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Investigating the Link between Population Aging and Deflation

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Executive Summary

This study examines the question of whether demographic age structure is deflationary. It was funded by a grant from the Society of Actuaries (SOA) and prepared by a team of researchers at the University of Waterloo and the University of Kent (United Kingdom).

The report has four main components. We examine the literature and conclude that various researchers provide support that age structure may be inflationary or disinflationary; although few conclude that it is deflationary. We investigate two recent papers that reach the opposite conclusion regarding whether the older age group is deflationary or inflationary, despite using similar data. We reconcile this difference but then extend the data set to provide further analysis. We conclude that there is strong evidence that the very old age group is deflationary. This finding has significant implications for economics, asset returns, actuarial assumptions and policy.

We also analyze whether there is a relationship among six economic variables that provides support for the contention that demographic age structure impacts inflation. We fit a Vector Auto Regressive model to avoid having to specify in advance a structural model. This is a useful methodology given that there are many possible interactions among the variables across time and the difficulty in getting consistent data by country and across countries over long time periods. We use the fitted model to suggest the impact of demographic age structure on inflation in a subsequent ten year period.

This study is important for actuaries. It provides clear evidence that demographic age structure impacts inflation and for the very old age group is deflationary. The extent of such impacts and whether it has inflationary and deflationary effects on all or most asset classes is beyond the scope of this research, but worthy of further investigation. Given the methodological and data issues associated with such research and that populations in developed countries and many other countries are aging, it is important that this investigation continue.

1 Introduction

In most countries in the developed world and also in a number of other countries, the population is aging. What impact will a changing demographic structure have, if any, on economic factors such as growth and inflation? This question is of vital importance to actuaries who use demographic and economic projections in the pricing and valuation of products, design of risk management solutions, and in opinions regarding the sustainability of social programs. This research report, funded by the Society of Actuaries (SOA), provides background on research in this area and offers insights that may be of use to practicing actuaries.

Our work began with a review of relevant literature, some of which is referred to in the body of this report. The balance of the work during this study involved analyzing historical data, as described in this final report. In this report we embark on the task of systematically examining the potential impact of demographic (or age) structure, in particular, the proportion of older population, on inflation. We examine the link between population aging and inflation using panel regressions involving 22 countries over a 56 year period (1955-2010). We also use a reduced-form panel-data Vector Autoregression (VAR) methodology to capture dynamic interactions among the main macroeconomic variables without having to take an explicit stand on exogeneity.

The world population has experienced a drastic shift in terms of both size and composition in the past few decades. Using data from the UN's World Population Prospects (2013), Figure 1 depicts the (unweighted) mean proportions of three age cohorts (the Young 0-19, Working Age 20-64, and the Old 65+) across 22 OECD countries, by year (1955-2010). The average proportion of the Old group increased from 9% in 1955 to 16% in 2010, with most of the decline in share occurring in the Young group. The proportion of the population in the Working Age group increased from 57% in 1955 to 60% in 1993, and remained level thereafter.

Currently, several aging countries are also experiencing historically low inflation or even deflation. Recently, central bankers and researchers at policy institutions have suggested that there is a connection between low inflation and population aging.[1] Given the projected global aging, it is important to understand this link (if it exists), since it may have significant implications for actuarial practice. In Figure 2, Figure 3 and Figure 4, we plot the cumulative inflation versus the average shares of the Young 0-19, Working Age 20-64, and the Old 65+, respectively, over the period 1955 – 2010 for our sample of 22 countries. The plots do not offer clear guidance about the cross-country direction of the relationship between inflation and demographic changes. Considering the regression lines in the graph are highly sensitive to outliers, it is apparent that we need to control for other factors that influence inflation in order to understand the role of demographics in increasing or decreasing it.

In this report, we first report the results of static panel-data regressions of inflation on a range of explanatory variables including the age structure. Two recent papers have studied the impacts of an aging population on inflation using static panel regressions, albeit with contradictory conclusions. While Yoon et al. (2014), hereafter YKL2014, conclude that the impact of the older age group is deflationary, Juselius and Takáts (2015), hereafter JT2015, conclude that its impact is inflationary. We provide an analysis of these two papers to validate our empirical approach and to reconcile their findings.

The two papers use somewhat similar data for many of the same countries for similar time periods, but they do use different methodologies. We have not been able to obtain access to all of the data used in the two papers, so we are not able to replicate fully the results. However, we believe that the data to which we have access for the time periods that it is available is sufficient to provide insight into the differences in the conclusions of the two papers.

[1] See Shirakawa (2011a, 2011b, 2012 and 2013), Bullard et al. (2012), Anderson et al. (2014), Imam (2013) among others.

Our analysis suggests that the approach used by JT2015 may be the more relevant of the two for our purpose. However, with regard to their conclusions about the effect of the older age groups on inflation, we note that JT2015 include some reservations regarding the stability of their results in the tails of the distribution. Indeed, the 65 and up age group could form quite a large tail and there may be differences in results within subgroups within that tail group.

We conducted several further investigations using panel regressions. In the first, we investigated two distinct sub-periods, the first up to 1980 and the second during 1981 – 2010. A typical time trend of inflation among the OECD countries is that inflation rose in the late 1960s, after the late 1970s peak it gradually declined and stayed relatively low in the 1990s and thereafter. For the earlier sub-period, we found that the result for the older population is not statistically significant. This suggests that, before 1980s, inflation was mainly driven by factors such as oil price shocks and easy-money policies adopted in central banks, rather than by demographic changes. By contrast, in the 1981-2010 sub-period, we found demographic changes played an important role and older age groups exert significant negative impacts on inflation.

Secondly, following a suggestion of James Bridgeman of the POG, we performed a similar analysis, but rather than use cross-country data, we considered the eight Bureau of Economic Analysis (BEA) economic regions within the U.S. One advantage of this data is that it contains a more detailed breakdown of the older age groups in which we are interested. We found that during 1978 – 2010, older (80-85, 85+) cohorts' effect on inflation is significantly negative. This was also true for the OECD panel data for the same period.

Finally, we also investigated the OECD data for a shorter sub-period, 1990-2010, for which more age groupings in the older tail are available. We again found that the relationship at older ages is strongly deflationary. We expect that JT2015 obtained their conclusions because they aggregated the two sub-periods and had aggregated age groupings for the old. Hence, it is our view that if we are examining the impact of the older-old, it is deflationary.

Further, we also present an alternative analysis using a panel VAR estimated on data from twenty countries over the period 1999-2010. The short period is due to limited data availability for our variables of interest, and also due to structural changes in the time series of some of these variables that would make a VAR unstable. By using the VAR, we try to determine how much of the variation in inflation can be explained by the evolution of the demographic structure, when allowance is made for interactions among leading macroeconomic variables, such as growth, savings, investment, aggregate labor supply, and interest rates.

We find that the changing age profile across selected countries has an economically and statistically significant impact on leading macroeconomic variables, both in the long and short-run after controlling for oil prices. The changing age profile impact approximately follows a life-cycle pattern; that is, dependent cohorts in general have a negative impact on real macroeconomic variables. However, in contrast to our findings in panel regression studies, the old group adds slightly positive inflationary pressures in the long-run. Coarse demographic groups and short period of data may cause this result.

The remaining parts of this report are organized as follows. In Section 2, we present a selected review of literature. In Section 3, we conduct analysis on YKL2014 and JT2015 in the first two subsections, respectively. We also provide discussion of a technical reason that may cause their contrasting conclusion in Section 3.3. Then, in Section 4, we provide several further investigations, including analyses on the OECD panel with different sub-periods, on the U.S. economic regions, and on the OECD panel with more age groupings in the older tail. In Section 5, we provide further analysis using the reduced form panel-data VAR. Finally, Section 6 concludes and identifies areas for future research. The supporting tables and figures are included in the Appendix.

2 Selected Literature Review

In this section, we discuss the literature on the effects of demography, in particular the age structure of the population, on economic growth, inflation/deflation, and other leading macroeconomic variables.

Evidence of the economic significance of the impact of the age structure on the economy has not been clear cut. On the one hand, theoretical macroeconomic models, which are typically calibrated on the age profile of savings, have highlighted the importance of demographic structure, as have many commentaries on economic policy. On the other hand, the econometric evidence assembled for its importance has been seen to be less compelling. There are a number of reasons for this.

In particular, most of the changes in demographic structure have occurred at low frequencies. This renders it difficult to distinguish the impact of demographic structure from the other low frequency trends that typically dominate economic time series. In addition, the vector of proportions in each age group is also inevitably highly collinear, making precise estimation of the effect of each age group a difficult, if not impossible, task. Faced with these difficulties, it has become a common practice in this literature simply to impose strong restrictions on the effect of the demographic structure, for instance, through the use of a single proxy, known as the *dependency ratio*.

The aggregate real GDP growth is affected by demographic structure in a somewhat straightforward way. For example, Feyrer (2007) considers the age structure of the workforce, instead of the population as a whole, and its impact on productivity and hence output. The author reports a strong demographic effect, with the 40-50 year age group having the most positive impact on aggregate GDP growth.

The impact on per capita real GDP is not so straightforward and thus has been studied extensively. Lindh and Malmberg (1999) consider age structure in a transitional growth regression on a panel of 5-year periods in OECD countries. Their evidence indicates that age structure as a whole does have both a statistically and economically significant impact on per capita growth. Also the shares of upper middle-aged people (50 – 64 years) has a positive influence, and the group above 65 contributes negatively. Acemoglu and Johnson (2007) study a large panel of 75 countries and argue that the increases in life expectancy (and the associated increases and aging in population) appear to have reduced income per capita. Using a large cross-country panel spanning the past fifty years, Gomez and Hernandez de Cos (2008) present evidence that suggests that the proportions of 'mature' (15-64 year olds) and 'prime age' (34-54 year olds) people in the population can explain more than half of global growth since 1960. Bloom et al. (2007) find that inclusion of life expectancy and the initial working-age share in their model improves per capita income growth forecast performance for the period of 1980-2000 for a large panel of 67 economies. See also Bloom et al. (2010), and references therein.

Moreover, Jaimovich and Siu (2009) study the effect of demography on business cycle volatility in the G7 countries and find that the young and old workforce have more volatile hours and employment than the prime-age workforce. As a result, an increasing share of prime-age workforce may have contributed to the great moderation.

Changes in demographic structure also influence per capita GDP growth. Chapter 3 of the 2004 World Economic Outlook by Callen et al. (2004) found that per capita GDP growth is positively correlated with changes in the working age population share, but is negatively correlated with changes in the elderly share. By adapting a demographic polynomial curve-fitting technique on a panel covering 22 countries, Arnott and Chaves (2011) get statistically significant conclusions to confirm the above relationships, in terms of both levels and changes in shares of population cohorts.

In addition to examining this empirical evidence, many studies incorporate demographic features into economic models to investigate future paths of important macro variables. The effect of demography on leading macroeconomic variables is usually hypothesized to have arisen from life cycle effects on savings and from differences in productivity, because different age groups tend to have different participation rates and different human capital. A standard representative-agent macroeconomic model is not very helpful in this respect because it, by its very construction, precludes the existence of such effects. Even overlapping generations models allow for these effects only in a highly restricted way - see, for instance, Auerbach and Kotlikoff (1992). Miles (1999) highlights the advantages and disadvantages of using different types of evidence to assess the impact of demographic changes and argues for the use of calibrated general equilibrium models.

McMorrow and Roeger (1999) use the QUEST II model[2] to make projections through 2050 for the European Community's Member States (15 countries), the U.S. and Japan. Their simulation scenarios suggest that there could be a cumulative GDP loss over the 50 year period of 20%, 10%, and 21% for the EU, U.S., and Japan respectively. Konishi and Ueda (2013) explore the macroeconomic impact of population aging using a full-fledged overlapping generation model. They find that Japan's population aging as a whole adversely affects GNP growth by dampening factor inputs. Their simulations predict that the adverse effects will expand during the next few decades.

Given the plentiful evidence of an older age structure's negative impact on economic growth, it is reasonable to observe that an economy with an aging population, when accompanied by high debt and low employment, may be an environment that has a tendency to have low inflation or even deflation.

Recently, Yoon et al. (2014) and Juselius and Takáts (2015) study the effect of demographic changes on inflation using post-war panel data of developed countries. Their results, however, are mixed. On the one hand, using a panel dataset covering 30 OECD economies for the period 1960-2013, Yoon et al. (2014) find that population growth is inflationary, while aging is significantly deflationary. They argue that these observations are probably because of the fact that aggregate supply adjusts at a slower pace than aggregate demand in responding to demographic shocks in the short or medium run. On the other hand, looking at a similar panel of 22 OECD countries from 1955 – 2010, Juselius and Takáts (2015) find that aging is inflationary rather than deflationary. That is, a larger share of dependents (both young and old) is correlated with higher inflation, whereas having more working population leads to lower inflation. They explain that dependents could exert an inflationary pressure through excess demand because they consume more goods and services than they produce, while the working population could lead to a deflationary bias because of excess supply.

Japan has the most rapidly aging population in the world and experienced persistent deflation over the past two decades. Various channels through which demographic changes affect inflation in Japan have been examined in the past few years. Using a deterministic life-cycle economic model with capital, Bullard et al. (2012) find that the optimal inflation rates suggest that aging population structures like those in Japan may contribute to observed low rates of inflation or even deflation. Katagiri (2012) investigates the effects of changes in demand structure caused by population aging on the Japanese economy using a multi-sector Keynesian model with job creation/destruction. He finds that such demand shocks caused around 0.3 percentage point deflationary pressure on year-to-year inflation from the early 1990s to the 2000s in Japan. More

[2] The QUEST II model is a general equilibrium macro model with a broad geographical coverage. Such models can avoid problems in estimating the effects of aging to which partial equilibrium models are prone.

important, Katagiri (2012) shows that the repetition of such upward revisions made those effects look more persistent.

Based on simulation of a calibrated IMF Global Integrated Fiscal and Monetary (GIMF) model, Anderson et al. (2014) find that substantial deflationary pressures arise from population aging, mainly from declining growth and falling land prices. Moreover, the repatriation of foreign assets by the elderly leads to real exchange rate appreciation, which exerts downward pressure on inflation because of increased demand for relatively cheaper foreign goods and services[3]. By embedding the fiscal theory of the price level[4] into an OLG model, Katagiri et al. (2014) find that the effects of aging depend on its causes. Aging is deflationary when caused by an increase in longevity but inflationary when caused by a decline in birth rate. In the case of Japan, they believe it is unexpected longevity, not simply aging, that has led to deflation.

In addition to economic growth and inflation, there is also a large literature on demography's impacts on other macro variables as well. An early study by Fair and Dominguez (1991) examines the effect of demographics on various U.S. macro variables. They discuss the aggregation issues and use a low order polynomial function for the coefficients of the vector of 55 age distribution shares. They report a significant impact of U.S. age distribution on consumption, money demand, housing investment and labor force participation.

Savings rate is one of the most important factors that affects the macro economy, e.g. through the capital accumulation channel. Thus, the savings behavior of age cohorts is quite relevant and attracts attention for analysis. For example, Higgins and Williamson (1997) study the dependency hypothesis for Asia and argue that the large increase in the Asian savings rates is attributed to the significant decline in youth dependency ratios. These ratios, in turn, are shown to be associated with increased investment and reduced foreign capital dependency. In a subsequent study, Higgins (1998) shows that demographic effects, e.g. increases in both youth and old-age dependency ratios, can explain different levels of decline in savings and investments and increase in capital imports. Using a panel VAR model, Kim and Lee (2008) find that an increase in the dependency rate significantly lowers savings rates, especially public saving rates, in the major advanced (G-7) countries. Further, a higher dependency rate significantly worsens current account balances.

The link between changing demographic structure and return of assets has been widely studied. Poterba (2001) finds that it is difficult to find a robust relationship between asset returns on stocks, bonds, or bills, and the age structure of the U.S. population over the last seventy years of the twentieth century. In contrast, Davis and Li (2003) explore the relationship between

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[3] There is a considerable increase in the proportion of imported foreign goods in domestic consumption in Japan over the last decade. According to World Bank national account data, this ratio was 9.8% in 2001 and continuously increased to 19.0% in 2013.

[4] Fiscal theory of the price level states that the government will reduce the impact of its (debt) obligations of an unsustainable policy through inflation.

demographics and aggregate financial asset prices in 7 OECD countries over the period 1950 to 2000 and make projections through 2025. They find that an increase in the fraction of middle-aged people (aged 40 – 64) tends to boost real asset prices and a subsequent decline in this cohort, such as due to the aging of the baby boom, will tend to weaken them. Park (2010) finds that there is a significant impact from prime working-age consumers on the stock price, and that this impact is robust for all G5 countries (France, Germany, Japan, the UK and the U.S.). Arnott and Chaves (2011) also find that changes in the older age cohort are forecast to lead to higher excess bond returns. In addition, there is an extensive literature regarding the impact of the baby boom on asset prices, which is summarized in Andrews et al. (2014) and not repeated here.

3 Panel Regression

The purpose of this section is to present our analysis of the two papers, Yoon et al. (2014) and Juselius and Takáts (2015), with respect to a topic on which they have contrasting conclusions that is directly relevant to our research. A detailed analysis of the two papers is organized follows. We first describe the analysis of results in YKL2014 and JT2015, respectively. Then we discuss the possible reasons that may cause the opposite conclusions in these two papers.

3.1 Analysis of YKL2014

3.1.1 Data

YKL2014 construct most of the relevant variables by compiling data from the internal version of IMF's World Economic Outlook (WEO) database, which is reserved for IMF's staff. WEO only publishes part of the database on the external webpage, i.e. no data prior to 1980, fewer variables. To attempt to replicate their results, we constructed the series by collecting data from other sources, which may cover different time periods and even have different series' definitions.

3.1.2 Comparison

The panel-regression model in YKL2014 is the following

$$\pi_{it} = \mu_0 + \mu_i + \beta Demo_{it} + \gamma Z_{it} + \varepsilon_{it}. \qquad [1]$$

where π is the inflation, which is detrended using a quadratic filter. μ_0 is a constant and μ_i is the country-specific fixed effect. $Demo$ are relevant measures of demographic structures of individual countries, including detrended population growth, share of working age and old, and life expectancy. Z is a set of control variables, including terms of trade, real GDP growth, M2 growth, and change in budget balance/GDP. ε_{it} is the error term. Subscripts i and t denote the country and the time period, respectively.

The comparison between our panel regression estimations and those in YKL2014 is reported in Table 1 and Table 2, using the five models defined in YKL2014. For each model, there are three columns. The first column represents the figures taken directly from the paper. The second column lists the estimates of our panel regression. In the third column, figures are from the panel regression with non-detrended inflation and population growth.

It is important to note the following differences. First of all, the number of observations is much smaller in our regressions than in theirs, 650 versus 1167. Moreover, 3 countries are excluded from the panel-regression due to lack of data. Secondly, for our panel-regression (second column in each case), even though the coefficients of the variable of interest (share of old) have the same (negative) signs and magnitudes as those in YKL2014, they are not statistically significant in models (2), (3) and (4). When life expectancy is introduced, model (5) replicates YKL2014's estimator reasonably well. Thirdly, if we use non-detrended inflation as the dependent variable (third columns), the coefficients on the share of old become significant but have larger magnitudes in models (2), (3) and (4). Again, model (5) is a better replication. Finally, in contrast to the original paper, most of the estimators on control variables are insignificant in our panel estimations, possibly due to the smaller sample size.

3.2 Analysis of JT2015

3.2.1 Data

JT2015 use data from multiple sources, including Datastream, Global Financial Data (GFD), Consensus Forecasts (CF), OECD, IMF WEO, national data, etc. We have access to most of these sources, except GFD and CF. We have collected data for the benchmark model, including inflation, demographic measures, output gaps, and nominal interest rate. We would say there is no big distinction between our database and theirs. The only exception is for the nominal interest rate (nominal overnight inter-bank rate). In their paper, the data on the overnight inter-bank rate has full coverage for all 22 countries, i.e. from 1955 to 2010. However, after investigating various on-line data sources[5] for the nominal rate, we were unable to build up the series with full coverage. Thus, we have a smaller number of observations on the interest rate (1023), compared to theirs (1232).

3.2.2 Comparison

JT2015 present results for a number of models. For ease of comparison we only present results for some of their models including the benchmark model[6], which is model 10 in their paper. The benchmark panel regression model in JT2015 uses fourth order polynomials[7], and is written as

$$\pi_{it} = \mu_0 + \mu_i + \sum_{p=1}^{P} \gamma_p \tilde{n}_{pit} + \beta_1 r_{it} + \beta_2 \hat{y}_{it} + \beta_3 d74 + \beta_4 d80 + \varepsilon_{it}. \qquad [2]$$

[5] All data sources used in JT2015 were checked. Even though we have no access to the actual data in GFD, we can still browse series information there. Other possible sources were also investigated, such as FRED St. Louis, World Development Indicators.

[6] Only selected models are reported in this report. Estimates of other models (those with time effects) are available upon request.

[7] See Fair and Dominguez (1991), Higgins (1998), and Arnott and Chaves (2012) for details.

where π is the yearly inflation rate. μ_0 is a constant and μ_i is the country-specific fixed effect. $\tilde{n}_{pit}$ are fourth order population polynomials, which are used to overcome the estimation problems associated with direct use of age cohorts. Once estimates of the γ_p have been obtained, the corresponding coefficients on age cohorts can be directly computed. r_{it} and $\hat{y}_{it}$ are real interest rates and output gaps respectively. $d74$ and $d80$ are two dummy variables that account for the impact of the two oil crises in the 1970s. Subscripts i and t denote the country and the time period, respectively. In model (1), (2), (3) and (4) in JT2015, instead of using population polynomials as is the case for the benchmark model, they use dependency ratio, shares of the young, the working population and the old as the measures of demography. We follow this approach.

The comparison between our panel regression estimations and those in JT2015 is reported in Table 3 and Table 4. For each model, there are three columns. The first column represents the figures taken directly from JT2015. The second column lists the estimates of our panel regression. Finally, we enhanced the dataset by including eight more OECD countries that were used in YKL2014 and report these estimates in the third column.

Since there is no big difference between our panel and theirs, we would expect our estimates of the panel-regression to be similar to those in JT2015. This is true for all models, in terms of signs, significance, and magnitudes. Figure 5 shows that our estimation reconciles their finding that the impact of each age cohort on inflation exhibits a “U-shaped relationship”: the young and the old age cohorts have a positive impact on inflation, whereas the working age population has a negative effect. Moreover, Figure 6 depicts similar patterns for regressions without any control variable, i.e. Model (5). In addition, Figure 7 illustrates that Japan has a very different age cohort pattern: the young exert an inflationary pressure, the working population are slightly inflationary, and the old is quite deflationary. Finally, including more countries does not qualitatively change the results.

3.3 Why different conclusions?

In this subsection, we investigate why these two papers conclude so differently on the impact of aging on inflation.

3.3.1 Data

The datasets used in these two papers are similar in terms of country groups and time periods, but are very different in terms of control variables. Moreover, there are also differences in the definition of demographic variables. For example, YKL2014 define the share of working population to cover 15 – 64 age cohorts, while JT2015 define workers to be those who are in the 20 – 64 age cohorts. It is definitely reasonable to believe that different datasets lead to different results. To test this, we constructed new datasets by combining the two used in both analyses. Then respective regressions were conducted to see if coincident conclusions are achieved.

Table 5 reports the regression results on two new datasets: one with 22 OECD countries as in JT2015 and the other with 30 OECD countries as in YKL2014. Both cover the period from 1960 to 2010. Note that we do not include any control variable in these regressions.

For each dataset, four models are regressed. The first two models use the share of working population following YKL2014, while the last two follow JT2015's definition. The odd number models take the specification, Equation [3], and the even number models use the specification, Equation [4], shown below in sub-section 3.3.2. Note that the significance of the coefficients decreases and the goodness of fit drops when eight more countries are included. Thus, our following discussion focuses on the former dataset, i.e. model (1), (2), (3) and (4) with 22 OECD countries.

YKL2014's results (significantly negative coefficient on the share of old) are robust for the new 22 country dataset (model 1), and for JT2015's definition of population shares (model 3). Similarly, JT2015's results (significantly positive coefficients on shares of the young and the old) are also robust to inclusion of more data. Thus, these two papers' opposite conclusions seem to be not caused by the distinctions in their datasets.

3.3.2 Technical issues

We would say it may be the following technical difference that causes their opposite conclusions. YKL2014 use population growth, share of working age and old, and life expectancy as explanatory variables, while JT2015 mainly rely on population polynomials. Nevertheless, we can still make a comparison based on the following two similar panel-regressions.

$$\pi_{it} = \mu_0 + \mu_i + \beta_1 n_{it}^{work} + \beta_2 n_{it}^{old} + \varepsilon_{it}, \qquad [3]$$

$$\pi_{it} = u_i + \theta_1 n_{it}^{young} + \theta_2 n_{it}^{work} + \theta_3 n_{it}^{old} + \epsilon_{it}. \qquad [4]$$

where n_{it}^{young}, n_{it}^{work}, and n_{it}^{old} are the shares of young, working age and old, respectively. Again, μ_0 is a constant and μ_i is the country-specific fixed effect. Equation [3] corresponds to model (3) in YKL2014, while Equation [4] corresponds to model (3) in JT2015. Note that there is no constant in Equation [4] because the three population shares sum to one. Let us see the coefficients on n_{it}^{old}. Interestingly, as illustrated in columns labeled with (3) and (4) in Table 5, β_2 has the value -0.18 which is significantly negative as in YKL2014, while θ_3 has the value 0.24 which is significantly positive as in JT2015. In other words, everything else being the same, the above two specifications predict opposite directions for the impact of aging on inflation. However, this does not mean there is inconsistency in the estimates between Equation [3] and Equation [4]. To see this, rearrange Equation [3] to the following.

$$\pi_{it} = \frac{\mu_0}{100}(n_{it}^{young} + n_{it}^{work} + n_{it}^{old}) + \mu_i + \beta_1 n_{it}^{work} + \beta_2 n_{it}^{old} + \varepsilon_{it}, \qquad [3']$$

$$\pi_{it} = u_i + \frac{\mu_0}{100} n_{it}^{young} + \left(\frac{\mu_0}{100} + \beta_1\right) n_{it}^{work} + (\frac{\mu_0}{100} + \beta_2) n_{it}^{old} + \varepsilon_{it}. \qquad [3'']$$

given $n_{it}^{young} + n_{it}^{work} + n_{it}^{old} = 100$ (percentage). The Equation [3''] exactly corresponds to Equation [4], i.e. $\theta_1 = \frac{\mu_0}{100}$, $\theta_2 = \frac{\mu_0}{100} + \beta_1$, and $\theta_3 = \frac{\mu_0}{100} + \beta_2$. The figures in column (3) and (4) in Table 5 confirm these relationships. Now, it seems to us that YKL2014 conclude that aging is deflationary because of the negative coefficient on n_{it}^{old} following regression (3). In contrast, JT2015 follow regression (4) to conclude that aging is inflationary. We would say JT2015 deliver the "true" information regarding the overall impact of the old on inflation.

In addition, one interesting observation appears. Even though both the young and the old impact inflation positively, the old is less inflationary than the young, i.e. $0 < \theta_3 < \theta_1$. We may connect this observation to the literature. First, as explained in JT2015, dependents (both young and old) could exert an inflationary pressure through excess demand because they consume more goods and services than they produce. Second, the old may exert a deflationary pressure because of either political reasons (Katagiri et al. (2014)) or economic reasons (Anderson et al. (2014)). At this point, it seems that the first effect dominates, *i.e.* the overall impact of the old on the inflation is positive. The second effect, however, makes the old less inflationary than the young.

4 Further Analysis

In this section, we first examine the relationship between age and inflation in two different sub-periods of the OECD panel. In the second subsection, we conduct analysis using data on the U.S. economic regions and make comparisons with the results from OECD panel regressions. Finally, we analyze the age impact on inflation for the old population using more refined demographic data from 1990.

4.1 Analysis on the OECD panel with different sub-periods

In this subsection, we explicitly examine the age patterns on inflation for the OECD panel with various sub-periods, including those years before and after 1980. Figure 8 shows the results. The green and dark blue curves are derived from the panel regressions over the sub-period 1955 – 1979 and the sub-period 1980-2010, respectively.

Compared with the full period benchmark model (the light blue dotted line), in the sub-period 1955 – 1979, the young is more deflationary but the old is much more inflationary. However, the coefficients are all insignificant over this sub-period. A possible reason for the insignificancy is that before the 1980s, inflation was mainly driven by factors such as oil price shocks and easy-money policies adopted in central banks, rather than by demographic changes. By contrast, in the sub-period 1980 – 2010, demographic structure has significant impacts on inflation. Young exert positive pressure on inflation, while the old is strongly deflationary.

4.2 Analysis on the U.S. economic regions

4.2.1 Data

We use data on states of the U.S. as the building blocks to construct the panel. The panel covers eight economic regions defined by the Bureau of Economic Analysis (BEA)[8]. For these economic regions, annual series for nominal and real regional Gross Regional Product (GRP) are available from BEA over the period 1978 – 2010. From real and nominal GRP we can derive a regional GRP-deflator. Regional inflation is measured as the percentage change from the previous year of the regional GRP-deflator.[9] We then construct a measure for the output gap by using the deviations in real GRP from a Hodrick-Prescott filtered trend[10]. As for the interest rate, all regions share the same real interest rate over the period 1978 – 2010. Demographic data of all 50 states and 1 federal district over 1978 – 2010 is compiled from the U.S. Census Bureau's State Projection tables[11]. Then, regional demographic data is built up by grouping the states for each BEA area.

4.2.2 Analysis

We conduct the analysis following JT2015, Equation [2]. Note that the dummy $d74$ has been dropped since year 1974 is not covered in the panel. Table 6 reports the panel-regression estimates of various model specifications for the U.S. BEA regions[12].

The dependency ratio appears to be positively correlated with inflation (model 1). From model (3), we can see that the young and the old have opposite impacts on inflation: the former exert an inflationary pressure while the latter exert a deflationary pressure. The working population's impact is small and not significant.

Using the estimates from model (10), we can visually check the age profile on inflation in the US economy. There are two curves in Figure 9. The green curve is from the panel regression on U.S. BEA regions during 1978 – 2010. The dotted blue curve represents the estimates from the OECD panel over the same period. The BEA regional panel generates qualitatively similar age patterns on inflation as that for the OECD panel over the same period. Quantitatively, the green curve seems to be flatter than the dotted blue curve. More important, both curves show that the older group is significantly deflationary. Thus, the negative impact of aging on inflation in the recent three decades that we observed from the OECD panel also holds for the U.S. regional panel.

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[8] For component state list for BEA regions, see http://www.bea.gov/regional/docs/regions.cfm.

[9] In contrast to using CPI based inflation in the study of OECD panels, here we use GRP deflator to measure inflation. This is because not all states have CPI based inflation data. For detail, see Bureau of Labor Statistics website: http://www.bls.gov/cpi/cpiovrvw.htm.

[10] In macroeconomics, the Hodrick-Prescott filter is used to remove the cyclical component of a time series from raw data.

[11] The upper group for the old is 80+ in the OECD panel, but 85+ for the U.S. regional panel.

[12] Only selected models are reported in this report. Estimates of other models (those with time effects) are available upon request.

4.3 Analysis on the OECD panel with more refined older groups

From observations of age patterns on inflation obtained, it is quite interesting and reasonable to hypothesize that the "younger old" may be inflationary but the "older old" are deflationary. Since the U.N. population table does provide more refined demographic data for "older old" from 1990, i.e. data on 80-84, 85-89, 90-94, 95-99, 100+ age cohorts, we can test the hypothesis using a sub-period OECD panel over 1990 – 2010. Figure 10 shows the result. The green curve represents the age pattern derived from the new sub-period panel regression with finer demographic data and the dark blue dotted line is for the same sub-period panel but with the original age group definition. The light blue dotted line is again for the benchmark model with full panel. From the graph, it is obvious that our hypothesis is supported. That is, for the old population, the older the age, the more deflationary the cohort is. In addition, the working population is (slightly) inflationary for the new sub-period panel.

5 Panel VAR Regression

The adoption of the reduced-form panel VAR methodology is from a working hypothesis that demographic (or age) structure matters for the economy. This assertion is motivated by at least two important considerations. First, the life-cycle theory predicts that different age groups have different savings behavior. Second, available empirical observations on the age profile of wages from labor markets suggest that different age groups appear to have different productivities and to work different amounts of hours, with the very young and very old tending to work the least number of hours. Both of these factors have implications for labor input. Also different age groups appear to generate different types of investment opportunities, as firms target their different demands. These adjustments of savings and investment in response to changes in the age structure are hypothesized to have an impact on real interest rates, inflation and real output in the economy.

The approach undertaken in this section has three important characteristics. First, we consider one-year periods and adopt a panel time-series approach to estimation of our VAR models. Second, we allow for interaction effects among a number of leading macroeconomic variables by estimating a VAR model instead of an individual equation. Third, we make no assumptions about the underlying economic processes and hence impose a minimal structure on the data.

The parts of this section are organized as follows. Subsection 5.1 provides the econometric framework for the reduced-form panel VAR methodology. Subsection 5.2 reports and discusses the reduced-form panel-data VAR estimates, followed by a series of robustness tests. Subsection 5.3 presents results for selected individual countries. Finally, Subsection 5.4 discusses the out-of-sample forecasting accuracy of our VAR model with demographic transition changes vis-a-vis a VAR model without demographic transition.

5.1 Data and econometric model

The annual dataset covers the period over 1999-2010 covering twenty countries in four continents. They comprise:

- one Asian country[13]: Japan;
- two North American countries: United States, Canada;
- fifteen European countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Netherlands, Norway, Sweden, Switzerland, and United Kingdom; and
- Australia and New Zealand.

The demographic data was obtained from the United Nations (2012). The annual data on savings and investment rates were calculated from Nominal GDP, Investment and Savings series obtained from the OECD (2012), which also supplied the data on hours worked. Annual data on policy rates and the Consumer Price Index (CPI) were obtained from the IMF (2012). Per-capita GDP growth rates were calculated from per-capita real GDP obtained from Penn World Tables.

We index country by i where, $i = 1,2, \ldots, N$, and year by t where, $t = 1,2, \ldots, T$. In the empirical analysis, we are faced with two challenging problems. First we have at our disposal a relatively small number of time-series observations at the annual frequency. Second for each country, we also have a large number of macroeconomic control variables which are low frequency and, hence, likely to be highly co-linear. Both factors can contribute to low precision of the parameter estimates of the panel-data VAR regressions. As a result, we decide on coarser demographic proportions by decade. Denote the share of age group $j = 0,1, \ldots, 7$ (0 -9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70+) in total population by w_{jit} and suppose the effect on the variable of interest, say x_{it}, takes the form:

$$x_{it} = \alpha + \sum_{j=0}^{7} \delta_j w_{jit} + u_{it}. \qquad [5]$$

As $\sum_{j=0}^{7} w_{jit} = 1$, there is perfect collinearity among the demographic proportions if all the demographic shares are included. To deal with this, we restrict the coefficients to sum to 0, use $w_{jit} - w_{7it}$ as explanatory variables and recover the coefficient of the oldest age group from $\delta_7 = -\sum_{j=0}^{6} \delta_j$. We denote the 7 elements vector of $w_{jit} - w_{7it}$ as W_{it}.

The six endogenous variables of the system are:

1. the growth rate of the real GDP, y_{it};
2. the share of investment in GDP, I_{it};
3. the share of personal savings in GDP, S_{it};

[13] In this short panel, Korea is excluded as an outlier.

4. the logarithm of hours worked[14], H_{it};
5. the nominal short interest rate, R_{it}; and
6. the rate of inflation, π_{it}.

We denote the vector of these six variables as $Y_{it} = \left(y_{it}, I_{it}, S_{it}, H_{it}, R_{it}, \pi_{it}\right)$. The exogenous variables are: W_{it} and two lags of the logarithm of the real oil price[15].

There are likely to be complicated dynamic interactions among the six economic variables, but there is relatively little research aimed at suggesting an appropriate model for panel data. Bond et al. (2010) consider a relationship between y_{it} and I_{it} in detail. However we also expect interaction with the other variables because of the other theoretical linkages mentioned earlier.

Ideally we would like to estimate an identified structural system between these six variables allowing for expectations. Suppose, ignoring oil prices, that such a structural system would be given by:

$$\Phi_0 Y_t = \Phi_1 \mathrm{E}[Y_{t+1}] + \Phi_2 Y_{t+2} + \mathrm{T} W_t + \varepsilon_t. \qquad [6]$$

Then there is a unique and stationary solution if all the eigenvalues of A and $(I - \Phi_1 A)^{-1}\Phi_1$ lie strictly inside the unit circle, where A solves the quadratic matrix equation:

$$\Phi_1 A^2 - \Phi_0 A + \Phi_2 = 0. \qquad [7]$$

In that case the solution is:

$$Y_t = A Y_{t-1} + \Phi_0^{-1} \mathrm{T} W_t + \Phi_0^{-1} \varepsilon_t. \qquad [8]$$

It is difficult to identify the structural system such as Equation [6]. If there are m endogenous variables, to identify Equation [6] we need to impose $2m^2$ identifying restrictions (see the discussion in Koop et al., 2011; Komunjer and Ng, 2011). For this reason, in this project, we opt for estimating the solution or reduced form of such a structural system and assume that conditional on the exogenous variables it can be written as a VAR, such as Equation [9] below. Notice that since A will be a complicated function of all the structural parameters, as the Equation in [7] shows, it would be difficult to interpret the coefficients of the equation.

The objective of this analysis is primarily to provide predictions of the long-run effect of the demographic variables. These predictions could be obtained from a structural model as in Equation [9]. Over-identifying restrictions, if they are available and binding, would increase the efficiency of the estimation, but given that we have a relatively large panel, the efficiency issue would not be a paramount issue here.

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[14] It is customary in empirical studies to take the logarithm of *continuous* variables in order to (i) stabilize the variance of the variables a bit, to capture potential nonlinearities in the variable; (ii) to render residuals more symmetrically distributed; and (iii) to facilitate interpretation of the coefficient estimates of parameters as elasticities.

[15] The reason we use two lags on the oil price, rather than one, is because the second lag is statistically significantly different from 0.

We allow for intercept heterogeneity through a_i but assume slope homogeneity and estimate a one-way fixed-effect augmented-panel VAR (2) of the form:

$$Y_{it} = a_i + A_1 Y_{i,t-1} + A_2 Y_{i,t-2} + \mathrm{D}W_{it} + u_{it}. \quad [9]$$

plus two lags of the oil price. D is the matrix of coefficients of the demographic variables.

Our estimate of the effect of the demographic variables captures the marginal effect after having controlled for lagged Y_{it} and the oil price. Implicitly we assume either that all the variables are weakly stationary or that an unrestricted VAR will capture stationary combinations by either differencing or co-integrating linear combinations. Even these variables may be non-stationary. We do not exploit efficiency that comes from looking at long-run regressions such as co-integrating regressions. We are more concerned with policy effects and hence emphasize the endogeneity and short-term nature of the relationships. Bond et al. (2010) discuss this issue with respect to the investment share and Phillips and Moon (1999) and Coakley et al. (2006) suggest that spurious regression may be less of a problem in panel data with a dominating cross-sectional dimension.

Slope heterogeneity, if it is ignored, could have an adverse effect on dynamic panel data. In particular, Pesaran and Smith (1995) show that it can produce bias in the coefficient estimates of the lagged dependent variable towards one and the coefficient of the exogenous variable towards zero. However these two biases may offset each other in the calculation of the long-run effects, which is the focus of our interest. We adopt a fixed effect estimator which imposes slope homogeneity across countries, partly because we are estimating a great number of slope parameters and partly because the demographic variables show very low frequency variation relative to annual time-series and the elements are highly correlated. Thus heterogeneous estimates based on relatively few degrees of freedom may be poorly determined and likely to produce outliers. We found this to be the case when we experimented with VARs for each country. In addition, Baltagi and Griffin (1997) and Baltagi et al. (2000) show that the homogeneous estimators tend to have better forecasting properties. Therefore, since our main aim in this analysis is to predict the variables conditional on demographics, the homogeneous estimators may provide better predictors of this demographic contribution.

The long-run moving equilibrium for system is then given by:

$$Y_{it}^{*} = (I - A_1 - A_2)^{-1} a_i + (I - A_1 - A_2)^{-1} D W_{it}. \quad [10]$$

where $(I - A_1 - A_2)^{-1} D$ captures the effect of the demographic variables. This reflects both the direct effect of demographics on each variable and the feedback between the endogenous variables. This allows, for instance, the effects of demography on savings to influence growth through the effect of savings on growth.

We can isolate the long-run contribution of demography to each variable in each country by:

$$Y_{it}^{D} = (I - A_1 - A_2)^{-1} D W_{it}. \quad [11]$$

This is the demographic attractor for the economic variables at any given time. This is a long-run estimate in a specific sense of being the long run forecast for the economic variables conditional on a particular vector of demographic shares after the completion of the endogenous adjustment of the economic variables. But over time the shares would also change as people grow older, so this is not a long-run steady state which would also allow for the extra adjustment of the demographic shares to their equilibrium, which we do not model here. In this analysis, we will examine the movements of elements of this vector, Y_{it}^{D}, over time, to indicate the low frequency contribution of demographics to the evolution of a particular variable in a particular country.

5.2 Results of Panel-data VAR regressions

We choose between the panel-data VAR (1) and panel-data VAR (2) specification on the basis of the Schwarz Bayesian Information Criterion (BIC). On that basis, we find that a one-way fixed-effect model with country intercepts was preferred for every equation to a two-way fixed-effect model with country and year intercepts, but without the oil price. This suggests that cross-section dependence or common trends is not a major problem with the VAR specification, but we investigate the robustness of our results to this below. A panel-data VAR (1) specification and a panel-data VAR (2) specification had almost identical BICs, although the VAR (2) specification has slightly smaller BIC values, indicating that it fits the data slightly better. As a result, we decided to use a VAR (2) specification primarily to allow for more flexible dynamics and to deal with potential non-stationarity.

Allowing for more flexible dynamics in the VAR specification is critical for our setting since there are complicated dynamic interactions between the six economic variables and there is relatively little known results in the literature suggesting an appropriate model for panel data. For instance, even if we focus on the relationship between output and investment, we would still need to take into account interaction with the other variables because of the other theoretical linkages that exist in a dynamic stochastic general equilibrium setting. General equilibrium effects are critically relevant in a study of this sort, as other variables adjust. In particular, crucial intervening variables in the transmission of demographic structure to growth and savings are years in education; the age, sex and skill specific labour force participation rates and pension wealth. Although there are difficult measurement issues associated with each of these factors, all seem to have shown large variations over our sample. In addition in an explicitly dynamic stochastic general equilibrium framework, savings (hence consumption) is subject to both substitution and wealth (income) effects. In our savings analysis, we have included nominal short term policy rates and inflation in order to capture inter-temporal consumption preferences. Moreover, working with a VAR (2) specification (instead of VAR(1) specification) reduces the potential of spurious regression although we believe that spurious regression is less of a problem in the panel data setting, in particular when the cross-section dimension is large relatively to the dimension of time series.

Table 7 reports the $A_1 + A_2$ matrix. In this table, each row represents an equation in the panel-data VAR representation. We observe that hours are highly persistent and investment, savings, nominal interest rates and inflation rate are equally so. We also note that there is evidence that all of the endogenous variables Granger cause[16] some other variables in the system, perhaps with the exception of savings which is found not to be a significant influence on any other variable. Lagged growth is shown to significantly affect all the variables including savings and interest rates. Investment is found to significantly influence growth, inflation and savings. Hours also significantly impact interest rates and inflation. Interest rates significantly influence growth, investment and hours. Inflation significantly affects interest rates. Lastly oil prices are shown to significantly influence all of the six variables with the exception of investment. We are surprised to find that lagged investment has a negative effect on growth, despite the fact, as noted below, that there is a strong positive contemporaneous correlation between the growth and investment residuals. For OECD countries Bond et al. (2010) found a small positive effect in the bivariate relationship. The nominal interest rate has a negative effect on all the other variables, and although inflation has a positive effect, the coefficients are quantitatively small, indicating that this is not picking up a real interest rate effect.

Table 8 reports the D matrix of *short term* demographic impacts on the six endogenous variables. We find that the individual coefficients are not very well determined due to high collinearity among the variables in the VAR specification, but the hypothesis that the coefficients of the demographic variables are jointly not significantly different from zero is strongly rejected for all equations except hours worked (see Table 16 and Table 17). In theory, we would expect that the demographic structure has significant impacts on hours worked. That it does not in our empirical results may indicate that there are likely to be offsetting adjustments in the labor force participation rates. Generally the results are plausible, although there are some unexpected results. For instance there is a negative effect of the 30-39 age group on growth and a positive effect of teenagers on savings and of the 60-69 years cohort on investment.

Table 9 gives the $(I - A_1 - A_2)^{-1}D$ matrix. We note that by allowing for rich dynamics and interactions among the macroeconomic variables, the long-run effects are found to be much larger. In particular, we notice that the effect on hours is markedly more pronounced in our empirical results, perhaps due to this variable being highly persistent over time.

Table 10 reports the matrix of correlations between the residuals of each equation of the panel-data VAR regression. We see evidence of strong contemporaneous correlations between the residuals of some of the equations, potentially capturing business cycle effects. The correlation coefficient between the residuals from the growth equation and the residuals from the investment equation is recorded at 0.432, the savings equation 0.486 and the hours equation 0.410 respectively.

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[16] "Granger cause" is a term for a specific notion of causality in time-series analysis, first proposed in Granger (1969). The idea is: A variable X Granger-causes Y if Y can be better predicted using the histories of both X and Y than it can using the history of Y alone.

These are the largest recorded sample correlation coefficients in our analysis. All of the sample correlations are expected to be positive, except, for a very small negative correlation between savings and interest rates.

5.2.1 Robustness to the presence of time effects

As mentioned earlier, the model chosen according to BIC assumes one-way fixed-effects and includes oil prices as a measure of technology shocks across countries. One potential drawback of this approach concerns the presence of marked trends in our data. If there are shared, cross-country, factors driving the trend in the dependent variable as well as the demographic variables, this trend may be wrongly attributed to the demographic variables in the one-way, country, fixed-effect model. A two-way effects model avoids this issue by removing any common cross-country factors from all variables prior to estimation.

Table 11 shows the *long-term* impact of demographic variables under a two-way fixed-effects VAR model. When comparing the results in this table with those reported in Table 9, we observe that although the impact does change significantly for inflation, hours and savings, the impact on GDP growth is remarkably robust to the chosen effect. This result leads us to conclude that the impact of demographic variables on growth and investment identified by the panel-data VAR (2) specification is not a statistical artifact of a spurious correlation.

5.2.2 Robustness to exclusion of individual countries

In this subsection, we test the robustness of our results with respect to the selected countries by re-estimating the specification in the panel-data VAR (2) regression on a dataset with each country excluded in turn.

The results are not presented in this report for brevity. Briefly we obtain results that are relatively stable with respect to these exclusions, as are the tests as to whether the demographic variables are significant in each equation.

5.2.3 Structural Change

We also test for potential structural change by estimating the panel-data VAR regression on various sub-periods of the entire dataset, and then selecting the preferred panel-data VAR specification using the BIC.

Again, for brevity, we do not include the results of this specification in this report. Briefly we find that for the first four equations in the VAR models, namely, growth, investment, savings and hours worked, a country-by-country VAR specification over the full sample period is preferred over the VAR specifications with structural breaks in any given year. For the last two equations, interest rates and inflation, we find that the VAR models with 2008 and 2004 as the break points tend to be preferred based on the BIC.

Estimating the panel-data VAR regression over two subsamples spanning 1999-2005 and 2006-2010 respectively yields results that differ from the full sample estimation as well as each other, indicating the possible presence of structural instability. For brevity, the results are not reported here. Briefly the ranges of the demographic variables for the two sub-periods are also found to be somewhat different, however, and the second period has a vastly reduced variation in interest rates since the Euro member countries in our sample shared a common rate for much of the period.

5.3 Country-specific study

In this section, we consider how the results obtained in our study may shed some light on the question of whether the baby boomers squandered the demographic dividend. For this purpose, we conduct a counterfactual analysis. Table 12 shows, for the countries with available data, the impact on the six variables of the change in demographic structure between 1970 when the baby boomers were participating in the labor market, and 2010, when they were approaching retirement. This is calculated using Equation [10] and the long-run estimates from the one way fixed effect model.[17] Note that only for the purpose of conducting a counterfactual exercise do we include observations starting from 1970 in our empirical analysis. In all other analysis, the estimation starts from 1999. This is because our experiment suggests that the panel-data VAR regressions exhibit major structural instabilities when the earlier samples from 1970 to 1998 are included in the estimation, producing highly biased estimates of the parameters.

The estimated impact of demographic changes on GDP is expected to vary across countries, but given our VAR model, 2010 real GDP growth would have been 2.88% less for Japan as compared to 1970 and 0.69% less for the U.S. In general, given our estimated panel-data VAR regression, Japan in 2010, as compared to 1970, has been mostly affected by the changes in the age profile, as all variables would have been substantively depressed including the hours worked. It appears, that given our panel-data VAR specification, while in various countries there would have been some form of contrarian adjustment in the hours worked as a response to demographic pressures, Japanese and, to a limited extent, we expect that Finnish and Swedish labor markets would not have followed such a pattern.

We also find that the estimated impact of demographic changes on both the interest rate and inflation is strongly negative and of quite similar orders of magnitude, consistent with real interest rate effects. Since the 1970s were the decade when the baby boomers entered the labor force strongly, we might have expected the supply-side effect to be deflationary, the arrival of such a large cohort depressing wages, but the demand-side effects might have been inflationary. Although both interest rates and inflation are expected to be higher around 1970 than in 2010, the change over the period is not expected to be as large as predicted by demographic factors. However,

[17] The nature of low frequency variables increases the likelihood of high collinearity among these variables in individual country regressions. Pooling variables across countries may mitigate the dominance of those variables and enhance efficiency by having more observations and taking advantages of "common" shocks faced by the countries. But at the same time, it might mask some of the idiosyncratic shocks associated with each country.

the two-way fixed-effects estimates above suggest that the demographic effects on these two variables might be overstated.

The estimated panel-data VAR regression can also be applied to the predicted future demographic structure. Using both historic data and forecasts for the demographic structure, Table 13 provides forecasts of the average impact of demographic structure on average annual per-capita GDP growth over the decade 2010 - 2019, and compares it to that over 2000-2009. It suggests that in all countries in our sample the impact of demographic factors over this decade will put downward pressure on GDP growth. The magnitude of this pressure is likely to be economically highly significant: for the U.S., for example, it is -1.35%.

5.4 Forecast Performance

An important measure of the usefulness of any econometric model is the extent to which it is capable of forecasting future events out of samples. With this in mind we carry out an ex-post forecasting exercise of our panel-data VAR model; that is, we estimate the model using the data available up to 2005 and use that model to forecast the path of the economy over the following five years, 2005-2010.

Table 14 presents the results from a series of one-year-ahead forecasts, where period t realized values are used to forecast period $t+1$ outcomes. We find that adding demographic variables to the panel-data VAR specification improves the accuracy in this sample for all variables other than savings and hours worked.

Table 15 reports results from five-year-rolling forecasts. Here, the forecasts for the current year are used as inputs to forecast the next year, consistent with a long-range forecast. Again the demographic variables are shown to improve the forecasts of inflation and interest rates over the VAR model without demographics.

6 Conclusion and Future Research

Two types of analyses have been conducted. Here we summarize the key features of what we learned from each of the exercises, and also the weaknesses.

The first piece of analysis involved the use of cross-country panel data regressions, subsequently applied to regions in the United States. We identified two recent working papers that purportedly find opposite effects despite using data for a similar group of countries from a similar period. We replicated the benchmark results of the two studies to determine if there were any technical features that were leading to the apparent disagreement. On careful comparison, we found that the difference in results does not appear to be simply a feature of the data, as a comparable specification has the same results. Thus, we looked at the key differences in their methodologies and their interpretation of their results.

In terms of interpretation, when YKL2014 find negative coefficients for elderly age groups when they regress inflation on a set of variables, they should only be able to conclude that aging is disinflationary, not deflationary (as the coefficients are relative rather than absolute). Thus, their findings are not as different as they seem to those of JT2015. The latter authors also find that a polynomial function reflecting the effect of various age groups on inflation turns downwards at the higher ages, but they discount this finding.

The model specification of YKL2014 incorporates the effect of population growth, an important consideration that is not covered in all the other analyses discussed here. However, their methodology makes the odd choice of running a regression (on annual frequency) of detrended inflation on detrended demographic variables. This is unfortunate, as our interest is in discovering the relationship between the trends rather than the annual deviations from trend in these variables. The annual frequency remains a limitation of all the papers discussed.

The replication analysis suggests that the different choice of specification and methodology results in different findings between the two studies. Besides, there is only weak support for the points where there is any contention between the two studies.

Our analyses on the OECD panel over different sub-periods and on the U.S. regional panel suggest that it is the sub-period, rather than the panel sample, that determines the pattern of the impact of aging on inflation. In addition, we believe that, as supported by the study on OECD data after 1990, a finer adjustment to age categories is needed to capture the potentially different effects of the older and younger of the 65+ age group. That is, for the old population, the older the age, the more deflationary the cohort is. This finding suggests that studies on the old should use a greater number of age groups. This is particularly important because the size and the length of this age group is increasing due to increasing longevity.

The challenge of determining the link between aging and inflation is that demographic changes exert (according to theory) opposing forces on price levels. Keeping population size constant, aging causes reduced expectations of growth and consumption (deflationary), while also reducing the resources available for production. This latter effect can take place directly or through structural transformation, which are both inflationary. An empirical examination of the relationship suffers from the danger of failing to control for other more salient factors that affect inflation. Moreover, the data appears to be a source of another problem – there is very little evidence of deflationary episodes in our sample period, making it difficult to analyse the prospects for deflation as opposed to disinflation, or inflation falling to low levels.

The second piece of analysis attempts to address this problem through a cross-country panel vector auto regression (VAR) model, whereby several key variables were modelled jointly to be able to identify the effect of the age distribution on inflation. Our results indicate that the age profile of the population can have both an economically and a statistically significant impact on output growth, investment, savings, hours worked, interest rates and inflation. However, the panel

VAR analysis suggests that the older age group is slightly inflationary. This result may be caused by coarse demographic groups and the short period studied. We report that our model is robust to the presence of time effects and exclusion of individual countries. We also find that our model with demographic structure improves the panel-data VAR specification that excludes demographic variables. This leads us to conclude that using such a model should provide more accurate predictions for growth over the long term horizon.

The panel VAR analysis had several limitations. Firstly, to better identify demographic shocks, it would be desirable to use a longer period of data. The short period of data also necessitated analysis at the annual frequency, though it would be reasonable to assume that demography affects the economy in more subtle ways over longer periods of time. However, to understand relationships such as that between aging and inflation, the VAR could prove to be a useful methodology. Both age structure and inflation demonstrate long memory and there is a risk of detecting spurious relationships if the possibility of co-integration is not properly tested.

Secondly, estimation of the coefficients of low frequency and highly collinear determinants is highly sensitive to the specification of the model and the estimation method used. Endogeneity is also another serious problem in this type of study. Although the proportions in each age group are plausibly exogenous, the other leading macroeconomic variables in the system are likely to be responding to the low frequency demographic impacts. For example, the high birth rate that produced the baby boomers after the Second World War is unlikely to be influenced by growth rates in the 1990s, but these growth rates may be driven, at least in part, by this baby boom. This has the effect of reducing the marginal contribution of the demographic variables to the overall performance of the economy.

Lastly, there are likely to be nontrivial second-round general equilibrium effects, as other variables adjust in the system in response to shocks impinging on the economy. This is particularly the case with key intermediate variables engaged in the transmission of demographic structure to growth and savings, such as years in education; the age, sex and skill-specific labor force participation rates and pension wealth. In various studies, all of these variables have been shown to have large variations over time and across countries.

By taking into account the advantages of each of the approaches, we could improve the empirical analysis by including the appropriate variables over a longer horizon and adopting methodologies that take into account the smoother long-term variation in age structure. Such a methodology would involve either trend comparisons by sampling data over lower frequencies or conducting a co-integration analysis. Further exploration of the frequency domain of the underlying variables would also be useful. But such analysis is beyond the scope of this project.

In conclusion, the research demonstrates that demographic structure does affect economic factors such as growth and inflation. However, the measurement and quantification of this impact remain challenging problems worthy of further research. This effect has significant implications for actuaries who make and rely on projections of demographic and economic effects in their work. The actuarial profession should stay informed regarding developing research in this area.

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8 Appendix

8.1 Tables

Table 1: Comparison with YKL2014

Model	(1)			(2)			(3)		
	YKL2014	Our Est.	No Detrend	YKL2014	Our Est.	No Detrend	YKL2014	Our Est.	No Detrend
Pop. Growth_de	0.339	2.593**		0.524	2.694**				
Pop. Growth			0.906			0.454			
Share_old				**-0.176*** **	**-0.121**	**-1.484*** **	**-0.125** **	**-0.0837**	**-1.331*** **
Share_work							-0.101	0.135	-1.718***
GDP growth	-0.145***	-4.774	-11.02	-0.144***	-5.210	-16.12	-0.145***	-5.717	-5.832
Life Exp.	-0.750***	-0.336**	-0.162	-0.795***	-0.345**	-0.271	-0.799***	-0.348**	-0.141
M2 growth	0.192***	0.0202	0.0963**	0.183***	0.0180	0.0676*	0.180***	0.0187	0.0305
Budget chg.	0.129*	-0.0934	0.0619	0.153**	-0.0922	0.0644	0.153**	-0.0945	-0.0611
Constant	-0.053	1.229	3.955***	2.418*	2.637	21.84***	8.443	-6.857	134.5***
Observations	1167	650	650	1167	650	650	1167	650	650
Num. country	30	27	27	30	27	27	30	27	27
R-squared	0.212	0.311	0.310	0.216	0.316	0.405	0.217	0.309	0.500
RMSE	5.235	5.907	5.875	5.227	5.909	5.451	5.223	5.936	5.000

1. Models correspond to those in the left part of Table 4 in YKL2014.
2. Fixed-effect estimation for OECD regression using annual data.
3. The estimates of fixed effects are omitted.
4. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 2: Comparison with YKL2014 (Cont.)

Model	(4)			(5)					
	YKL2014	Our Est.	No Detrend	YKL2014	Our Est.	No Detrend			
Pop. Growth_de	0.549	2.674**		0.317	2.963**				
Pop. Growth			3.533***			4.245***			
Share_old	-0.137***	-0.121	-1.273***	-0.416***	-0.485***	-0.476**			
Share_work	-0.103	0.0132	-1.970***	-0.330**	-0.225	-1.530***			
Life Exp.				0.304**	0.418**	-0.913***			
TOT chg	-0.144***	-5.286	-5.945	-0.143***	-7.587	-0.838			
GDP growth	-0.802***	-0.346**	-0.137	-0.784***	-0.345**	-0.138			
M2 growth	0.180***	0.0183	0.0272	0.176***	0.0195	0.0238			
Budget chg.	0.158**	-0.0913	-0.0243	0.150**	-0.0722	-0.0579			
Constant	8.739	1.770	145.8***	4.132	-10.66	177.2***			
Observations	1167	650	650	1167	650	650			
Num. country	30	27	27	30	27	27			
R-squared	0.217	0.314	0.515	0.222	0.317	0.531			
RMSE	5.223	5.914	4.923	5.209	5.904	4.840			

1. Models correspond to those in the left part of Table 4 in YKL2014.
2. Fixed-effect estimation for OECD regression using annual data.
3. The estimates of fixed effects are omitted.
4. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 3: Comparison with JT2015

Model	(1)			(3)			(5)		
	JT2015	Our Est.	30 countries	JT2015	Our Est.	30 countries	JT2015	Our Est.	30 countries
Dep. rate	0.17	0.18	0.13						
	(11.16)	(14.05)	(4.62)						
Share_young				0.31	0.40	0.31			
				(10.61)	(14.55)	(6.62)			
Share_work				-0.23	-0.22	-0.00			
				(-7.67)	(-7.86)	(-3.63)			
Share_old				0.31	0.44	0.00			
				(4.25)	(5.45)	(2.65)			
Poly n1							1.95	1.99	3.02
							(14.15)	(14.22)	(5.81)
Poly n2							-4.62	-4.86	-6.77
(×10)							(-14.97)	(-14.91)	(-5.77)
Poly n3							3.90	4.18	5.42
(×10^2)							(14.62)	(14.60)	(5.39)
Poly n4							-1.07	-1.16	-1.41
(×10^3)							(-13.92)	(-14.04)	(-4.93)
R-squared	0.16	0.27	0.16	0.16	0.65	0.28	0.30	0.38	0.18
Observations	1276	1232	1568	1276	1232	1568	1276	1232	1568

1. Models correspond to those in Table 1 of JT2015.
2. Fixed-effect estimation for OECD regression using annual data.
3. The estimates of constant and fixed effects are omitted.
4. Robust t statistics in brackets.

Table 4: Comparison with JT2015 (Cont.)

Model	(7)			(8)			**(10) Bench Mark Model**		
	JT2015	Our Est.	30 countries	JT2015	Our Est.	30 countries	**JT2015**	**Our Est.**	**30 countries**
Poly n1	1.72	1.76	2.85				**1.91**	**1.34**	**2.88**
	(12.68)	(12.75)	(5.45)				**(18.43)**	**(12.32)**	**(11.32)**
Poly n2	-4.10	-4.32	-6.37				**-4.16**	**-3.00**	**-5.91**
(×10)	(-13.49)	(-13.51)	(-5.42)				**(-17.66)**	**(-12.80)**	**(-11.05)**
Poly n3	3.46	3.72	5.09				**3.26**	**2.35**	**4.39**
($\times 10^2$)	(13.21)	(13.31)	(5.06)				**(16.01)**	**(11.93)**	**(10.02)**
Poly n4	-0.95	-1.04	-1.32				**-0.84**	**-0.60**	**-1.07**
($\times 10^3$)	(-12.59)	(-12.85)	(-4.63)				**(-18.13)**	**(-10.70)**	**(-8.80)**
Real int.				-0.56	-0.58	-0.99	**-0.59**	**-0.59**	**-1.00**
				(-14.46)	(-12.65)	(-13.22)	**(-18.13)**	**(-15.42)**	**(-14.06)**
Out. gap				0.08	0.06	0.01	**0.15**	**0.06**	**0.02**
				(1.78)	(3.21)	(0.29)	**(3.94)**	**(4.90)**	**(0.74)**
D74	6.95	6.37	3.16	4.79	5.22	1.20	**2.37**	**2.89**	**-1.21**
	(6.45)	(6.82)	(1.56)	(8.89)	(10.09)	(0.92)	**(3.49)**	**(5.50)**	**(-0.96)**
D80	5.36	5.48	6.12	6.67	5.90	5.05	**3.87**	**3.56**	**1.35**
	(6.07)	(6.61)	(1.90)	(11.20)	(9.34)	(5.24)	**(5.56)**	**(6.18)**	**(1.47)**
R-squared	0.36	0.42	0.18	0.39	0.47	0.65	**0.62**	**0.70**	**0.72**
Observations	1276	1232	1568	1232	1023	1280	**1232**	**1023**	**1280**

1. Models correspond to those in Table 2 of JT2015.
2. Fixed-effect estimation for OECD regression using annual data.
3. The estimates of constant and fixed effects are omitted.
4. Robust t statistics in brackets.

Table 5: Combined datasets, no control variables

	22 OECD Countries, 1960-2010				30 OECD countries, 1960-2010			
Model	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Share of young, 0-14		0.43***				0.37***		
Share of work, 15-64	-0.52***	-0.08***			-0.39*	-0.02		
Share of young, 0-19				**0.42****				0.40***
Share of work, 20-64			**-0.61*****	**-0.19*****			-0.55***	-0.15**
Share of old, 65+	-0.43***	-0.00	**-0.18****	**0.24****	-0.62***	-0.25	-0.33**	0.07
Constant	43.34***		**41.81*****		37.19***		40.20***	
R-squared	0.30	0.68	0.34	0.69	0.16	0.29	0.16	0.29
Observations	1122	1122	1122	1122	1438	1438	1438	1438

1 Models (1) and (3) correspond to Equation [3], and model (2) and (4) correspond to Equation [4].
2 Fixed-effect estimation for OECD regression using annual data.
3 The estimates of fixed effects are omitted.
4. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 6: Panel Analysis on the U.S. economic regions

Model	(1)	(3)	(5)	(7)	(8)	**(10)**
Dep. rate	0.28***					
Share_young		0.39***				
Share_work		-0.01				
Share_old		-0.71*				
Poly n1			1.11**	0.96**		**0.80****
Poly n2 (×10)			-2.36***	-2.13***		**-1.97*****
Poly n3 ($\times 10^2$)			1.83***	1.68***		**1.64*****
Poly n4 ($\times 10^3$)			-0.48***	-0.43***		**-0.44*****
Real int.					0.19**	**0.11**
Out. gap					0.09	**0.07**
D80				4.77***	5.84***	**4.86*****
R-squared	0.13	0.74	0.35	0.46	0.23	**0.48**
Observations	264	264	264	264	264	**264**

1. Models correspond to those in Table 1 and Table 2 of JT2015.
2. Model (10) is the benchmark specification.
3. Fixed-effect estimation for US economic regions using annual data.
4. The estimates of constant and fixed effects are omitted.
5. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 7: Sum of VAR Coefficients, $A_1 + A_2$

	y (GDP growth)	I (share of invest)	S (share of saving)	H (log of hours)	R (nominal int)	π (inflation)
y	0.278***	-0.396***	0.014***	0.0156*	-0.272***	-0.083***
I	0.132***	0.698***	0.017***	0.043	-0.145***	0.010***
S	-0.149***	-0.141***	0.810***	-0.005	-0.184***	0.026**
H	0.244***	-0.075***	-0.000***	0.049	0. 141***	0.025***
R	0.335***	0.019***	-0.045***	0.047***	0.774***	0.049***
π	0.424***	0.245***	0.238***	-0.023***	-0.182***	0.723***

1. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 8: Short-run Demographic Impacts

	y (GDP growth)	I (share of invest)	S (share of saving)	H (log of hours)	R (nominal int)	π (inflation)
δ_0	-0.002	0.063*	-0.066**	-0.010	0.018	0.492
δ_1	0. 21	-0. 040	0.053	-0.070	0.037	0.100
δ_2	0.232	0.097	0.025	0.059*	-0.05	-0.131
δ_3	-0.004	-0.069*	0.116**	0.106	-0.174	-0. 43
δ_4	0.045	0.017	0.137	0.013**	-0. 09	-0. 218
δ_5	0.042	0.055	0.215*	0.14	0.074	-0.041
δ_6	-0.000	0.258	0.048	0.100	0.091	-0.041
δ_7	-0.415	-0.312	-0.580	-0.320	-0. 191	0. 163

1. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.
2. δ_i are coefficients of age cohorts.
3. δ_7 is derived from restrictions as described in Section 5.1

Table 9: Long-Run Demographic Impact

	y (GDP growth)	I (share of invest)	S (share of saving)	H (log of hours)	R (nominal int)	π (inflation)
δ_0	-0. 267	-0.190	-0.185	-0.109	0. 575	0.975
δ_1	0.268	-0.170	0. 591	-0. 420	0.281	0.518
δ_2	0.088	0.432	-0. 246	0. 535	0. 432	-0.213
δ_3	0.112	0.231*	0.361	1.864	-0. 540	-1.002
δ_4	0.082	0.049	0.411	0.610	-0. 553	-0. 584
δ_5	-0.037	0.139	0.802	0.822	0.261	-0.1341
δ_6	-0.314	0.310	-0.141	-1.015	0.470	0. 172
δ_7	0.0611	-1.021	-1. 538	-1. 433	-0.755	0.043

1. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.
2. δ_i are coefficients of age cohorts.

Table 10: Residual Correlation Matrix of VAR

	y (GDP growth)	I (share of invest)	S (share of saving)	H (log of hours)	R (nominal int)	π (inflation)
Y	1.000	0.432	0.486	0.410	0.391	0.278
I	0.432	1.000	0.027	0.262	0.148	0.235
S	0.486	0.027	1.000	-0.279	-0.037	0.061
H	0.410	0.262	-0.279	1.000	0.195	0.182
R	0.391	0.148	-0.037	0.195	1.000	0.295
π	0.278	0.235	0.061	0.182	0.295	1.000

Table 11: Long-run Demographic Impact in a Model with Two-way Fixed Effects

	y (GDP growth)	I (share of invest)	S (share of saving)	H (log of hours)	R (nominal int)	π (inflation)
δ_0	-0. 239	-0.310	-0.084	-1.523	0. 371	0.386
δ_1	0.251	-0.262	0.948	-0.070	0.157	0.325
δ_2	0.716	0.375	-0.012	0. 512	-0.105	-0. 411
δ_3	0.108	0. 195	0.370	2.022	-0.723	-0.648
δ_4	0.106	0. 561	0. 214	0.958	0.031	-0.013
δ_5	-0.040	0.060	0.231	0.461	0.392	-0. 073
δ_6	-0.030	0.546	0.041	-0.701	0.176	-0. 178
δ_7	0.032	-1.14	-1.760	-1.716	-0.430	0.536

Table 12: Difference in Predicted Impact of Demographic Factors between 1970 and 2010 (in percentage points, except H where it is a percentage)

	y (GDP growth)	*I* (share of invest)	*S* (share of saving)	*H* (log of hours)	*R* (nominal int)	π (inflation)
Australia	-0.357	-0.174	-4.336	7.829	-7.911	-11. 816
Austria	1.448	-0. 555	-0.879	11.041	-9.522	-11. 895
Belgium	0.183	-2.579	-4.962	4.187	-7.059	-7.250
Canada	-1.251	-0.655	-3.922	11.694	-9.639	-15.141
Denmark	-0.496	-1.781	-1.833	1.758	-5.675	-6.256
Finland	-1.750	-4.393	-9.207	-3.667	-7.590	-7.433
France	-0.261	-2.498	-4.292	3.896	-6.580	-7.627
Germany	1.404	-7.101	-10.007	-8.796	-12.773	-9.584
Greece	0.215	-3.587	-9.478	5.017	-11.058	-11.411
Iceland	-0.18340	2.065	-0.752	16.220	-8.736	-14. 764
Ireland	0.830	5.093	0.934	22.338	-9.908	-17.299
Italy	0.105	-5.575	-11.659	1.1865	-11.069	-11.576
Japan	-2.884	-10.418	-17.562	-16.961	-9.913	-7.166
Netherlands	-0.751	-0.852	-2.051	5.855	-7.690	-10.916
New Zealand	0.018	0.883	-3.149	13.266	-9. 063	-13. 647
Norway	0.455	0.095	-0.817	9.392	-6.475	-9.083
Sweden	-0.052	-3.631	-4.885	-1.390	-5.488	-4.262
Switzerland	0.240	-2.626	-3.188	3. 862	-8.473	-9.169
United Kingdom	0.985	-1.32	-4.075	5.238	-8.327	-8.425
United States	-0.686	0.822	-2.501	9. 120	-6.426	-10.331

1. This was calculated by applying the estimated long-run demographic coefficients to the demographic structure in each country as it was in 1970 and in 2010, and subtracting the result of the former from the latter. Updated April 20, 2015 to include Germany based on same parameter estimates as used for other countries.

Table 13: Average Predicted Impact on GDP Growth by Country, in percentage points

	2000-2009	2010-2019	Change
Australia	1.914	0.898	-1.016
Austria	1.628	0.938	-0.69
Belgium	1.397	0.353	-1.044
Canada	2.134	0.469	-1.665
Denmark	0.753	0.296	-0.457
Finland	0.985	-0.037	-1.022
France	1.538	0.693	-0.845
Germany	0.952	0.614	-0.338
Greece	1.479	0.692	-0.787
Iceland	2.220	1.013	-1.207
Ireland	2.118	0.970	-1.148
Italy	1.047	0.489	-0.558
Japan	0.341	-0.104	-0.445
Netherlands	1.337	0.277	-1.06
New Zealand	1.970	0.771	-1.199
Norway	1.548	0.565	-0.983
Sweden	1.137	0.187	-0.95
Switzerland	1.568	0.700	-0.868
United Kingdom	1.461	0.647	-0.814
United States	1.969	0.622	-1.347

1. These results are calculated by applying estimated long-run demographic impacts on growth to the demographic structure of the population each year, and averaging the results over each period. The latter period is based on demographic forecasts from United Nations (2012). We use the long-run impact to allow for interaction effects. Updated April 20, 2015 to include Germany based on same parameter estimates as used for other countries.

Table 14: 1-Year-Ahead VAR Forecast, 2005-2010

	Without Demographics			With Demographics		
	RMSE	Bias	cum.Corr	RMSE	Bias	cum.Corr
Y (GDP growth)	0.027	0.115	0.208	0.025	-0.000	0.422
I (share of invest)	0.014	0.004	0.888	0.016	-0.001	0.945
S (share of saving)	0.018	0.004	0.886	0.031	-0.010	0.874
H (log of hours)	0.016	0.000	0.494	0.016	-0.006	0.631
R (nominal int)	0.021	0.006	0.780	0.019	-0.001	0.711
π (inflation)	0.038	0.015	0.256	0.032	0.006	0.117

1. Cum.Corr is the correlation between the sum of forecast and actual outcomes over the entire period; since each cumulative outcome is the outcome for a single country, this indicates how well the model forecasts cross-country differences.

Table 15: Rolling VAR Forecast, 2005-2010

	Without Demographics	With Demographics
	cum.RMSE	cum.RMSE
Y (GDP growth)	0.152	0.150
I (share of invest)	0.036	0.031
S (share of saving)	0.057	0.059
H (log of hours)	0.006	0.001
R (nominal int)	0.044	0.029
π (inflation)	0.072	0.027

1. Cum.RMSE is the root mean square error of the cumulative forecast over the entire period.

Table 16: Results for Growth, Investment and Savings

	GDP growth (y)			Share of investment (I)			Share of savings (S)		
	Estimate	Std. Err	|t-stat|	Estimate	Std. Err	|t-stat|	Estimate	Std. Err	|t-stat|
y_{t-1}	0.277***	0.058	4.775	0.138*	0.041	3.366	-0.071**	0.051	0.062
I_{t-1}	-0.310***	0.116	2.672	0.929***	0.072	12.903	0.056	0.082	0.683
S_{t-1}	0.084	0.074	1.135	0.048	0.038	1.263	0.954***	0.057***	16.737
H_{t-1}	0.027	0.015	1.800	-0.024	0.018	1.333	0.011*	0.041	0.268
R_{t-1}	-0.225	0.101	2.228	-0.090	0.029	3.103	-0.052	0.051	1.020
π_{t-1}	-0.063*	0.051	1.235	0.021	0.041	5.122	0.013	0.032	0.406
y_{t-2}	0.011***	0.037	0.297	0.062***	0.032	1.937	-0.047	0.042	1.119
I_{t-2}	0.059	0.011	5.364	-0.194	0.048	4.042	-0.203*	0.082**	2.476
S_{t-2}	-0.065	0.060	1.083	-0.051	0.029	1.759	-0.210	0.075***	2.800
H_{t-2}	-0.009	0.065	0.138	0.047	0.035	1.343	-0.129*	0.040***	3.225
R_{t-2}	-0.062	0.012	5.167	-0.021	0.031	0.677	-0.064*	0.041	1.561
π_{t-2}	-0.052*	0.014	3.714	-0.012*	0.041	0.293	0.020	0.022	0.909
$POIL_{t-1}$	-0.019***	0.014	1.357	0.003	0.000	2.717	-0.011	0.000**	2.245
$POIL_{t-2}$	0.021	0.015	0.140	0.001***	0.000	1.988	0.001	0.000*	1.929
δ_0	-0.029	0.081	0.358	0.062*	0.041	1.512	-0.065**	0.072	0.903
δ_1	0.217	0.101	2.148	-0.040	0.051	0.784	0.139	0.052	2.673
δ_2	0.182	0.071	2.563	0.093*	0.030	3.100	0.020	0.063	0.317
δ_3	-0.004*	0.006	0.667	-0.067**	0.041	1.634	0.102***	0.083	1.229
δ_4	0.040	0.082	0.488	0.010	0.040	0.250	0.124	0.073*	1.700
δ_5	0.045	0.082	0.549	0.040	0.051	0.784	0.210*	0.010**	2.100
δ_6	-0.000	0.101	0.004	0.230	0.101	2.277	0.031	0.102	0.304
R^2	0.29			0.79			0.70		
$\Pr(\delta_j = 0)$	0.000			0.00			0.000		
OBS	238			238			238		

1. The row for $\Pr(\delta_j = 0)$ reports the joint significance of the 7 demographic variables in the equation.
2. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

Table 17: Results for Hours, Interest Rate and Inflation

	Log of hours (H)			Nominal interest rate (R)			Inflation (π)		
	Estimate	Std. Err	|t-stat|	Estimate	Std. Err	|t-stat|	Estimate	Std. Err	|t-stat|
y_{t-1}	0.204***	0.041	4.976	0.150	0.162	0.926	0.252***	0.084	3.000
I_{t-1}	0.002	0.081	0.025	-0.195	0.168	1.161	-0.390**	0.170	2.294
S_{t-1}	0.064	0.040	1.600	0.006*	0.063	0.095	0.031	0.182	0.170
H_{t-1}	1.128***	0.055	20.509	0.241***	0.049	4.918	0.153*	0.072	2.100
R_{t-1}	-0.140	0.032	4.375	0.033	0.378	0.087	-0.123***	0.155	0.793
π_{t-1}	0.010	0.031	0.322	0.124	0.132	0.939	0.541*	0.227**	2.383
y_{t-2}	0.041	0.033	1.242	0.062*	0.034	1.823	0.133	0.083	1.602
I_{t-2}	-0.083	0.091	0.912	0.209	0.206	1.015	0.573	0.408	1.404
S_{t-2}	-0.062	0.039	1.589	-0.038	0.054	0.703	0.040	0.084	0.476
H_{t-2}	-0.192***	0.045	4.267	0.386*	0.214	1.800	-0.159	0.077**	2.467
R_{t-2}	-0.002	0.032	0.062	0.383*	0.211	1.815	-0.048	0.122	0.393
π_{t-2}	0.021	0.040	0.525	-0.071**	0.031	2.290	0.019	0.047	0.404
$POIL_{t-1}$	-0.010***	0.003	3.333	-0.011	0.003	0.367	-0.018***	0.002	9.000
$POIL_{t-2}$	0.010***	0.003	3.333	0.001	0.003	0.333	0.018***	0.012	1.500
δ_0	-0.010	0.073	0.136	0.161***	0.011	14.636	0.460	0.017***	27.059
δ_1	-0.070	0.082	0.853	0.041	0.091	0.450	0.100	0.158	0.633
δ_2	0.060*	0.064	0.937	-0.040	0.061	0.656	-0.140	0.129	1.085
δ_3	0.090	0.065	1.384	-0.181	0.121	1.496	-0.450	0.210**	2.143
δ_4	0.020	0.062	0.323	-0.090	0.110	0.818	-0.261	0.203	1.286
δ_5	0.120	0.094	1.277	0.070	0.151	0.463	-0.041	0.211*	0.194
δ_6	0.090	0.091	0.989	0.220*	0.131	1.679	0.181	0.293	0.618
R^2	0.95			0.89			0.87		
$\Pr(\delta_j = 0)$	0.101			0.001			0.001		
OBS	238			238			238		

1. The row for $\Pr(\delta_j = 0)$ reports the joint significance of the 7 demographic variables in the equation.
2. * denotes significance at the 10% level; ** denotes significance at the 5% level; and *** denotes significance at the 1% level.

8.2 Figures

Figure 1: Unweighted cross-country average share of three age groups 1955-2010

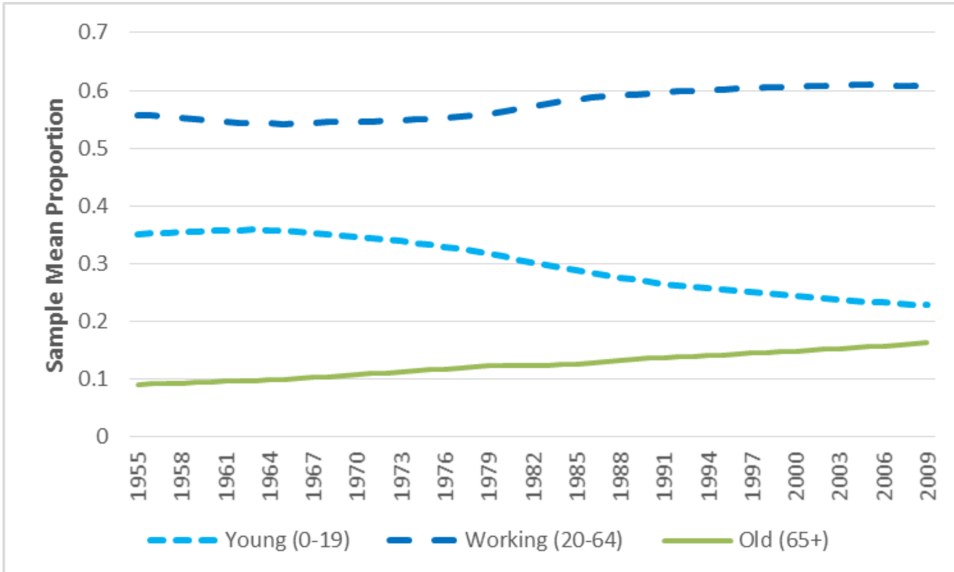

Figure 2: Cumulative Inflation (1955 – 2010) vs. Average share of population under 20

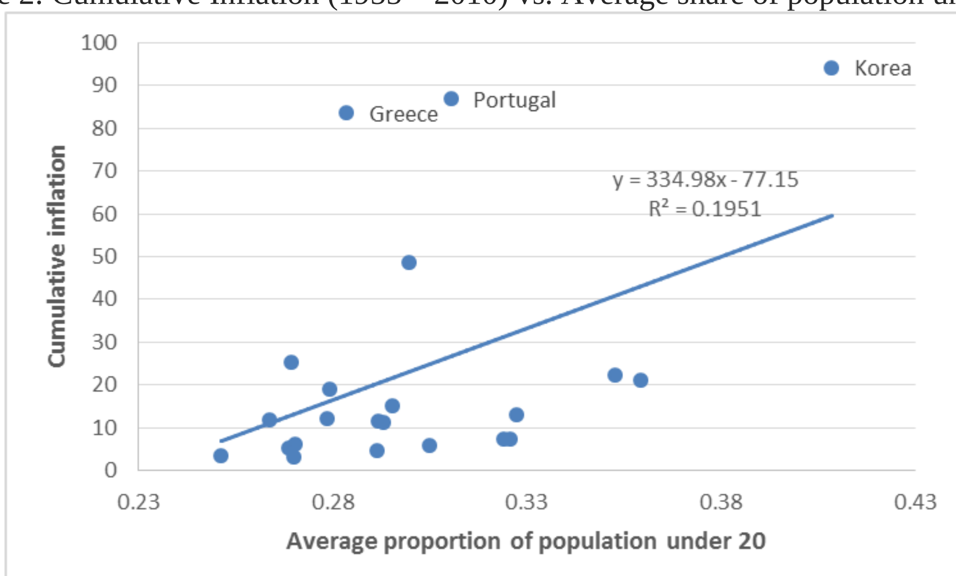

Figure 3: Cumulative Inflation (1955 – 2010) vs. Average share of population 20-64 years old

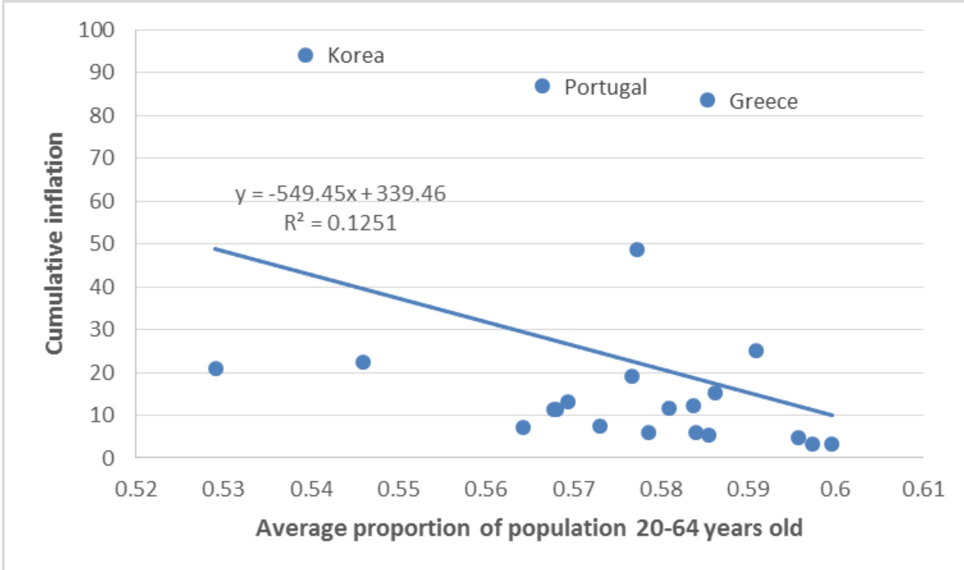

Figure 4: Cumulative Inflation (1955 – 2010) vs. Average share of population above 64

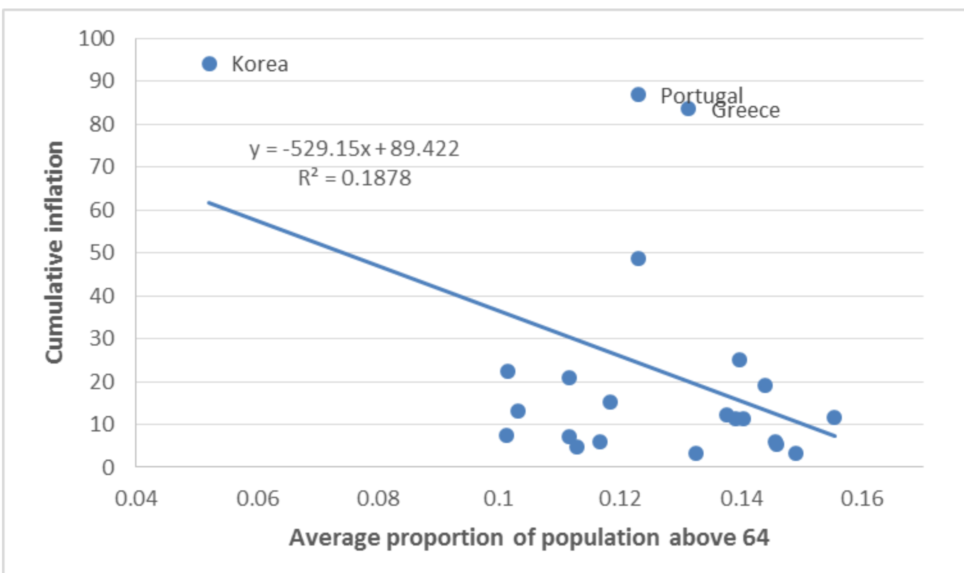

Figure 5: Age cohort impacts on inflation, benchmark model in JT2015

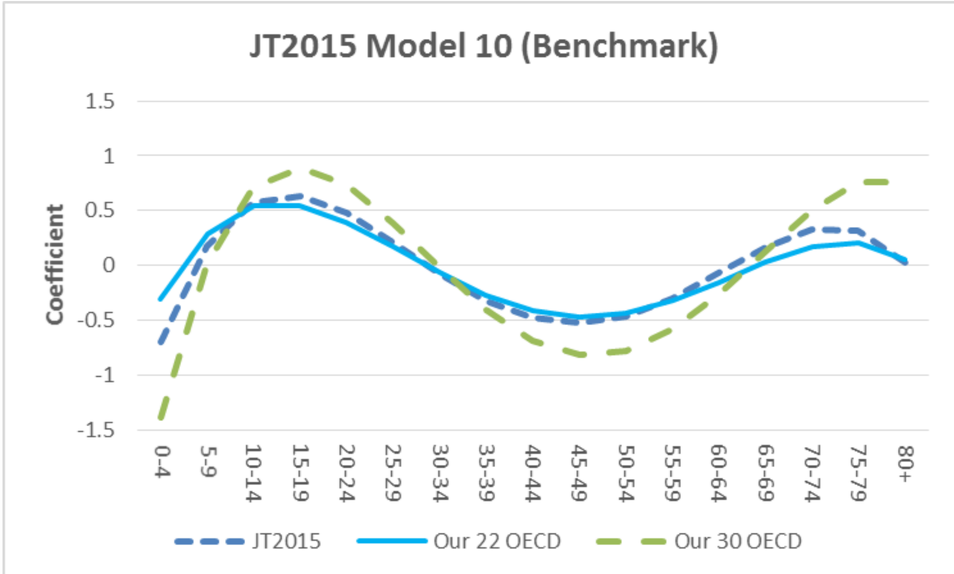

Figure 6: Age cohort impacts on inflation, without control variables in JT2015

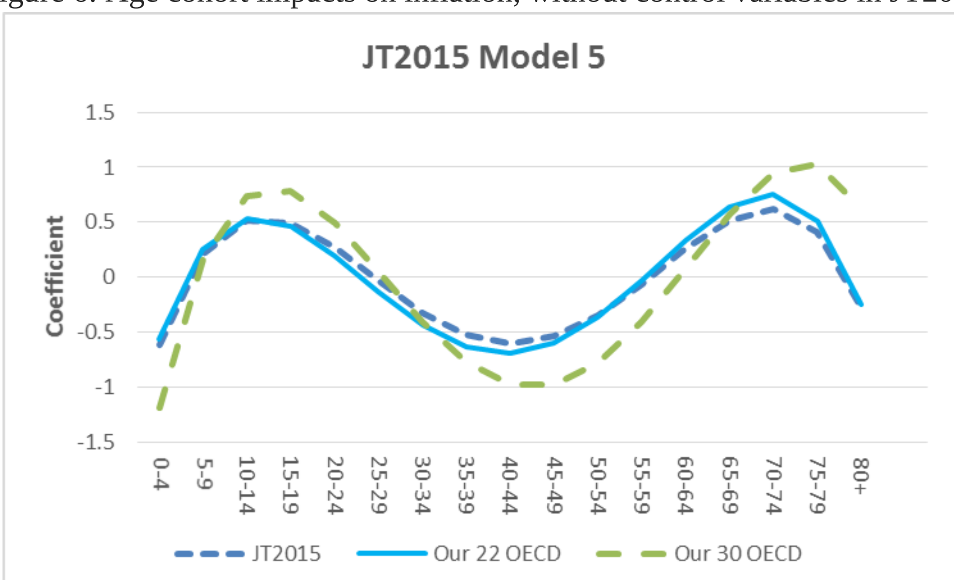

Figure 7: Age cohort impacts on inflation, OECD panel & Japan

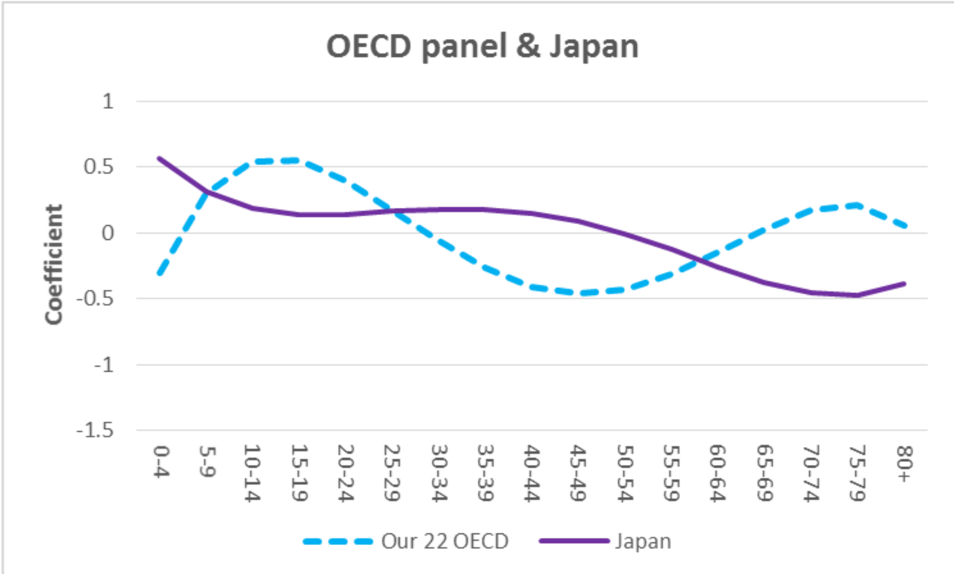

Figure 8: Age cohort impacts on inflation: OECD sub-periods

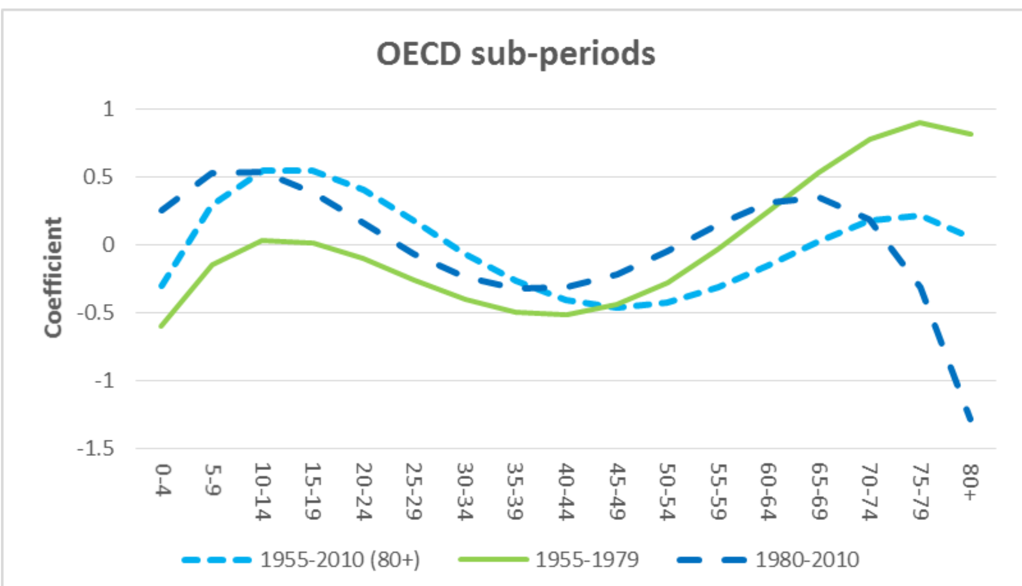

Figure 9: Age cohort impacts on inflation: U.S. economic regions

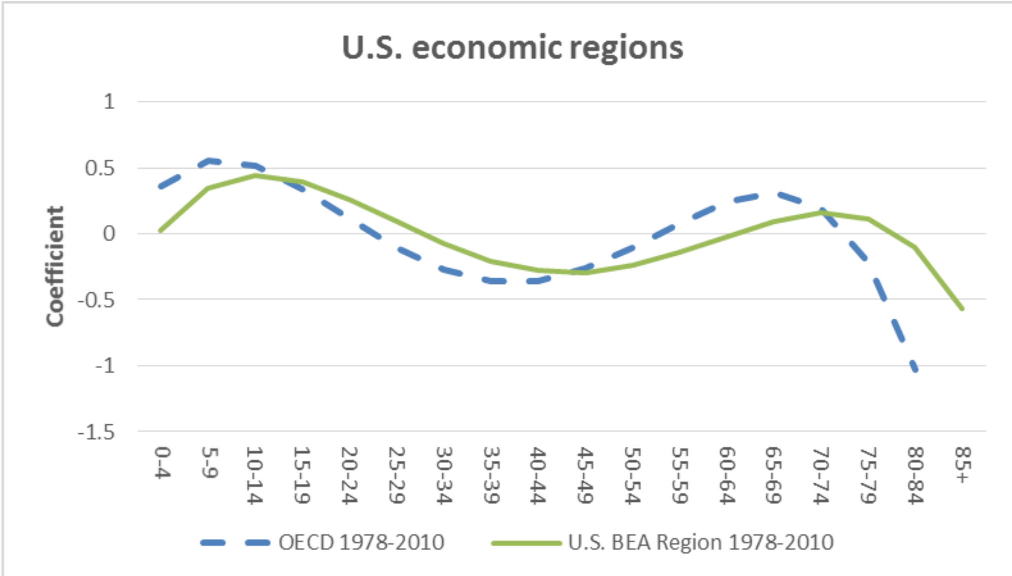

Figure 10: Age cohort impacts on inflation: refined age groups