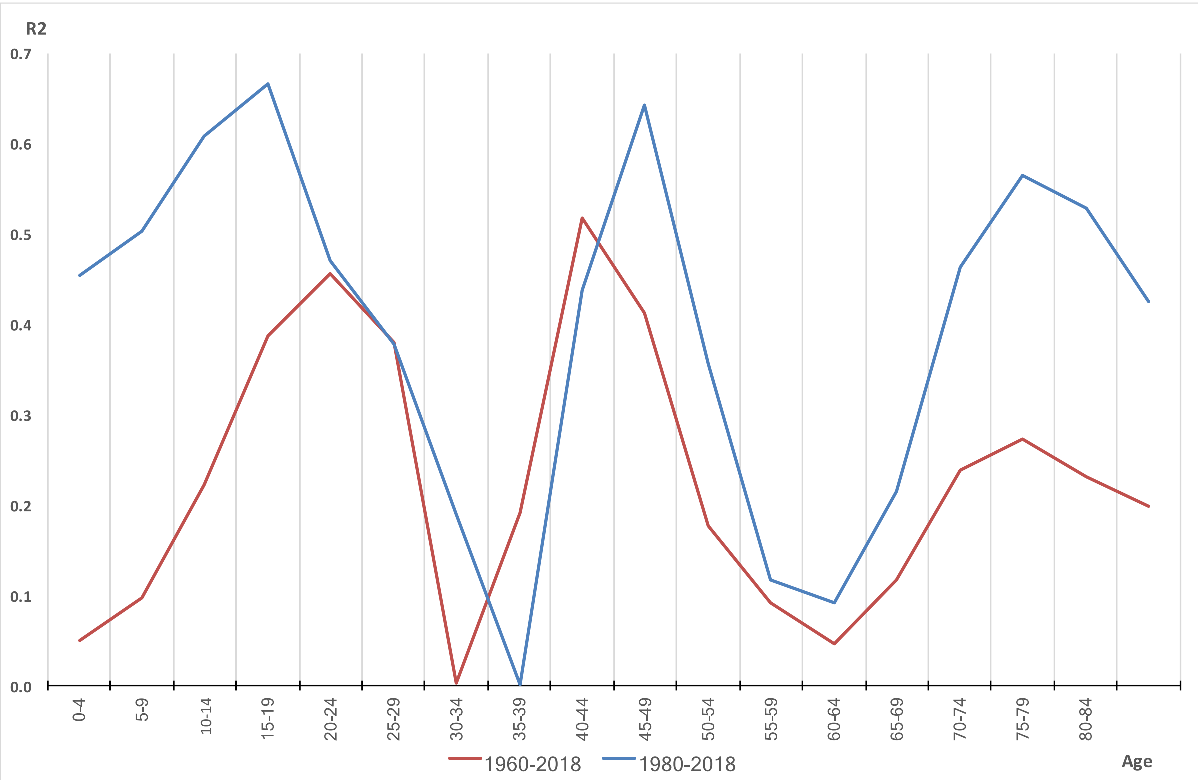

Figure 8: The Correlation of Each Age Share against Annual CPI Inflation

Figure 8 shows that not all cohorts are well correlated with inflation. The pattern is clear: late young and late middle ages are particularly well correlated with inflation, and the early old cohort also has some significance. The peaks appear to represent three key stages in life: early working life when people build new households and undertake all the expenditure associated with that, later working life when the children are grown and people begin to save for retirement, and finally after retirement when people often downsize housing and change expenditure patterns to reflect lower retirement earnings.

The key ages with the highest correlation with inflation in the early years appear to be 15-29 years. The key ages in middle years have changed a little over time – moving from 40-44 to 45-49 years in the more recent sample.

The change in the timing of the middle age peak is consistent with the change in timing of mothers having their first child. The median age of the mother for their first confinement was 24 years in 1974 and this has steadily increased to greater than 30 years from 2002 onwards (ABS-3105.0.65.001). The middle disinflationary peak appears to be around 15-20 years after the birth of the first child.

The correlation of the later years with inflation is generally higher for people from 65-79 years than for 60-64 years. This may reflect the heterogeneous nature of people in their early 60s – it is a time of flux when people are moving from one phase (employment) to another (retirement). Employment status varies significantly throughout the 60s; for example, 55% of 60-64 year olds work and 45% are retired (ABS-6238). In contrast 82% of people over 70 are retired.

Figure 8 implies that ratios that cover the three peaks in correlation between population and inflation – 15-29, 40-54, and 65-79 – are likely to capture most of the impact of age structure on inflation. The advantage of using more ratios may be outweighed by the disadvantage of increased multicollinearity. Similarly Lindh and Malmberg (1999) analysis suggests that capturing more of the age structure by using the population polynomial approach may also result in the age structure coefficients being significantly affected by multicollinearity.

The correlation coefficients for the three ratios (15-29, 40-54, 65-79) are high (Table 7) and above or around the threshold (0.7 Doorman et al. (2013)) usually associated with multicollinearity particularly for the late middle cohort relative to the late young and to the early old.

Table 7: Correlation Matrix for 15-29, 40-54, 65-79 as a Proportion of Population 1961:2018

	15-29	40-54	65-79
15-29	1.00	-0.88	-0.61
40-54	-0.88	1.00	0.67
65-79	-0.61	0.67	1.00

Further tests of multicollinearity were undertaken (Table 8 shows the results). The variance inflation factor (VIF) was calculated for the three age ratios. The VIF provides a summary measure of the degree of variance in one predictor that is explained by other predictors. Generally a VIF of 4 to 10 indicates significant multicollinearity (O'brien, 2007). The VIFs calculated for the three ratios are high, particularly for the late young and late middle age ratios.

Another way of measuring collinearity is to estimate the conditions indices - ratios of the largest eigenvalue to other eigenvalues (Belsley, 1980). The maximum conditions index provides an indication of the degree of potential collinearity. If it is around 10 then collinearity is unlikely to be an issue (Belsley, 1991). If conditions indexes are around 30 collinearity is likely to be an issue and if they are higher than 50, they are likely to be significantly affecting the regression (Belsley, 1991). Belsley (1991) suggests that the conditions indices be ordered from lowest to highest. Where there is a large jump from one conditions index to the next largest conditions index, a dependency between two or more of the variables is likely to be found. When that occurs, he suggests that the variance decomposition proportions for the larger of the two conditions indexes be examined to see if there are any that exceed 0.5 (indicating near dependencies).

The maximum conditions index for the three ratios is 23.4, which is not particularly high. It was, however, a significant increase on the next largest index of 10.9 – a sign that there may be a dependency at the conditions index level of 23.4. The variance decomposition for the conditions index at 23.4 suggests the dependency is between 40-54 and 65-74 year old cohorts (the variance decomposition proportion is 0.96 and 0.86 respectively for these age cohorts – Table 8 shows the variance decomposition amounts). Together this indicates there are some collinearity issues between these two age cohorts.

The Belsley analysis and the VIF estimates imply collinearity between the cohorts is likely to bias coefficients in equations that include all three population ratios.

Table 8: Multicollinearity Tests for Different Combinations of Ratios

Age Ratios	VIF	Belsley Criteria	
		Max Conditions Index	Variance Decomposition
15-29, 40-54, 65-79	4.4, 5.0, 1.8	23.4	.15, .96, .86
15-29/40-54, 65-79/40-54	1.0, 1.0	9.5	-

To reduce multicollinearity, the three ratios can be combined into two ratios – late young to late middle (15-29/40-54 years) and early old to late middle (65-79/40-54). Using these two ratios in inflation regressions will still enable inferences about the impact of aging on inflation. An assessment of the relative impact of late young, late middle and early older age cohorts can be made since both ratios have a common denominator – the late middle cohort. The correlation between these two ratios is reasonably low (around 0.03), and the VIF and maximum conditions indices are both low (Table 8), indicating that multicollinearity will not be an issue for these two ratios.

Thus, this thesis will use either single age ratios or these two ratios (15-29/40-54 and 65-79/40-54) in all regressions to minimise multicollinearity.

4.5 Regression Diagnostics

The errors from each regression equation in Chapters 5 and 6 are assessed for non-stationarity using the Augmented Dickey Fuller test (Dickey and Fuller, 1979) and for non-normality using the Shapiro-Wilk test (Royston, 1992). The Shapiro-Wilk test has been shown to have the best overall performance among commonly used normality tests (Yap and Sim, 2011). The errors are also tested for heteroscedasticity using the ARCH test (Engle, 1982). The Breusch–Godfrey test (Breusch, 1978) is used to test for serial correlation as the Durbin Watson test (Durbin and Watson, 1950) has been shown to be asymptotically biased in models with lagged dependent variables (Nerlove and Wallis, 1966) - as is the case in Chapters 5 and 6. When heteroscedasticity and/or serial correlation are detected, the Newey and West heteroscedasticity and autocorrelation consistent (HAC) standard errors are estimated and included in the results (Newey and West, 1987).

Chapter 5: Impact of Age Ratios on Factors Driving Inflation

This chapter aims to answer the question: what, if any, of the factors driving inflation are affected by age structure?

5.1 Factor Analysis Methodology

Factor analysis is used on the 58 CPI inflation series to simplify the structure of the data and isolate a small number of factors that describe the key dynamics of the data. The demographic variables are then modelled against these factors to see which of the factors, if any, they influence.

Dynamic factor analysis using principal components is undertaken on the year on year change in the log of 58 CPI price series as detailed in Chapter 4. Each inflation series was standardised to mean 0 and a standard deviation of 1. The inflation series were tested for unit roots using the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979). Five of the 58 series did not reject the unit root null at the 5% level (audio visual equipment, education, dental services, tobacco, and spirits), and one at the 10% level (audio visual equipment). A quadratic trend was applied to audio visual and computing equipment and a linear trend to the other four series to make them stationary (ADF null rejected at 5% significance level for all five de-trended series).

The optimal number of factors were then analysed using the 'scree test' (based on the methodology proposed by Cattell (1966), Bai and Ng (2002), and Alessi, Barigozzi and Capasso (2010).

Principal components analysis is an orthogonal transformation – meaning that it produces factors that are uncorrelated with each other. In the case of inflation series, this assumption is unlikely to hold true as the forces that affect all inflation variables are likely to have some cross-correlation. The factors will need to be rotated if they are to represent potential real life drivers of inflation.

It is likely that each inflation series is impacted by a range of economic influences, with certain series more responsive to certain influences than others. For example, in Chapter 3 the dynamics of traded and non-traded price inflation were shown to be quite different. Traded prices are more likely than non-traded prices to be affected by international influences (import prices, exchange rate, international inflation). However, both may be affected by some domestic factors – for example wage costs. In addition, some prices will have specific forces acting on them.

In other words, there are likely to be common influences that affect many prices by different amounts and there will also be influences that predominantly only affect some prices. All of these influences may be correlated to some extent – for example, the domestic output gap may be correlated with international growth. To capture these interactions, the factors were recalculated using a common factor model with maximum likelihood estimation of factor loadings Λ from:

$$x_t = \mu + \Lambda \mathrm{f}_t + \varepsilon_t \quad (2)$$

where x_t is a vector of inflation series at time t, f_t is a vector of independent specific factors, μ is a constant vector of means, and ε_t is a random error vector. The loadings are then obliquely rotated so that each inflation series is loaded onto only a few factors, with some correlation between factors allowed.

Promax and Equimax are both oblique rotations that allow for correlation between factors but still load variables predominantly onto a few specific factors (Gorsuch, 1983). These oblique rotations were undertaken. The rotated factors were then analysed using partial correlations between individual price series and the factors. Promax rotations were found to be the most interpretable and thus the factors derived from Promax were used for the factor regressions.

5.2 Factor Regression Methodology

The factors derived from the rotations should be stationary as the inflation series used for the factor analysis rejected the unit root null at 5% for the ADF test (as outlined in 5.1)[5]. To confirm this the six rotated factors were tested for unit roots using ADF, Phillips-Peron (PP) (Perron, 1988), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests (Kwiatkowski, Phillips, Schmidt and Shin, 1992). The results generally indicate that the factors are stationary for at least two of the three tests – that is, rejecting the unit root null (ADF and PP with a no intercept and trend specification) and failing to reject the stationary null (KPSS with an intercept specification).

Table 9: Unit Root Tests for the 6 Rotated Factors

	ADF	PP	KPPS
F1	-2.5*	-2.9*	0.2
F2	-1.2	-2.6*	0.1#
F3	-2.2*	-2.8*	0.147#
F4	-2.4*	-4.5*	0.2#
F5	-2.2*	-2.7*	0.6
F6	-2.5*	-3.0*	.51#
* reject null at 5%			
# fail to reject stationary null at 5%			

As discussed in section 4.2, a dynamic structure (with a lagged dependent variable) is preferred if the dependent variable is stationary, and so the factor regressions have the following form:

$$F_t^i = \alpha^i + \theta^i F_{t-1}^i + \beta^i Y_t + \delta^i O_t + \gamma^i X_t^i + \varepsilon_t^i \quad (3)$$

where F_t^i is factor *i* at time t where *i* is an integer from 1 to 6, and α^i is the intercept for factor *i*, θ^i is the coefficient on the lagged dependent variable, Y_t is the proportion of population 15-29 years relative to 40-54 years and β^i its coefficient, O_t is the proportion of population 65-79 years relative to 40-54 years and δ^i its coefficient, $X_t^i$are other independent variables that help explain factor *i* and γ^i is the coefficient vector for those variables, and ε_t^i is the error term for factor *i*. The population ratios are interpolated to quarterly ratios using a smoothed average

[5] A linear combination of stationary series should itself be stationary.

(since population data is published only on an annual basis). The other independent variables include an output gap variable (OutGapHP) estimated using a Hodrick Prescott filter (Hodrick and Prescott, 1997) on the log of real GDP leading four quarters[6], the year on year change in the log of the imports of goods and services implicit price deflator (ImpP) leading two quarters[7], and the year on year change in the log of health and social services capital productivity (Health)[8]. Two dummy variables were used to remove the effect of the introduction of the GST in 2001 (GST dummy and GST dummy2)[9].

Factor 4's equation also uses a dummy for the introduction and later repeal of the carbon tax (CARBON), the year on year change in the log of real net capital stock for Utilities (Util). The descriptive statistics for the independent variables in the regressions can be found in Appendix 1.

The residual diagnostics are assessed for normality, heteroscedasticity, serial correlation and stationarity. The estimation results were analysed to see which of the factors, if any, were influenced by age structure.

5.3 Factor Analysis Results

The variance explained by each of the first 10 factors from principal components factor analysis of the standardised inflation series is displayed in Figure 9 below. Around 39% of the variance of all inflation series is explained by the first factor and around 7 % by the second factor. The variance explained by each factor declines quickly and eventually a point is reached where the variance explained by the extra factor is not sufficient to warrant its inclusion – that is, the improvement in goodness of fit is not sufficient to outweigh parsimony.

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[6] As outlined in section 4.3.
[7] As outlined in section 4.3.
[8] Used as a proxy for childcare productivity as childcare is included in the social services category. Calculated as the year on year change in the level of real gross value added in an industry divided by the value of its real capital stock (ABS-5206). This provides a capital productivity measure. This type of industry productivity proxy was the only one available over the full estimation period.
[9] It was necessary to have two dummies rather than one to ensure that the impact of the introduction of the GST did not affect the coefficient of the lagged dependent variable.

Several methods were used to determine the optimal number of factors. These are summarised in Appendix 2. The ‘scree test’ points to between 3 and 7 factors (see Appendix 2 for details). Bai and Ng (2002) tests suggest between 3 and 10 factors are optimal, and the Alessi, Barigozzi and Capasso (2010) test suggests 6 factors are optimal (see Appendix 2 for details).

The first 6 factors were rotated using Promax rotation. Appendix 3 shows the correlations between the price series and each individual factor calculated using Promax rotation. The correlations show:

- Factor 1 is predominantly a non-traded services based factor with transport services, telecommunications services, postal services, hairdressing, maintenance of dwelling services, restaurant meals and take away all highly correlated with this factor. In addition clothing, footwear and household related items – furniture, textiles, carpets, major appliances – are all well correlated with this factor.

- Factor 2 is correlated predominantly with food products excluding meats, cleaning, personal care products and pet products.

- Factor 3 is a mixed factor correlated with meats, spirits, rents, dental services and motor vehicle spare parts, international holidays and education.

- Factor 4 is predominantly a utilities and electricity factor.

- Factor 5 is correlated with tools and equipment for garden, childcare, and domestic holiday travel and accomodation. Cleaning and maintenance products and motor vehicles are also highly correlated with this factor.

- Factor 6 is correlated predominantly with internationally sourced goods – audio visual equipment, motor vehicles and small electrical appliances.

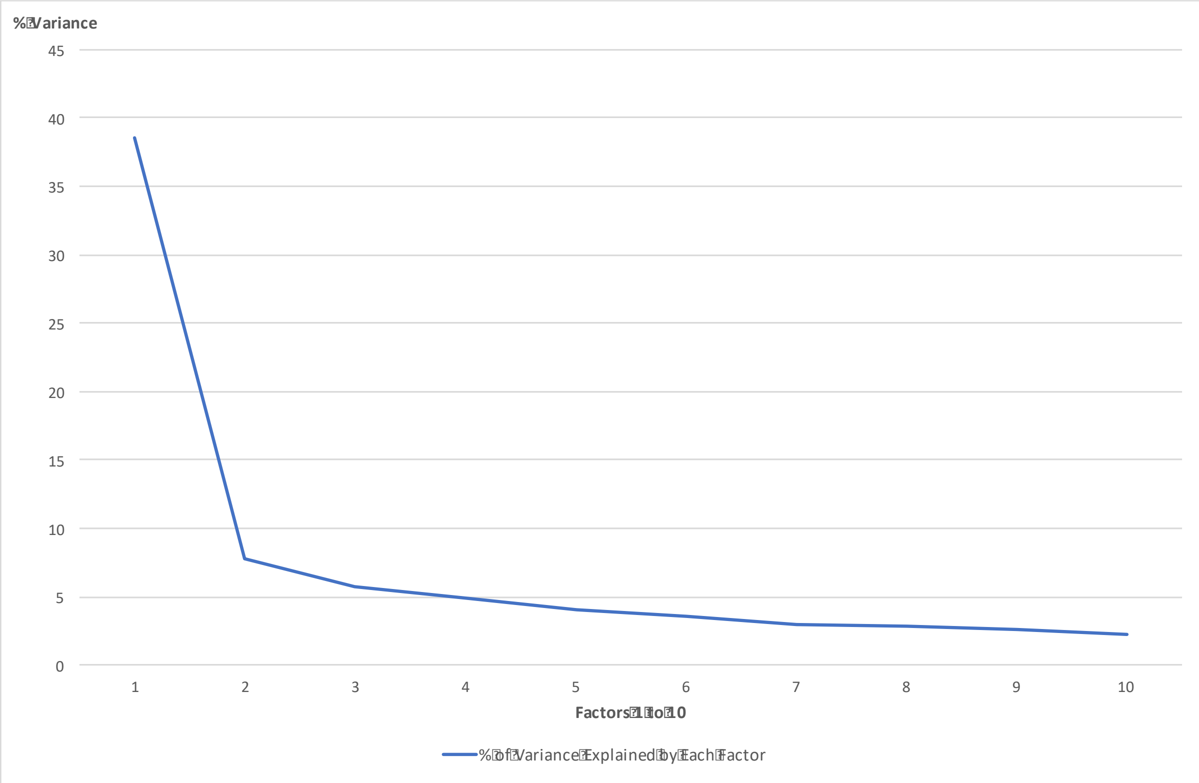

Figure 9: Percentage of Variance of 58 CPI Prices YOY Explained by Each Factor

Partial correlations were used to assess which factors were correlated with age structure ratios. Table 10 shows the statistically significant (with a p-value of less than 5%) correlations (1 represents 100% correlation and 0 represents 0% correlation). A negative correlation suggests the cohort is negatively correlated with the factor. The partial correlation results show that age ratios are correlated particularly with factor 1, 2, 5, and 6. A few of the age ratios have some correlation with factor 3 and 4 – see Table 10.

Table 10: Partial Correlations Factors and Age Cohorts March 1983 to Jun 2018

	0-9	**10-19**	**20-29**	**30-39**	**40-49**	**50-59**	**60-69**	**70-79**	**80+**	**65-74**
F1	0.69	0.81	0.67	0.49	-0.68	-0.60	-0.43	-0.71	-0.72	-0.51
F2	0.66	0.76	0.57	0.63	-0.37	-0.63	-0.63	-0.76	-0.72	-0.67
F3		0.32			-0.34			-0.29		-0.17
F4		0.29	0.30		-0.46			-0.39		
F5	0.47	0.61	0.56	0.20	-0.70	-0.37		-0.56	-0.47	-0.23
F6	0.43	0.35	0.50	0.36	-0.36	-0.49		-0.35	-0.40	

The pattern is the same across factors – cohorts up to 39 years of age are positively correlated and cohorts after 40 are negatively correlated. This points to aging being disinflationary for ages 40 and above.

For factor 1 the highest correlations are for cohorts between 10-29 years and beyond 70 years, and for factor 2 they are for cohorts between 10-39 years and after 70 years. This is consistent with factor 1 being correlated with many non-traded items and thus more likely to be affected by domestic factors – like age structure. Factor 2 is predominantly related to food, and it would be expected that younger cohorts would be positively associated with food intake as the young eat more than the old (Wakimoto and Block, 2001).

Factor 3 is a mixed factor that is not strongly correlated with age cohorts. Factor 4 includes utilities and electricity and is only moderately correlated with the 40-49 years and 70-79 years old cohorts.

Factor 5 is correlated with domestic services and the young cohorts are positively correlated and the older cohorts negatively correlated with this factor. For factor 6, which is a predominantly traded factor, the correlations with age cohorts are lower but similar across all cohorts except for the 60-69 years old cohort.

5.4 Factor Regression Results

The factors were regressed against the late young to late middle (Y) and early old to late middle (O) ratios as outlined in 5.2. The results are summarised in Table 12 with the significant coefficients (at 5%) for Y and O bolded and the residual tests shown at the bottom of the table.

Tests on the residuals show the ADF unit root null is rejected at 5% for all equations (Dickey and Fuller, 1979). The Shapiro-Wilk (SW) test (Royston, 1992) normality null failed to be rejected for all equations (indicating that the distributions are unlikely to be non-normal) except for factor 4 . Factor 4's equation also rejected the null of no heteroscedacity using the ARCH test (Engle, 1982), although the Breusch-Godfrey (BGLM) test (Breusch, 1978) for no serial correlation was not rejected at 5%. The ARCH test failed to be rejected for the other factors, indicating that heteroscedacisticity is unlikely to be affecting those equations. The equations for factors 2, 3 and 6 showed signs of serial correlation, rejecting the null at 5% significance levels. Together, these results suggest the coefficients and standard errors may be biased for factor 4, and the standard errors may be impacted by serial correlation in factor 2, 3, and 6 equations. To adjust for this, the table reports the Newey-West heteroscedacity and autocorrelation (HAC) adjusted standard errors.

Factor 4 is predominantly correlated with utilities and electricity. Utilities and electricity pricing has changed over the past two decades due to Government policy and regulation (Plumb and Davis, 2010). The residual test results potentially reflect some of these regulatory changes not being captured by the model. Plumb and Davis (2010) argue that the change in regulatory policy has increased the link between the change in utilities real net capital stock and inflation, as providers are able to include a component for recouping capital investment costs in their pricing. This link is modelled by using the year on year change in the log of real net capital stock for the utilities sector (UTIL).

The coefficients of Y (late young to late middle ratio) are positive and significant for factors 1, 2 and 5. This suggests that the late young ratio is inflationary for these factors. Factor 1 is correlated with a range of domestic products and services including products associated with building a household. Factor 2 is correlated with food, which, as discussed in section 5.3 is an item that this cohort is likely to consume proportionately more of. Similarly, factor 5 is correlated with childcare and domestic travel which may also be impacted by demand from this cohort.

The coefficients of O (early old to late middle ratio) are negative and significant for factors 1 and 2. The early old ratio is disinflationary for these factors, particularly for factor 2. This may reflect this ratio’s impact on the demand for food, as discussed in section 5.3.

The coefficients on the other independent variables were as expected with the coefficient on import inflation (ImportP) being positive and significant for factors 1, 3, 5 and 6; the coefficient on the output gap being positive and significant for factors 1 and 2; and the growth in utilities real net capital stock being significant and positive for factor 4.

The two GST dummy variables were included for all variables to take account of the impact of the introduction of the GST on the factors. The sign of the coefficient of these dummies varied between factors. This change in sign is probably an artefact of the promax factor rotation.

Table 11: Factor Regression Results – Coefficients and Standard Errors ()

	F1	F2	F3	F4	F5	F6
F (-1)	0.82	0.81	0.93	0.74	0.82	0.87
	(0.05)*	(0.05)*	(0.04)*	(0.05)*	(0.04)*	(0.03)*
Y	**0.65**	**0.62**	-0.06	0.31	**0.45**	0.06
	(0.23*)	(0.25)*	(0.28)	(0.32)	(0.24)*	(0.26)
O	**-0.62**	**-2.78**	-0.14	0.73	0.15	-0.24
	(0.31)*	(0.84)*	(0.94)	(0.82)	(0.70)	(0.90)
ImportP	0.66	0.68	0.92		0.97	3.50
	(0.31)*	(0.47)	(0.50)*		(0.47)*	(0.48)*
C	-0.48	0.64	0.10	-0.91	-0.64	0.00
	(0.22)*	(0.32)*	(0.43)	(0.51)*	(0.44)	(0.43)
OutGapHP	5.06	9.05				
	(2.12)*	(4.29)*				
GSTdummy	0.38	-1.59	-0.94	0.29	-0.42	-1.87
	(0.12)*	(0.08)*	(0.07)*	(0.07)*	(0.14)*	(0.08)*
GSTdummy2	2.46	-0.22	0.45	0.57	-1.46	-0.06
	(0.13)*	(0.13)*	(0.10)*	(0.15)*	(0.10)*	(0.10)
Util				8.24		
				(2.61)*		
Carbon				1.59		
				(0.21)*		
Health					-2.81	
					(1.17)*	
Adjusted R2	0.98	0.92	0.91	0.86	0.87	0.89

Sample Period: March 1983-December 2018

* Coefficient significant at 5%

Residual Diagnostics				
	ADF	SW	ARCH	BGLM
F1	-5.5**	0.99*	1.35*	3.19*
F2	-4.73**	.993*	0.10*	14.6
F3	-6.53**	.992*	0.45*	32.6
F4	-11.8**	0.93	8.7	1.42*
F5	-2.4**	0.99*	1.35*	3.19*
F6	-10.90**	.992*	0.16*	7.85

* Fail to reject null at 5% (that is SW – normality, ARCH – no heteroscedasticity, BGLM – no autocorrelation)

** Reject unit root null at 5% (ADF)

5.5 Summary of Factor Regression Results

The factor regression results indicate that aging is disinflationary. A relative rise in the late young to late middle ratio increases inflation, and a relative rise in the late middle to late young or early old to late middle ratios reduces inflation. The results also indicate that the effects of aging vary across prices – that aging impacts relative prices. Some factors are more impacted by a rise in the late young to late middle ratio, some factors more by a rise in early old to late middle, and some factors are not significantly affected by either.

Chapter 6: Age Structure and Disaggregated Prices

Having established that aging affects some of the factors that drive Australia's inflation and potentially impacts relative prices, this chapter seeks to quantify the impact of different parts of the age structure on disaggregated price inflation. The aim is to test whether specific parts of the age structure have specific effects on relative prices, and whether these effects align with the demand pattern for that part of the age structure. If they do, this will point towards relative demand as being the potential link between age structure and prices.

6.1 Disaggregated CPI Inflation Series Regressions Methodology

A consistent modelling structure is required for these regressions to enable comparisons between ratios and inflation series, as discussed in section 4.2. The inflation series were tested for unit roots using the Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979). Five of the 58 series do not reject the unit root null at the 5% level (audio visual equipment, education, dental services, tobacco, and spirits), and one at the 10% level (audio visual equipment). As 53 of the 58 series reject the unit root null, a dynamic structure (using a lagged dependent variable) will be used in the estimations. This structure may show some bias for the five non-stationary series (Keele and Kelly, 2006) – particularly for audio visual equipment which has a stronger trend.

The 58 individual inflation series from June 1983 to June 2018 were regressed against different population ratios variables using the following regression structure:

$$\pi_t^i = \alpha^i + \beta^i \pi_{t-1}^i + \gamma^i Ageshare_h + \delta^i OutGap_{t-4} + \theta^i Imp_{t-2} + \sigma^i GST_t + \rho^i Oil_t + \varepsilon_t^i \quad (3)$$

where π_t^i is the annual change in the log of consumer price series *i* at time *t*, *i* is an integer between 1 and 58 (58 CPI disaggregated prices), $Ageshare_h$ is the age share *h*, from the ratios of 0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70-79, 80+, and 65-74 years to total population with all the ratios rebased to equal to 1 in 1983, where *h* is the number of age shares (an integer from 1 to 10), $OutGap_{t-4}$ is the GDP gap estimated using a Hodrick Prescott filter (Hodrick and Prescott, 1997) led four quarters[10], Imp_{t-2} is the annual change in the log of import prices led two quarters[11], GST is a dummy variable for the introduction of the GST in 2001, *Oil* is the annual change in the log of the price of West Texas Crude in Australian dollars, α^i is the intercept, β^i, θ^i, δ^i, γ^i, ρ^j, and σ^i are coefficients derived for the independent variables in the regression of inflation series *i* and ε_t^i is the error term for the regression of inflation series *i*. All data is annual. Price data was annualised using the average of the four quarter index levels.

The t-Statistics for each coefficient were used to determine whether the coefficient is significant at 5% significance levels and the significant coefficients were analysed to look for patterns across age cohorts.

The patterns in relative prices were then compared with patterns in relative demand for older and younger households using National Accounts data (ABS-5204.0.55).

6.2 Household Consumption Expenditure Inflation Regression Methodology

As a robustness check on the disaggregated inflation regressions, annual National Accounts data from 1959 to 2018 were used to regress the annual change in the log of 12 household consumption price deflators against age structure variables. These price deflators were estimated by dividing the item in current prices by its value in chain weighted constant prices. After differencing and lagging the dependent variable, this enabled the regression to cover the period 1961 to 2018. Nine of the 12 National Accounts household expenditure components rejected the unit root null at the 5% significance level, and 3 at 10% significance level.

The regression structure followed that of equation 3 with π_t^i representing the change in the log of *i*th household expenditure inflation series, where *i* is an integer between 1 and 12 (12 disaggregated prices).

[10] See 4.2 for a rationale and method for determining this lead.
[11] See 4.2 for a rationale and method for determining this lead.

6.3 Disaggregated CPI Inflation Series Regression Results

58 CPI price series were regressed on each of the age variables as specified in equation 3. The residuals from each regression were assessed. The ADF test rejects the unit root null for all the residuals at 5% significance level. Heteroscedasticity was generally not an issue, with 92% of the residuals not rejecting the null of no heteroscedasticity using the ARCH test at the 5% significance level. Serial correlation was reasonably limited with 92% not rejecting the null of no serial correlation at 1% significance levels (BGLM test) and around 79% at 5% significance levels. The Shapiro-Wilk test for normality did not reject the null of normality for 76% of residuals at the 5% level and 87% at the 1% level. Together these tests suggest that the coefficients from the equations for the age ratios should be reasonably unbiased.

The t-Statistics of each age ratio coefficient (γ in equation 3) were used to eliminate all age structure coefficients not significant at the 5% level from the analysis. The following tables (Tables 12,13 and 14) list all the significant γ estimates for each price and each ratio.

The age ratios have been rebased to equal 1 in 1983 to enable the size of the γ coefficients for each inflation series to be compared. If an inflation series is more impacted by one ratio compared to others, the γ coefficient of that ratio should be higher than the γ coefficient of other age ratios for that inflation series. Thus, the relative sizes of the γ coefficients for each inflation series provide an indication of the relative importance of each age ratio.

Table 12 shows that all four of the younger age ratios tend to have positive coefficients (that is, they are inflationary). The pattern of coefficients is consistent with the likely demand profile for a young household – positive coefficients for food, clothing, and expenditure items associated with establishing a household (furniture, textiles, appliances, maintenance and repair of dwelling), and having children (personal care products – which includes nappies – for the 0-9 cohort, dental services for 10-19 cohort, and education for 0-9, 10-19 and 20-29 year cohorts).

Table 12: Statistically Significant γ Coefficients – Younger Ratios

	0-9	**10-19**	**20-29**	**30-39**
Bread	0.22	0.18		0.24
Cakes and biscuits		0.23		
Breakfast cereals	0.25	0.38	0.26	
Milk	0.20	0.13		0.31
Jams, honey and spreads	0.27	0.31		0.25
Other food products		0.17		
Coffee, tea and cocoa			0.28	
Restaurant meals	0.11	0.14	0.17	
Take away and fast foods		0.09	0.12	
Wine	0.25	0.23	0.24	0.16
Beer		0.12	0.19	
Clothing and footwear		0.18	0.22	
Footwear for men		0.15	0.22	
Footwear for women	0.25	0.29	0.35	
Footwear for infants and children	0.21	0.22	0.35	
Cleaning, repair, hire of clothing & footwear	0.13	0.15	0.18	
Maintenance & repair of the dwelling	0.09	0.11	0.14	
Utilities	-0.17			-0.21
Electricity				-0.26
Furniture	0.19	0.21	0.22	
Carpets and other floor coverings		0.12		
Household textiles	0.55	0.41	0.64	0.26
Major household appliances	0.19	0.18		0.16
Small electric household appliances	0.21	0.16	0.25	
Cleaning and maintenance products	0.34	0.36	0.40	0.25
Personal care products	0.27	0.35		0.18
Hairdressing, personal grooming services	0.17	0.18	0.23	
Pharmaceutical products	0.26	0.32	0.35	
Dental services		0.10		
Spare parts, accessories for motor vehicles		0.10		
Automotive fuel		0.19	0.26	
Maintenance, repair of motor vehicles		0.11		
Urban transport fares	0.26	0.27	0.34	
Telecommunication equipment & services		0.18	0.18	
Audio, visual and computing equipment				0.32
Education	0.12	0.16	0.17	

Table 13: Statistically Significant γ Coefficients – Middle Ratios

	40-49	**50-59**
Bread		-0.09
Breakfast cereals		-0.09
Milk		-0.08
Jams, honey and spreads		-0.09
Restaurant meals	-0.10	-0.04
Take away and fast foods	-0.09	
Wine		-0.08
Beer	-0.12	
Tobacco	-0.24	
Clothing and footwear	-0.10	
Footwear for men	-0.16	
Footwear for women	-0.18	-0.09
Footwear for infants and children	-0.25	
Cleaning, repair, hire of clothing & footwear	-0.10	-0.05
Maintenance & repair of the dwelling	-0.10	-0.03
Furniture		-0.07
Household textiles		-0.18
Major household appliances		-0.07
Small electric household appliances		-0.09
Cleaning and maintenance products		-0.12
Personal care products		-0.09
Hairdressing, personal grooming services	-0.11	-0.06
Pharmaceutical products		-0.10
Spare parts, accessories for motor vehicles	-0.12	
Automotive fuel	-0.18	
Urban transport fares	-0.13	-0.10
Postal services	-0.11	
Education	-0.10	

Table 13 shows that the 40-59 cohorts are generally disinflationary. 40-49 is associated with lower clothing and footwear, eating out, education, and transport inflation, and 50-59 with lower food and household related expenditure (furniture, textiles, appliances) inflation.

Table 14 shows this disinflationary trend continues for older age cohorts. The pattern is similar to the middle cohorts with significant negative coefficients for food, clothing, and household related items (maintenance and repair of dwelling, furniture, textiles, and appliances).

Table 14: Statistically Significant γ Coefficients - Older Ratios

	60-69	65-74	70-79	80+
Bread	-0.10	-0.13	-0.16	-0.04
Cakes and biscuits		-0.09	-0.22	-0.03
Breakfast cereals		-0.11	-0.30	-0.04
Other cereal products		-0.10	-0.17	
Milk	-0.12	-0.12		-0.03
Ice cream and other dairy products		-0.10		
Eggs	-0.16	-0.15		
Jams, honey and spreads	-0.12	-0.17	-0.24	-0.05
Other food products	-0.06	-0.09	-0.14	-0.02
Coffee, tea and cocoa			-0.17	
Restaurant meals			-0.10	-0.02
Take away and fast foods			-0.08	
Spirits			-0.10	
Wine		-0.08	-0.14	-0.04
Beer			-0.09	
Clothing and footwear			-0.11	-0.02
Footwear for men			-0.10	
Footwear for women			-0.16	-0.04
Footwear for infants and children			-0.14	-0.03
Cleaning, repair, hire of clothing & footwear			-0.09	-0.02
Maintenance & repair of the dwelling			-0.08	-0.01
Utilities	0.10			
Electricity	0.14	0.11		
Furniture		-0.06	-0.12	-0.03
Household textiles	-0.10	-0.12	-0.20	-0.08
Major household appliances	-0.06	-0.07	-0.10	-0.03
Small electric household appliances		-0.07	-0.11	-0.03
Cleaning and maintenance products	-0.10	-0.13	-0.28	-0.05
Personal care products	-0.07	-0.09	-0.15	-0.05
Hairdressing, personal grooming services		-0.05	-0.12	-0.03
Pharmaceutical products			-0.19	-0.04
Spare parts, accessories for motor vehicles			-0.08	
Automotive fuel			-0.16	
Maintenance, repair of motor vehicles			-0.08	
Other motor vehicle services			-0.07	
Urban transport fares			-0.20	-0.04
Telecommunication equipment & services			-0.20	
Pets and related products			-0.18	
Education			-0.11	-0.02

The pattern of the young being inflationary and the old being disinflationary appears to be very consistent as the population ages. Regressions of 5 year age shares suggest that the crossover point – where aging starts to be disinflationary – is in the 35-40 years of age cohort. Up to 35 years of age, the age ratios tend to be predominantly associated with higher inflation in individual price series, and after 35 they tend to reduce inflation in most prices.

This is summarised in Table 15 which shows the statistically significant (at 5%) coefficients of the ratio of the share of the population from 0-34 years to 35 years plus. It shows that an increase in the share of the young correlates with a rise in inflation for many items. The strongest effects tend to be clustered in items related to child rearing: personal care products (this expenditure item includes nappies) 0.22 and cleaning products 0.24, footwear for infants and children 0.17; food – cereals 0.21, jams, honey and spreads 0.17, cakes and biscuits 0.13; and establishing a household – household textiles 0.36, furniture 0.16, small electrical appliances 0.13, major household appliances 0.12.

As a robustness check, equation 3 was altered to include the two age ratios used in the previous chapter. Both (Y) late young to late middle (15-29/40-54) and (O) early old to late middle (65-79/40-54) ratios are included in each price equation to see if the results change if more of the age structure is included. Table 16 shows the results of these regressions, listing the coefficients of each age variable that are statistically significant at the 5% level.

Table 15: Statistically Significant Coefficients for Ratio of 0-34/35+ Years

	0-34/35+
Household textiles	0.36
Cleaning and maintenance products	0.24
Personal care products	0.22
Pharmaceutical products	0.21
Breakfast cereals	0.21
Footwear for women	0.19
Urban transport fares	0.19
Jams, honey and spreads	0.17
Footwear for infants and children	0.17
Furniture	0.16
Wine	0.15
Automotive fuel	0.13
Small electric household appliances	0.13
Cakes and biscuits	0.13
Hairdressing, personal grooming services	0.12
Major household appliances	0.12
Clothing and footwear	0.11
Bread	0.11
Footwear for men	0.11
Telecommunication equipment & services	0.10
Cleaning, repair, hire of clothing & footwear	0.10
Education	0.10
Restaurant meals	0.09
Beer	0.09
Milk	0.09
Maintenance & repair of the dwelling	0.07

The results from Table 16 are consistent with the other regressions from equation 3. The late young to late middle ratio is positively correlated with many prices, particularly with household related items (textiles, furniture, appliances, cleaning materials), and items related to having a young family (personal care products which includes nappies, clothing and footwear, and food). The early old to late middle ratio is negatively correlated with food, telecommunications, pets, cleaning and personal care products. The only positive correlation for the early old ratio is for tobacco products.

Table 16: Statistically Significant Coefficients of Y and O in inflation series regressions

	15-29/40-54	**65-79/40-54**
Bread	0.09	-0.32
Cakes and biscuits	0.11	-0.27
Breakfast cereals	0.17	-0.33
Other cereal products		-0.31
Cheese		-0.32
Ice cream and other dairy products		-0.28
Eggs		-0.44
Jams, honey and spreads	0.12	-0.41
Other food products	0.07	-0.25
Restaurant meals	0.07	
Take away and fast foods	0.05	
Wine	0.10	-0.18
Beer	0.08	
Tobacco		0.44
Clothing and footwear	0.10	
Footwear for men	0.09	
Footwear for women	0.15	
Footwear for infants and children	0.15	
Cleaning, repair, hire of clothing & footwear	0.07	
Maintenance and repair of the dwelling	0.06	
Furniture	0.11	-0.15
Household textiles	0.21	-0.26
Major household appliances	0.07	
Small electric household appliances	0.08	
Tools, equipment for house & garden	0.11	
Cleaning and maintenance products	0.18	-0.30
Personal care products	0.14	-0.31
Hairdressing, personal grooming services	0.09	
Pharmaceutical products	0.16	
Dental services	0.04	
Motor vehicles	0.09	
Spare parts, accessories for motor vehicles	0.06	
Automotive fuel	0.09	
Urban transport fares	0.13	-0.18
Telecommunication equipment & services	0.09	
Pets and related products	0.07	
Education	0.08	

6.4 Does the Relative Price Profile Reflect Relative Demand?

The relative price effects of different cohorts appear consistent with what would be expected of a life cycle demand profile, especially in terms of the effect of an increase in the ratio of young persons on food, housing and household items inflation.

Household consumption statistics enable a further assessment of whether these relative prices changes do reflect age structure demand differences. The ABS publish a breakdown of household expenditure by age of the head of the household in the National Accounts (ABS-5204.0.55). While this does not give an exact match for the impact of age structure on demand, the differences between the older and younger household cohorts provide an indication of the different demand preferences between old and young.

Table 17: $'000 Spent per Young (25-64) and Old (65 and over) Household

	25-34	65 and over	Young - old
Actual rent for housing	4.9	0.8	4.1
Catering	4.5	1.7	2.8
Other goods and services	4.4	2.1	2.2
Operation of vehicles	3.7	1.8	1.8
Purchase of vehicles	2.7	1.0	1.7
Goods for recreation and culture	2.9	1.2	1.7
Furnishings and household equipment	3.5	1.9	1.6
Recreational and cultural services	3.2	2.0	1.3
Clothing and footwear	2.5	1.3	1.2
Education services	1.3	0.2	1.1
Transport services	1.8	0.8	1.1
Food	5.9	4.8	1.0
Cigarettes and tobacco	1.4	0.5	1.0
Communication	1.9	1.0	1.0
Other financial Services	2.2	1.7	0.5
Alcoholic beverages	1.1	0.6	0.5
Electricity, gas and other fuel	1.2	0.9	0.3
Accommodation services	0.6	0.3	0.2
Books, papers, stationery and artists goods	0.8	0.7	0.1
Water and sewerage services	0.4	0.4	0.0
Insurance	1.7	1.8	-0.1
Health	2.1	2.5	-0.4
Imputed rent for owner-occupiers	6.1	8.5	-2.4

Table 17 shows that younger households spend more per household than older households on rent, eating out (catering), vehicles, household related items (furnishings and equipment), clothing, education, transport and food. Imputed rent for owner-occupiers, health and insurance are the items on which older households spend more compared with young.

These spending patterns are consistent with the relative price patterns from the regression equations. Overall, these results point to the age structure's impact on relative demand having a significant impact on relative prices.

6.5 National Accounts Household Expenditure Inflation Regressions

120 price series regressions were conducted and the residuals assessed. The ADF test indicates the residuals from all equations reject the null of unit root at 5% significance level. 67% of the residuals fail to reject the null of no heteroscedasticity using the ARCH test at the 5% significance level. The null of no serial correlation is not rejected in 55% of equations at 5% significance and 92% at the 1% level (BG test). The Shapiro-Wilk test for normality suggests that 58% of residuals fail to reject the null of normality at the 5% level, and 74% fail to reject at the 1% level. Together these tests suggest that the coefficients from the equations for the age ratios may have some degree of bias.

The t-Statistics for each age ratio coefficient were used to eliminate all age structure coefficients not significant at the 5% level from the analysis. Tables 18, 19 and 20 show the statistically significant coefficients of various age ratios for each price series.

The 0-9 age cohort affected two prices significantly – reducing cigarettes and tobacco and increasing clothing and footwear (Table 18). The patterns for 10-19 and 20-29 years cohorts are similar to the results from the CPI data. They were significant for clothing, housing, and furnishings related components, and both were significant for hotels, restaurants and cafes. 20-29 years was significant for food, tobacco and alcohol, and 10-19 years for communications.

Table 18: Statistically Significant γ Coefficients for the Younger Cohorts

	0-9	10-19	20-29	30-39
Food			1.2	
Cigarettes and tobacco	-0.6		1.9	
Alcoholic beverages			1.4	
Clothing and footwear	0.2	0.3	0.6	
Actual rent for housing		0.2		
Imputed rent for owner-occupiers		0.2		
Furnishings, household equipment		0.3	0.8	
Communication		1.2		
Total hotels, cafes and restaurants		0.3	1.2	

30-39 had no significant coefficients. This is different to the pattern seen in the CPI data 1983 to 2018 estimations.

Table 19 shows that the 40-59 cohorts had significantly negative coefficients for food, furnishings, clothing, alcohol, transport and restaurants.

Table 19: Significant γ Coefficients on Middle Year Cohorts

	40-49	50-59
Food	-1.0	
Alcoholic beverages	-1.1	
Clothing and footwear	-0.7	-0.6
Furnishings, household equipment	-0.7	-0.5
Transport services	-1.6	
Total hotels, cafes and restaurants	-1.0	

Table 20: Statistically significant γ Coefficients on Older Cohorts

	60-69	65-74	70-79	80+
Cigarettes and tobacco	1.4	3.2		
Clothing and footwear			-0.9	-0.8
Actual rent for housing		-0.7		
Imputed rent for owner-occupiers		-0.7		
Furnishings, household equipment			-0.7	-0.6
Communication	-2.1	-5.0	-3.1	-2.5

Table 20 shows that the older cohorts had a disinflationary effect on furnishings, clothing, rent or imputed rent, and communications. This is a similar pattern to the CPI data. The 60-69 and 65-74 cohorts had positive coefficients for tobacco.

6.6 Summary of Results

This chapter’s cohort regressions indicate that the early and late young have an inflationary impact on many inflation series, particularly for goods and services on which those cohorts spend proportionately more money per household. Late middle, early old and late old years have a disinflationary effect, particularly for items that they spend proportionately less money per household on.

This is an important result because it points strongly to relative demand being a key link between age structure and inflation. Aging changes the amount of money spent on particular items and this appears to then change the rate of inflation in those items. Thus, aging is likely to be important for both relative and aggregate inflation.

Chapter 7 Relative Importance of Late Young, Late Middle and Early Old Cohorts

7.1 Methodology

The results of the disaggregated inflation regressions point to a consistent pattern of younger cohorts being inflationary, and late middle and older cohorts being disinflationary. This appears to reflect changes in relative demand for goods and services. What is also apparent from the coefficients is that some cohorts appear to impact more inflation series than others.

Two possibilities emerge from this analysis:

1. the young provide the major inflationary stimulus and the results for older cohorts reflect the proportion of young people falling as the population ages, or
2. the changing demand profile of older cohorts has a disinflationary effect in addition to the effects of the changing level of young people in the population.

The objective of this chapter is to assess the long run relationship between age structure and inflation, particularly the relative impact of different parts of the age structure. To estimate this, the late young to late middle age ratio and early old to late middle ratio are modelled against inflation. This enables conclusions to be drawn about what effect an increase in the number of retirees will have on inflation, and inflation projections based on Australia's changing age structure to be determined.

The data series used are the annual change in log of the CPI, the ratio of 15-29 years to 40-54 years population, and the ratio of 65-79 to 40-54 years population from 1961 to 2018.

The levels of integration of the age cohorts and inflation are first assessed to help determine the most appropriate method for estimation. If inflation and age cohorts are non-stationary then it is appropriate to test for cointegration.

Unit root tests are performed using the Augmented Dickey Fuller (ADF), Phillips Perron(PP) (Perron, 1988), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (Kwiatkowski, Phillips, Schmidt and Shin, 1992) tests.

If the variables are non-stationary, tests for cointegration will be conducted. Cointegration implies that there is a stable long run relationship between the variables, and the impact of the age ratios will be able to be determined.

Cointegration is assessed using the Engle-Granger cointegration test (Engle, 1987) and the Johansen maximum likelihood cointegration test (Johansen, 1991). The Engle-Granger test is a test of the residuals of the standard ordinary least squares regression of:

$$\pi_t = \alpha + \beta Y_t + \gamma O_t + \sigma D_t + \varepsilon_t \quad (5)$$

where π_t is the annual change in the log of the CPI at time t, Y_t is the ratio of population of 15-29 years to 40-54 years, O_t is the ratio of population of 65-79 to 40-54 years, D_t is a deterministic linear time trend, α is the intercept, β, σ and γ are coefficients, and ε_t is the error term. The null hypothesis of no cointegration is tested by using ADF to test the residual for a unit root.

In the Johansen test (Johansen, 1991) the rank of the matrix Π is identified in the equation:

$$\Delta X_t = \delta + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + BD_t + \varepsilon_t \quad (6)$$

where X_t is a column vector of k variables, D_t is a vector of deterministic terms and B is the coefficient matrix for those terms, δ is an intercept, Γ is a matrix of coefficients for the lagged first difference of the variables, and ε_t is the error term. In this case X_t contains CPI inflation, the ratio of population of 15-29 years to 40-54 years, and ratio of population of 65-79 to 40-54 years. If the rank of Π is less than the number of variables, then there are r cointegrating vectors. The cointegrating vectors and adjustment parameters are derived from Π. Thus, the Johansen test assesses cointegration and derives the long run relationships between the variables.

Stock and Watson (1993) dynamic ordinary least squares (DOLS) approach to estimating cointegrating vectors is used to determine the long run relationships between the age variables and inflation. DOLS has several advantages over other methods of estimation. It controls for endogeneity by including leads and lags of the first differences of the regressors, it corrects for serially correlated errors using a generalised least squares procedure or HAC standard errors (Newey and West, 1987), and performs well relative to other estimation techniques even where variables are of differing levels of integration and cointegrated (Hawdon, 1999, Stakėnas, 2010, Stock and Watson, 1993).

A dynamic ordinary least squares (DOLS) model is estimated with the following structure:

$$\pi_t = M'X_t + \sum_{i=-m}^{i=n} \phi_i \Delta Y_{t-i} + \sum_{i=-m}^{i=n} \theta_i \Delta O_{t-i} + \sigma D_t + \epsilon_t \quad (7)$$

where π_t is the change in the log of the CPI at time *t*, *Y* is the ratio of population of 15-29 years to 40-54 years, *O* is the ratio of population of 65-79 to 40-54 years, *M* is a cointegrating vector of coefficients showing the long run impact of the explanatory variables X_t (constant, *Y, O*), D_t is the deterministic dummy variable for the GST and a deterministic linear time trend and σ is the coefficient vector for these deterministic terms, ϵ_t is the error term, ϕ, and θ are coefficients of the first difference of the regressors, and *m* and *n* are leads and lags of the first difference of the regressors.

The Akaike information criteria (Akaike, 1974) and Bayesian information criteria (Schwarz, 1978) are used to calculate the optimal number of lags and leads. Where these information criteria choose 0 leads and 0 lags, 1 lead and 1 lag are used in order to include the dynamic aspects (the change variables) in equation 7. Without leads and lags equation 7 becomes a standard ordinary least squares regression.

The estimated coefficients are compared with the coefficients derived from the Johansen cointegration test. The coefficients are then used to project forward the impact of age structure on inflation in Australia based on the Australian Bureau of Statistics projections for population (ABS 3222.0). The scenario chosen is scenario B which is the middle case based on recent demographic trends.

7.2 Results

Unit root tests (see Table 21) results vary. There is little support for the variables being stationary in levels. The KPSS null hypothesis is that the series is stationary. It points to all variables in levels rejecting stationarity at 5% significance levels. In first differences all variables fail to reject the null at 5%. ADF and Phillips Perron test the null hypothesis that the variables are non-stationary (have a unit root). They suggest that the variables in levels fail to reject the non-stationary null at 5% significance levels, with the exception of the late young ratio for the ADF test. CPI inflation unit root nulls in first differences are rejected at 5% and the age ratios unit root nulls are rejected in second differences at 5% for Phillips Perron. The late young ratio for ADF unit root null is rejected in second differences at 5% and the early old unit root null is not rejected by ADF in second differences. Together these tests suggest that the variables are not I(0). This means that it will be appropriate to test for cointegration.

Table 21: Unit Root Tests

	Level	**1st difference**	**2nd difference**
ADF Unit Root Tests H_o=unit root			
CPI Annual Change	-2.07	-7.52**	-6.92**
15-29/40-54 ratio	-3.37**	-1.02	-7.06**
65-79/40-54 ratio	-1.10	-1.86	-2.41
** Unit root Null rejected at 5% significance			
PP Unit Root Tests H_o=unit root			
CPI Annual Change	-2.07	-7.59**	-23.83**
15-29/40-54 ratio	-0.98	-1.26	-7.06**
65-79/40-54 ratio	-0.29	-0.98	-7.73**
** Unit root null rejected at 5% significance			
KPSS Stationarity Tests			
H_o=stationary			
CPI Annual Change	.34	.01##	.056##
15-29/40-54 ratio	.50	.30##	.18##
65-79/40-54 ratio	.47	.18##	.18##

Stationary null not rejected at 5% significance

The Engle-Granger test was used to test null of no cointegration with a deterministic trend and without a deterministic trend. The null is rejected with and without a deterministic trend at 5% for the tau-statistic (-4.7 and -3.9 respectively) and 5% for the z-statistic (-29.5 and -30.3 respectively) – the z-statistic is the normalised autocorrelation coefficient. The estimate uses 1 lag (selected using Akaike information criteria for lag selection with a maximum lag of 10). Thus, the Engle-Granger test suggests that the variables are cointegrated.

A Johansen test was estimated with CPI inflation, late young to late middle and early old to late middle ratios, a GST dummy as an exogenous variable, and one lag for the difference equation. The test was estimated with and without a deterministic linear trend. The estimated coefficient for the deterministic trend was statistically significant, suggesting that there is a deterministic time trend common to the cointegrating variables. The test results for the Johanson test with the deterministic linear trend are shown in Table 22.

Table 22: Johansen Cointegration Tests

Unrestricted Cointegration Rank Test (Trace)

Hypothesised No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.354384	51.29450	42.91525	0.0059
At most 1 *	0.269084	26.79165	25.87211	0.0384
At most 2	0.152077	9.238039	12.51798	0.1662

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesised No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.354384	24.50286	25.82321	0.0739
At most 1	0.269084	17.55361	19.38704	0.0905
At most 2	0.152077	9.238039	12.51798	0.1662

* denotes rejection of the hypothesis at the 0.05 level
** p-values from MacKinnon, Haug and Michelis (1999)

The trace test suggests the variables are cointegrated with a rank of two (two cointegrating equations) as the nulls of none and at most one cointegrating equations are rejected at 5% but the null of at most two cointegrating equations is not rejected at 5% at the level.

The maximum eigenvalue test fails to reject the null of no cointegration at 5% (probability 0.07). At 10% the maximum eigenvalue test rejects the null of no cointegration and rejects a rank of at most one cointegrating equation but fails to reject the null of at most two cointegrating equations.

Lüutkepohl, Saikkonen and Trenkler (2001) show that for cointegrating systems of rank 2 and above with a small sample (which is the case here) the trace test is more sensitive and has an advantage over the maximum eigenvalue test. Given this, the above results are consistent with the series being cointegrated with a rank of two. From the cointegrating vector the following long run equation for CPI inflation can be derived (Table 23).

Table 23: Johansen Long Run Equation for CPI Inflation

π =	0.21 Y	- 0.42 O	0.00145 TREND
(Standard Errors)	(0.036)	(0.174)	(0.0007)

where π is the CPI inflation rate, Y is the ratio 15-29/40-54 years and O is the ratio 65-79/40-54 years and TREND is a linear time trend (rising from 1 to the number of observations). The coefficients indicate that inflation is positively correlated with the late young to late middle ratio and negatively correlated with the early old to late middle population ratio. This means that from late middle years onward, aging is increasingly disinflationary.

Given that both Engle and Granger and Johanson tests support cointegration, the long run relationship is modelled using DOLS (Table 24). DOLS estimation requires an optimal lag and lead length to be chosen. The optimal lag length selected using Akaike information criteria and Bayesian information criteria was 0 lead and 0 lag which, if implemented, would have resulted in equation 7 simplifying to a standard ordinary least squares estimation.

To ensure dynamics are included a lead of 1 and lag of 1 were selected and the results are shown in Table 24. The standard errors in Table 24 are HAC standard errors using Akaike criteria to select the optimal number of lags.

The standard errors are low relative to the size of the Y and O coefficients suggesting that they are statistically significant – t-Statistics imply that they are statistically significant at 1% significance levels. Estimations of the coefficients remain similar for longer leads and lags – for example, an estimation (not reported) using a lead of 2 and a lag of 2 produces approximately the same estimate of the coefficient of Y (0.22) and a slightly larger estimate of the coefficient of O (-0.73). The standard OLS estimate (not reported) with a zero lead and zero lag produces a slightly lower estimate for the coefficient of Y (0.19) and a lower estimate of the coefficient of O (-0.42).

The DOLS estimate of the coefficient of Y is similar to that derived from the Johansen maximum likelihood estimation (.22 versus .21) and the coefficient of O is larger (-0.64 versus -0.44). Both estimations imply that rises in the Y ratio are inflationary and rises in the O ratio are disinflationary.

The residuals fail to reject the null of normality at 5% (Shapiro Wilks (SW) test) and the null of no heteroscedasticity at 5% (ARCH test) but reject the null of no serial correlation at 5% (BGLM test) – see the bottom of Table 24. This is less of a problem for DOLS estimations as they perform relatively well in the presence of serial correlation (McCoskey and Kao, 1998).

Table 24: DOLS Estimation 1961:2017 1 Lead 1 Lag (Equation A)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
15-29/40-54	0.22	0.031	7.2	0.000
65-79/40-54	-0.64	0.179	-3.6	0.009
Intercept	0.003	0.081	0.0	0.972
TREND	0.0019	0.0005	3.7	0.006
GST	0.052	0.0064	8.0	0.000

R-squared	0.77	Mean dependent var.	0.05
Adj R-squared	0.72	S.D. dependent var.	0.04
S.E. of regression	0.02	Sum squared residual	0.02
SW (normality)	.96*	BGLM (no serial Corr.)	17.4
ARCH (no Heterosc.)	1.88*		

* Fail to reject null at 5%

Tests on the residuals show the residuals are not non-stationary at 1% significance levels (ADF and PP reject null at 1%) and stationarity is not rejected at 10% (KPPS does not reject null at 10%). This is consistent with there being cointegration between the variables (see Table 25).

To test the stability of coefficients across time the regressions were rerun from 1980 to 2018 – see Table 26. The estimation used 1 lead and 1 lag – the same as for Equation A. ADF and PP tests on the residuals of the equation reject the null of a unit root at 1% and KPPS tests fail to reject the null of stationarity at 10%, consistent with the residuals being stationary and the variables in the equation being cointegrated – see Table 25, row 'residuals Equation B'. The other residual tests (bottom of Table 26) fail to reject the null of no heteroscedasticity and normality at 5%. The BGLM test rejects the null of no serial correlation at 5%.

Table 25: Unit Root Tests on DOLS Regression Residuals

Test:	ADF (unit root)	PP (unit root)	KPPS (stationary)
Residuals Equation A	-5.61***	-4.15***	0.03###
Residuals Equation B	-5.81***	-5.35***	0.24###

*** Reject unit root null at 1%,
Accept stationary null at 10%

The coefficient for Y is a little larger than for the full sample (0.25 versus 0.22) and the coefficient for O is smaller than for the full sample (-0.43 versus -0.64) but is still statistically significant at 1%. The estimates are affected by the lags and leads chosen. An estimation with 0 lead and 0 lag (not reported) produced a reasonably similar coefficient for Y (.22) and a smaller coefficient for O (-0.27).

The results from Equation A and B are broadly comparable to the results from the disaggregated regressions detailed in Chapter 6 that used Y and O ratios (Table 16), although they are not strictly comparable because estimations here also include a deterministic linear time trend. The average coefficient for Y in the disaggregated inflation estimations (Table 16) was 0.1 and for 0 was -0.24; which indicates that the Y ratio is inflationary and the O ratio is disinflationary and that the impact of a given rise in O is roughly double that of a fall in Y. This is similar to the results outlined in this chapter – the coefficients have the same signs (positive for Y and negative for O) and roughly the same relative magnitudes (the Y coefficient being around half the absolute size of the O coefficient).

Table 26: DOLS Estimation 1980:2018 1 Lead 1 Lag (Equation B)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
15-29/40-54	0.25	0.008	30.67	0.000
65-79/40-54	-0.43	0.103	-4.16	0.022
Intercept	-0.16	0.034	-4.68	0.003
TREND	0.0030	0.00005	56.03	0.009
GST	0.050	0.001	49.87	0.000
R-squared	0.82	Mean dependent variance		0.0427
Adj R-squared	0.76	S.D. dependent variance		0.0309
S.E. of regression	0.015	Sum squared residuals		0.0062
SW (normality)	.98*	BGLM (no serial Corr.)		6.1
ARCH (no Heterosc.)	2.48*			

* Fail to reject null at 5%

7.3 Summary of Cointegration Results

The conclusion from the regression analysis is that late young to late middle and early old to late middle ratios are cointegrated with inflation. The impact of aging seems to be consistent – inflation falls as the proportion of late middle rises relative to late young, and early old rises relative to late middle. Thus, aging is associated with increasing disinflation. This pattern exists for both Johansen and DOLS estimations.

The estimation of the coefficients of O are more variable across time and estimation methods than the coefficients for Y. This may reflect changing behaviour in middle and early old years due to changes in the average age of retirement, changes in expected longevity, and changes in the average age that parents begin to increase saving rates as children finish school (because parents are having children later).

In terms of the relative impact of late young to late middle versus early old to late middle ratios, the Johansen and DOLS coefficients estimate the absolute size of the coefficient of O is larger than the size of the coefficient of Y over the full sample. This implies that a given sized rise in O will have a greater impact than a comparable fall in the Y ratio on the level of inflation.

7.4 Estimated Impact on Future Inflation

ABS population projection Scenario B is a middle scenario based on recent trends for population growth. It implies that the late young to late middle age cohort (15-29/40-54) will peak in 2021 and then fall substantially, and the early old to late middle cohort (65-79/40-54) will rise rapidly through to end of the 2020s, then fall slowly through to 2045, and then rise significantly through to 2065 – see Figure 10 below.

Together this implies that both the falling late young ratio and the rising early old ratio will contribute to lower inflation through to the end of 2030, and then the movements of both will be partially offsetting each other until the mid 2040s.

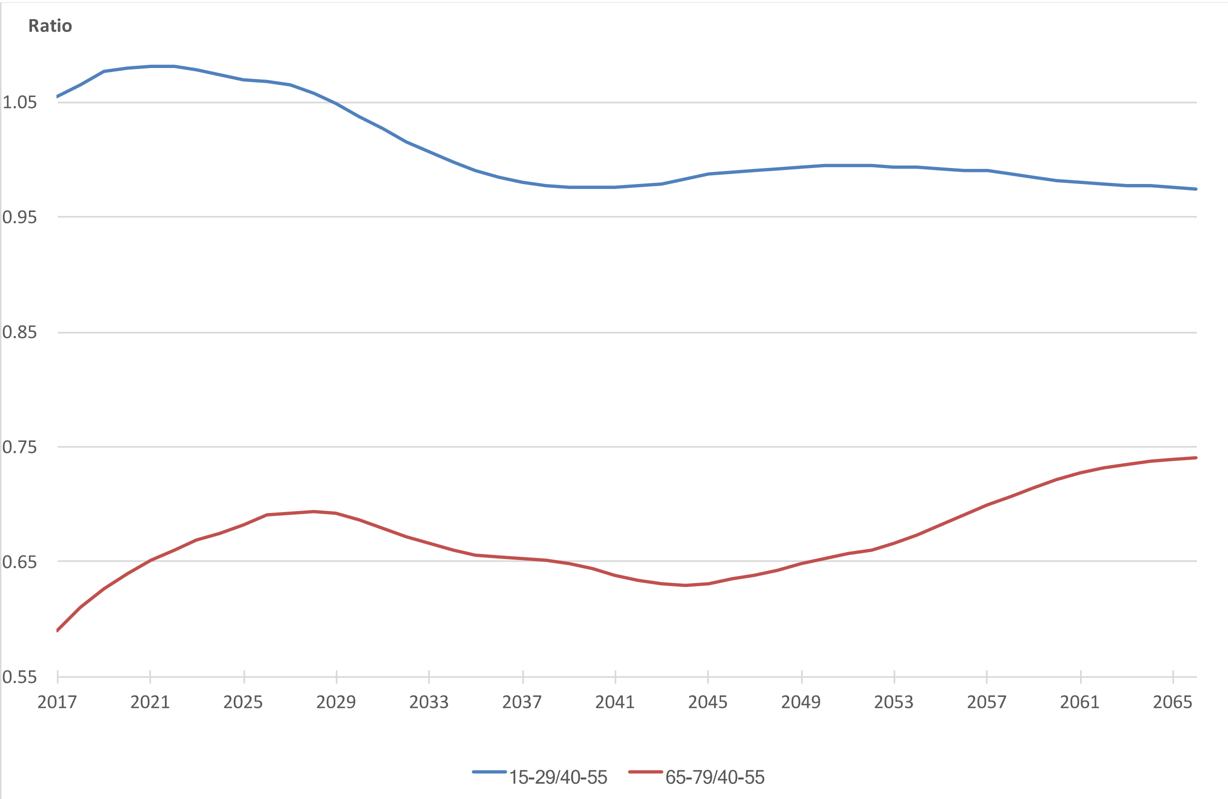

Figure 10: Ratio Projections based on ABS Middle Scenario Projections (Scenario B)

Table 27 calculates the impact on inflation of the change in population ratios based on the estimated coefficients from the Johansen and DOLS estimations. It shows that the impact of the aging population in Australia is likely to reduce inflation by around 2 percentage points in the next 5 years and 2.5 percentage points over the period 2018 to 2030. Over the 32 years to

2060 the models predict that the aging of the population will continue to have a disinflationary effect relative to 2018.

This contrasts significantly with the projections of Takats (2016), who estimated that age structure would increase inflation in Australia by around 2 percentage points from 2010-2050. The difference in estimates primarily reflects the divergence in the coefficients related to the early old – which is the component that changes most over that period.

Table 27: Inflation Projections Based on Age Cohort Coefficients

Coefficient Estimates

	(1) Johansen 1960-2018	**(2)** DOLS 1960-2018
15-29/40-54	0.21	0.22
65-79/40-54	-0.42	-0.64
Trend	0.00145	0.0019

Projected Changes in Variables

	2018-2024	**2024-2030**	**2030-2060**
15-29/40-54	0.009	-0.037	-0.056
65-79/40-54	0.065	0.011	0.035
Trend	6	6	30

Inflation Projections (percentage point changes)

	2018-2024	**2024-2030**	**2030-2060**
Johansen (1)	-1.7	-0.4	1.7
DOLS (2)	-2.9	-0.4	2.2
Average Change	-2.3	-0.4	1.9
Cumulative Sum from 2018	-2.3	-2.6	-0.7

As with all long-term projections the results should be interpreted with caution. As the results of the cointegration analysis showed, demographic patterns can shift over time as behaviour changes – such as the age at which women have children – and this can impact the coefficients of the age ratios. The further out that inflation is projected the more likely it is that the actual coefficients will diverge from those estimated in the cointegration analysis.

Chapter 8: Conclusions

This is the first study to our knowledge to model the effects of age structure on disaggregated prices. The results suggest an increase in the relative size of the young cohorts tends to be inflationary, and middle and older cohorts disinflationary, in Australia.

The analysis suggests that the disinflationary impetus will increase as more of the population moves into retirement. This has been area of dispute in the published literature and is important given the projected proportional rise in older cohorts in Australia and many other countries in the next decade.

The results also point to age structure impacting inflation by affecting relative demand and relative prices. The factor regressions, disaggregated inflation regressions and analysis of household consumption patterns produce a consistent picture. Growth in younger population ratios affect demand for food, housing, and household related items. This demand then appears to flow through to price inflation for these items. Then, from around 35-40 years of age, these relative demand and price effects shift as relative demand for these items falls placing downward pressure on the relative price changes of these items. These patterns persist into retirement.

The disaggregated results are further supported by cointegration modelling of age structure and aggregate inflation. This modelling suggests aging reduces inflation: inflation falls with an increase in the late middle (40-54) relative to late young (15-29) cohorts and an increase in early old (65-79) relative to late middle (40-54) cohorts. This supports a consistent pattern of inflation falling as the population ages.

The estimate of the net effect of age structure on Australia's inflation looking forward is that it will have a significant disinflationary effect, particularly over the next decade. This contrasts with previous estimates (Takats, 2016) that suggested that the rise in the proportion of newly retired would increase Australia's inflation significantly.

One of the key differences between this thesis and earlier papers is in the selection of age ratios that minimise the issues of multicollinearity. Multicollinearity may well explain the conflicting results in earlier studies if the collinearity analysis in this thesis is reflective of age structure data in other countries. It would be worthwhile to do a similar analysis using a cross country panel to see if other countries' demographics have similar collinearity between older and younger profiles. Lindh and Malmberg (1998) noted that collinearity was greatest between the young and old in their cross-country study – which is consistent with the findings of this thesis for Australia.

The multicollinearity issue has been minimised in this thesis by choosing at most two population ratios in any single regression. By using the share of young to middle and old to middle ratios, inferences about much of the age structure can still be made.

One of the limitations of this approach is that only part of the impact of age structure is captured by the ratios. Studies with more ratios and covering more of the age structure will gain explanatory power relative to the approach used here. These other studies enable greater precision in estimating the net impact of age structure to date.

Using more of the age structure in projecting inflation forward is potentially problematic as estimates of individual coefficients may be biased in terms of sign and level because of multicollinearity. This may lead to incorrect conclusions where key ratios change significantly – as will be happening in many countries in the next 20 years as the proportion of new retirees increases.

The reduction in explanatory power from modelling only a part of the age structure may not be that significant for Australia given the analysis in Chapter 4 that showed that there are three peak times in life when age structure has a significant impact on inflation - 15-29, 40-54 and 65-79. Other parts of the age structure have low correlations with inflation. The two age ratios used in this thesis cover the three peak times of life when age structure impacts inflation, and thus should capture most of the impact of the entire age structure on inflation.

The impact of age structure on relative demand and relative prices, and particularly the impact on housing and household related items, raises another key issue that would be worthwhile exploring – do changes in demand for certain types of goods and services have a more pronounced effect on inflation than demand for others? This question could be explored by mapping different components of consumption demand against changes in inflation. This more disaggregated approach may lead to gap variables that map to inflation better than current gap variables.

Extending the disaggregated analysis of inflation and age structure to a cross-country panel study would enable an assessment of whether the results for Australia can be generalised. If the results hold for a larger sample of countries it will help to clarify the mechanism of action of the relationship between age structure and inflation and point to a need to focus attention on relative demand and price changes in inflation modelling.

Faust and Wright (2013) comprehensive review of inflation forecasting concluded that a major rethink of trend inflation was crucial for improving forecasting accuracy. The results of this study and other recent age structure studies point strongly to age structure as potentially offering the solution to understanding these long cycle swings in inflation.

It is estimated that aging will reduce Australian inflation by 2 percentage points in the next 5 years. This result has importance for monetary policy looking forward. Through much of the last 5 years inflation has been below the Reserve Bank of Australia’s target band of 2-3%. The estimated impact of aging implies a significant risk of deflation and points to a very challenging policy environment for the Reserve Bank of Australia over the next five years.

Appendix 1: Descriptive Statistics Data

Table 28: Descriptive Statistics Data 1961-2018

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability	Sum	Sum Sq. Dev.	Observations
0-9	0.16	0.15	0.21	0.13	0.03	0.59	1.88	6.41	0.04	9.08	0.04	58
10-19	0.16	0.16	0.18	0.12	0.02	-0.11	1.45	5.90	0.05	9.04	0.03	58
20-29	0.15	0.15	0.17	0.13	0.01	-0.10	1.73	4.00	0.14	8.83	0.01	58
30-39	0.14	0.14	0.16	0.12	0.01	-0.36	1.96	3.89	0.14	8.32	0.01	58
40-49	0.13	0.13	0.15	0.11	0.01	-0.31	1.86	4.08	0.13	7.51	0.01	58
50-59	0.11	0.10	0.13	0.09	0.01	0.49	1.64	6.75	0.03	6.23	0.01	58
60-69	0.08	0.08	0.10	0.07	0.01	0.95	2.90	8.71	0.01	4.67	0.01	58
65-74	0.04	0.04	0.05	0.03	0.01	0.92	3.32	8.45	0.01	2.13	0.00	58
70-79	0.05	0.05	0.07	0.04	0.01	0.05	1.73	3.95	0.14	2.93	0.00	58
Y	1.26	1.22	1.63	0.96	0.23	0.28	1.58	5.68	0.06	72.84	3.11	58
O	0.47	0.46	0.61	0.39	0.05	0.38	2.73	1.61	0.45	27.15	0.16	58
80+	0.02	0.02	0.04	0.01	0.01	0.38	1.61	6.06	0.05	1.39	0.01	58
CPI	0.05	0.03	0.17	0.00	0.04	1.16	3.66	13.96	0.00	2.81	0.08	58
OutGapHP	0.00	0.00	0.02	-0.02	0.01	0.00	3.26	0.16	0.92	-0.01	0.00	58
ACTUAL RENT FOR HOUSING	0.06	0.05	0.19	0.00	0.04	0.94	3.83	10.27	0.01	3.53	0.10	58

ALCOHOLIC BEVERAGES	0.05	0.04	0.24	0.00	0.04	2.16	8.59	120.42	0.00	2.95	0.11	58
CIGARETTES AND TOBACCO	0.09	0.08	0.22	-0.01	0.06	0.47	2.71	2.29	0.32	4.96	0.18	58
CLOTHING AND FOOTWEAR	0.03	0.01	0.21	-0.03	0.05	1.38	4.80	26.25	0.00	1.94	0.14	58
COMMUNICATION	0.03	0.01	0.46	-0.13	0.08	2.73	16.09	485.79	0.00	1.52	0.36	58
CONSUMPTION IPD	0.05	0.03	0.18	0.01	0.04	1.35	4.49	23.05	0.00	2.78	0.08	58
ELECTRICITY, GAS AND OTHER	0.06	0.04	0.23	-0.03	0.06	1.00	3.35	9.95	0.01	3.19	0.20	58
FOOD	0.05	0.03	0.18	-0.03	0.04	0.87	3.65	8.33	0.02	2.67	0.09	58
FURNISHINGS AND HOUSEHOLD EQUIP.	0.04	0.02	0.20	-0.02	0.05	1.27	4.51	21.05	0.00	2.09	0.12	58
GST Dummy	0.02	0.00	1.00	0.00	0.13	7.42	56.02	7324.75	0.00	1.00	0.98	58
ImportP	0.03	0.02	0.28	-0.12	0.07	0.80	4.69	13.14	0.00	1.97	0.28	58
IMPUTED RENT FOR OWNER O.	0.06	0.05	0.19	0.00	0.04	0.94	3.83	10.27	0.01	3.53	0.10	58
OIL	0.09	0.03	1.13	-0.33	0.26	1.87	7.25	77.30	0.00	4.95	3.92	58
PURCHASE OF VEHICLES	0.03	0.01	0.20	-0.07	0.06	0.94	3.86	10.33	0.01	1.64	0.19	58
HOTELS, CAFES, RESTRAURANTS	0.05	0.03	0.17	-0.01	0.04	1.11	3.79	13.31	0.00	2.90	0.08	58
TRANSPORT SERVICES	0.05	0.04	0.19	-0.06	0.05	0.51	4.05	5.17	0.08	2.67	0.13	58

Table 29: Descriptive Statistics 1983-2018

	Mean	Median	Maximum	Minimum	Std. Dev.	Skew ness	Kurtosis	Jarque-Bera	Probability	Sum	Sum Sq. Dev.	Observ ations
Y	1.15	1.04	1.61	0.96	0.20	1.09	2.73	28.40	0.00	163.33	5.88	142
O	0.49	0.48	0.61	0.44	0.04	0.93	3.30	20.94	0.00	69.88	0.26	142
CARBON	0.00	0.00	1.00	-1.00	0.12	0.00	71.00	27358.67	0.00	0.00	2.00	142
F1	0.02	-0.48	2.84	-1.10	1.02	1.16	2.91	31.69	0.00	2.83	145.53	142
F6	-0.01	-0.23	3.25	-2.73	1.05	0.58	3.43	9.15	0.01	-1.62	156.56	142
F5	0.03	-0.12	3.11	-2.74	1.05	0.66	4.13	17.92	0.00	4.36	155.89	142
F4	0.03	-0.06	4.02	-1.82	1.00	0.78	4.27	24.04	0.00	4.66	140.44	142
F3	0.01	-0.17	2.29	-2.14	1.06	0.33	2.29	5.57	0.06	0.89	158.00	142
F2	0.03	0.23	2.46	-2.27	1.03	-0.21	2.23	4.52	0.10	3.82	150.86	142
OutGapHP	0.00	0.00	0.01	-0.02	0.00	-0.84	6.30	81.29	0.00	-0.04	0.00	142
GSTDummy	0.03	0.00	1.00	0.00	0.17	5.70	33.53	6284.30	0.00	4.00	3.89	142
GSTDummy2	0.00	0.00	1.00	-1.00	0.12	0.00	71.00	27358.67	0.00	0.00	2.00	142
Health	-0.01	-0.01	0.05	-0.10	0.03	-0.38	3.43	4.49	0.11	-1.84	0.09	142
ImpP	0.01	0.01	0.26	-0.18	0.07	0.40	4.37	15.03	0.00	2.02	0.71	142
Util	0.02	0.02	0.06	-0.01	0.02	0.50	2.51	7.46	0.02	3.08	0.05	142
Oil	0.06	0.03	1.21	-0.53	0.28	0.75	4.52	26.88	0.00	8.43	11.12	142

Appendix 2: Tests for Determining the Optimal Number of Factors

Several methods have been developed to determine the optimal number of factors. Cattell (1966) used figure analysis (the 'scree test'), looking for the point where the line of eigenvalues becomes a straight line with almost horizontal slope. With this test the optimal number of factors is reached at the point immediately before the line straightens. The point where the line becomes straight and almost horizontal is at around 7 factors (Figure 11 below). This would point to 6 factors (one less than 7) being optimal. However, from 3 to 6 factors the line is mostly straight and only slowly sloping so the 'scree test' is not particularly definitive and could be said to point to 3-7 factors being optimal.

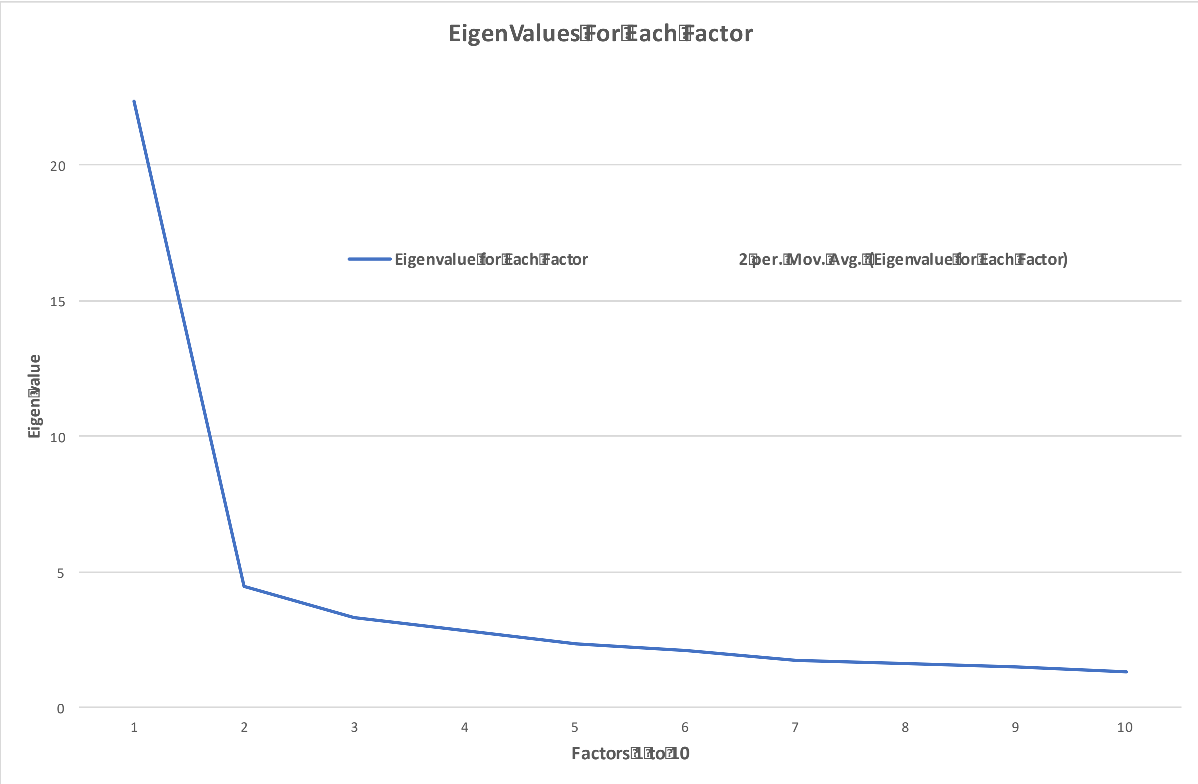

Figure 11: Scree Test for Disaggregate Price Inflation PCA

Bai and Ng (2002)tests were performed on the data set. These tests modify the BIC criteria to impose a penalty function that takes account of both the number of dimensions of the data and sample length and increases as the number of factors grows. Their estimates for optimal number of factors is a trade-off between goodness of fit and parsimony.

They provide six formulations of information criteria, with the first two shown in Table 30 (IC1 and IC2) tending to perform best in simulations (Alessi, Barigozzi and Capasso, 2010, Bai and Wang, 2016). These criteria are modified BIC criteria that incorporate the number of variables in the penalty function.

The six criteria are of two types, PC and IC, which are of the form (Pesaran, 2015):

$$PC(h) = V\left(h, \hat{F}^{(h)}\right) + h \times g(m, T)$$
$$IC(h) = \ln\left[\mathrm{V}\left(h, \hat{F}^{(h)}\right)\right] + h \times g(m, T)$$

where the cross sectional average variance of the idiosyncratic variance $\mathrm{V}\left(h, \hat{F}^{(h)}\right)$is

$$\mathrm{V}\left(h, \hat{F}^{(h)}\right) = \min \frac{1}{NT} \sum_{i=1}^{n} \sum_{t=1}^{T} (y_{it} - \gamma_i^{(h)} \hat{f}_t^{(h)})$$

where *m* is the number of variables *i*, *T* is the time dimension of the data, *g* is the penalty function due to over-fitting, *h* is the number of factors, y_{it} are the variable *i* and time *t* and $\gamma_i^{(h)} \hat{f}_t^{(h)}$ are the factor loadings and factors.

Table 30: Bai and Ng (2002) Tests for Optimal Number of Factors

	Optimal Number of Factors (assuming max factors = 10)					
	IC1	IC2	IC3	PC1	PC2	PC3
No. factor	9	5	10	10	9	10

The Bai and Ng (2002) estimate can under-estimate and over-estimate the optimal number of factors (Alessi, Barigozzi and Capasso, 2010). Alessi, Barigozzi and Capasso (2010) improve on the Bai and Ng (2002) approach by introducing an extra parameter to the penalty function that enables a more accurate estimate to be made of the optimal number of factors. The parameter is added to the IC1 and IC2 Bai and Ng (2002) criteria. The purpose of this parameter is to allow for the penalty function to be systematically altered and compared. It is known that the penalty function can under-estimate and over-estimate factors. By adding this extra multiplicative parameter, the degree of penalty can be altered to see how it affects the number of estimated optimal factors.

The parameter is varied over a range. Bai and Ng argue there exists a range for this parameter over which the optimal number of factors is neither over-estimated nor under-estimated. To determine the optimal number of factors, they vary the parameter and estimate the second stability interval (where estimates are stable over a given range of the parameter).

The optimal number of factors estimated using the Alessi, Barigozzi and Capasso (2010) approach is 6. Alessi, Barigozzi and Capasso (2010) argue their approach can under-estimate the number of factors but does not tend to over-estimate the number of factors.

Figure 12 graphically illustrates the Alessi, Barigozzi and Capasso (2010) (ABC) test for the optimal number of factors. It shows the optimal number of factors (y axis) against the penalty parameter (c). As c rises the estimated optimal number of factors declines. Alessi, Barigozzi and Capasso (2010) look for the second period of comparative stability in the estimate of the optimal number of factors that arises as c rises – that is, the most stable point beyond where the line starts falling from the highest number of factors (this is an input at the start of the estimation and in this case is 10 factors). In Figure 12 they would be looking for where the line is horizontal for a comparatively long period of time as c rises.

The first stability interval is at low values of c and is equal to the maximum number of factors (10). Between c values of 0.2 and 0.4 there is a point of stability at 9 factors – this is highlighted by the circle (consistent with two of the Bai and Ng criteria) and the longest point of stability is for 6 factors (see the area highlighted by the second circle). As c rises above this level there is a long period of stability at 4 factors.

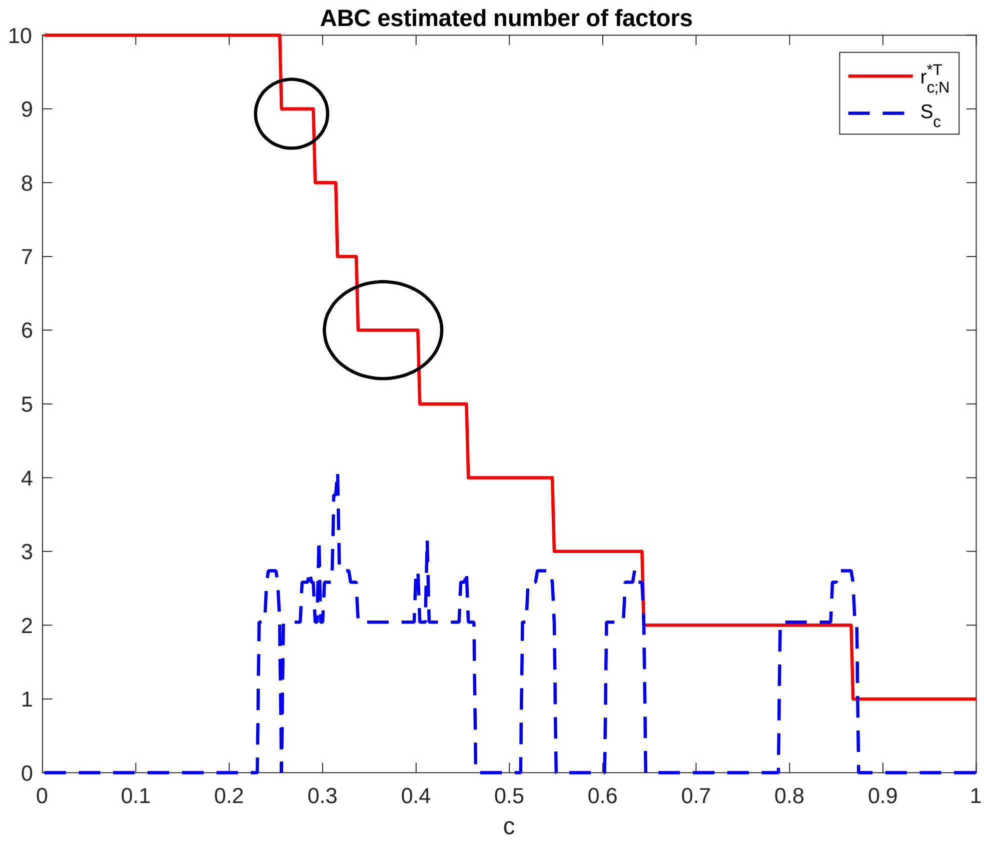

Figure 12 Alessi, Barigozzi, Capasso (ABC) Esimated Number of Factors

So this analysis shows that 4, 6 and 9 factors have the potential to be optimal, but that 6 is the most optimal given it's the first significant period of stability after the optimal number of factors falls below the maximum of 10.

Appendix 3: Correlations Between Inflation Series and Each Rotated Factor

Table 31 displays the statistically significant (p values statistically significant at 5%) correlations for each inflation series against each factor. 1 represents a correlation of 100% and 0 a correlation of 0%. The highest correlation for each inflation series is highlighted in yellow.

Table 31: Correlations between Each Price and Factor

	F1	F2	F3	F4	F5	F6
Bread	0.48	0.80	0.26			0.24
Cakes and biscuits	0.73	0.71	0.57	0.36	0.41	
Breakfast cereals	0.62	0.70	0.42	0.39	0.52	
Other cereal products	0.50	0.80	0.53	0.36	0.29	0.30
Beef and veal	0.35		0.59		0.25	0.23
Pork		0.26	0.56			
Lamb and goat			0.42			0.34
Poultry		0.36	0.43			
Other meats	0.32	0.28	0.77			0.23
Fish and other seafood	0.52	0.44	0.55	0.32	0.54	0.51
Milk	0.24	0.72				0.25
Cheese	0.36	0.59	0.70	0.23	0.23	
Ice cream and other dairy products	0.48	0.58	0.56			
Eggs		0.47				
Jams, honey and spreads	0.53	0.64	0.43		0.47	0.31
Other food products	0.70	0.74	0.63	0.37	0.43	0.32
Coffee, tea and cocoa	0.36	0.48			0.38	
Restaurant meals	0.93	0.40	0.51	0.39	0.39	
Take away and fast foods	0.88	0.44	0.63	0.48	0.30	
Spirits	0.42		0.63	0.42		

	F1	F2	F3	F4	F5	F6
Wine	0.64	0.49		0.28	0.34	0.32
Beer	0.79	0.41	0.37	0.47	0.52	
Tobacco						
Clothing and footwear	0.92	0.50	0.49	0.38	0.52	0.40
Footwear for men	0.76	0.40	0.50	0.33	0.47	0.23
Footwear for women	0.79	0.43	0.41	0.37	0.49	0.32
Footwear for infants and children	0.70	0.38	0.38	0.35	0.45	0.25
Cleaning, repair, hire clothing, footwear	0.82	0.32	0.49	0.29		
Rents	0.73	0.60	0.73	0.56	0.57	0.32
Maintenance & repair of the dwelling	0.88	0.26	0.49	0.40		
Utilities	0.30			0.95		
Electricity	0.27			0.92		
Furniture	0.83	0.58	0.45	0.30	0.53	0.44
Carpets & other floor coverings	0.76	0.43	0.65	0.27	0.50	0.33
Household textiles	0.76	0.60	0.29	0.28	0.51	0.50
Major household appliances	0.65	0.39	0.39		0.23	0.62
Small electric household appliances	0.63	0.50	0.40		0.31	0.80
Tools, equipment for house & garden	0.66	0.51	0.47	0.42	0.78	0.62
Cleaning and maintenance products	0.50	0.77	0.41	0.37	0.70	0.23
Personal care products	0.72	0.74	0.27	0.40	0.67	0.25
Child care					0.53	
Hairdressing & grooming services	0.92	0.33	0.40	0.36	0.27	
Pharmaceutical products	0.73	0.56	0.34	0.44	0.61	0.35
Medical and hospital services						0.32
Dental services	0.41		0.69	0.34	0.33	
Motor vehicles	0.66	0.56	0.40	0.36	0.68	0.71
Spare parts, accessories motor vehicles	0.43	0.57	0.68	0.35	0.55	0.40
Automotive fuel	0.26					-0.51
Maintenance & repair of motor vehicles	0.75	0.57	0.58	0.51	0.64	0.37

	F1	F2	F3	F4	F5	F6
Other services for motor vehicles	0.25			0.37	0.27	
Urban transport fares	0.82	0.53	0.26	0.45	0.24	
Postal services	0.44		0.34	0.37	0.26	
Telecommunication equip't & services	0.70	0.43		0.53	0.36	
Audio, visual and computing equipment				-0.30		0.61
Domestic travel, accommodation	0.48	0.27	0.37		0.51	
International travel & accommodation	0.41	0.49	0.59	0.22	0.41	0.25
Pets and related products		0.48	0.35	0.41	0.44	0.29
Education	0.34		0.48	0.34	0.32	

- Factor 1 is predominantly a services based factor with transport services, telecommunications services, postal services, hairdressing, maintenance of dwelling services, restaurant meals and take away all highly correlated with this factor. In addition clothing, footwear and household related items – furniture, textiles, carpets, major appliances – are all well correlated with this factor.

- Factor 2 is correlated with predominantly domestic products, particularly food products excluding meats, cleaning, personal care products and pet products.

- Factor 3 is a mixed factor - correlated with meats, spirits, rents, dental services, and motor vehicle spare parts, international holidays and education.

- Factor 4 is predominantly a utilities and electricity factor.

- Factor 5 is correlated with tools and equipment for garden, childcare, and domestic holiday travel and accomodation. Cleaning and maintenance products and motor vehicles are also highly correlated with this factor.

- Factor 6 is correlated predominantly with internationally sourced goods – audio visual equipment, motor vehicles and small electrical appliances.

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