Essays on the Impact of Demography and Aging on Capital, Innovation and Energy Consumption

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Andreas Tusch
from
Germany

Approved on the application of

Prof. Simon Evenett, PhD
and
Prof. Dr. Uwe Sunde

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Short Overview

This dissertation consists of three essays that empirically analyze the impact of demographic factors on differing economic aspects. Thereby, the focus lies on the group of developed countries within the OECD where considerable population aging is already under way and hence demographic age effects should be most pronounced in this group. The first essay examines whether and to what extent demographic factors can explain the build-up of large and persistent current account surplus positions in some OECD countries since the mid-1990s. Thereby, it takes a saving-investment perspective and analyzes not only the effects of present demography, but also examines potential anticipation effects stemming from expectations about future demographic developments. The second essay analyzes empirically whether and to what extent population and workforce aging affects the aggregated innovative performance from a macroeconomic perspective. Thereby, the analysis uses beside triadic patents as an indicator for technological innovation also cross-border trademarks which have been recently suggested to be a reliable indicator for capturing marketing and product innovation. Finally, the third and last essay tests the performance of demographically based long-term electricity consumption forecasts. The forecast performance is evaluated with ex ante out-of-sample experiments based on historical demographic projections and using a set of homogeneous and heterogeneous panel estimators. The results are compared to a GDP-based benchmark model as well as to naïve forecasts. Finally, the demographic model is used to generate forecasts up to the year 2025 for individual OECD countries.

Kurzzusammenfassung

Die vorliegende Dissertation besteht aus drei einzelnen Aufsätzen, die empirisch die Auswirkungen von demographischen Größen auf unterschiedliche ökonomische Aspekte untersucht. Dabei liegt der Fokus auf Industrienationen, die der OECD angehören. Diese Ländergruppe ist bereits stark vom demografischen Wandel und einer zunehmenden Überalterung der Gesellschaft betroffen und eignet sich daher insbesondere für das Untersuchen von demografischen Alterseffekten. Der erste Aufsatz untersucht, inwiefern demografische Faktoren für die Entstehung von Leistungsbilanzüberschüssen, wie sie in einigen OECD-Mitgliedsstaaten seit Mitte der 1990er Jahre beobachtet werden, verantwortlich gemacht werden können. Die Analyse basiert auf einer detaillierten empirischen Untersuchung möglicher demografischer Effekte auf Investitionen und Sparverhalten. Dabei prüft die Studie nicht nur die Wirkungen des bereits eingetretenen demografischen Wandels, sondern auch mögliche Antizipationseffekte, die sich aus Erwartungen über zukünftige demografische Entwicklungen ergeben. Der zweite Aufsatz überprüft empirisch, ob und wie stark eine Überalterung der Bevölkerung bzw. der Erwerbspersonen die aggregierte makroökonomische Innovationsleistung auf nationaler Ebene beeinflusst. Dabei bedient sich die Studie neben der Anzahl triadischer Patentanmeldungen als Indikator für technologische Innovationen auch der Anzahl grenzüberschreitender Markenanmeldungen, um Marketing- und Produktinnovationen zu erfassen. Der dritte und letzte Aufsatz untersucht schliesslich die Prognoseperformance von demographisch basierten Modellen zur Langzeitvorhersage des aggregierten Endverbrauchs von Strom. Die Güte der Vorhersagen wird anhand von ex ante Out-of-Sample Experimenten bestimmt, wobei auf historische demografische Prognosen zurückgegriffen wird und homogene sowie heterogene Panel-Schätzverfahren Anwendung finden. Die Ergebnisse werden mit einem BIP-basierten Benchmark-Modell sowie mit naiven Vorhersagen verglichen. Zuletzt werden anhand eines demografischen Modells Prognosen für eine Reihe von OECD-Mitgliedsstaaten erstellt, die bis in das Jahr 2025 reichen.

1. Introduction

Our world undergoes an unprecedented demographic transition which started some decades ago and has now reached almost all countries in both, the industrialized and the developing world. This transition is induced by decreasing fertility rates as well as increasing life expectancy and leads to a fundamental shift in the age structure towards the elderly. Given these developments there is growing academic interest in understanding the consequences of profound shifts in age structure on social and economic conditions.

This dissertation consists of three essays that empirically analyze the impact of demographic factors on differing economic aspects: (1) saving and investment behavior and capital flows, (2) innovation generation, and (3) energy consumption. Thereby, the focus lies on the group of developed countries within the OECD where considerable population aging is already under way and hence demographic age effects should be most pronounced in this group. Each of the three essays is self-contained and can be read independently. For better readability, tables and figures are attached at the end of each essay.

The first essay in chapter 2 studies the interaction of demography and aggregated saving and investment rates. More concretely, it examines whether and to what extent demographic factors can explain the build-up of large and persistent current account surplus positions in some OECD countries since the mid-1990s. The topic is of practical relevance for the issue whether these surpluses are harmful and should be reduced by policy-induced countermeasures. If they are the result of demographic transition effects induced by rational saving and investment decisions of an aging population, the surpluses may be the product of a more efficient allocation of capital across countries rather than reflecting distortions and rigidities on national and international markets. In order to shed more light on this issue, the study analyzes not only the effects of present demography, but also examines potential anticipation effects stemming from expectations about future demographic developments. The latter assumes that economic agents make forward-looking decisions and adapt their saving and investment behavior according to their expectations about the future. Further, the econometric model capitalizes upon a semi-structural concept that is based on the national income identity and allows for cross-country interdependencies under special consideration of the degree of openness at home and abroad. The inclusion of both anticipation effects and international interdependency effects allows to study thoroughly the link between demographics and saving, investment and capital flows, thereby contributing to the understanding of the emergence of contemporary global imbalances.

In the second essay (chapter 3), another economic field is analyzed that is potentially affected by population aging: the generation of innovation. This issue is of general importance as innovation and technological progress are the key drivers of economic growth in advanced economies. However, empirical studies examining the link between aging and innovation on aggregated country level are still an exception in literature. The essay steps into this gap and analyzes empirically whether and to what extent population and workforce aging affects the aggregated innovative performance from a macroeconomic perspective. Thereby, the analysis uses beside triadic patents as an indicator for technological innovation also cross-border trademarks which have been recently suggested to be a reliable indicator for capturing marketing and product innovation. Assuming that differences in educational attainment across age cohorts may drive age effects on innovative performance, the study employs also a recently available dataset that allows to control for cohort-specific education levels.

Finally, the third and last essay (chapter 4) follows the stream of literature that suggests age structure information as a long-term forecasting device in differing fields. Demographic data is interesting in the forecasting context because shifts in the population age composition have effects on a variety of social and economic aspects and at the same time these demographic shifts can be predicted comparatively reliable over long time horizons. Concretely, the third paper tests the performance of demographically based long-term electricity consumption forecasts. These forecasts play a crucial role in the strategic energy planning process and are integral for both management decision-making in utility companies as well as for energy policy formulation of governmental authorities. The forecast performance is evaluated with ex ante out-of-sample experiments based on historical demographic projections using a set of homogeneous and heterogeneous panel estimators. The results are compared to a GDP-based benchmark model as well as to naïve forecasts. Finally, the demographic model is used to generate forecasts up to the year 2025 for individual OECD countries.

At the end of this thesis, in Chapter 5, there is a brief conclusion and summary of the findings of all three essays.

2. Demographic Change and Current Account Surpluses in OECD Countries from a Saving and Investment Perspective

Abstract

This paper studies empirically whether and to what extent demographic factors can explain the build-up of considerable current account surplus positions in a number of OECD countries since the mid-1990s. Thereby it follows a saving-investment perspective and applies a framework that rests upon the national income identities for closed and open economies in order to examine the relationship between the present age distribution as well as anticipated future demographic change on the one side and saving, investment and the current account on the other side. The analysis provides evidence for substantial demographic effects using a broad cross-country panel sample. An increase in present old age dependency rates significantly lowers domestic saving and investment rates and the current account. Similarly, projected changes in the future age distribution show to have an impact on present saving and investment behavior. The estimated demographic effects are rather strong for some OECD surplus countries and can explain to some extent the saving and investment pattern which could be observed since the early 1990s.

Keywords: demography, saving, investment, current account surplus, population aging, OECD

2.1 Introduction

Since the mid-1990s a number of economies have been experiencing large and persistent imbalances in their current account positions. Even though these imbalances have narrowed considerably in the course of the most recent financial crisis, they remain at historically high levels and are proposed to rise again in the long run as the world economy recovers.[1] This pattern

[1]There is some evidence that the recent narrowing of current account imbalances since the financial crisis is related to various short-term, cyclical factors rather than mid- and long-term, structural factors. Thus, this narrowing may be expected to reverse as the world economy recovers. This view is supported by the fact that the recent economic upswing was accompanied by a renewed widening of current account imbalances. For further discussion see Cheung and Furceri (2010) and Kerdrain et al. (2010).

has attracted a large discussion about the causes and determinants of unbalanced external positions across countries. However, until recently the discussion regularly focused on the current account deficit in the United States and the surpluses in China and emerging Asia. In contrast, the sizable surpluses in some OECD countries such as Germany, Japan, the Netherlands, Sweden, Finland or Switzerland were often neglected. Even though the current account positions of some major European countries, especially the German surpluses, have raised some attention in the context of the ongoing sovereign crisis in the euro area, comprehensive assessments of OECD current account surpluses in the global imbalance literature are still an exception.

A common feature of surplus countries in the advanced world is the aging demographic structure, which is sometimes suggested as a main driving factor behind their persistently large current account surpluses.[2] According to this view, for countries facing an aging population in the coming years and decades it is rational to save more than to invest domestically on a national level since - due to a shrinking workforce - the number of investment opportunities at home with promising future returns is declining, but at the same time individuals have to accumulate assets in order to finance their consumption during retirement. As a consequence, this leads to excess saving in countries that are on the brink of a demographic transition towards older population structures and capital should flow from these countries to countries with younger demographic profiles and better investment opportunities. Thus, if large and persistent current account surpluses in advanced economies are the result of demographic transition effects, the build-up of global imbalances might to a large extent be the result of a more efficient allocation of global savings across countries rather than reflecting distortions and rigidities at national or international level. In that sense mature countries might be well advised to maintain their surplus positions over a longer period of time in order to build up foreign assets and fund the future consumption of an aging population. However, the net effect of population aging on saving and investment rates and the current account is very complex and may be determined by present as well as anticipated future demographic developments within and across countries. A better understanding of these factors and interdependencies is crucial in order to assess the possible outcomes of global imbalances and formulate appropriate policy recommendations.[3]

This paper empirically examines to which extent the saving and investment pattern and the build-up of large and persistent current account surpluses in OECD countries since the 1990s can be predicted by demographic variables. The degree of predictability can be seen as an indication whether the levels of the current account position are a 'normal' outcome of demographic developments and hence indirectly provides insights about the sustainability of the current account surpluses in the OECD. The present study contributes to existing literature in

[2]A hypothesis about the link between demographic aging and the contemporary build-up of considerable external positions is prominently given by Bernanke (2005). Bernanke (2005) argues that excess saving in some regions of the world is the main explanation for the external imbalances. This 'global saving glut' is mainly the result of high precautionary saving and the build-up of large currency reserves in emerging Asia in response to the Asian financial crisis of 1997-98 as well as high saving rates in developed countries that undergo a fundamental transition in demographics.

[3]For a general comprehensive analysis of the central facets and differing views regarding global imbalances see Claessens et al. (2010).

several aspects. First, prior research on contemporary global imbalances has mainly focused on the United States and emerging Asia. In contrast, the focus of this study lies on the sub-group of surplus countries within the OECD. Second, while the empirical literature on the causes and drivers of contemporary imbalances commonly uses econometric models with a broad spectrum of macroeconomic determinants, I am especially interested in the impact of demographic factors. Thereby, I analyze not only the effects of present demography, but also the effects of anticipated future demographic developments. While there are good reasons to think of agents behaving in a forward-looking manner, anticipation measures for longevity and future changes in the demographic age structure have still been used very rarely in empirical work and to the best of my knowledge there is no study that analyzes systematically the impact of both of these anticipation measures in the context of saving and investment rates. Third, while previous papers on aging, saving and investment regularly focus on domestic determinants and neglect the potential impact from foreign developments, this paper uses a recently proposed semi-structural equation approach based on the national income identity that allows to include foreign effects under special consideration of the degree of openness at home and abroad. Overall, extending the commonly used models by current and anticipated future demographics beside other economic and institutional determinants and applying these factors in a (partially) open economy framework allows to comprehensively study the link between demographic change and saving, investment and the current account in OECD countries. Beside broadly used panel estimation procedures, I test the robustness of the obtained results by using advanced estimation techniques, namely instrumental variables (IV) models and dynamic panel frameworks with generalized method of moments (GMM) estimators.

The paper is organized as follows. Section 2.2 gives an overview of the theoretical foundations whereas section 2.3 reviews the current state of research. Section 2.4 introduces the dataset, the econometric models and the methodology of the study. Section 2.5 reports and interprets the estimation results, robustness checks and predictions and, finally, section 2.6 concludes the findings.

2.2 Theoretical Foundation

The intertemporal approach as described by Obstfeld and Rogoff (1996) regards the current account balance as the outcome of forward-looking dynamic saving and investment decisions of utility-maximizing economic agents. Furthermore, following a simple national accounting identity, the difference between a country's aggregated saving and investment position is equal to its current account balance. While in a closed economy framework the size of savings and investments positions have to equal each other by definition, they can differ in open economies where agents are able to borrow and lend on international financial markets and capital is allowed to flow freely across countries.[4] Thus, a way to study the role that demographic

[4]From a theoretical viewpoint and under the assumption that capital flows freely across countries, capital should be invested in parts of the world with relative high returns per unit of investment. However, Feldstein

aging plays in the build-up of imbalances in current accounts is to analyze the link between aging on the one side and saving and investment on the other side. Such a saving-investment perspective allows to analyze the channels through which the OECD current account surpluses are affected in more detail and to examine whether these surpluses are driven from the saving or the investment side or both. However, from a theoretical standpoint a range of other factors besides demographics may play a crucial role in the determination of saving, investment and the current account and - as mentioned by Chinn and Prasad (2003) and Barnes et al. (2010) - there is no single theoretical framework that captures the entire range of these relationships. Therefore, instead of presenting a single theoretical model, the following two sub-sections focus solely on demographic factors and discuss a number of theoretical channels through which present as well as anticipated future demographic change may affect saving and investment rates.[5]

2.2.1 Life Cycle Dynamics and Dependency Effects

Two theoretical concepts provide a link between the present age composition within a country and saving behavior. The *dependency hypothesis* formulated by Coale and Hoover (1958) argues that due to low incomes of children and young people that is disposable for savings there is a negative relationship between the share of young individuals within overall population and national saving rates. Furthermore, a high youth dependency rate limits the active working population's capacity to save as they have to provide for the educational and material needs of a large number of children. Similarly, the *life cycle hypothesis* of saving and consumption introduced by Modigliani and Brumberg (1954) and Ando and Modigliani (1963) states that saving behavior differs over the lifetime of individuals and households due to time-varying levels of income and the desire of households to smooth consumption over their lifetime. While saving is low at early stages of life as young people are still in education and earn low wages, saving increases in middle age when individuals enter the job market and productivity and incomes rise. Finally, savings decrease again in old age when individuals leave the job market and retire. The life cycle hypothesis thus implies a hump-shaped saving profile for individuals over their lifetime. At the aggregated country level, domestic and national savings rates depend on a country's overall age structure, determined in the long run by birth and mortality rates as well as migration flows. The life cycle hypothesis predicts a negative relationship between savings and the share of young and old individuals within the overall population who have relatively low earnings and a positive relationship between savings and the fraction of high earning middle-aged individuals. Hence, in an early stage of the demographic transition process national savings should increase as the ratio of young people in the population decreases due to a drop in fertility rates while the ratio of old people remains still at a rather constant level. Yet, when

and Horioka (1980) show that in real world there is a strong bias towards domestic investment, keeping saving and investment rates highly correlated even in relatively open economies. In recent years this close relationship has become weaker in OECD countries.

[5] The theoretical links for other, non-demographic determinants are briefly discussed in section 2.4.4.

fertility rates remain at a low level, after some decades national savings should drop as still only a small fraction of young people enter the job market while more and more individuals get old and retire. This effect is further intensified when decreasing fertility rates go along with a drop in mortality rates that is over-proportional distributed in older cohorts - a trend that can be observed in most advanced economies today.

While the hypotheses of dependency and life cycle provide a well-founded theoretical guidance for aging effects on savings, the theoretical foundations regarding the impact of aging on investment rates are far less discussed in literature. But there are various channels through which aging may affect investment rates. In general, in the absence of technological progress and other productivity enhancing factors, a slower growth (or even decrease) in the working age population should translate into a slow-down in economic growth and the returns on investment, thus putting negative pressure on investment in the long-run. However, in the short-run, firms may respond to a shortage of labor supply by higher investment efforts and substituting labor by capital in order to compensate the negative effects of population aging (Park and Shin, 2009). Another perspective is given by Lindh and Malmberg (1999a) who argue that the inflow of young workers into labor force requires new investment in equipment in order to maintain capital intensity. Middle-aged workers also foster new investment due to learning-by-doing effects that enhance productivity. As higher productivity leads to increases in effective labor supply, additional investment is needed in order to keep the ratio between capital and a unit of effective labor constant. Young and middle-aged individuals may also tend to invest strongly in real estate and construction services due to household formation. Older generations in contrast may have a low demand for investment as they leave the workforce thus dampening new capital formation. Furthermore, they tend to decumulate their assets in order to finance their consumption during retirement. Yet, the age effects on public investment may differ considerably from private investment decisions. While the working age population tends to have an under-proportional demand for public services, public investment may especially be high when there is a large share of dependent individuals among the overall population. Large shares of young individuals require high public investments in nursing and the educational system, whereas the elderly may request more healthcare-related public services.

2.2.2 Anticipation Effects of Future Demographic Developments

Models based on the dependency and life cycle hypotheses provide a simple and appealing framework to explain age effects and have been used extensively in literature to describe the macroeconomic impacts of a demographic transition. However, these frameworks have the major shortcoming that they neglect the importance of anticipation effects regarding future demographic developments. Any age effects are assumed to take place via changes in the aggregated age composition of the population while individual life cycle profiles are commonly regarded as staying rather constant and being affected, if at all, only by current demographic developments. But there are good reasons to assume that individuals anticipate the pressure of future demographic developments and adapt their behavior in the present. Many theoretical and conceptional frameworks in economics build upon the assumption of agents that behave in a rational, forward-looking manner and optimize their behavior by accounting for present and future developments. The question up to what degree these anticipation effects matter depends on various factors such as access to information and awareness regarding future demographic developments as well as the planning horizon and time preferences of agents. In the following I describe three potential transmission channels through which the anticipation of future demographic trends may affect the saving and investment behavior of individuals in the present.

First, there is a potential link between longevity and saving behavior. When rises in life expectancy are the result of projected additional years of life distributed mainly in old ages (due to over-proportional decreases in mortality in old age cohorts), individuals should anticipate that they have good chances to live a longer life than their parents and grandparents. Provided that the length of the active working life period of individuals remains stable, longer life time translates into a longer inactive period of retirement whereas the life cycle budget constraint remains unchanged. Bloom et al. (2003a) suggest that as longevity is supposed to rise, individuals should adapt their behavior over their life cycle to the new conditions and increase their saving efforts at every age in order to meet the increased need for assets to finance their consumption during the extended period of retirement. While in a stationary population these effects may be offset on an aggregated level by increased old age dependency, during transition phases, when rises in longevity are still ongoing, the effect on aggregate saving rates may be substantial. However, Bloom et al. (2003a) remark that increases in life expectancy are likely to be the result of general health improvements which lead not only to reduced mortality rates and longevity but also to a better overall health constitution. Better health and less disability in old age in combination with the pressure to finance a longer retirement period may incentivize individuals to postpone retirement and work additional years of their life thus dampening or even offsetting respectively reversing the need to increase saving efforts due to longevity. Yet, institutional and legal regulations that impose mandatory retirement ages as well as the widely observed tendency of individuals to retire earlier in life rather than later suggest that the positive effect of longevity on saving rates prevails (Bloom et al., 2003a).

Second, individuals may not only anticipate that compared to the retirement periods of earlier cohorts the length of their retirement period is likely to be longer in the future, but at the same time that they will have to rely on less support from younger cohorts when they grow old as the ratio of working age population to retirees decreases. In traditional societies these effects may occur through changes in the family structure. Some authors such as Schultz (2004) have stressed the role of children on individual's savings behavior. Instead of regarding the number of children in a household and the household's saving choices as independent (as the life cycle hypothesis in its classical form implicitly does), children may act as a substitute to saving. Schultz (2004) argues that children are regarded as a form of social insurance for parents. When fertility rates decrease and parents can no longer rely on a high number of children that support them during periods of retirement and disability this insurance has to be replaced through other forms, notably increases in precautionary saving and wealth accumulation. Likewise, the individual future burden of children supporting their parents will increase with ceasing fertility rates and smaller familiy sizes, encouraging children to save more in order to provide for the future consumption and care needs of their parents.[6] While such intra-household transfers are in general more common in developing countries with traditional societies, Lee et al. (2000) remark that similar mechanisms are in place in advanced countries with classical tax-financed pay-as-you-go pension systems. Private transfers from children to their retired parents are simply replaced by a public pension system that transfers wealth from the active cohorts that are currently working towards the retired cohorts. The prospect that the number of tax payers shrinks while at the same time public spending on pensions, health care and other age-related social services increases is probable to put pressure on fiscal policy to raise taxes. If households anticipate that their future tax burden will rise, they should (in accordance with the Ricardian equivalence) increase their savings today in order to meet future tax obligations. Alternatively, the government may cut age-related social services in the future, and again, forward-looking agents should anticipate the need for precautionary saving to compensate the future loss in public social benefits.[7]

Finally, future demographic change may have an impact on present saving and capital formation via anticipated effects on future asset prices and interest rates. As the population ages the demand and supply of assets may change, too. A popular view in this regard is the so-called *asset market meltdown hypothesis* which states that prices for assets will fall severely when large age cohorts (such as the baby boom generation) enter into retirement and start to decumulate their stocks and savings whereas at the same time there are only relative small cohorts of younger buyers. According to Poterba (2001) and Luehrmann (2003), rational forward-looking investors should anticipate this decreasing demand for capital in the future and adjust their saving and investment behavior in advance on the basis of present discounted values of future capital earnings, thus affecting asset prices quite before age effects resulting from life cycle dynamics occur. While there is no clear consensus about the asset market meltdown hypothesis in academic literature, authors such as Börsch-Supan et al. (2006) have stressed the role of international capital flows that allow diversification across countries and attenuate the negative effects on asset prices. In general, the magnitude of age effects on capital returns and thus on saving and investment behavior should critically depend on the degree of openness of international capital markets as well as on the degree of variation of demographic age profiles across countries. Luehrmann (2003) remarks that in a closed economy with no access to international capital

[6]Schultz (2004) remarks that decreasing fertility rates are not exogenously given but rather a complex process of endogenous factors that affect the incentives of parents to have children. Especially better career prospects for women due to institutional and economic changes may increase the opportunity costs of having children. Thus, the theoretical relation between the number of children and saving behavior has to be embedded into broader frameworks that endogenize the fertility rate (e.g. household demand models for children).

[7]Of course, governments in aging countries might also run a farsighted policy of fiscal contraction in order to be prepared on future fiscal pressures and smooth taxes over time and generations thus reducing distortionary tax effects (as proposed by Jensen and Nielsen, 1996). Fiscal contradiction could be either achieved by higher taxes today or by a reduction of contemporary public services.

markets forward-looking agents have only a limited scope for using the information about the future as they cannot escape from domestic financial markets. Either they can increase their current saving efforts trying to compensate the anticipated losses in capital returns in the future and to ensure sufficient consumption during retirement or, alternatively, they can shift their behavior towards earlier consumption due to substitution effects. In contrast, if capital is perfectly mobile, individuals should align their investment decisions only on a short-term basis and neglect any anticipated long-term future age effects on asset prices for the moment as they can reallocate their investments to countries where demographic pressures are less pronounced at any later point in time. However, as stated also by Luehrmann (2003), most capital markets are far from being perfect due to factors such as information and transaction costs which give incentives for investment decisions on a long-term basis.

2.3 Literature Review

This paper is related to two different, but closely connected streams of literature. The first of these streams analyzes empirically the determinants of the current account balance in general and the potential causes of the build-up of contemporary global imbalances in particular. For instance, Chinn and Prasad (2003) provide an empirical investigation of the medium-term determinants of current accounts by using cross-sectional and panel data techniques for a large sample of industrial and developing countries. They find that current account balances are correlated with government budget balances, initial stocks of net foreign assets, measures of financial deepening as well as indicators of openness to international trade. The authors find also a negative relationship between demographic dependency rates and the current account. Yet, most of the demographic coefficients are not statistically significant in their model. Since the dataset of Chinn and Prasad (2003) covers only the period of 1971-1995, the pattern of global imbalances since the mid-1990s is not included in their data. More recent studies such as Chinn and Ito (2007), Gruber and Kamin (2007) and Chinn et al. (2011) build upon the methodology developed by Chinn and Prasad (2003) and explicitly aim to identify the main causes and key drivers of contemporary external imbalances which have emerged within the last two decades. Gruber and Kamin (2007) assess some of the explanations that have been put forward for the global pattern of imbalances, whereby they mainly focus on the huge US current account deficit and the large surpluses of the Asian developing countries. The authors find that the Asian surpluses are explained well by a model that incorporates beside standard determinants and demographic factors also variables on the impact of financial crises on current accounts. However, their model fails to explain the large current account deficit in the United States. Chinn and Ito (2007) assess several of the key assertions underlying the global saving glut hypothesis by focusing on Asia and including institutional and financial development indicators in their model. They conclude that Asian current account surpluses seem to be driven by depressed investment, not excess saving. Chinn et al. (2011) reestimate the previous mentioned model with updated data and focus especially on the period preceding the global crisis of 2008-09. A similar study that is also focused on the current account surpluses in developing Asia is conducted by Park and Shin (2009). They suggest that even though current account surpluses in Asia may be driven to some extent by fundamentals such as demographics or rising per capita income, a large share of the surpluses cannot be explained by their model. The authors propose that precautionary saving after the Asian financial crisis of 1997-98 may be a main contributor to the region's surpluses. A similar study is conducted by Terada-Hagiwara and Horioka (2012), but they solely focus on saving rates in Asia. They suggest that the main determinants of saving trends in Asia over the last decades have been demographic factors as well as income levels and the level of financial development. Finally, Barnes et al. (2010) and Jaumotte and Sodsriwiboon (2010) focus on current account imbalances in the euro area. Barnes et al. (2010) find that fundamental economic factors play a crucial role but cannot fully explain the extent of intra-euro area imbalances over the past decade. Similar results are provided by Jaumotte and Sodsriwiboon (2010) who study in particular the current account deficits in the southern euro area.

While the literature stated above studies the determinants of current account balances on a general basis and includes a large selection of macroeconomic and structural factors in the analysis, the second stream of literature focuses specifically on the link between demographics on the one side and saving, investment and the current account on the other side. Thereby, these studies are commonly interested in general patterns rather than studying specifically the role of population aging on recent global imbalances and draw much more attention on the right specification of demographic effects. One stream of these studies uses conceptual general equilibrium models to explore the macroeconomic impact of demographic change (Fougère and Mérette, 1998; Brooks, 2003; Domeij and Floden, 2003; Attanasio and Violante, 2005; Börsch-Supan et al., 2006; Feroli, 2006). However, the branch of literature that uses econometric methods to empirically analyze the link between demographic factors, saving, investment and the current account is of more interest for this study. For instance, in an early study, Leff (1969) empirically backs the hypothesis of age-specific saving decisions of individuals. In a later study, Higgins (1998) examines at the country level the link between age distributions, aggregated national saving and investment and the current account balance by using a panel dataset with more than 100 countries. He finds substantial demographic effects with a strong negative relationship between youth and old age dependency rates on the one side and domestic saving, investment and the current account on the other side. Lindh and Malmberg (1999a) come to similar results using panel data of OECD countries. Luehrmann (2003) refines the framework used by Higgins (1998) and includes not only the contemporaneous age structure but also the anticipation of future changes in young and old age dependency ratios in her analysis of capital flows. But in contrast to Higgins (1998) she does not analyze saving and investment rates explicitly but focuses on capital flows only. Luehrmann (2003) finds that both present and anticipated demographic changes relative to other countries significantly affect net capital outflows of a country. Besides the population age structure, Bloom et al. (2003a) focus on the impact of life expectancy and find a rather strong and positive effect of longevity on saving rates. Bosworth and Chodorow-Reich (2007) find a significant negative correlation between population aging and national rates of saving and investment, but in their study the effect varies substantially across regions. Furthermore, they show that demographic aging affects both public and private saving. Kim and Lee (2008) use an analysis based on a panel vector autoregressive (VAR) model in order to investigate the macroeconomic effects of demographic change, focusing on saving rates and current account balances. According to the authors, the VAR framework has the advantage of combining the dynamics of simulation approaches with the empirical data foundation of panel data approaches. They confirm the findings of earlier studies by showing substantial demographic effects on saving rates and the current account in the G-7 countries. Finally, Graff et al. (2008, 2012) use an extended modeling framework that is based on the national income principle and accounts for the fact that external balances have to sum up to zero in the world. Their saving and investment regression results are broadly in line with previous findings. However, the authors do not find a clear evidence of age effects on the current account balance.

From the literature stated above the present paper retrieves several elements and is in particular closely related to three papers. It takes a similar stand as Bosworth and Chodorow-Reich (2007) regarding its purpose by following the global imbalance literature, but using the special focus and methodology of the literature on population aging. However, instead of using the simple and parsimonious specification structure commonly used in the empirical literature on demographic change, I extend the methodology in two ways. First, I add systematic measures for the anticipation of future demographic age structure shifts to the specification. The first and to the best of my knowledge only study which has done this before is Luehrmann (2003), but her work differs in several aspects to this study, not at least as she does not use saving and investment regressions and builds her measures on a limited dataset of underlying historical projections. Second, the current paper uses the semi-structural equation framework suggested by Graff et al. (2008, 2012) which pays attention to domestic as well as foreign effects under special consideration of the roles of openness and relative economic size. Merging and extending the anticipation concept of Luehrmann (2003) with the open economy framework of Graff et al. (2008, 2012) and applying it to the special context of OECD surplus countries allows to give a comprehensive and inclusive picture of the demographic effects on saving and investment in these countries.

2.4 Model

The analysis whether demographic factors are able to explain the current account pattern in OECD countries is based on an econometric modeling approach. If demographic variables (besides other fundamentals) in the model can explain a large share of the saving and investment patterns and the build-up of current account surpluses since the mid-1990s, imbalances could be the result of efficient, rational behavior of individuals that is driven by demographic developments. However, if neither demographic variables nor other fundamental variables are able to explain much of the current account surpluses, it is more likely that contemporary imbalances are an anomalous phenomenon and the result of distortions and misallocations that lead to oversaving or underinvestment. In the following I will describe the dataset as well as the econometric model and its specification.

2.4.1 Dataset

The empirical analysis is based on a panel dataset that includes time series of 67 advanced, emerging and developing countries. I excluded countries with an average population less than one million over the study period. Furthermore, I had to skip a number of countries from the dataset because of lacking data availability. Using a large country sample allows to explore the varying cross-sectional stages of the demographic transition in some detail. But there is also a technical argument for a large country sample as some of the used estimators in the study rest upon asymptotic properties and require a minimum number of cross-sectional units in order to produce consistent estimates. This is especially true for the GMM techniques where a high number of internal instruments and a small number of cross-sectional units can produce inconsistent estimates. However, as a robustness check, I run the regressions with a sub-set of 24 OECD countries, too. Beside the special interest in advanced current account surplus countries in this study, this allows to compare the estimation results of the sub-sample with the full sample and examine whether there is parameter heterogeneity in the sense that demographic effects differ across countries and regions that are in different development stages. Appendix 1 reports the list of all countries included in the full sample as well as the OECD countries included in the sub-sample.

The time series data are available on an annual basis from 1971-2010. Data are taken from different sources. The main sources are the World Development Indicators (WDI) from the World Bank and the Penn World Table (PWT) database. Information about the composition of the demographic age profiles as well as projections for future demographic developments is based on present and past versions of the UN World Population Prospects (WPP) report. As WPP data are only available in 5-year intervals (or even larger intervals in case of some older reports), I linearly interpolate the data to get yearly data points. The dataset is unbalanced as especially for developing countries data are missing during some time periods.

2.4.2 Econometric Model

Given that there is no single guiding theoretical model that encompasses the broad range of empirical links assumed in this study to determine saving, investment and current account patterns, I follow the common practice in the macroeconomic aging literature and base the baseline econometric model on a reduced-form approach rather than a specific full structural model specification. In detail, the baseline estimates are based on a fixed effects panel data model that follows the form

$$y_{it} = \alpha + \beta_p p_{it} + \beta_z z_{it} + \beta_\varphi \varphi_{it} + \delta_t + c_i + \varepsilon_{it}, \tag{2.1}$$

where y_{it} is the dependent variable in country i at time t, p_{it} is a vector of explanatory variables incorporating the present age structure, z_{it} is a vector of variables capturing future demographic trends, φ_{it} is a vector of non-demographic control variables capturing economic and institutional factors, δ_t controls for time-specific effects, c_i denotes country-specific effects, and ε_{it} is the idiosyncratic error term. The variables in the model are expressed as ratios (e.g. relative to GDP) or as levels. Transforming level variables into logarithmic form (as sometimes done in literature) does not change the results significantly.

y_{it} is defined as the GDP ratios of saving and investment. There are various ways how to compute aggregates of saving and investment and the choice of one specific procedure over another may significantly influence the estimation results. Previous studies have used different measures for national or domestic saving and investment and sometimes it is not clear which measure was used in detail. In this study I define saving and investment as real domestic rates which are adjusted for purchasing power parity (PPP) at current prices and measured in international dollars. Alternatively, I run the main regressions also with real domestic rates but at constant prices (with 2005 as base year) as well as nominal gross national and domestic rates in order to test the stability of the estimates.[8] From a national accounting perspective, the current account is directly determined by saving and investment and estimating separate saving and investment equations instead of a single equation for the current account balance gives further insights about the channels through which the current account is determined and whether there may be an oversaving or underinvestment in OECD surplus countries. Nevertheless, I run also the regression with the current account balance as dependent variable for transparency reasons, even though this third estimated equation should be, at least in theory, redundant due to the direct linkages between saving, investment and the current account.

Using a simple reduced-form specification has the advantage that a broad variety of differing demographic and non-demographic variables can be included in the econometric model to analyze their overall direct and indirect effects without the need to derive an explicit structural model from a guiding theoretical framework. However, this is at the cost that it is difficult to infer information about the underlying mechanisms (see e.g. Calderon et al., 2002, or Barnes et al., 2010). A main drawback emanating from the baseline model described in equation (2.1) is the fact that it focuses (as commonly done in the macroeconomic empirical demography literature) solely on domestic determinants of saving and investment rates and neglects foreign factors and international interdependencies. However, unless we expect the countries in the

[8] The real domestic saving and investment rates are computed from the PWT database while data for alternative nominal domestic saving and capital formation respectively national saving are taken from the WDI database.

sample to follow a closed economy pattern it is more reasonable to assume that saving and investment decisions and the current account are not only affected by domestic factors but also by developments in the rest of the world. Some authors have stressed the important role that the level of openness plays when looking at demographic effects and add to their models single variables measuring the degree of openness respectively interaction terms of openness indicators with the demographic variables. But a more direct measurement of foreign factors is not included in these models. In order to give more weight on open economy dynamics, I follow the semi-structural equation methodology proposed by Graff et al. (2008, 2012) that accounts not only for purely domestic influences but also allows for foreign influences from the rest of the world. The authors refer to their approach as 'semi-structural' as they derive their model from the national income identities of open and closed economies but do not formally base it on an utility maximizing concept. Following Graff et al. (2008), the saving and investment regressions can be extended to the following equations:

$$S_{it} = \alpha_S + \beta_1 X_{it} + \beta_2 \theta_{it} \sigma_{it} (X_{it} - \bar{X}_{it}) + \delta_t + c_i + \varepsilon_{it} \tag{2.2}$$

$$I_{it} = \alpha_I + \beta_1 X_{it} + \beta_2 \theta_{it} \sigma_{it} (X_{it} - \bar{X}_{it}) + \delta_t + c_i + \varepsilon_{it} \tag{2.3}$$

X_{it} is a vector of domestic explanatory variables which in our case incorporates all regressors from the baseline model in equation (2.1): the present age structure, p_{it}, anticipated future demographic change, z_{it}, as well other, non-demographic control variables, φ_{it}. $\bar{X}_{it}$ captures the same variables as X_{it} but for the rest of the world. Thus, the term $(X_{it} - \bar{X}_{it})$ reflects the relative difference of demographic and non-demographic factors between the domestic economy and the rest of the world. θ_{it} is an indicator for the openness of the country while σ_{it} measures the relative size of the domestic economy compared to the rest of the world.

$\bar{X}_{it}$ is calculated as a composite measure of the X's of all countries except the domestic country weighted by their GDP and adjusted by the openness of each country:

$$\bar{X}_{it} = \frac{\sum_{j \neq i} \theta_{jt} GDP_{jt} x_{jt}}{\sum_{j \neq i} \theta_{jt} GDP_{jt}} \tag{2.4}$$

As $\bar{X}_{it}$ is adjusted by θ_{jt} while θ_{it} enters the model directly, the cross-border influence of foreign countries depends on the degree of openness in both the home country and the countries in the rest of the world. Openness is measured by the financial openness indicator from Chinn and Ito (2008) which quantifies the extensity of capital controls and is rescaled here in this study to a value between 0 and 1. In that sense the model regards the closed economy framework ($\theta_{it} = 0$ and/or $\frac{\sum_{j \neq i} \theta_{jt}}{N_{j \neq i}} = 0$) as well as the open economy framework ($\theta_{it} = 1$ and $\frac{\sum_{j \neq i} \theta_{jt}}{N_{j \neq i}} = 1$) as special cases and captures all modes of partially open economies that lie in between these two extremes. For a perfectly closed economy, I assume that there are no spillover effects from and to the rest of the world and thus the model resembles the baseline model where only domestic factors matter regarding the determination of saving and investment.[9] Besides the degree of openness, the relative size of the home economy compared to the rest of the world, σ_{it}, is crucial for the effect resulting from $(X_{it} - \bar{X}_{it})$. σ_{it} is based on GDP, again adjusted by openness, and is an inverse in the sense that larger countries have smaller values:

$$\sigma_{it} = \frac{1}{GDP_{it}} \frac{\sum_j \theta_{jt} GDP_{jt}}{\sum_j \theta_{jt}} \tag{2.5}$$

Hence, the larger the home economy is relative to the rest of the world, the smaller is the impact of changes in foreign factors from abroad on domestic saving and investment.

While our primary interest lies in the saving and investment pattern, for the reasons stated before I also run regressions for the current account balance. Given that the current account balance is directly determined by saving and investment, it should also be influenced by the same variables and be a function of both domestic and foreign factors:

$$CA_{it} = \alpha_{CA} + \beta_1 X_{it} + \beta_2 \theta_{it} \sigma_{it} (X_{it} - \bar{X}_{it}) + \delta_t + c_i + \varepsilon_{it} \tag{2.6}$$

However, if we assume a totally closed economy ($\theta_{it} = 0$), saving and investment have to equal each other per definition and the current account balance should be zero from a national income identity. Hence, domestic factors alone should have no impact on the current account position per se, but only to the extent that they change relative to the rest of the world. While savings and investment have not necessarily to be symmetric on an international scale, the general equilibrium condition requires the current accounts to sum up to zero for the world as a whole. Graff et al. (2012, 2008) argue that domestic factors and their foreign counterparts should have same (but in opposite directions acting) effects on the current account, or in other words, if a domestic factor affects the current account of the home economy, it should also have an effect in the opposite direction for the current accounts in the rest of the world. Therefore, the authors suggest the following equation that I use as a second specification for the current account:

$$CA_{it} = \alpha_{CA} + \beta_2 \theta_{it} \sigma_{it} (X_{it} - \bar{X}_{it}) + \delta_t + c_i + \varepsilon_{it} \tag{2.7}$$

Applying equations (2.2), (2.3) and (2.7) to the special context of demographic change, it shows that not only a change in the domestic age distribution in absolute terms has an impact on domestic saving and investment rates, but also that it matters how the age distribution at home changes relative to the rest of the world. In contrast, the current account is only affected by relative changes in demographic determinants and, hence, the magnitude of demographically induced shifts in capital across borders critically depends on the differences in the pace of demographic aging patterns across regions and countries.

[9] Of course, the baseline model fulfills not the strict definition of a closed economy model, not at least as simple indicators for financial and trade openness are included.

The models described above follow a country and time fixed effects specification thus controlling for time-invariant heterogeneity across countries as well as for unobserved global time-specific effects that affect all countries at the same point of time. However, there is no clear consensus in the literature analyzing the determinants of saving, investment and the current account balance about the issue of using fixed effects models. Some authors such as Chinn and Prasad (2003) argue that using country fixed effects may neglect too much of the cross-country variation that might be essential for the analysis of the determinants of current account balances. Indeed, the demographic variables in the dataset do not only differ significantly across time within countries, but also vary considerably across countries. Furthermore, controlling for time-invariant country effects may require to drop important variables from the model as these might have too low variation over the time dimension and could be too collinear with the country effects.[10] Therefore, in order to investigate cross-country effects more detailed, in a further specification the country fixed effect is abandoned from the model and a pooled ordinary least squares (OLS) panel specification with time dummies is used instead. In contrast to a pure cross-sectional analysis, keeping the panel structure has the advantage that demographic information from the time series still runs into the analysis. Hence, using both fixed effects and pooled OLS estimations allows to study separately any within-country effects and cross-country relationships. Besides the baseline fixed effects model and the pooled OLS model, a number of additional specifications are estimated in order to test the robustness of the results. First, the baseline specification is complemented by an autoregressive term in order to allow for potential dynamics and feedback effects from the lagged dependent variable. Furthermore, I control for potential endogeneity resulting from reverse causation and simultaneity between some independent regressors and the dependent variable by using GMM techniques that employ lagged values of the potential endogenous variables as internal instruments as well as an instrumental variable (IV) approach that uses geographic measures as external instruments.

Given that the usual tests of significance are unreliable in the presence of heteroscedascity and conventional heteroscedasticity-robust standard errors are inconsistent in a fixed effects setting with serially correlated errors (Stock and Watson, 2008), I use cluster-robust standard errors for the fixed effects and pooled OLS specifications. Thereby, the non-nested two-way clustering procedure proposed by Cameron et al. (2011) is applied that allows to cluster at both the cross-sectional and time dimenson. This produces consistent statistical inference in the presence of heteroscedascity and autocorrelation, even in case when errors are correlated within countries and time periods which may occur despite including country and time fixed effects.[11]

Data are used on different frequency levels in the models. On the one hand, as the fixed

[10] See also Bosworth and Chodorow-Reich (2007). Potential candidates with low variation over time in our models might be the level of income, life expectancy and financial openness. However, I find no evidence that these regressors cause problems within the fixed effects regressions.

[11] Two-way clustering relies on both N and T being large enough in order to produce consistent estimates. Testing the robustness of the procedure, I conducted all estimates also with a conventional heteroscedascity robust approach as well as with one-way clustering by countries, which produced quite smaller standard errors and in general higher statistical significance of the coefficients. Therefore, this suggests that the two-way clustering approach generates rather conservative estimates for the standard errors.

effects specification captures in particular within-country variation over time, in general high-frequency data with a sufficient number of data points for each country is preferable in order to exploit the full information in the time series. But, on the other hand, demographic variables in general are rather persistent and follow slow moving trends, and there is the risk that data noise drowns out any age effects from the data. Aggregated low-frequency data allow to filter out any short-term variations such as business cycle fluctuations, but this is at the cost of loosing information from the time series. Therefore, I run separate regressions for both annual data as well as non-overlapping 5-year aggregates in the baseline fixed effects model and examine whether the results remain stable over both specifications. In contrast, in the alternative analysis with pooled OLS the interest lies especially in the long-term, cross-country differences and thus aggregated low frequency data are the preferred choice. However, Higgins (1998) remarks that the level of temporal aggregation should not be too high in order to prevent the destruction of information contained in the demographic variables, but at the same time also high enough to ensure that the pooled OLS estimates are driven by cross-sectional rather than time series variation. Hence, I use non-overlapping 5-year aggregates but run also a robustness test with an alternative specification that orientates on Higgins (1998) who divides his sample for the cross-sectional analysis in three non-overlapping 13-year aggregates.[12] Following Lindh and Malmberg (1999a), the demographic aggregates refer to the value of the initial year in each period in order to mitigate potential endogeneity. The remaining variables are averages of the aggregated periods.

2.4.3 Specification of Age Effects

The main explanatory variables in the econometric equations capture present as well as anticipated future demographic developments in some detail. The following two sections describe the methodology to incorporate demographic measures into the models.

Present Demographic Structure

Estimates of demographic data for the age structure are available from the United Nations for a broad sample of countries. The population is divided into 17 age share groups each representing a 5-year age interval (0-4, 5-9, ..., 75-79 and 80+). However, as outlined by previous work (see e.g. Higgins, 1998, Lindh and Malmberg, 1999a or Bloom and Canning, 2001) the age groups are likely to be highly correlated with each other which makes the identification and isolation of the individual effects of any particular age group difficult. As multicollinearity prevents the use of all 17 age share groups in a single regression model, commonly specifications are applied that aim to reduce the level of detail for the age structure profiles to a more parsimonious form. A widely-used approach is to compress the number of age groups and to aggregate them to a smaller set of groups. For instance, Lindh and Malmberg (1999a) aggregate the

[12] In detail, I aggregate the data in two non-overlapping 13-year sections (1971-1983, 1984-1996) and one 14-year section (1997-2010).

population age structure into six age share groups. An even more parsimonious and simple way are categorical variables that only include old age and young age dependency ratios in the model. This implicitly relates the young population group (0-14 years) and the old population group (65+ years) to a third group of working age (15-64 years). However, reducing the number of age groups has some drawbacks. First, the decision about the degree of parsimony by modeling the age structure is a balancing act between effectively alleviating problems arising from multicollinearity on the one side and not loosing too much potentially relevant information about the age structure on the other side. Furthermore, the selection of the specific age share groups is somehow ad hoc as there are no clear rules where to define the boundaries of each group. Finally, the procedure builds upon the not very realistic assumption that the age effects are identical and uniform within the borders of each group but vary abruptly at the borders between two age groups. Despite these drawbacks, I use in the baseline specifications categorical dependency variables because they provide with only two regressors (OLD and YNG) a simple and in literature widely used way to incorporate age effects into our model in which the present demographic structure is only one aspect of demography besides others. This approach is the more compelling as a number of studies have shown that more detailed specifications of age effects have no major benefits over broad categorical variables (see e.g. Bloom et al., 2003a, or Bosworth and Chodorow-Reich, 2007). In addition, a special appeal of the dependency approach might be seen in the definition of the borders between the differing age groups which divide the population in an intuitive manner into sub-groups of young and old non-working individuals as well as middle-aged working agents.

However, in order to test the robustness of the estimation results obtained with dependency measures and to assure that not too much information from the age structure data is filtered out, I use also an alternative, more sophisticated procedure pioneered by Fair and Dominguez (1991) and further elaborated by Higgins (1998) which restricts the coefficients of the age groups to lie along a low-order polynomial curve. This has the advantage that the full information of all age groups can be incorporated into the model and at the same time the number of parameters is kept small thus avoiding to run into problems arising from multicollinearity and too few degrees of freedom. In addition, as outlined by Arnott and Chaves (2012), the use of polynomials allows for more realistic continuity in the demographic effects across age groups given that the behavior of individuals should not change abruptly but rather smoothly from one age cohort to the next. Yet, constraining the age coefficients to fit a low-order polynomial curve may not be without problems, too. Through the smoothing effect (which tends to be stronger the lower the order of the polynomial), the overall results of the polynomial technique might be driven by strong effects of single age groups. For instance, Lindh and Malmberg (1999a) argue that the polynomial approach seems to perform rather poor for saving, investment and current account regressions in a sample of 20 OECD countries for the time period 1960-1995. Broadly speaking, the higher the degree of the polynomial the less constrained are the age parameters and the better should be the fit of the function. In this study I opt for a cubic polynomial form which seems to be a good compromise between reducing the number of parameters to avoid multicollinearity on the one hand and keeping the statistical power of the coefficients on the other hand.[13] The details of the methodology and transformations of the polynomial approach are shown in Appendix 2.

Anticipated Future Demographic Trends

As outlined before, from a theoretical standpoint there are good arguments to include variables about projected future demographic developments in the model. I add the following three measures for capturing the anticipation of future demographics: life expectancy at birth (LIFE) as well as aggregated forecasts of future young (YNG_{fut}) and old age (OLD_{fut}) dependency rates. Life expectancy is used as a proxy for longevity and the expected length of the retirement period. Thus, this variable is incorporated into the model to test the proposition that individuals change their saving and investment behavior as they anticipate the need to finance a longer period of retirement. Of course, life expectancy is not a perfect proxy for at least two reasons. First, as an averaged measure, life expectancy at birth captures mortality rates in all age groups and is only an approximation for the expected further lifetime (and thus the length of the retirement period) for individuals at different ages. For instance, in countries with high infant mortality or deaths in young adulthood it underestimates the further lifetime of individuals who have surpassed those periods of high mortality. Thus, it would be more accurate to use age-specific data on further life expectancy, but missing time series for many countries detains me from using this more accurate indicator. Second, as stated by Bloom et al. (2003a), life expectancy is in practice rather a proxy for general health improvements thus making it difficult to separate out the effects of increased longevity and reduced morbidity. Better health conditions in old age could give incentives to individuals to work longer and postpone retirement. Thus, the variable life expectancy should be seen as a proxy for both longevity and lack of disability. An alternative would be to include data on healthy life expectancy (HALE) as an indicator. But again, as data on HALE is not available for many countries, the usage of this indicator is no option in this study.

In order to implement anticipated future dependency ratios into the model I follow closely Luehrmann (2003). Instead of using a projection period that is arbitrarily set at a given point in the future, I compute each age group's planning horizon individually. The cohort specific foresight horizons are computed by the difference between the life expectancy at birth and the individual age of each age cohort at a given point in time, thus assuming that individuals plan over their expected further lifetime.[14] Anticipated future dependency rates are based on the medium scenario of the projections from the UN which are according to Luehrmann (2003)

[13] Bloom et al. (2003a) extend the procedure by adding also a step function to a cubic polynomial specification with steps at the ages 20 and 60. According to them, this encompasses the approach of using young and old age dependency ratio variables with the flexible function approach of polynomial-fitting. However, tests reveal that for their sample of 68 countries there is no advantage of the polynomial technique (with and without a step function) compared to using simple dependency measures for domestic saving regressions.

[14] Again, as stated also by Luehrmann (2003), due to the specific construction of life expectancy as an average, the planning horizon of older cohorts might be underestimated and even take negative values. For simplicity, I assume for negative values of the planning horizon that individuals plan only on a short term basis by setting the further life expectancy and thus the planning horizon equal to one time period.

broadly cited and a main data source for demographic information that is publicly available. This implies that individuals have access to projection data and use it in order to build their expectations. However, this information basis is imperfect and forecast errors in the UN data translate into errors in their expectations, too. While Luehrmann (2003) uses historical forecast data not before 1980 and assumes that expectations about future demographic developments built before 1980 were correct and matched the demographic reality, I also incorporate earlier projections starting in the early 1960s. Individuals are then allowed to update their expectations stepwise as new projections are available to them. As the publication of the forecasts sometimes takes several years,[15] I allow agents to update their information at the date of publication rather than at the projection base year in order to reconstruct the information basis that was actually available to individuals in the past in a more accurate way. In total, I build anticipation measures upon six projections from the past with the following base years: 1963, 1973, 1984, 1994, 2002 and 2010. There is considerable variation between the different projections and I implicitly assume that individuals revise their saving and investment decisions due to adjustments in their expectations about future demographic developments. In a number of cases the calculated individual planning horizon exceeds the forecast horizon of the relevant projection. For these cases I use data from the next available projection that covers the required period. In a last step, the age group-specific anticipated future dependency ratios are aggregated over all groups for each country and weighted by the relative size of each age cohort, giving two variables representing aggregated anticipated future changes in young and old age dependency.

2.4.4 Non-Demographic Determinants

While demographic factors may only explain a minor part of the overall variation in the dependent variables, it is important to control for other fundamentals within the regressions. Thus, the following non-demographic explanatory variables are added to the models. Table 2.1 gives an overview and further details regarding all variables used in the models while Table 2.2 reports the descriptive statistics.[16]

Per capita income [GDP]: The level of per capita income is assumed to play a crucial role in the determination of saving, investment and external balances. First, individuals with higher incomes tend to save more than individuals with lower incomes. If at the same time the investment rate remains constant or changes with different pace, there should be an effect on external balances, too. Second, the level of per capita income can be used as a proxy to capture the stage of development of a country. According to theory, countries should become exporters

[15] For instance, the 1973 projections were not published before 1977.

[16] Following the practice of other studies I do not include the real interest rate in the model as empirical work suggests it to have no crucial long-term impact on saving and investment rates. Furthermore, Graff et al. (2008) argue that including the real interest rate will lead to an underestimation of other fundamental determinants of saving and investment because it is a price that may adjust in response to excessive demand or supply of capital until investment and saving are in equilibrium.

of capital as they get more developed because their capital-to-labor ratio increases. In general, a higher capital-to-labor ratio implies lower marginal returns on capital and thus capital should flow from more advanced countries with relative labor scarcity to lower developed countries that have low capital-to-labor ratios and higher marginal returns on capital. Per capita income is measured as GDP per capita.[17]

Income growth [GDPGR]: Beside the level of per capita income also the growth rate of income might play a crucial role in the determination of saving and investment rates and the current account. If incomes grow rapidly, habit formation in consumption behavior may prelude individuals to expand their consumption at the same pace as their incomes rise during these periods of high growth thus boosting savings rates. However, demand for investment tends also to be higher during periods of strong economic growth, thus making the effect of economic growth on the current account ambiguous. In general, fast growing economies are expected to give higher returns on investments and thus should attract capital from abroad. GDPGR is measured by GDP per capita growth in percent.

Relative price of investment [RPI]: The relative price of investment goods has been suggested to be a crucial determinant of saving and investment rates (Taylor, 1994; Higgins, 1998; Lindh and Malmberg, 1999a). Higher relative investment prices and hence higher factor costs should depress the profitability of investments and thus lead to a lower demand for investment goods. In contrast, the theoretical link between savings and the relative investment price is ambiguous. As remarked by Lindh and Malmberg (1999a), depressed demand for investment should also spill over to saving demand in an imperfectly open economy. On the other side, when high prices of investment goods are the result of high demand for investments goods, rising returns on savings should foster saving efforts. Graff et al. (2008) suggest to use a lag of the relative price of investment as a control variable for business cycles. Higher prices of investment in the previous period may indicate an economic boom with high investment rates which are likely to come down in the subsequent period.

Financial development [FIN]: Studies such as Edwards (1995) or Chinn and Ito (2007) suggest that the deepness and sophistication of financial markets have an impact on savings, investment and the current account. From a theoretical perspective, however, this link is not unambiguous. On the one side, sophisticated and deep financial markets should encourage savings by facilitating risk management, providing more transparency and lowering transaction costs. On the other side, financial market development may induce lower saving rates by removing borrowing constraints and reducing the need for precautionary savings, implying a negative impact on the current account. More generally, countries with deep financial markets are supposed to attract foreign capital more easily than countries with underdeveloped and illiquid markets. The level of financial development is proxied by the ratio of private credit to GDP.

[17] While I use GDP per capita measured in constant 2000 US dollars from the WDI database, using purchasing power parity (PPP) adjusted GDP per capita in international dollars and current prices from the PWT database instead lets the estimation results nearly unchanged. There are no qualitative differences using one measure over the other.

Legal development [LEG]: Chinn and Ito (2007) stress the importance of the legal environment in determining saving and investment rates. The legal and regulatory foundations of a country influence the environment in which agents make their economic decisions and affect the rate of returns from saving and investment activities. Chinn and Ito (2007) use the first principal component of a set of variables based on the International Country Risk Guide (ICRG). However, data from ICRG are not available before 1984, so instead I use the sub-index "Legal system and Property Rights" from the Economic Freedom index published by Gwartney et al. (2012) where time series are available since 1970. The index measures aspects such as the integrity of the legal system, the protection of property rights and the degree of judicial independence.

Education [EDU]: The level of education and human capital is a crucial determinant of labor productivity. Higher labor productivity should lead to higher incomes and yet higher saving rates. Similarly, higher labor productivity generates better investment opportunities and should attract more capital. In addition, as stated for example by Luehrmann (2003), there might be a link between demographic aging and education in the sense that population aging leads to labor scarcity that in turn fosters investment in human capital in order to make the scarce factor labor more productive. If this is the case, it is essential to include human capital to the model in order to separate demographic and human capital effects from each other and obtain consistent estimates. The variable EDU is measured as average years of total schooling based on the dataset published by Barro and Lee (2012). Using instead the indicator for human capital from Feenstra et al. (2013) based on the educational attainment data of Barro and Lee (2012) and the findings about returns to education from Psacharopoulos (1994) produces somehow different estimation results for the educational effects but leaves the parameters of other variables widely unchanged.

Trade openness [OPE_{trd}]: A country's openness to trade may affect its current account balance as it allows for raises in cross-border trade. Thus, the widening of global imbalances may in part be the result of a consequent easing of trade barriers and increasing globalization. Trade openness is defined as the sum of gross imports and gross exports in goods and services relative to GDP.

Financial openness [OPE_{fin}]: Besides trade openness, also the degree of financial openness of a country determines the current account position of a country. Strict capital controls hamper capital to flow freely across countries and provoke domestic and national saving and investment rates to relate strongly on each other. Restrictive capital mobility may also undermine demographic effects on capital flows thus making it essential to control for these effects. In order to define $\mathrm{OPE}_{\mathrm{fin}}$ I use the index suggested by Chinn and Ito (2008) which quantifies the extensity of capital controls. As announced before, this index is rescaled to values between 0 (very closed) and 1 (very open).

Public spending on pensions [PEN]: Conceptional and simulation-based studies such as Börsch-Supan et al. (2006) show that the pension system in place plays a crucial role for demography-induced changes in saving, investment and capital flows. In general, a tax-financed public pension system may crowd out savings by taking away the need for individuals to accumulate assets to finance their future consumption during the retirement period. However, empirical studies regularly neglect the effects of public pensions in their analysis. In order to account for this important factor, the public social expenditures on pension as percentage of GDP is added to the model. Unfortunately, this data set is only available for the sub-sample of OECD countries.

EMU membership [EMU]: As a considerable part of the countries in the OECD sub-sample belongs to the euro area, I control for potential effects of the common currency union by introducing euro dummies in the sub-sample regressions. This is especially important as the emergence of imbalances within the euro area coincided with the foundation of the European Monetary Union (EMU) in the 1990s and the subsequent introduction of the euro. Following Jaumotte and Sodsriwiboon (2010), I introduce separate dummies for northern and southern European euro member states, thus testing for heterogeneity between these two regions.

There is the risk that some of the variables cause reverse causation in the model. This might be especially true for the level and growth rate of income which are according to common growth literature essentially affected by saving and investment patterns and thus should fail to enter the model exogenously. Similarly, the price of investment may be plagued by endogeneity as a high saving rate might also raise the supply of investments goods, hence putting pressure on investment good prices (Higgins, 1998). In order to mitigate potential simultaneity bias resulting from reverse causality when estimating the model, I use lagged values of GDP, GDPGR and RPI as variables.

2.5 Estimation Results

2.5.1 Saving Regression Results

This section reports the estimation results of the saving model using six different specifications. The estimated effects are reported in Table 2.3. The first column (SAV1) shows the baseline model from equation (2.1) which includes country as well as time fixed effects and follows the classical closed economy framework commonly used in the empirical literature on demographic aging and saving respectively investment. It uses simple categorical age variables in order to represent the current demographic structure, thus allowing a more intuitive and direct interpretation of the age coefficients. The baseline model shows a negative relationship between the old age dependency ratio and the real domestic saving rate. This result gives support for the existence of life cycle effects on aggregated saving behavior. In contrast, the youth dependency rate is statistically and economically insignificant. Similar results are found by previous studies such as Bosworth and Chodorow-Reich (2007) or Park and Shin (2009) who find a rather strong negative coefficient for the old age dependency rate and weaker effects for the youth dependency ratio. In contrast, the variables OLD_{fut} and YNG_{fut} have both a positive sign, suggesting that the anticipation of future increases in old and young age dependency rates fosters precautionary saving today. With a value of 0.28 the effect is higher for future increases in the share of old individuals than for future rises of the young (0.09). Life expectancy as a proxy for the expected length of the retirement period and the real domestic saving rate are positive correlated with each other and back the assumption that due to longevity individuals increase saving efforts today in order to finance their future consumption during retirement. However, in line with findings from Bosworth and Chodorow-Reich (2007) or Park and Shin (2009), the coefficient is rather small. Interestingly, when replacing the real domestic saving rate as dependent variable by other measures of aggregated saving such as the nominal domestic saving rate or the national saving rate, LIFE becomes highly statistically significant and has positive values around 0.5 and higher while most other variables remain rather constant.[18] The parameters for the non-demographic control variables in SAV1 are in line with what we would expect regarding their signs. There is a positive association between the income level and saving which confirms the common findings in literature that richer individuals save a larger part of their income than poorer ones. Also the coefficient of income growth has a positive sign which can be explained by habit formation in consumption. In contrast, the lag of the relative price of investment has a statistically and economically significant negative relationship with savings. Finally, the coefficients of the variables for financial and legal development, education as well as for the two measures for trade and financial openness have a positive sign, but are statistically not different from zero.

SAV1 uses annual data. As stated before, the fixed effects specification allows to study in particular the within-country variation over time and thus high frequency annual data are preferred in order to capture the full information that is available in the time series. On the other side, annual data might be driven by short-term business cycle fluctuations which predominate the slow moving age effects. Therefore, SAV2 estimates the same specification as the baseline model, but with non-overlapping aggregated 5-year data. A comparison between the SAV1 and SAV2 regression results reveals that LIFE changes its sign, but remains small and statistically insignificant. The parameter for anticipated future old age dependency becomes larger (0.38) and statistically significant at the 3 percent level. Overall, the results remain rather stable and there are no major variations between the two different time dimensions, indicating that the slow moving age effects are not overwhelmed by short-term fluctuations and data noise is no serious problem.

In SAV3 the categorical variables of young and old age dependency ratios are replaced by a cubic polynomial approximation in order to represent the age structure of the current population. The estimated implied age profiles for saving follow the classical hump-shaped pattern also found by previous studies (see graph on the top in Figure 2.1). The Wald test indicates that all

[18]These values are of similar magnitude as found by Bloom et al. (2003a). They also use the nominal gross domestic saving rate as dependent variable, suggesting that the choice of the measure for the saving rate in the model is crucial for the results of LIFE.

three polynomial terms are highly jointly significant. The propensity to save is low in the young age tail of the distribution, peaks by ages around 40 and 45, and then decreases drastically, especially beyond the age of 65.[19] Thus, the polynomial specification confirms the previous results obtained with simple categorical variables that a high share of old individuals has a negative impact on domestic saving rates which is consistent with the life cycle hypothesis of saving and consumption.

SAV4 extends the SAV1 model to an open economy setting as described in equation (2.2) by adding variables that capture foreign influences to the specification. The foreign variables capture changes in domestic factors relative to the rest of the world, adjusted by economic size and financial openness.[20] As proposed by Graff et al. (2008) I add also a control variable for effective openness (OPE) to the model which is the financial openness indicator multiplicated with the relative size of the home economy compared to the rest of the world, $\theta_{it} * \sigma_{it}$, thus avoiding that the effects of the open economy variables are driven by this interaction term. The domestic parameters in SAV4 are very similar to the closed economy baseline model and have the same signs. A look at the newly added foreign variables reveals that their coefficients are statistically insignificant at the 10 percent level, with exception of OLD_{fut}_row, LIFE_row and FIN_row. Furthermore, the effects of the foreign variables are rather small. In order to ease the interpretation and compare the effects of the foreign variables with their domestic counterparts, I follow the procedure used by Graff et al. (2008) and multiplicate the values of the coefficients with the mean value of the relative economic size times financial openness, $\theta_{it} * \sigma_{it}$. This allows to compare the marginal effects of domestic and foreign factors. For instance, the marginal effect of an increase in the anticipated future old age dependency at home is almost four times larger than the marginal effect of an increase in the same variable in the rest of the world.[21] This is mainly in line with Graff et al. (2008) who found in their model that the marginal effects of the foreign variables are much smaller than their domestic counterparts. The signs of the open economy parameters differ between the variables. For instance, OLD_{fut}_row has a positive sign and thus indicates that an increase in the anticipated future domestic old age dependency relative to the rest of the world has a positive impact on real domestic savings at home, or in other words, increases in anticipated future old dependency in the rest of the world are negatively associated with saving rates at home. This is intuitive if we assume that projected future increases in the share of old individuals in the rest of the world causes precautionary saving in these countries. Higher saving rates in the rest of the world should put negative pressure on world interest rates, thus making saving less attractive in the home country, too, if its capital markets are internationally integrated. In contrast, LIFE_row has a somehow

[19] As noted by Higgins (1998), it is important to keep in mind that the age coefficients are no behavioral parameters and do not describe the actions of individuals belonging to a specific age cohort. In fact the parameters capture the relationship between the overall population age structure and the saving behavior of individuals of all ages within the population. Hence, the negative age coefficients found for groups beyond the age of 65 in the saving regression do not necessarily imply that old individuals themselves are dissavers.

[20] For instance, following equations (2.2) and (2.3) the variable OLD_row is defined as $\theta_{it}\sigma_{it}(OLD_{it} - \overline{OLD}_{it})$.

[21] The mean value of $\theta * \sigma$ is 5.278. In this specific example the marginal effect of a domestic change in OLD_{fut} is computed as: 0.270+0.0182*5.278= 0.366. In contrast, the marginal effect of a foreign change is 0.0182*5.278*(-1)= -0.096. Calculating the ratio of the absolute values gives $\mid \frac{0.366}{-0.096} \mid = 3.81$.

counterintuitive negative sign suggesting that increases in life expectancy abroad foster saving behavior at home. This indicates that saving has not necessarily to follow a symmetric pattern at home and abroad and the direction of foreign effects not always follows a clear pattern. Even though the results give evidence that saving rates are affected by interdependencies between the home country and the rest of the world, the finding that the marginal effects are rather small and statistically insignificant for most open economy variables suggests that savings rates are mainly driven by domestic factors. This conclusion is affirmed by the fact that the coefficients of the domestic variables remain remarkable constant between the closed and open economy framework and at the same time the explanatory power of the open economy model improves only slightly with an R^2 value of 0.867 compared to the closed economy version ($R^2 = 0.860$). The same is true for the adjusted R^2 (0.859 vs. 0.852).

As noted before, besides the fixed effects specification a pooled OLS model with lower time frequency is used in order to study the cross-sectional variation between countries rather than the variation within countries. However, skipping the country fixed effects from the model bears a greater risk that crucial unobserved determinants are excluded from the model. While the fixed effects model is not immune against endogeneity bias resulting from omitted time-variant variables, the pooled OLS may suffer from both time-variant and invariant omitted variables. Even though the model controls for a number of economic and institutional factors, there is still the risk that there are country-specific effects that, if omitted, will bias the estimation result. Hence, the pooled OLS regression models in SAV5 and SAV6 are not the preferred specification in this paper and the following cross-sectional analysis should be interpreted with some caution and rather be seen as an additional robustness test. The models differ in several aspects from the baseline models with country fixed effects. The negative effects of present young and old age dependency are more pronounced in the pooled OLS versions. In contrast, the coefficients of the future demography variables are all statistically insignificant. The coefficient for education turns its sign in both SAV5 and SAV6, but remains statistically insignificant, too. A robustness check of the pooled OLS specifications with 13-year aggregates (results not reported) produces rather similar results, but in general the coefficients in the 5-year regressions tend to be more significant than the results obtained with 13-year time aggregates.

2.5.2 Investment Regression Results

Table 2.4 reports the same regressions as discussed in the previous section but for the real investment rate as dependent variable. In general, the link between demographics and investment is less significant compared to the saving regressions. In line with previous studies, I find for the baseline closed economy model with country fixed effects (INV1) a negative link between investment and old age dependency. However, the negative effect is smaller compared to the saving model and has a p-value of only 0.05. In contrast to the saving model, the variable for anticipated future old age dependency has a negative sign. This is what we would expect because investors should anticipate in advance that the population will age in the future and expect lower productivity and decreasing returns to their investments thus making long-term investments less attractive. Similarly, a high share of old individuals might also mean that there is a high number of asset decumulators in the future, thus further suppressing interest rates. However, the coefficient of $\mathrm{OLD}_{\mathrm{fut}}$ is statistically significant only at the 15 percent level. The coefficient for anticipated future young age dependency is very small and statistically insignificant. Life expectancy is positively associated with investment rates but barely fails the significance level of 10 percent. A positive relation is also found by Bosworth and Chodorow-Reich (2007) or Park and Shin (2009). Given that higher life expectancy also reflects better overall health conditions, this positive relation might be the result of a more healthy and thus more productive population that attracts investment. Furthermore, longer life time may make long-term investments goods more attractive for individuals as they can profit longer from it. The positive and statistically highly significant coefficient of GDPGR gives support for the common wisdom that economies with high growth rates are more attractive for investors. Similarly, the positive signs of FIN, LEG and EDU signify that financially and legally developed economies with a highly educated population foster investment. While trade openness seams to play no crucial role, I find financial openness to be a meaningful determinant for investment. Finally, the estimation results indicate that higher relative prices of investment depress investment rates.

When replacing the annual data by 5-year aggregates (INV2), OLD becomes statistically insignificant and EDU changes its sign, but remains statistically insignificant, too. Forcing the age coefficients for the current age distribution to lie on a cubic polynomial (INV3) provides very similar estimations. The weak old age dependency effects found in the previous two regressions translate also in an only slightly hump-shaped polynomial curve (see middle graph in Figure 2.1). INV4 shows the estimations for the open economy extension of INV1. As in the saving model, the overall explanatory power of the open investment model does not impove considerably and the effects of the open economy variables are rather small compared to their domestic counterparts. Furthermore, the results of the domestic variables are in line with the findings of INV1. Only $\mathrm{YNG}_{\mathrm{fut}}$ turns its sign and becomes statistically significant and positive. This is plausible if we assume that investors anticipate that more young individuals will enter the labor market in the future and raise the demand for capital. Hence, the result can be regarded as a hint that forward-looking investors incorporate these forecasted developments in their current investment decisions and adapt their behavior. INV5 and INV6 report the estimation results for the closed respectively open economy model without country fixed effects. While the pooled OLS regression produces mostly similar coefficients as their fixed effects counterparts, $\mathrm{OLD}_{\mathrm{fut}}$ changes its sign to an implausible positive relationship between investment and expected future old age dependency. But for reasons stated before, there is some doubt about the consistency of estimations without controlling for country-specific effects.

2.5.3 Current Account Regression Results

Even though the main interest lies in a saving-investment perspective of the current account, for completeness and transparency this section reports briefly the current account regression results, whereby the focus lies on the estimations for demographic effects only. Table 2.5 uses the same specifications as used for the saving and investment regressions. There is a significant negative relationship between the old age dependency rate and the current account balance over all specifications. This is not unexpected and in line with the findings from the previous two sections where the estimation results pointed to more pronounced negative old age effects for saving regressions compared to the investment regressions. From a national accounting identity this should indeed translate into a tendency of mature countries with an older age distribution to run current account deficits. The coefficient for the anticipated change in the future old age dependency rate is positive and statistically significant in the conventional baseline model (CAB1). Again, this is what we would expect from a saving-investment perspective as the investment regressions suggest $\mathrm{OLD_{fut}}$ to be negatively related with investment activity while at the same time the saving models give evidence that $\mathrm{OLD_{fut}}$ fosters precautionary saving behavior. Overall, these results can be interpreted in the way that countries which are in an early stage of a demographic transition and have still a low share of old people within the population tend to run a current account surplus given that the negative pressure of present old age dependency on external positions is still limited and the positive effect stemming from expectations about future population aging prevails. However, as the demographic transition process proceeds, the negative pressure on the current account increases due to a rising share of old individuals within the population. At the same time the positive anticipation effects diminish since with already high shares of old individuals there will be no further room for large increases in the old age dependency ratio in future, respectively the future old age dependency ratios will even reduce again when the demographic transition towards an aged population has already reached its peak. Thus, in an advanced stage of the demographic transitions the negative impact of present demographics will outweigh the positive effect of future anticipations on the current account. While the coefficient of $\mathrm{OLD_{fut}}$ is positive and statistically significant in CAB1, it keeps its sign in the baseline model with aggregated 5-year data (CAB2) and the open economy model (CAB4), even though it looses its statistical significance in both models. CAB4 follows equation (2.6) from section 2.4.2 using the open economy form of the saving and investment regressions, but neglecting the special general equilibrium character of the current account balance in some aspects. The effect of $\mathrm{OLD_{fut}}$ is not stable over all specifications. When using a cubic polynomial instead of categorical variables for the present age structure (CAB3), the effect of $\mathrm{OLD_{fut}}$ diminishes. Furthermore, when dropping the controls for time-invariant country-specific effects the coefficient turns even to negative (CAB5). I find slightly positive but statistically insignificant effects of the life expectancy on the current account for all six specifications.

Table 2.6 reports the current account estimation results as specified in equation (2.7) in section 2.4.2 under the assumption of a general equilibrium framework. Thus, it is assumed that absolute changes in domestic factors on their own have no impact on the current account balance but only to the extent that they lead to relative changes in the determinants between the home country and the rest of the world. Similar to Graff et al. (2012) I find no clear evidence for demographic effects on the current account balance when skipping domestic variables in absolute terms. For both estimated specifications, fixed effects and pooled OLS, the demographic parameters are very small and mostly statistically insignificant. This shows that the results of the current account regressions are very sensitive to the structure of the underlying model.

2.5.4 Robustness Checks

A number of robustness checks are conducted in order to test the stability of the previous results and to get a more comprehensive picture of the relationship between savings, investment and the current account on the one side and present and future demographics on the other side. The detailed results are shown in tables in the appendix.

Dynamic Fixed Effects

As a first robustness check, I include a first-order lag of the dependent variable in the models. Adding an autoregressive term allows to account for potential dynamic feedback effects as well as gradually adjustment processes. Dynamics in the models may arise because of various reasons. For instance, there is the possibility of habit formation in consumption that affects the response of saving rates to income shocks. Similarly, rigidities and transactions costs in capital markets may delay any adjustment of investment rates towards a new equilibrium. Table 2.8 shows the results for the dynamic specifications with country fixed effects for saving, investment and the current account in the conventional closed economy case (columns 1-3) and the open economy case (columns 4-6). The autoregressive term is significant both economically and statistically for all models. This suggests that dynamics matter and that saving, investment and current account rates are to some degree persistent and likely to adjust not immediately but gradually to external shocks. The signs of the coefficients for the demographic variables remain mainly stable even though their magnitude gets smaller in some cases. Only the effect of $\mathrm{OLD}_{\mathrm{fut}}$ seems to disappear in the dynamic saving regressions but remains in the investment and current account models. The coefficients of the control variables get smaller and change in some cases their sign. It is important to mention that including the autoregressive term to the standard fixed effects models may cause endogeneity problems as the lagged dependent variable and the error term are correlated by construction. Even though Nickell (1981) shows that this particular bias diminishes as the time dimension gets longer, Judson and Owen (1999) argue that the bias can still be significant for models using time series with high time dimensions such as T=20. Nevertheless, the time dimension in our models is up to T=40 when non-aggregated annual time series are used and should be long enough to limit this bias. And indeed, additional tests using a bias-corrected LSDV estimator as proposed by Kiviet (1995) and Bruno (2005) give no signs of a serious bias.

Difference and System GMM

While for the standard fixed effects models the assumption of strict exogeneity has to hold in order to produce consistent estimates, GMM techniques can handle specifications suffering from weak exogeneity and endogeneity. In a further sensitivity test I estimate dynamic models that rest upon the difference GMM procedure developed by Arellano and Bond (1991) as well as the system GMM procedure proposed by Arellano and Bover (1995) and Blundell and Bond (1998). While the difference GMM is based on a first differencing approach to eliminate the country fixed effect from the equation (which is - as mentioned above - a source of endogeneity in dynamic specifications) and uses lagged level variables as instruments, the system GMM builds its estimations upon a joint system of equations in differences and levels with specific lagged versions of the variables as instruments. The latter procedure produces more instruments and allows to attain more efficient estimates, especially when there is high persistency in the dependent variable. Besides controlling for endogeneity resulting from the lagged dependent variable, I also use lagged instruments to control for potential endogeneity resulting from other regressors. Namely I treat per capita income and per capita income growth as endogenous. As stated before, saving and investment are widely regarded to be crucial factors to economic growth, so including the uninstrumented variables GDP and GDPGR is likely to trigger reverse causation and simultaneity bias, even though the usage of lagged versions of these variables in the previous models should already alleviate this problem to some extent. A critical aspect when using the difference and especially the system GMM approach is the number of involved instruments. If there are too many instruments, estimation results as well as related specification tests may be inconsistent (Roodman, 2009b). In order to mitigate any problems of instrument proliferation, I only use non-overlapping 5-year data which keeps the number of instruments at a reasonable level. The usage of annual time series in the GMM regressions would lead to an explosion in the number of instruments. As the number of instruments still exceeds the number of countries and hence fails to fulfill the (somehow arbitrarily set) rule of thumb to keep the number of internal instruments below the number of cross-sectional units (Roodman, 2009a), I restrict the number of lags used as instruments to a maximum of two. Yet, sensitivity analyses show that the results are rather similar for both unrestricted specifications using the full set of available internal instruments and the restricted specifications reported here. The coefficients for the system GMM procedure are estimated using a one-step procedure, but a two-step estimation with corrected estimators (see Windmeijer, 2005) in order to avoid downwardly biased standard errors produces similar (albeit less statistically significant) coefficients.

Table 2.9 shows the results for the difference GMM estimator, Table 2.10 for the system GMM estimator. Overall, both estimators produce quite similar results which are in general less significant than the estimates obtained earlier in this study. The autoregressive term is highly significant for saving and investment, but less significant for the current account regression.

Interestingly, the relative price of investment, RPI, has implausible positive signs in saving and investment regressions. However, the results from the GMM models should be interpreted with some caution. The Arellano-Bond test gives in general only little evidence that the GMM models suffer from second-order autocorrelation (first-order autocorrelation is common when using the difference and system GMM procedures), but casts some doubts about the validity of the internal instruments used in the open economy saving regressions. The Sargan test gives more evident results in this direction, indicating that the instruments used in the difference GMM models are not exogenous and thus invalid. For the system GMM the results of the Sargan test are even worse: for all specifications the null hypothesis that the overidentifying restrictions are valid is rejected at least at the 10 percent level, for some even at the 1 percent level (see bottom lines of Table 2.9 and 2.10). Overall, these test results give reason to assume that the usage of difference and system GMM estimators and their internal instruments is inappropriate for our models.

Geographical Instruments

Given that lagged values as instruments seem not to be appropriate to account for potential endogeneity in our demographic models, I test also an instrumental variable (IV) approach with external instruments in a static stetting to improve the consistency of the estimates. However, finding good external instruments which are highly correlated with the potential endogenous variables but uncorrelated with the error term is not an easy task. I rely on a set of geographical variables that have been proposed by Gallup et al. (1999) and Bloom et al. (2003a): latitude, percentage of land area within 100 kilometers of the coast or a major waterway, and percentage of land area in the tropics. According to the authors, these variables are major determinants of the income level and income growth rate and should not have a direct impact on saving rates. However, these instruments have the major drawback that they are time-invariant and cannot be used with a fixed effects specification. Table 2.11 shows the results for the IV approach with the two-stage least squares (2SLS) estimator using annual data for both the closed and open economy models for saving, investment and the current account. I regard only GDP growth to be endogenous in the regressions, but instrumenting for both the level and the growth rate of GDP provides (with some exceptions) similar estimation and test results. In general, the results need to be compared to the pooled OLS regressions from the previous sections, as both the pooled OLS and the IV regressions do not control for time-invariant country specific effects. And indeed, the IV regression estimations are similar to the results obtained from the pooled OLS model for saving, investment and the current account. I also conduct a number of tests (see bottom lines of Table 2.11). An endogeneity check based on the robust score test proposed by Wooldridge (1995) shows significant results for most of the regressions, thus indicating that GDPGR should indeed be treated as endogenous. Only for the open economy specifications with the investment rate respectively the current account balance as dependent variable, the null hypothesis that income growth is exogenous cannot be rejected at standard significance levels. As there are more instruments than endogenous variables, it is also possible to run overidentification tests in order to test the validity of the instruments. Interestingly, the robust score test from Wooldridge (1995) clearly rejects the null hypothesis that the geographical variables are exogenous and therefore suggests that they are inappropriate as instruments in our models. An exception are the investment and current account regressions incorporating foreign effects, but even there the p-value is with 0.12 respectively 0.13 rather small. In addition, the robust F-statistics from the first-stage regressions are all quite beyond the value of 10 (thus failing to fulfill an often in the literature stipulated requirement for instrumental relevance) and indicate rather weak instruments in the sense that there might be insufficient correlation between the instrumented variable GDPGR and the geographical instruments. Overall, the test results give some indications that again the results of our instrumented regressions should the be interpreted with caution.

OECD Sub-Sample, Public Pension Systems and the Euro

Finally, I replace the full country sample by a sub-sample of 24 OECD countries. Besides the special interest in OECD current account surplus countries in this study, using a sample with a limited number of industrialized countries with similar properties minimizes potential problems arising from parameter heterogeneity. As outlined by Lindh and Malmberg (1999a) and Bosworth and Chodorow-Reich (2007), age effects might differ across countries and regions and using a country-set where the cross-sectional units are broadly similar in their institutional and socio-economic characteristics should suffer less from parameter heterogeneity than a larger world sample. I extend the set of control variables for the OECD sample in two ways. First, most developed countries have installed tax-financed pay-as-you-go pension systems which may have a crucial impact on the age effects on saving, investment and the current account. Thus, I add the variable PEN to the model which measures public social expenditures on pension as percentage of GDP. Second, as a significant number of countries within the OECD sample have entered the European Monetary Union, I also add euro dummies to the model in order to control for special effects resulting from the membership in the euro area. Thereby, I allow effects to differ for southern and northern European member countries.[22]

Table 2.12 shows the saving results for the OECD regressions. The specification of OECD-SAV1 is identical to the closed economy model (SAV1) of the full country sample. The estimates differ in some respects from the world sample. While the estimated negative impact of present old age dependency on saving is robust over both samples, the coefficient of YNG becomes positive but remains statistically insignificant in the OECD sample. Bosworth and Chodorow-Reich (2007) find also a positive relationship between saving and present youth dependency for their country fixed effects specification and an industrial country sub-sample, and the findings of Barnes et al. (2010), even though focused on the current account balance, suggest that the role of young age dependency is less reliable for the OECD countries. However, using a cubic polynomial (results not reported) instead of the categorical dependency rates in our model reveals the classical

[22]Even though from its geographical position a northern country, I count Ireland to the set of southern European countries because in economic terms it fits better to this group of periphery countries than to the core EMU countries.

hump-shaped age-saving pattern for the OECD sample. The measures for anticipation of future demographic developments are all statistically insignificant. In contrast to the world sample, the openness measure for trade, OPE_{trd}, is both statistically and economically significant, thus suggesting that the OECD economies are more internationally integrated and stronger affected by developments from abroad. Adding the variable PEN that measures public social expenditures on pension to the model (see OECD-SAV2) shows the expected significant negative coefficient suggesting that there is a crowding-out effect and public pension expenditures and precautionary savings for retirement may behave like substitutes. Further, after controlling for PEN, the negative effect of old age dependency on real domestic saving rates gets significantly smaller and the effect of life expectancy changes its sign but remains statistically insignificant. Adding euro dummies to the sample suggests that EMU membership has a positive impact on saving rates for both northern and southern European countries (see OECD-SAV3), but this impact is neither statistically significant nor does it considerably change the coefficients of the other variables. In order to shed further light on the interdependencies between public pension expenditures and the age effects, I add in the next specification (OECD-SAV4) interaction terms between PEN and the three variables OLD, OLD_{fut} and LIFE. OLD*PEN results in a statistically significant positive effect, indicating that retired individuals do have less pressure to dissave if there is a strong public pension system in place and this effect overwhelms any potential negative impacts of higher taxes on income and savings in the working population. In contrast, the coefficients of OLD_{fut}*PEN and LIFE*PEN have a negative (but statistically insignificant) sign, giving some hints that public pensions may lessen the need for precautionary savings. The coefficient of PEN becomes less pronounced and statistically insignificant after adding the three interaction terms. Overall, these results suggest that considering public pensions systems is important when studying age effects on savings, but more empirical research is needed in order to undertand the underlying mechanisms in more detail. Finally, the open economy framework in the spirit of Graff et al. (2008) (OECD-SAV5) confirms our previous findings that the OECD countries are more affected by foreign developments. In contrast to the world sample, some of the coefficients for the variables measuring the relative difference between the determinants at home and abroad are now statistically and economically significant. For instance, OLD_row has the same negative sign as OLD and the marginal effect of the foreign effect $\overline{OLD}$ is with 0.24 in absolute terms not so much smaller than to the (opposing) domestic effect OLD (-0.36).[23] This indicates that rising old age dependency abroad has an opposite (positive) effect on the domestic saving rate compared to the negative impact resulting from high shares of old individuals in the home country. A possible explanation is given by Graff et al. (2008) who argue that higher shares of old people in the rest of the world should reduce foreign savings. This again should raise the world interest rate relative to the domestic interest rate and stimulate domestic savings and capital outflows. However, the signs of most other variables in the model differ between the domestic variables and their foreign counterparts, indicating that symmetry is not fully given in the saving equation of the OECD sub-sample.

[23]Again, remember that OLD_row is defined as $\theta_{it}\sigma_{it}(OLD_{it} - \overline{OLD}_{it})$. The marginal effect is computed with the mean value of the relative economic size times financial openness, $\theta_{it} * \sigma_{it}$, which is 2.14 for the OECD sub-sample.

The investment regressions (see Table 2.13) are quite similar between the world sample and the OECD sub-sample. One exception is LIFE, which changes its sign in the closed economy specifications. However, this effect disappears when the extended open economy framework is used. PEN has also a negative association with investment, but the magnitude is smaller compared to the saving regressions and the inclusion of the variable does not considerably change the demographic effects. Yet, the specification including the interaction terms of PEN (OECD-INV4) differs from the pattern of the other models in Table 2.13, but there is strong evidence that the model suffers from mulitcollinearity between PEN and its interaction terms. Finally, the euro variables suggest that joining the EMU fostered investment in the southern European countries. However, the age effects remain mainly unchanged when the EMU dummies are included.

2.5.5 Predicted Demographic Effects on Selected OECD Countries

Finally, in this section I examine to which extent the estimated demographic effects obtained from the previous regression analysis can predict the saving and investment pattern since the early 1990s in selected OECD surplus countries. As a first simple exercise, I analyze the country-specific goodness of fit of the models over the period 1990-2010. Thereby, I concentrate on the the baseline fixed effects model specification with categorical age variables in the closed economy framework (SAV1 and INV1) as well as the open economy setting (SAV4 and INV4). Table 2.7 reports the determination coefficient R^2 and the root mean square errors (RMSE) for the saving and investment regressions and each country. As expected from the previous findings, there are no large differences between the closed and open economy models. The results indicate that the saving models can explain much of the variation found for the surplus countries Japan, the Netherlands, Denmark, Sweden and Switzerland since the 1990s. A good model fit is also suggested for these countries by the comparatively small prediction errors. In contrast, the models have less predictive power for the saving pattern in Germany and South Korea as well as for two deficit countries which I add here for comparison reasons, the United Kingdom and the United States. This suggests that other factors omitted from the models were crucial determinants for saving in these countries during the observation period. In the case of Germany it is not unlikely that non-observed special effects resulting from the German reunification played some role during the early 1990s. Similarly, it is likely that extraordinary effects during and in the aftermath of the Asian financial crisis in the late 1990s were responsible for some of the saving-investment pattern found in South Korea. A possible explanation for the bad model fit for saving rates in the United Kingdom and the United States are for example wealth effects on consumption behavior which are not captured by our models. Driven by increasing prices at the stock and real estate markets during the 1990s and the first half of the 2000s, the (perceived) rise in wealth may have had a significant effect on consumption behavior and saving rates in these two countries. Surprisingly, the investment models perform poor to explain the variation of investment rates in the Netherlands which does, however, not translate into exceptionally high prediction errors for this country.

Given that our primary interest lies in the pure age effects, in a second exercise I use solely the point estimates of the demographic coefficients and skip any other effects resulting from the control variables from the models in order to predict saving and investment pattern since the 1990s. In other words, the following results report solely the predicted impact of present and anticipated future demographics on saving and investment rates under the assumption that the remaining covariates in the model did not change during the prediction period. Besides in-sample predictions with the full dataset, I also use alternative out-of-sample estimations by skipping the selected OECD surplus countries from the world sample and estimate once more the coefficients for the closed and open economy model specifications with the reduced country sample.[24] The predictions for the demographically implied saving and investment time series cover the historical period 1990-2010 and use 1990 as reference year for calibration.

Figure 2.2 illustrates the out-of-sample projection results compared with the actual values of saving and investment rates for eight selected OECD countries. The alternative in-sample forecasts with the estimated parameters from the full country sample are not reported but produce nearly identical fitted values. In general, the results again show that there are no substantial differences between the closed and the open economy predictions, reflecting our previous findings that saving and investment are mainly determined by domestic rather than foreign factors. Overall, the investment rates seem to be somewhat higher in the open economy predictions compared to the closed economy setting. The first two rows in Figure 2.2 depict the saving and investment pattern for Germany and Japan, both countries which have reached a very advanced stage of the demographic transition and are already experiencing a high degree of population aging. As one would expect, the models predict a demographic-induced downward pressure on saving rates for these two countries. The predictions for savings fit quite well the historical pattern that could be observed in Japan with decreasing rates over the full period of 1990-2010. In contrast, for Germany the predictions for saving differ significantly from the observed rates. The model predicts a decrease in saving rates after 2000, but in fact the observed historical saving rates remained quite stable and increased even after 2005 (but fell then again towards the previous level during the financial crisis). The predicted fall in investment rates for Japan can indeed be observed, even though the actual decrease was quite stronger than the demographic model predicts. In contrast, for Germany the model predicts rather stable investment rates (a slight decrease in investment in the closed economy setting and a slight increase in the open economy version) instead of the decreases that took place during the observed time period. Overall, the implied demographic effects predict that Germany and Japan should already experience considerable pressure from population aging and instead of having large current account surpluses they should have started to run current account deficits. For the Netherlands and Denmark, the estimated demographic coefficients imply saving rates that are broadly in line with the historical pattern over the last twenty years. However, in the case of the Netherlands the models predicts a narrowing of the gap between saving and investment since the early 2000s while for Denmark a widening of the gap is predicted. Both

[24] The estimated coefficients for the sample excluding eight selected OECD countries are similar to the results obtained for the full country sample and available upon request.

pattern cannot be observed in the actual time series. Similar, for Sweden and Switzerland the model predicts a diverging movement of saving and investment rates, especially from 2002 onwards, which should indeed result in rising current account surpluses. In general, the saving rates in Sweden and Switzerland are quite well explained by the demographic factors, but the models fail to predict the sharp decline in investment rates in the early 1990s. For South Korea, one of the fastest growing economies within the OECD sample, the demographic model assumes a rather constant saving rate. But actually, saving rates decreased after the Asian financial crisis during 1997-98. Of course, demographics fail to forecast the sharp drop in investment in Korea in the course of the crisis, but the predicted investment rate converges to the actual investment rate in the subsequent years. While the previous country selection focuses on OECD current account surplus countries, I also compare fitted saving and investment values with actual values in the currently biggest deficit country, the United States. Obviously, the demographic parameters cannot explain the sharp decline in saving rates in the United States since the mid-1990s. This gives evidence that other factors than demographics played a crucial role in the emergence of the US current account deficit.

2.6 Conclusion

Previous literature suggests that demographic factors play a crucial role in the determination of saving and investment rates and the current account balance. This paper has studied empirically whether and to what extent demographic factors can explain the build-up of considerable current account surplus positions in a number of OECD countries since the mid-1990s. Thereby, it has taken a saving-investment perspective and examined the relationship between the present age distribution as well as anticipated future demographic change on the one side and real domestic saving, investment and the current account on the other side. On the theoretical level, the current age distribution of the population affects saving and investment rates via life cycle dynamics that influence individual behavior. In addition, future demographic trends, namely expected increases in longevity and projected changes in the population age structure, may induce behavioral changes in saving and investment pattern today. Individuals should anticipate longer retirement periods that need to be financed in the future while at the same time the support from individuals in working age is likely to decline as a shrinking workforce has to carry the burden to finance a rising number of retirees. Furthermore, forward-looking investors should adapt their investment decisions in advance as they anticipate demographically induced future changes in the demand and supply of assets that affect the expected returns.

As the overall age effects on saving and investment should not only critically depend on domestic factors but also on developments from abroad, the empirical model in this study has followed a framework that regards closed and open economies as special cases and allows for foreign effects by considering the relative economic size and the level of openness both at home and abroad. The analysis has been built upon a broad sample of advanced, emerging and developing countries with time series for demographic and non-demographic variables as well as aggregated anticipation measures that are based on past population projections dating back to the 1960s. The empirical analysis in this paper suggests that there are indeed considerable age effects on real domestic saving rates and, to a lesser extent, on investment rates that seem to translate into demographic induced movements in the current account balance. Similar to previous studies, I find a negative relation between high shares of old individuals within the population and the dependent variables, hence confirming the theoretical proposition of life cycle dynamics in saving and investment behavior. These results have been obtained by capturing the present age structure both with simple categorical dependency measures, or alternatively by using the full information in the age profiles and restricting the age effects to lie on a cubic polynomial curve. Measures capturing anticipated future demographic trends show to have effects on saving and investment rates, too. First, life expectancy as a proxy for the expected length of the retirement period tends to be positively associated with saving and investment, but the relation is not very significant. I also find some evidence that a projected future increase in old age dependency seems to induce precautionary saving behavior and at the same time provokes a negative impact on investment rates. This positive effect on saving rates in combination with the negative impact on investment translates into an upward pressure on the current account. The results between the conventional closed economy baseline model and the extended open economy framework are very similar and the small coefficients of the foreign variables compared to their domestic counterparts suggest that domestic factors prevail in the determination of saving and investment rates.

In order to get further insights regarding the relation between demographics, saving and investment, some robustness tests have been conducted. Adding a lagged version of the dependent variable to the specifications suggests that dynamic feedback effects play a crucial role and that saving and investment adapt gradually rather than abrupt to changes in their determinants. Endogeneity problems may be an issue in our model, potentially arising from reverse causation and direct feedback effects, for instance from saving and investment to per capita income and per capita income growth. Even though this problem was addressed by using one-period lags of these variables in the regressions, I have conducted alternative estimations using difference and system GMM estimators with internal instruments as well as IV approaches with external instruments. However, tests suggest that these approaches are inappropriate for the used model and that both the selected internal and external instruments are correlated with the error term and thus invalid. An investigation of a sub-sample of OECD countries also showed demographic effects on saving and investment, even though these effects differ in some respects compared to the full sample. In general, the effects of foreign variables are more pronounced, thus suggesting that the OECD economies are to a larger extent internationally integrated and affected by foreign influences. Furthermore, adding public social expenditures on pension to the model shows to have a significant negative association with savings and changes the coefficients of the age effects, suggesting that public pension expenditures crowd-out savings and affect the way how demographic change affects saving behavior. Hence, considering public pensions systems seems to be important when studying age effects on savings, but further research is needed to investigate this link and the underlying mechanisms in more detail. Finally, the inclusion of euro dummies had no crucial impact on the other variables in the OECD model.

The demographic estimations have been used for in-sample and out-of-sample predictions in order to test whether and to what extent demographics can predict the saving and investment pattern and the emergence of current account surpluses in OECD countries since the 1990s. Our demographic models suggest a fall in saving rates for Japan and Germany. While this drop could be witnessed in Japan quite well over the last 20 years, Germany showed actually quite stable saving rates over this period. Further, the model predicts rather stable or slightly decreasing investment rates for both countries, but these decreases are more moderate than could be observed in the two countries. Indeed, the demographic estimates would suggest both countries to run current account deficits and not surpluses since the mid-1990s (Japan) or the early 2000s (Germany). In contrast, the model is fairly in line with the saving rates observed in Sweden, Denmark, the Netherlands and Switzerland, which remained rather stable or even increased. But the models fail to predict the sharp decline in investment rates in Sweden and Switzerland in the early 1990s thus suggesting that this pattern has to be attributed to other factors than demographic change. Finally, demographics fail to forecast the sharp drop in investment in South Korea in the course of the Asian financial crisis, but the predicted investment rate converges to the actual investment rate in the subsequent years.

Table 2.1: List of Variables

Dependent variables	Description	Source
Saving [SAV]	Real domestic savings in percent of GDP	PWT
Investment [INV]	Real investment in percent of GDP	PWT
Current account [CA]	Current account balance in percent of GDP	WDI
Demographic variables	**Description**	**Source**
Old age dependency [OLD]	Age dependency ratio of older (age 65+) in percent of working-age population (age 15-64)	WDI
Young age dependency [YNG]	Age dependency ratio of young (age <15) in percent of working-age population (age 15-64)	WDI
Polynomial term [D1..D3]	Polynomial emanating from restricted present age structure effects	WPP
Anticipated future dependency old [OLD_{fut}]	Anticipated future change in dependency ratio old (individual anticipations aggregated over all cohorts)	WPP
Anticipated future dependency young [YNG_{fut}]	Anticipated future change in dependency ratio young (individual anticipations aggregated over all cohorts)	WPP
Life expectancy [EXP]	Life expectancy at birth (total) in years	WDI
Other variables	**Description**	**Source**
GDP per capita [GDP]	GDP per capita in thsd. USD (constant USD, year 2000)	WDI
GDP per capita growth [GDPGR]	GDP per capita growth, annual (in percent)	WDI
Relative price of investment [RPI]	Price level of investment relative to price level of consumption	PWT
Financial development [FIN]	Domestic credit to private sector in percent of GDP	WDI
Legal development [LEG]	Index measuring legal system and property rights (higher values indicate higher degree of development)	Fraser Inst.
Education [EDU]	Average years of total schooling	Barro/Lee
Trade Openness [OPE_{trd}]	Imports + exports of goods and services in percent of GDP	WDI
Financial Openness [OPE_{fin}]	Index measuring degree of capital account openness (higher values indicate higher degree of openness)	Chinn/Ito
Public pension expenditure [PEN]	Public social expenditures on pension in percent of GDP	OECD
EMU-Membership [EMU]	Dummy for membership in European Monetary Union	-

Abreviations: WDI = World Development Indicators (World Bank), PWT = Penn World Table, WPP= World Population Prospects (United Nations), OECD = Organisation for Economic Co-operation and Development

Table 2.2: Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Dependent variables				
Saving rate	23.14	10.13	-3.16	59.63
Investment rate	24.29	7.81	5.24	54.41
Current account balance	-1.65	5.61	-27.16	31.98
Demographic variables				
Old age dependency	13.15	7.23	3.44	35.47
Young age dependency	50.87	22.64	19.50	106.43
Ant. change old age dependency	12.38	7.80	-3.43	41.93
Ant. change young age dependency	-14.58	14.63	-70.85	29.13
Life expectancy	69.33	8.85	39.53	82.93
Control variables				
GDP per capita	8.90	9.73	0.13	41.25
GDP per capita growth	2.20	3.76	-19.08	17.93
Relative price of investment	0.98	0.28	0.11	2.98
Financial development	56.04	43.79	1.39	234.54
Legal development	5.84	1.89	1.15	9.62
Education	7.01	2.95	0.39	13.27
Trade openness	68.50	50.78	6.32	460.47
Financial openness	0.51	0.36	0	1
Public social pension expenditure*	7.01	2.99	0.17	14.05

Note: Unit measures as defined in Table 2.1. * Only for OECD sub-sample.

Table 2.3: Population Age Effects on Saving

	(1) SAV1		(2) SAV2		(3) SAV3		(4) SAV4		(5) SAV5		(6) SAV6	
OLD	-0.575***	(-3.41)	-0.557***	(-2.85)			-0.588***	(-2.89)	-0.954***	(-4.42)	-0.917***	(-3.53)
YNG	0.0258	(0.29)	0.0456	(0.37)			0.0466	(0.39)	-0.313***	(-2.88)	-0.192*	(-1.77)
D1					0.0000226	(0.14)						
D2					0.0158***	(2.65)						
D3					-0.00120***	(-3.01)						
OLD_{fut}	0.280*	(1.78)	0.383**	(2.17)	0.178	(1.11)	0.270	(1.50)	0.0493	(0.30)	0.284	(1.25)
YNG_{fut}	0.0889*	(1.83)	0.0676	(0.70)	0.0417	(0.84)	0.120	(1.42)	-0.0898	(-0.59)	0.0281	(0.20)
LIFE	0.0552	(0.35)	-0.0519	(-0.32)	0.0645	(0.39)	0.175	(1.02)	-0.0255	(-0.13)	-0.0150	(-0.07)
$GDP_{(t-1)}$	0.536***	(3.69)	0.411*	(1.91)	0.667***	(4.77)	0.544***	(3.30)	0.354**	(2.40)	0.393**	(2.17)
$GDPGR_{(t-1)}$	0.159***	(2.69)	0.249	(1.50)	0.156***	(2.67)	0.163***	(3.09)	0.757***	(2.65)	0.672***	(2.69)
$RPI_{(t-1)}$	-5.855***	(-3.39)	-6.325***	(-2.65)	-5.959***	(-3.38)	-5.304***	(-3.31)	-10.92***	(-4.75)	-8.938***	(-3.49)
FIN	0.00464	(0.33)	-0.00162	(-0.09)	0.00244	(0.17)	0.0199	(1.18)	-0.00788	(-0.32)	0.0127	(0.43)
LEG	0.232	(0.78)	0.210	(0.47)	0.267	(0.88)	0.186	(0.56)	0.828	(1.60)	0.123	(0.27)
EDU	0.142	(0.27)	0.242	(0.41)	-0.103	(-0.18)	0.254	(0.45)	-0.357	(-0.86)	-0.503	(-1.21)
OPE_{trd}	0.0321	(1.44)	0.00973	(0.37)	0.0315	(1.38)			0.0424***	(2.86)		
OPE_{fin}	1.283	(1.07)	0.806	(0.59)	1.721	(1.42)			1.002	(0.58)		
OLD_row							0.0199	(1.26)			0.0168	(0.62)
YNG_row							-0.00361	(-0.42)			0.00171	(0.19)
OLD_{fut}_row							0.0182*	(1.68)			0.00952	(0.30)
YNG_{fut}_row							-0.00574	(-0.84)			-0.00339	(-0.48)
LIFE_row							-0.0153*	(-1.84)			-0.00989	(-0.65)
$GDP_{(t-1)}$_row							0.00398	(1.03)			-0.000132	(-0.03)
$GDPGR_{(t-1)}$_row							0.000271	(0.05)			0.00594	(0.41)
$RPI_{(t-1)}$_row							-0.257	(-1.47)			-0.347	(-1.48)
FIN_row							-0.00322**	(-2.01)			-0.00145	(-0.33)
LEG_row							0.0279	(1.11)			0.136***	(3.02)
EDU_row							0.00518	(0.10)			0.0642	(1.39)
OPE							-0.0924	(-0.52)			0.536**	(2.49)
Time freq.	annual		5year		annual		annual		5year		5year	
No. countries	67		67		67		67		67		67	
Coun. fixed effect	yes		yes		yes		yes		no		no	
Obs.	2209		428		2209		2207		428		420	
R^2	0.860		0.890		0.861		0.867		0.589		0.621	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.4: Population Age Effects on Investment

	(1) INV1		(2) INV2		(3) INV3		(4) INV4		(5) INV5		(6) INV6	
OLD	-0.358*	(-1.93)	-0.188	(-0.65)			-0.279	(-1.55)	-0.274*	(-1.77)	-0.220*	(-1.65)
YNG	-0.0965	(-1.24)	-0.0792	(-0.78)			0.0712	(0.80)	-0.145*	(-1.77)	0.0216	(0.16)
D1					0.0000748	(0.29)						
D2					0.0000861	(0.01)						
D3					-0.000131	(-0.28)						
OLD_{fut}	-0.290	(-1.45)	-0.142	(-0.54)	-0.129	(-0.80)	-0.246	(-1.29)	0.166	(1.29)	0.281**	(2.40)
YNG_{fut}	-0.0114	(-0.25)	-0.0658	(-0.64)	0.0396	(0.75)	0.113*	(1.77)	-0.106	(-0.85)	0.0700	(0.46)
LIFE	0.305	(1.60)	0.164	(0.84)	0.236	(1.29)	0.430**	(2.44)	-0.116	(-0.70)	0.00859	(0.07)
$GDP_{(t-1)}$	-0.0881	(-0.51)	-0.224	(-1.05)	-0.131	(-0.74)	-0.0673	(-0.43)	-0.0165	(-0.19)	-0.0530	(-0.55)
$GDPGR_{(t-1)}$	0.419***	(6.81)	0.445**	(2.47)	0.419***	(6.48)	0.445***	(6.22)	0.943***	(3.65)	0.875***	(4.87)
$RPI_{(t-1)}$	-4.421**	(-2.43)	-3.204	(-1.43)	-4.335**	(-2.40)	-4.884***	(-2.75)	-10.37***	(-5.46)	-7.957***	(-4.78)
FIN	0.0438***	(3.06)	0.0346**	(2.19)	0.0459***	(2.92)	0.0396***	(2.99)	0.00346	(0.23)	0.0157	(1.07)
LEG	0.345	(1.56)	0.338	(0.95)	0.329	(1.49)	0.256	(1.05)	0.755**	(2.05)	0.172	(0.68)
EDU	0.0703	(0.13)	-0.209	(-0.29)	0.200	(0.38)	0.181	(0.34)	-0.185	(-0.56)	-0.123	(-0.37)
OPE_{trd}	-0.00911	(-0.49)	0.00254	(0.11)	-0.00800	(-0.45)			0.0177*	(1.75)		
OPE_{fin}	2.726**	(2.10)	2.606**	(2.02)	2.662**	(2.16)			-0.890	(-0.74)		
OLD_row							-0.0182	(-1.01)			-0.00124	(-0.04)
YNG_row							-0.0201***	(-2.81)			-0.0173*	(-1.73)
OLD_{fut}_row							0.0169	(1.39)			-0.00215	(-0.06)
YNG_{fut}_row							-0.0137**	(-2.45)			-0.0159*	(-1.67)
LIFE_row							-0.0167*	(-1.76)			-0.0154	(-0.60)
$GDP_{(t-1)}$_row							0.00170	(0.29)			-0.00364	(-0.69)
$GDPGR_{(t-1)}$_row							-0.00129	(-0.20)			0.00784	(0.87)
$RPI_{(t-1)}$_row							0.0734	(0.49)			-0.307**	(-2.11)
FIN_row							0.00123	(0.78)			0.000195	(0.08)
LEG_row							0.0249	(1.04)			0.0848***	(2.89)
EDU_row							-0.0454	(-0.91)			-0.0395	(-0.79)
OPE							0.189	(1.05)			0.0833	(0.44)
Time freq.	annual		5year		annual		annual		5year		5year	
No. countries	67		67		67		67		67		67	
Coun. fixed effect	yes		yes		yes		yes		no		no	
Obs.	2209		428		2209		2207		428		420	
R^2	0.763		0.816		0.762		0.778		0.537		0.598	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.5: Population Age Effects on Current Account Balance I

	(1) CAB1		(2) CAB2		(3) CAB3		(4) CAB4		(5) CAB5		(6) CAB6	
OLD	-0.315*	(-1.82)	-0.494***	(-2.95)			-0.338*	(-1.87)	-0.543***	(-4.38)	-0.505***	(-3.40)
YNG	0.00223	(0.03)	0.00983	(0.13)			-0.0597	(-0.61)	-0.171***	(-3.10)	-0.160**	(-1.98)
D1					-0.000522**	(-2.42)						
D2					0.0228**	(2.44)						
D3					-0.00155**	(-2.53)						
OLD_{fut}	0.237*	(1.66)	0.166	(1.29)	-0.00743	(-0.06)	0.207	(1.26)	-0.119	(-1.37)	0.0363	(0.28)
YNG_{fut}	0.00963	(0.16)	0.0405	(1.04)	-0.0611	(-1.03)	0.0164	(0.22)	-0.0382	(-0.81)	-0.0498	(-0.70)
LIFE	0.0582	(0.44)	0.0454	(0.38)	0.131	(0.98)	0.0464	(0.26)	0.122	(1.31)	0.0233	(0.20)
$GDP_{(t-1)}$	0.552**	(2.35)	0.640***	(3.08)	0.661***	(2.84)	0.505**	(2.37)	0.508***	(5.88)	0.500***	(4.80)
$GDPGR_{(t-1)}$	-0.236***	(-3.07)	-0.0752	(-0.67)	-0.236***	(-3.14)	-0.240***	(-2.97)	-0.0141	(-0.11)	0.0277	(0.21)
$RPI_{(t-1)}$	-0.141	(-0.12)	-1.766	(-1.58)	-0.232	(-0.20)	0.101	(0.09)	0.803	(0.82)	1.017	(1.48)
FIN	-0.0597***	(-3.73)	-0.0620***	(-3.24)	-0.0645***	(-3.78)	-0.0474***	(-2.67)	-0.0262*	(-1.69)	-0.0176	(-0.98)
LEG	-0.191	(-0.84)	-0.186	(-0.62)	-0.140	(-0.61)	-0.134	(-0.52)	-0.166	(-0.73)	-0.313	(-1.23)
EDU	0.117	(0.22)	0.441	(0.64)	-0.209	(-0.46)	-0.0632	(-0.12)	-0.571***	(-3.07)	-0.702***	(-3.14)
OPE_{trd}	0.0365**	(2.53)	0.0170	(0.72)	0.0329**	(2.35)			0.0207**	(2.11)		
OPE_{fin}	-2.111*	(-1.93)	-2.249*	(-1.79)	-1.515	(-1.47)			-1.567	(-1.62)		
OLD_row							0.00891	(0.45)			-0.0108	(-0.59)
YNG_row							0.0153**	(1.96)			0.00881	(1.26)
OLD_{fut}_row							0.00870	(0.55)			-0.0118	(-0.80)
YNG_{fut}_row							0.00122	(0.19)			0.00900*	(1.65)
LIFE_row							-0.00473	(-0.35)			0.0192*	(1.78)
$GDP_{(t-1)}$_row							0.00135	(0.29)			0.00701	(1.08)
$GDPGR_{(t-1)}$_row							-0.00162	(-0.47)			-0.00665	(-1.11)
$RPI_{(t-1)}$_row							0.0163	(0.12)			-0.109	(-0.92)
FIN_row							-0.00232	(-1.26)			-0.00267	(-1.21)
LEG_row							-0.00875	(-0.32)			0.0359	(1.26)
EDU_row							0.0904*	(1.84)			0.0474*	(1.91)
OPE							-0.279	(-1.43)			0.142	(1.39)
Time freq.	annual		5year		annual		annual		5year		5year	
No. countries	67		67		67		67		67		67	
Coun. fixed effect	yes		yes		yes		yes		no		no	
Obs.	2085		422		2085		2082		422		414	
R^2	0.574		0.708		0.586		0.578		0.399		0.438	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.6: Population Age Effects on Current Account Balance II

	(1) CAB4b		(2) CAB6b	
OLD_row	0.00726	(0.38)	-0.0269	(-1.13)
YNG_row	0.0219**	(1.96)	0.00379	(0.55)
OLD_{fut}_row	0.0204	(1.19)	-0.00287	(-0.14)
YNG_{fut}_row	0.00404	(0.64)	0.00620	(1.60)
LIFE_row	-0.00782	(-0.59)	0.0169	(1.02)
$GDP_{(t-1)}$_row	0.00399	(0.81)	0.0116	(1.07)
$GDPGR_{(t-1)}$_row	-0.00785*	(-1.73)	-0.00938	(-1.35)
$RPI_{(t-1)}$_row	-0.0536	(-0.41)	-0.222	(-1.34)
FIN_row	-0.00401**	(-2.20)	-0.00178	(-0.93)
LEG_row	-0.0237	(-0.76)	0.0501*	(1.76)
EDU_row	0.132*	(1.70)	0.0204	(0.61)
OPE	-0.425*	(-1.82)	0.118	(0.79)
Time freq.	annual		5year	
No. countries	67		67	
Coun. fixed effect	yes		no	
Obs.	2082		414	
R^2	0.522		0.220	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Figure 2.1: Age Coefficients for Present Demographic Structure - Third-order Polynomial

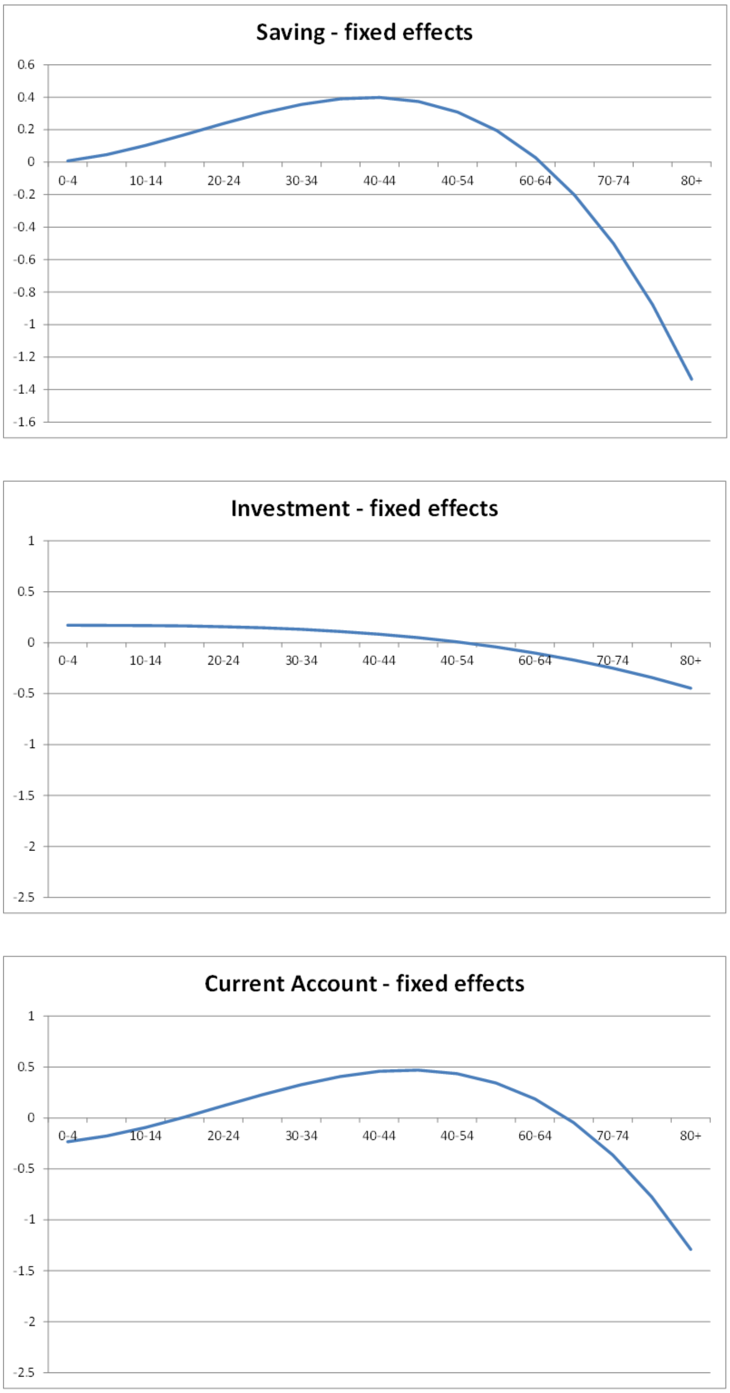


Table 2.7: Goodness of Fit for Selected OECD Countries over Period 1990-2010

(a) Savings

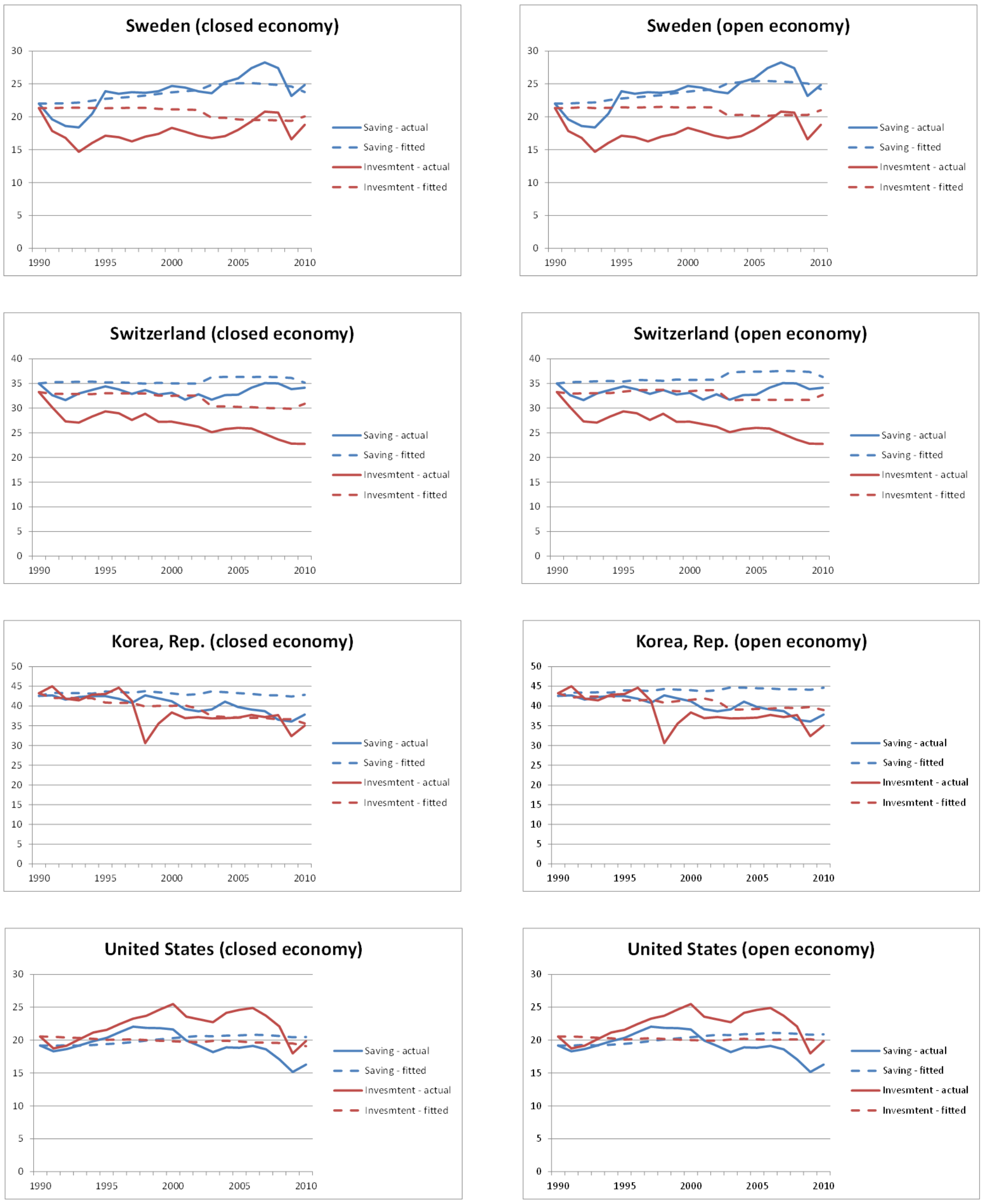
	closed economy (SAV1)		open economy (SAV4)	
	R^2	RMSE	R^2	RMSE
Germany	0.07	2.34	0.15	2.71
Japan	0.96	1.20	0.93	1.58
Netherlands	0.72	0.75	0.72	0.71
Denmark	0.68	1.69	0.73	1.80
Sweden	0.90	0.98	0.89	0.95
Switzerland	0.51	0.76	0.45	0.81
Korea, Rep.	0.37	3.99	0.25	3.64
United Kingdom	0.04	3.39	0.05	3.89
United States	0.01	3.29	0.01	3.67

(b) Investment

	closed economy (INV1)		open economy (INV4)	
	R^2	RMSE	R^2	RMSE
Germany	0.68	1.25	0.35	1.68
Japan	0.95	1.37	0.95	1.46
Netherlands	0.02	1.80	0.01	1.98
Denmark	0.31	2.19	0.33	2.37
Sweden	0.30	1.45	0.38	1.31
Switzerland	0.32	1.59	0.14	1.74
Korea, Rep.	0.43	5.39	0.38	5.26
United Kingdom	0.32	1.34	0.30	1.30
United States	0.33	2.28	0.30	2.13

Figure 2.2: Saving and Investment (Percent of GDP) - Actual vs Out-of-Sample Predicted Values (Demographic Effects only) for Selected OECD Countries

Figure 2.2: Saving and Investment (Percent of GDP) - Actual vs Out-of-Sample Predicted Values (Demographic Effects only) for Selected OECD Countries *(cont.)*



2.7 Appendix

Appendix 1: List of Countries

The country sample includes the following countries:

Argentina, Australia, Austria, Bangladesh, Belgium, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Canada, Chile, China, Costa Rica, Czech Republic, Denmark, Ecuador, Egypt, Finland, France, Germany, Ghana, Greece, Honduras, Hungary, India, Indonesia, Ireland, Israel, Italy, Japan, Kenya, Malawi, Malaysia, Mexico, Morocco, Namibia, the Netherlands, New Zealand, Niger, Norway, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Romania, Senegal, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Syria, Tanzania, Thailand, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Vietnam.

The OECD sub-sample includes the following countries:

Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, Mexico, the Netherlands, New Zealand, Norway, Portugal, Spain, South Korea, Sweden, Switzerland, United Kingdom, United States.

Appendix 2: Polynomial Restriction Methodology

In the following the approach of estimating age effects under a polynomial restriction as proposed by Fair and Dominguez (1991) and further elaborated by Higgins (1998) is briefly described. Using the baseline econometric model outlined by equation (2.1) in section 2.4.2 and specifying $\beta_p p_{it}$ as the sum of age share groups effects, $\sum_{k=1}^{n} \beta_k s_{kit}$, the linear regression specification to estimate is then:

$$y_{it} = \alpha + \textstyle\sum_{k=1}^{n} \beta_k s_{kit} + \beta_z z_{it} + \beta_\varphi \varphi_{it} + \delta_t + c_i + \varepsilon_{it}$$

where s_{kit} are the population age shares for the cohort aged k in country i at time period t. Now a constraint is imposed on the age share coefficients, β_k, assuming that they fit a polynomial curve of order J:

$$\beta_k = \textstyle\sum_{j=0}^{J} \gamma_j k^j = \gamma_0 + \gamma_1 k + \gamma_2 k^2 + ... + \gamma_J k^J$$

Given that $\sum_{k=1}^{n} s_{kit} = 1$, the sum of the demographic age effects becomes:

$$\begin{aligned} \sum_{k=1}^{n} \beta_k s_{kit} &= \sum_{k=1}^{n} (\gamma_0 + \gamma_1 k + \gamma_2 k^2 + ... + \gamma_J k^J) s_{kit} \\ &= \gamma_0 + \sum_{k=1}^{n} (\gamma_1 k + \gamma_2 k^2 + ... + \gamma_J k^J) s_{kit} \end{aligned}$$

In order to avoid multicollinearity as the age shares sum up to 1, a restriction is imposed on β_k to sum up to zero which presumes that for an uniform age distribution the single age effects net out each other and have in sum no net effect. This eliminates the constant γ_0 thus making the interpretation of the age share coefficients more straightforward:

$$\textstyle\sum_{k=1}^{n} \beta_k = 0 \Rightarrow \gamma_0 = -\frac{\gamma_1}{n} \sum_{k=1}^{n} k - \frac{\gamma_2}{n} \sum_{k=1}^{n} k^2 - ... - \frac{\gamma_J}{n} \sum_{k=1}^{n} k^J$$

Finally, the following transformed regression specification can be estimated:

$$y_{it} = \alpha + \gamma_1 \underbrace{\sum_{k=1}^{n} k(s_{kit} - \frac{1}{n})}_{D1} + \gamma_2 \underbrace{\sum_{k=1}^{n} k^2 (s_{kit} - \frac{1}{n})}_{D2} + ... + \gamma_J \underbrace{\sum_{k=1}^{n} k^J (s_{kit} - \frac{1}{n})}_{DJ} + \mu$$

where $\mu = \beta_z z_{it} + \beta_\varphi \varphi_{it} + \delta_t + c_i + \varepsilon_{it}$. Then, the specific effect of each age group, β_k, can be easily calculated with the formula $\beta_k = \gamma_0 + \gamma_1 k + \gamma_2 k^2 + ... + \gamma_J k^J$.

Appendix 3: Robustness Tests - Tables

Table 2.8: Population Age Effects on Saving, Investment and Current Account (Dynamic Specifications)

	(1) SAV7		(2) INV7		(3) CAB7		(4) SAV8		(5) INV8		(6) CAB8	
LAG	0.829***	(36.39)	0.755***	(22.03)	0.600***	(9.23)	0.832***	(35.24)	0.744***	(19.51)	0.602***	(8.66)
OLD	-0.117***	(-2.86)	-0.108*	(-1.69)	-0.125	(-1.53)	-0.172***	(-3.17)	-0.0829	(-1.20)	-0.143*	(-1.77)
YNG	0.0553**	(2.32)	-0.00702	(-0.28)	0.0261	(0.75)	0.0602**	(2.32)	0.0533	(1.61)	-0.00590	(-0.13)
OLD_{fut}	0.0491	(1.22)	-0.105*	(-1.73)	0.132**	(2.06)	-0.00199	(-0.05)	-0.0846	(-1.33)	0.116	(1.63)
YNG_{fut}	0.0328*	(1.69)	0.00374	(0.20)	0.00874	(0.33)	0.0701**	(2.39)	0.0613**	(2.02)	0.0108	(0.32)
LIFE	0.0191	(0.48)	0.0599	(1.03)	0.0246	(0.39)	0.0552	(1.23)	0.0942	(1.28)	-0.00782	(-0.09)
$GDP_{(t-1)}$	0.0394	(1.18)	-0.0251	(-0.61)	0.177*	(1.85)	0.0604	(1.62)	-0.0163	(-0.43)	0.144*	(1.71)
$GDPGR_{(t-1)}$	0.0101	(0.25)	0.144***	(3.58)	-0.158***	(-3.22)	0.00113	(0.03)	0.161***	(3.59)	-0.180***	(-3.00)
$RPI_{(t-1)}$	-0.0754	(-0.14)	0.251	(0.59)	0.00245	(0.01)	-0.148	(-0.28)	-0.101	(-0.19)	-0.257	(-0.51)
FIN	-0.00643*	(-1.79)	-0.00153	(-0.28)	-0.0209**	(-2.16)	-0.00558	(-1.04)	-0.00176	(-0.28)	-0.0172	(-1.60)
LEG	-0.0204	(-0.18)	0.0764	(0.62)	-0.0964	(-0.72)	-0.0260	(-0.21)	0.0343	(0.26)	-0.0453	(-0.33)
EDU	-0.121	(-1.06)	-0.0650	(-0.33)	0.000122	(0.00)	-0.123	(-1.09)	-0.0525	(-0.27)	-0.0861	(-0.38)
OPE_{trd}	0.0103*	(1.90)	0.00165	(0.25)	0.0107	(1.35)						
OPE_{fin}	0.591**	(1.97)	1.037*	(1.92)	-0.878	(-1.44)						
OLD_row							0.0173*	(1.75)	-0.00757	(-0.87)	0.00715	(0.47)
YNG_row							0.000945	(0.38)	-0.00436	(-0.97)	0.00635	(1.23)
OLD_{fut}_row							0.0113*	(1.78)	0.00540	(0.78)	0.00255	(0.22)
YNG_{fut}_row							-0.00364	(-1.01)	-0.00456	(-1.47)	0.000263	(0.07)
LIFE_row							-0.00969*	(-1.93)	-0.00517	(-0.91)	-0.00249	(-0.25)
$GDP_{(t-1)}$_row							-0.00351	(-1.01)	-0.00189	(-0.52)	0.00225	(0.47)
$GDPGR_{(t-1)}$_row							0.000803	(0.15)	-0.00115	(-0.15)	0.00163	(0.33)
$RPI_{(t-1)}$_row							0.0248	(0.51)	0.0609	(0.84)	0.0701	(0.88)
FIN_row							-0.000299	(-0.35)	0.000285	(0.39)	-0.000661	(-0.52)
LEG_row							0.0132	(0.74)	0.0213	(1.23)	-0.0116	(-0.68)
EDU_row							0.0142	(0.84)	-0.00320	(-0.13)	0.0322	(0.98)
OPE							0.0255	(0.42)	0.00481	(0.08)	-0.0760	(-1.00)
Time freq.	annual		annual		annual		annual		annual		annual	
No. countries	67		67		67		67		67		67	
Coun. fixed effect	yes		yes		yes		yes		yes		yes	
Obs.	2209		2209		2055		2207		2207		2052	
R^2	0.956		0.898		0.735		0.957		0.900		0.739	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.9: Population Age Effects on Saving, Investment and Current Account (Arellano-Bond difference GMM)

	(1) SAV9		(2) INV9		(3) CAB9		(4) SAV10		(5) INV10		(6) CAB10	
LAG	0.852***	(6.96)	0.631***	(6.11)	0.177	(1.53)	0.801***	(6.63)	0.622***	(5.10)	0.0206	(0.16)
OLD	-0.232	(-1.21)	-0.0123	(-0.07)	-0.313	(-1.58)	-0.488**	(-2.57)	-0.122	(-0.59)	-0.351	(-1.56)
YNG	0.0537	(0.73)	-0.0694	(-0.69)	0.0704	(0.95)	0.141*	(1.69)	-0.0423	(-0.32)	-0.0411	(-0.45)
OLD_{fut}	0.105	(0.69)	-0.100	(-0.60)	0.156	(1.44)	0.0191	(0.12)	-0.0701	(-0.37)	0.160	(1.10)
YNG_{fut}	-0.00930	(-0.17)	-0.00628	(-0.12)	0.0584	(1.20)	0.131	(1.38)	-0.0534	(-0.62)	0.0143	(0.19)
LIFE	-0.0551	(-0.30)	0.0586	(0.41)	0.0106	(0.09)	0.274	(1.21)	0.152	(0.67)	-0.0378	(-0.19)
GDP	0.428***	(2.90)	0.366**	(2.30)	0.360*	(1.80)	0.538***	(3.30)	0.501**	(2.30)	0.541**	(2.22)
GDPGR	1.046***	(3.10)	1.760***	(5.94)	-0.119	(-0.44)	0.842***	(3.06)	2.068***	(6.33)	-0.636***	(-3.15)
$RPI_{(t-1)}$	6.051***	(2.63)	7.313***	(2.63)	-0.935	(-0.45)	4.241*	(1.94)	5.834**	(2.25)	-2.599	(-1.07)
FIN	-0.00794	(-0.41)	0.0483**	(2.16)	-0.0448***	(-2.70)	-0.00863	(-0.58)	0.0615***	(2.60)	-0.0651***	(-3.40)
LEG	0.0802	(0.29)	0.383	(1.22)	-0.564***	(-2.94)	-0.165	(-0.47)	0.454	(1.11)	-0.510*	(-1.79)
EDU	-0.522	(-0.98)	-0.0751	(-0.13)	0.869	(1.23)	-0.0508	(-0.10)	0.487	(0.91)	0.539	(0.83)
OPE_{trd}	0.0264	(0.90)	-0.0413	(-1.11)	-0.00276	(-0.15)						
OPE_{fin}	0.762	(0.36)	0.731	(0.53)	-1.624	(-1.18)						
OLD_row							0.0393***	(2.62)	-0.00568	(-0.34)	0.00587	(0.36)
YNG_row							0.00334	(1.01)	0.000290	(0.06)	0.00688	(1.34)
OLD_{fut}_row							0.0328***	(3.16)	-0.00255	(-0.28)	0.00889	(0.87)
YNG_{fut}_row							-0.00802	(-1.50)	0.00247	(0.42)	0.00284	(0.53)
LIFE_row							-0.0222**	(-2.42)	-0.00433	(-0.55)	0.00794	(0.86)
$GDP_{(t-1)}$_row							-0.00629**	(-1.96)	-0.00345	(-1.13)	-0.000904	(-0.22)
$GDPGR_{(t-1)}$_row							-0.00177	(-0.38)	0.0231***	(2.72)	-0.0103	(-1.43)
$RPI_{(t-1)}$_row							-0.0971	(-0.88)	0.0266	(0.14)	0.226	(1.42)
FIN_row							-0.00153	(-0.83)	0.000842	(0.51)	-0.00300**	(-2.12)
LEG_row							0.127***	(3.70)	-0.0195	(-0.50)	0.0351	(1.20)
EDU_row							0.0526*	(1.87)	0.0375	(1.41)	0.0279	(0.90)
OPE							0.443**	(2.35)	0.0565	(0.36)	0.0464	(0.21)
Time freq.	5year		5year		5year		5year		5year		5year	
No. countries	67		67		67		67		67		67	
No. instruments	41		41		41		51		51		51	
Coun. fixed effect	yes		yes		yes		yes		yes		yes	
Obs.	364		364		335		353		353		327	
AB test (AR2)	0.13		0.26		0.23		0.02		0.76		0.47	
Sargan test	0.16		0.05		0.00		0.08		0.56		0.01	

Note: Robust t statistics in parentheses. Time dummies included, but coefficients not reported. Lagged intruments used for the autoregressive term as well as for $GDP_{(t-1)}$ and $GDPGR_{(t-1)}$. Internal instruments are restricted to two lags. Bottom lines show p-values for Arellano-Bond test (H0: no second-order autocorrelation) and Sargan test (H0: overidentifying restrictions are valid). ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.10: Population Age Effects on Saving, Investment and Current Account (Arellano-Bover/Blundell-Bond system GMM)

	(1) SAV11		(2) INV11		(3) CAB11		(4) SAV12		(5) INV12		(6) CAB12	
LAG	0.909***	(11.45)	0.658***	(9.22)	0.324***	(3.33)	0.808***	(11.77)	0.617***	(9.30)	0.303**	(2.52)
OLD	-0.198	(-1.02)	-0.173	(-0.92)	-0.436**	(-2.55)	-0.320**	(-2.29)	-0.0424	(-0.24)	-0.594***	(-3.09)
YNG	0.0701	(1.16)	0.0917	(1.28)	0.0193	(0.23)	0.102	(1.47)	0.125	(1.29)	0.00516	(0.04)
OLD$_{fut}$	0.0389	(0.31)	-0.136	(-0.80)	0.125	(1.00)	0.0638	(0.52)	-0.0914	(-0.59)	0.148	(1.08)
YNG$_{fut}$	-0.00200	(-0.03)	0.0742*	(1.89)	0.0253	(0.40)	0.113	(1.24)	0.0739	(0.88)	0.0344	(0.33)
LIFE	0.0112	(0.09)	0.0271	(0.19)	0.00381	(0.04)	0.0900	(0.67)	0.0366	(0.20)	-0.0630	(-0.47)
GDP	0.307***	(3.15)	0.139	(1.55)	0.504***	(5.09)	0.300***	(3.29)	0.126	(1.29)	0.507***	(4.11)
GDPGR	1.049***	(4.04)	1.419***	(5.95)	-0.0781	(-0.29)	0.714***	(2.87)	1.508***	(6.95)	-0.356	(-1.60)
RPI$_{(t-1)}$	5.626***	(2.76)	4.973**	(2.21)	-0.693	(-0.36)	3.209**	(2.19)	3.482*	(1.86)	-2.251	(-0.97)
FIN	-0.0110	(-0.68)	0.0321**	(2.24)	-0.0570***	(-3.49)	-0.00852	(-0.60)	0.0413***	(2.75)	-0.0590***	(-3.21)
LEG	0.180	(0.67)	0.480	(1.60)	-0.711***	(-3.38)	-0.163	(-0.46)	0.592	(1.56)	-0.803***	(-2.65)
EDU	-0.215	(-0.48)	-0.358	(-0.75)	0.802	(1.32)	-0.328	(-0.87)	-0.573	(-1.21)	0.970	(1.40)
OPE$_{trd}$	0.0219	(1.09)	-0.00318	(-0.22)	0.00304	(0.23)						
OPE$_{fin}$	0.661	(0.33)	0.894	(0.68)	-2.517*	(-1.73)						
OLD_row							0.0387***	(3.19)	0.00276	(0.17)	0.0140	(0.98)
YNG_row							0.00612	(1.54)	-0.00215	(-0.41)	0.00477	(0.80)
OLD$_{fut}$_row							0.0372***	(4.10)	0.00452	(0.51)	0.00242	(0.24)
YNG$_{fut}$_row							-0.00767	(-1.47)	-0.00229	(-0.37)	-0.00149	(-0.22)
LIFE_row							-0.0210***	(-3.09)	-0.0136*	(-1.80)	0.00572	(0.59)
GDP$_{(t-1)}$_row							-0.00389	(-1.23)	-0.00347	(-1.31)	0.000892	(0.20)
GDPGR$_{(t-1)}$_row							-0.00322	(-0.63)	0.0203**	(2.03)	-0.00443	(-0.59)
RPI$_{(t-1)}$_row							-0.174	(-1.52)	0.00670	(0.04)	0.115	(0.64)
FIN_row							-0.00153	(-0.95)	0.000454	(0.43)	-0.00314*	(-1.85)
LEG_row							0.136***	(4.46)	-0.0359	(-0.99)	0.0409	(1.13)
EDU_row							0.0601**	(2.31)	0.0358	(1.46)	0.00475	(0.15)
OPE							0.423***	(2.86)	-0.0188	(-0.13)	-0.0653	(-0.26)
Time freq.	5year		5year		5year		5year		5year		5year	
No. countries	67		67		67		67		67		67	
No. instruments	59		59		59		69		69		69	
Coun. fixed effect	yes		yes		yes		yes		yes		yes	
Obs.	428		428		400		420		420		394	
AB test (AR2)	0.14		0.19		0.20		0.01		0.94		0.21	
Sargan test	0.10		0.00		0.00		0.04		0.01		0.00	

Note: Robust t statistics in parentheses. Time dummies included, but coefficients not reported. Lagged intruments used for the autoregressive term as well as for GDP$_{(t-1)}$ and GDPGR$_{(t-1)}$. Internal instruments are restricted to two lags. Bottom lines show p-values for Arellano-Bond test (H0: no second-order autocorrelation) and Sargan test (H0: overidentifying restrictions are valid). ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.11: Population Age Effects on Saving, Investment and Current Account (2SLS IV)

	(1) SAV13		(2) INV13		(3) CAB13		(4) SAV14		(5) INV14		(6) CAB14	
OLD	-0.705***	(-4.80)	-0.151	(-1.33)	-0.334***	(-3.36)	-1.174***	(-5.58)	-0.232**	(-2.35)	-0.409***	(-5.04)
YNG	-0.107	(-1.27)	0.0159	(0.24)	-0.0582	(-1.04)	-0.500***	(-3.02)	0.0437	(0.57)	-0.207***	(-3.67)
OLD$_{\mathrm{fut}}$	0.161**	(2.57)	0.222***	(4.58)	-0.0732*	(-1.78)	0.201**	(2.06)	0.309***	(6.95)	-0.0195	(-0.53)
YNG$_{\mathrm{fut}}$	0.0475	(1.05)	0.0179	(0.49)	0.00909	(0.31)	-0.128	(-1.16)	0.116**	(2.13)	-0.100***	(-2.70)
LIFE	-0.0307	(-0.39)	-0.0700	(-1.11)	0.0938**	(2.01)	0.0858	(0.77)	0.119**	(2.33)	0.0534	(1.29)
GDP$_{\mathrm{(t-1)}}$	0.437***	(7.62)	0.0688	(1.54)	0.468***	(12.86)	0.0438	(0.43)	-0.126***	(-2.75)	0.359***	(9.91)
GDPGR	2.039***	(2.71)	1.799***	(3.02)	0.955**	(2.26)	-2.623**	(-2.21)	0.169	(0.30)	-0.113	(-0.32)
RPI$_{\mathrm{(t-1)}}$	-10.66***	(-11.76)	-10.99***	(-14.83)	1.543***	(2.68)	-9.937***	(-7.90)	-9.754***	(-15.00)	2.200***	(4.37)
FIN	0.0155*	(1.86)	0.0234***	(3.70)	-0.0144***	(-2.61)	0.0207*	(1.82)	0.0259***	(5.06)	-0.0104**	(-2.30)
LEG	0.0145	(0.05)	0.177	(0.72)	-0.388**	(-2.18)	1.189**	(2.35)	0.325	(1.34)	-0.288*	(-1.85)
EDU	-0.405**	(-2.19)	-0.205	(-1.46)	-0.474***	(-4.16)	-1.109***	(-3.62)	-0.329**	(-2.42)	-0.658***	(-6.89)
OPE$_{\mathrm{trd}}$	0.0525***	(5.31)	0.0182**	(2.51)	0.0161**	(2.29)						
OPE$_{\mathrm{fin}}$	1.712**	(2.09)	-0.462	(-0.71)	-0.880*	(-1.67)						
OLD_row							0.0113	(0.62)	-0.0279***	(-3.59)	-0.0108	(-1.33)
YNG_row							0.0285**	(2.12)	-0.0173***	(-2.67)	0.0150***	(3.24)
OLD$_{\mathrm{fut}}$_row							-0.0121	(-0.84)	-0.0245***	(-4.20)	-0.0190***	(-3.57)
YNG$_{\mathrm{fut}}$_row							0.0123	(1.32)	-0.0125***	(-2.87)	0.0114***	(3.64)
LIFE_row							0.0150	(1.14)	-0.00232	(-0.37)	0.0210***	(3.63)
GDP$_{\mathrm{(t-1)}}$_row							-0.000390	(-0.05)	0.00465	(1.32)	0.00378	(1.19)
GDPGR$_{\mathrm{(t-1)}}$_row							0.0180**	(1.99)	0.0103***	(2.74)	-0.00486**	(-2.49)
RPI$_{\mathrm{(t-1)}}$_row							-0.507***	(-3.58)	-0.241***	(-3.83)	-0.249***	(-3.62)
FIN_row							-0.00434*	(-1.95)	-0.000124	(-0.12)	-0.00172**	(-2.38)
LEG_row							0.102***	(3.31)	0.0666***	(4.99)	0.0351***	(2.91)
EDU_row							0.190***	(3.06)	-0.0341	(-1.19)	0.0741***	(3.45)
OPE							0.175	(0.92)	-0.0339	(-0.46)	0.0569	(0.88)
Time freq.	annual		annual		annual		annual		annual		annual	
No. countries	67		67		67		67		67		67	
Coun. fixed effect	no		no		no		no		no		no	
Obs.	2172		2172		2048		2168		2168		2043	
R^2	0.135		0.118		.		.		0.497		0.317	
Score test 1	0.00		0.01		0.00		0.00		0.54		0.86	
Score test 2	0.00		0.00		0.00		0.02		0.12		0.13	
F-stat GDPGR	4.1		4.1		4.8		3.0		3.0		4.3	

Note: Robust t statistics in parentheses. Time dummies included, but coefficients not reported. GDPGR is instrumented by latitude, percentage of land area within the tropics and land area within 100 km of the coast or a major waterway. Bottom lines show p-values for robust score test 1 (H0: variables are exogenous) and 2 (H0: instruments are valid) as well as first-stage robust F-statistics for the potentially endogenous variable. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.12: Population Age Effects on Saving (OECD-Subsample)

	(1) OECD-SAV1		(2) OECD-SAV2		(3) OECD-SAV3		(4) OECD-SAV4		(5) OECD-SAV5	
OLD	-0.522**	(-2.31)	-0.204	(-0.75)	-0.190	(-0.75)	-0.612*	(-1.93)	-0.121	(-0.50)
YNG	0.310	(1.18)	0.287	(1.12)	0.287	(1.07)	0.276	(1.07)	0.335	(1.19)
OLD_{fut}	-0.00626	(-0.03)	0.144	(0.66)	0.218	(0.96)	0.384	(1.44)	0.0446	(0.21)
YNG_{fut}	0.432	(1.41)	0.396	(1.31)	0.390	(1.25)	0.386	(1.19)	0.352	(1.01)
LIFE	0.102	(0.18)	-0.264	(-0.45)	-0.297	(-0.51)	-0.240	(-0.35)	0.588	(0.99)
$GDP_{(t-1)}$	0.296**	(2.23)	0.263**	(2.27)	0.274**	(2.50)	0.291**	(2.57)	0.194	(0.96)
$GDPGR_{(t-1)}$	0.201*	(1.86)	0.136	(1.35)	0.129	(1.28)	0.116	(1.13)	0.0585	(0.48)
$RPI_{(t-1)}$	-2.328	(-0.60)	-2.769	(-0.77)	-4.066	(-1.16)	-3.659	(-1.01)	-1.484	(-0.40)
FIN	-0.00236	(-0.32)	-0.00267	(-0.33)	-0.00552	(-0.59)	-0.00381	(-0.48)	-0.0250	(-1.58)
LEG	-0.234	(-0.56)	-0.248	(-0.64)	-0.239	(-0.63)	-0.181	(-0.46)	-0.798*	(-1.89)
EDU	-0.00969	(-0.02)	0.115	(0.24)	0.00935	(0.02)	0.0722	(0.17)	0.370	(0.77)
OPE_{trd}	0.0826***	(3.55)	0.0656***	(3.44)	0.0558***	(3.04)	0.0655***	(3.33)		
OPE_{fin}	2.036	(1.41)	3.133*	(1.88)	2.591	(1.52)	2.016	(1.19)		
PEN			-0.760**	(-2.50)	-0.837***	(-2.87)	-0.238	(-0.06)	-1.693***	(-4.04)
EMU_{south}					1.523	(1.42)			2.177	(1.58)
EMU_{north}					1.137	(1.37)			1.014	(1.17)
PEN*OLD							0.0702**	(2.22)		
PEN*OLD_{fut}							-0.0105	(-0.39)		
PEN*LIFE							-0.0245	(-0.42)		
OLD_row									-0.111*	(-1.77)
YNG_row									-0.146**	(-2.33)
OLD_{fut}_row									-0.0156	(-0.21)
YNG_{fut}_row									-0.167**	(-2.00)
LIFE_row									-0.254***	(-2.59)
$GDP_{(t-1)}$_row									0.0285	(0.89)
$GDPGR_{(t-1)}$_row									0.0482**	(1.97)
$RPI_{(t-1)}$_row									-0.743	(-1.15)
FIN_row									0.00408	(1.07)
LEG_row									0.324**	(2.17)
EDU_row									-0.328***	(-2.72)
OPE									1.076**	(2.58)
PEN_row									0.147**	(2.12)
Time freq.	annual		annual		annual		annual		annual	
No. countries	24		24		24		24		24	
Coun. fixed effect	yes		yes		yes		yes		yes	
Obs.	645		645		645		645		643	
R^2	0.933		0.938		0.940		0.941		0.947	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 2.13: Population Age Effects on Investment (OECD-Subsample)

	(1) OECD-INV1		(2) OECD-INV2		(3) OECD-INV3		(4) OECD-INV4		(5) OECD-INV5	
OLD	-0.361	(-1.61)	-0.212	(-0.86)	-0.198	(-0.92)	0.272	(0.64)	-0.695***	(-3.38)
YNG	-0.254	(-1.13)	-0.265	(-1.19)	-0.250	(-1.00)	-0.287	(-1.28)	-0.354	(-1.23)
OLD_{fut}	-0.207	(-0.88)	-0.136	(-0.59)	-0.0672	(-0.30)	0.539	(1.49)	-0.479**	(-2.03)
YNG_{fut}	-0.0872	(-0.32)	-0.104	(-0.39)	-0.114	(-0.39)	-0.0650	(-0.26)	-0.122	(-0.33)
LIFE	-0.652	(-1.42)	-0.823*	(-1.77)	-0.826*	(-1.85)	-2.103***	(-3.04)	0.167	(0.38)
$GDP_{(t-1)}$	-0.0279	(-0.28)	-0.0431	(-0.47)	-0.0318	(-0.36)	-0.0310	(-0.34)	0.159	(1.08)
$GDPGR_{(t-1)}$	0.422***	(6.15)	0.392***	(5.36)	0.381***	(5.81)	0.395***	(6.37)	0.376***	(4.62)
$RPI_{(t-1)}$	-3.743	(-1.33)	-3.949	(-1.43)	-5.417**	(-1.99)	-4.800*	(-1.69)	-1.310	(-0.48)
FIN	0.0239***	(2.64)	0.0238**	(2.44)	0.0187*	(1.68)	0.0291***	(3.05)	-0.00173	(-0.15)
LEG	0.0197	(0.06)	0.0128	(0.04)	0.0249	(0.07)	0.00580	(0.02)	-0.0670	(-0.18)
EDU	0.349	(0.86)	0.408	(1.02)	0.311	(0.83)	0.110	(0.28)	0.00736	(0.02)
OPE_{trd}	-0.0767***	(-2.99)	-0.0846***	(-3.41)	-0.0930***	(-3.39)	-0.0861***	(-3.53)		
OPE_{fin}	-0.368	(-0.29)	0.144	(0.10)	-0.574	(-0.38)	-0.0682	(-0.04)		
PEN			-0.355	(-1.51)	-0.469*	(-1.92)	-10.43**	(-2.18)	-0.570*	(-1.66)
EMU_{south}					1.936*	(1.80)			2.703***	(3.43)
EMU_{north}					0.816	(0.90)			-0.750	(-0.74)
PEN*OLD							-0.0510	(-1.02)		
PEN*OLD_{fut}							-0.0752**	(-2.25)		
PEN*LIFE							0.162**	(2.08)		
OLD_row									0.276***	(3.38)
YNG_row									0.00991	(0.10)
OLD_{fut}_row									0.0911	(1.15)
YNG_{fut}_row									-0.126	(-0.90)
LIFE_row									-0.398***	(-3.83)
$GDP_{(t-1)}$_row									-0.00420	(-0.21)
$GDPGR_{(t-1)}$_row									-0.0163	(-0.81)
$RPI_{(t-1)}$_row									-0.215	(-0.21)
FIN_row									0.00461	(1.44)
LEG_row									0.112	(0.65)
EDU_row									-0.150	(-0.81)
OPE									-0.0192	(-0.05)
PEN_row									-0.122	(-1.27)
Time freq.	annual		annual		annual		annual		annual	
No. countries	24		24		24		24		24	
Coun. fixed effect	yes		yes		yes		yes		yes	
Obs.	645		645		645		645		643	
R^2	0.861		0.862		0.866		0.867		0.885	

Note: Two-way cluster-robust standard errors with non-nested clustering by country and time dimension; t statistics in parentheses. Time dummies included, but coefficients not reported. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

3. Demography and Innovation: The Impact of Population and Workforce Aging on Innovative Performance

Abstract

Innovation and technological progress are the key drivers of economic growth in advanced economies. However, most developed countries undergo a considerable demographic transition towards older population age structures which will intensify in the coming decades. In this paper I empirically analyze the relationship between age and innovative performance from a macroeconomic perspective. Based on static and dynamic panel data approaches and a sample of 22 OECD countries, I analyze whether changes in the age distribution of the total population and workforce affect the aggregated innovative performance at the country level. Using triadic patent counts as a measure for technological innovation and the number of cross-border trademarks as a measure for marketing and product innovation, I find significant population age effects on innovative performance. These results remain robust over a number of tested specifications. In contrast, there is no clear evidence for workforce age effects on the number of filed patents and trademarks.

Keywords: demography, innovation, population aging, triadic patents, trademarks

3.1 Introduction

Innovation and technological progress are the key drivers of economic growth in advanced economies. However, most developed countries undergo a considerable demographic transition induced by decreasing fertility and old age mortality rates that leads to a shift towards aging societies. As this process is expected to further intensify in the coming decades, a critical issue in this context is whether today's innovation-driven economies can keep up their high pace of innovation and sustain economic growth in the future.

While previous empirical growth research has analyzed the impact of demographic change on economic performance in general, a detailed study of the macroeconomic link between an aging society and innovation has largely been neglected. In contrast, empirical innovation studies focusing specifically on the link between aging and innovative performance have mainly paid attention to the individual or firm rather than to the country level. This paper aims to bridge this gap by dealing with the question of whether and to what extent demographic change and population respectively workforce aging affect the aggregated innovative performance of industrialized countries from a macroeconomic perspective. This question is interesting at least for two reasons. First, it gives a better understanding of the age-innovation relationship in general. If there are age effects on innovative performance at the individual level, these effects are likely also to translate into changes in aggregated national innovative performance as the workforce and population ages. Second, studying the age-innovation link gives further insights about a potential transmission channel through which demographic change affects economic growth.

Beside the fact that studies on aging and innovation at the country level are still an exception, this paper contributes to existing literature in several further aspects. Whereas empirical innovation studies mostly focus on technological innovation by using indicators such as patent counts or scientific publications, marketing and product innovations have been neglected in the research of the age-innovation relationship until now. However, the latter kind of innovation is of particular importance for advanced countries with their strong service sectors. Therefore, the model in this paper uses beside triadic patents as an indicator for innovative performance also cross-border trademarks which are suggested to be a reliable indicator for capturing marketing and product innovations. Furthermore, the paper investigates whether potential age effects are driven by varying levels of educational attainment across age cohorts. Therefore, it employs a recently available macroeconomic dataset that provides cohort-specific education time-series by using demographic back- and forward projection methods. From a methodological standpoint, the study joins the increasing body of literature that uses linear dynamic panel estimation methods. Thereby, it accounts for new procedures and insights about the performance of estimators that are of particular relevance in the context of macroeconomic settings with a small number of cross-sectional units.

The remainder of this paper is structured as follows. Section 3.2 gives an overview of the theoretical framework of the paper, followed by a literature review regarding the empirical evidence of age effects on innovation in section 3.3. Section 3.4 introduces the datatset, the econometric models and the methodology, while section 3.5 reports and interprets the estimation results, including a number of robustness checks. Finally, section 3.6 concludes the findings.

3.2 Theoretical Background

From a theoretical perspective, demographic change caused by decreasing fertility rates and rising life expectancy may affect innovative output at the country level through various transmission channels. Beside mere population size and scale effects, also youth and old age dependency interactions as well as general lifecycle dynamics in the supply of labor, savings and physical capital should affect the production of new knowledge and innovation. Furthermore, age-specific human capital and productivity profiles should provoke macroeconomic shifts in innovativeness as the age decomposition of the workforce changes. Finally, demography-induced shifts in the demand of innovative products and services may play a crucial role.

Even though the role of demographics on economic growth in general has been gained more attention in recent years, there have been only limited attempts in the growth literature to enhance existing frameworks and incorporate demographics. While traditional concepts like the neoclassical growth model from Solow (1956) assume the rate of technical progress to be exogenous and thus leave the process of innovation unexplained, newer approaches in economic growth theory incorporate innovation and technological change endogenously in the models. These R&D-based growth models are of special interest in the context of this paper as they assume that technological change is the key determinant of long-term economic growth and explicitly explain the evolution of ideas and new knowledge, commonly via a knowledge production function. For instance, in his seminal paper Romer (1990) adds an additional R&D sector to his model that produces new ideas[1], which in turn are beside capital and labor an essential input factor for the production of intermediate and final goods. Even though the Romer model has been subject to some criticism since its formulation, its knowledge production function is a well-suited framework to analyze the age-innovation relationship from a theoretical perspective. In the following I will use this framework as theoretical foundation, thereby focusing in particular on the R&D sector in the model and describing the other sectors only insofar as they are relevant for the production of new ideas.

Assume a production function where in each time period t new ideas and knowledge, ΔA, are produced by combining the available amount of human capital in the R&D sector, H_A, at a certain level of productivity, δ_A, with the existing stock of ideas, A:

$$\Delta A = \delta_A {H_A}^{\sigma} A^{\phi} \tag{3.1}$$

The function follows a classical Cobb-Douglas form in the sense that σ and ϕ can be considered

[1] The abstract term 'ideas' is here used as a synonym for new knowledge that can be used for the production of innovative products and services. More concrete one can think of ideas manifesting in blueprints, designs or patents that can directly or indirectly translate into innovation.

as the partial production elasticities of each production factor.[2] The amount of human capital available to the research sector is subject to the resource constraint equation

$$H_A = H - H_Y \tag{3.2}$$

where H_Y is the amount of human capital devoted to non-R&D production sectors and H is the total stock of human capital available to the economy. As the model assumes perfect labor mobility between the different sectors, the allocation of human capital resources to the ideas producing R&D sector depends on the wages in the R&D sector, w_A, relative to the wages in the production sector, w_Y:

$$w_A = p_A \delta_A A^{\phi} = \alpha H_Y^{\alpha-1} L^{\beta} A \bar{x}^{1-\alpha-\beta} = w_Y \tag{3.3}$$

The wages in the R&D sector are determined by the market prices of new ideas or designs, p_A, as well as the productivity of researchers and the available stock of existing knowledge. In equilibrium, w_A equals w_Y. The latter is the marginal product in the production sector which is beside human capital and the stock of designs a function of labor, L, and physical capital in the form of different intermediate goods, $\bar{x}$. α and β denote the technology factors or elasticities of human capital respectively labor. Since knowledge is assumed to be a non-rival product, its stock can be used in the R&D as well as in the production sector at the same time. In the classical Romer model, the allocation of human capital in the production sector is finally derived by:

$$H_Y = \frac{1}{\delta_A} \frac{\alpha}{(1-\alpha-\beta)(\alpha+\beta)} r \tag{3.4}$$

Combining (3.4) with (3.2) reveals that, beside the productivity of researchers and the technology factors, the interest rate r is crucial in the allocation of human capital between both sectors and has a negative impact on the amount of human capital devoted to the R&D sector. Thus, higher interest rates hamper the creation of new ideas as the opportunity costs of doing research become higher and borrowing becomes more expensive for the producing sector, thus reducing profits and the willingness to pay high prices for blueprints and designs to the R&D

[2] Romer (1990) regards these elasticities to be equal to 1, thus assuming constant returns to ideas and labor. As a result, a permanent increase in labor devoted to research leads to a permanent increase of economic growth in the model. However, some authors find little empirical evidence for these scale effects (see for example Jones, 1995).

sector. Interest rates in turn are essentially determined by the supply of savings from private households.

Overall, the classical Romer model assumes that the production of new knowledge in the R&D sector is determined by the overall supply of human capital and savings as well as by the productivity of researchers. However, all these factors are widely recognized as being directly or indirectly affected by changes in the age structure of the population. A main driving force through which population aging may affect innovative output are dependency effects in the sense that the ratio of active groups in working age within the total population decreases as more people become older and retire. For instance, Bloom and Williamson (1998) and Bloom et al. (2003b) remark that the so-called *demographic dividend* induced by decreasing fertility rates that lead to a decrease in the youth dependency ratio and thus a rising ratio of the working age population relative to total population is a purely temporary, transitional effect that works only as long as the working population grows faster than the overall population. However, when the fertility rate remains low and a growing number of people leave the workforce and retire, the effect reverses to a demographic burden and depresses economic growth. This negative effect is further strengthened when mortality rates decrease especially in older age groups. Even though this theoretic concept focuses on economic growth and thus output in general, it can be directly transferred to the generation of ideas and innovation in the R&D sector as dependent age groups do not provide human capital and normally are assumed to dissave their assets.

However, the supply of human capital and savings is not only supposed to vary between active and dependent age groups but may be also subject to variation within active age groups. On the one hand, an individual's accumulated stock of human capital should decrease as education attained from formal schooling gets obsolete over time while on the other hand it is supposed to increase as workers gain experience with time. Similarly, as stated by the life cycle hypothesis of saving and consumption formulated by Modigliani and Brumberg (1954) and Ando and Modigliani (1963), saving behavior of individuals and households should differ not only between active and non-active life periods, but also within the working life period due to time-varying levels of income and the desire of households to smooth consumption over their lifetime. Finally, productivity levels of knowledge workers and researchers may be age-specific since factors such as cognitive capabilities, motivation and risk behavior may change.

While the classical Romer model does neither consider the age structure of the population nor account for age-related changes in its main parameters and variables, some few extensions of the framework have been suggested in literature. For instance, Malmberg (1994) incorporates demographics into the model by introducing lifecycle dynamics and allowing for age-group specific levels of human capital and saving rates:

$$H = \sum_{i=1}^{m} H_i n_i; \quad s = \sum_{i=1}^{m} (a_i - c_i) \frac{n_i}{N} \tag{3.5}$$

Thus, the overall stock of human capital available in the economy depends on H_i, which is the human capital endowment of an individual age group i, as well as on the number of individuals in each age group, n_i, and the overall number of age groups, m. Similarly, the overall national saving rate, s, is derived from earnings, a_i, and consumption, c_i, of individual age groups i, whereby a_i and c_i are assumed to be constant fractions of per capita income and N is the size of the total population. Through these enhancements, the overall endowment of human capital as well as saving rates in the model depend on the age structure of the population, which in turn directly and indirectly affects the output of the R&D sector. For instance, if the size of age groups with high human capital endowment increases, more human capital is directly available to the R&D sector and more ideas can be produced. The same is true if the share of age groups with high saving profiles increases, even though the effect on human capital and innovation is more indirect via decreasing interest rates.

However, the assumption that age specific pattern in human capital accumulation and saving behavior are constant over time has been challenged by a series of studies. For example, Kalemli-Ozcan et al. (2000), Cervellati and Sunde (2005) and Jayachandran and Lleras-Muney (2009) show that increases in life expectancy have an impact on human capital formation as the prospect of a longer lifetime makes investments in human capital more profitable. Similarly, Heijdra and Ligthart (2006) and Heijdra and Romp (2008) suggest that saving behavior over the lifecycle changes as life expectancy increases. Therefore, further concepts have been introduced recently that extent the Romer model and feature richer demographic structures. For instance, in order to model changes in fertility rates and in life expectancy, Prettner (2013) replaces the representative infinitely lived agent of the Romer (1990) model and introduces finite individual planning horizons as well as an overlapping generations framework that allows for heterogeneous individuals. By changing the birth rate and the mortality rate simultaneously (which is required to be consistent with the Romer model), Prettner (2013) changes the age structure within the model, which allows to study the effects of population aging. Rising life expectancy induced by decreasing mortality rates leads to changes in the saving behavior of households towards higher saving rates. As shown before, higher savings provoke lower interest rates that in turn foster innovation as investments in R&D are discounted less, thus making them more profitable. However, as the modified Romer model follows an OLG structure according to Blanchard (1985), all agents face the same age-independent risk of death rather than more realistic age-specific mortality rates.

3.3 Literature Review

Up to now there have been relatively few economic studies dealing with the issue of population aging and inventive performance. While most of the existing studies focus on individual or firm level analysis for examining the effects of aging on innovation, studies at an aggregated country level are still an exception. This section gives an overview of the main studies in the literature.[3]

[3] For a detailed literature survey on age and innovation see also Frosch (2011b).

3.3.1 Age-Innovation Studies in Microeconomic Literature

There is some empirical evidence that innovative creativity and performance of individual researchers change over their life cycle. One branch of studies analyzes these age effects by focusing on the inventive productivity of scientists and engineers in companies and academic institutions. Thereby, inventive productivity is usually measured by indicators capturing individual research output such as patents, scientific publications or management and peer evaluations. An early study from Dalton and Thompson (1971) based on management assessment for a sample of 2'500 engineers in six large firms finds that the performance of technically trained individuals peaks at an early age and declines steadily thereafter. Hoisl (2005) examines patent counts from 579 German inventors and finds an inversely U-shaped relation between age and research output. Mariani and Romanelli (2007) and Schettino et al. (2008) come to similar results by analyzing patent counts from a sample of 739 European inventors, respectively 106 Italian inventors. In a recent study with cross-sectional data of German inventors, Henseke and Tivig (2009) find that inventive productivity is age dependent, too.

Another branch of studies on individual level analyzes Nobel prize winners and other outstanding inventors regarding the point in time in their life cycle when they made their milestone discoveries. For instance, Stephan and Levin (1993) analyze the link between age and scientific productivity for Nobel prize winners in science during the period 1901–1992. They suggest that the relationship is field dependent and although it does not require extraordinary youth to do prizewinning work, the chances decrease measurably in mid-life and fall off sharply after the age of 50, especially in the disciplines of physics and chemistry. In another study, van Dalen (1999) focuses on Nobel laureates in economics and finds that their most important and creative contributions are written between the ages of 29 and 38. Finally, Jones (2010) finds similar results by investigating the scientific contributions of Nobel prize winners and other great inventors in the course of the 20th century.

Even though most authors find that individual inventive productivity peaks during early or middle age, the results regarding the age effects vary considerably between the different studies. This is not surprising given the fact that the authors mostly rely on small-scale samples focused on specific sectors, industries or scientific disciplines that vary across the different studies. Some of the previous mentioned studies have stressed the sector-specificity of the age-innovation relationship. For instance, Henseke and Tivig (2009) show that there are not only significant age effects in general, but that these age effects differ across industries. They suggest that younger researchers perform better in innovative and fast growing industries with high rates of technological change such as the biotechnology or information technology sector. In contrast, older and experienced inventors have comparative advantages in more traditional industries, in which the pace of technological change is slower, thus preventing existing knowledge from premature obsolescence. Similar differences in the age effects on innovative performance are also found between different scientific disciplines. However, Jones and Weinberg (2011) find that the age-creativity relationship varies not only across scientific fields, but also substantially over time within single scientific fields. The authors observe a shift over time in the peaks of innovative productivity from young towards older age in the life cycles of Nobel laureates over the 20th century. According to the authors, these age dynamics within fields closely mirror field-specific shifts in training requirements as well as the prevalence of experimental against conceptional contributions.[4]

Beside studies examining the age-innovation relationship for individual researchers and inventors, other studies use firms as unit of analysis and examine the effects of the age distribution of employees within firms. However, while there is a broad literature on the effects of aging on overall firm productivity, only a few studies examine the impact of aging on the innovative output at firm level. As one of the latter studies, Schneider (2008) uses cross-sectional data of over 1'000 German companies in order to analyze whether an older workforce lowers a firm's potential to generate product innovations. In line with the results of studies based on individual inventors, he finds evidence of significant age effects that follow an inversely U-shaped age-innovation profile that peaks around the age of 40 years. In contrast, Verworn and Hipp (2009) who also analyze a large cross-section of German firms do not find support for a negative effect of a high share of older employees in firms on inventive performance.

3.3.2 Age-Innovation Studies in Macroeconomic Literature

Even though there is some empirical evidence of an age-innovation relationship at the individual and firm level, due to the specific and small-scale samples the scope to transfer the insights from these studies to an aggregated country level are rather limited. However, empirical studies that analyze the effects of aging on innovative performance from a macroeconomic perspective are still rare. Instead of dealing particularly with innovation and innovation-driven growth, most existing macroeconomic studies analyze the impact of demographic change and population aging from a broader, more general perspective. For instance, one stream of research focuses on the consequences of demographic change on economic performance in general. This research finds that demographic developments such as decreasing fertility rates (e.g. Bloom and Williamson, 1998; Bloom et al., 2003b) or rising life expectancy (e.g. Acemoglu and Johnson, 2007; Cervellati and Sunde, 2011) have a significant impact on economic growth rates. Similar results are found by studies from Lindh and Malmberg (1999b, 2009) or Brunow and Hirte (2009) that suggest significant effects of a region's or country's demographic age structure on

[4]The accumulation of foundational knowledge as technology advances may increase training requirements for successive generations of inventors. This view assumes that foundational knowledge of a scientific field normally expands with time (even though by times there may be periods of contraction when new knowledge makes old knowledge obsolete). Jones (2009) calls this phenomenon the *burden of knowledge* that requires longer periods of education and makes it more difficult for scientists to make innovative contributions in young age. Similarly, Jones and Weinberg (2011) suggest that age dynamics within scientific fields closely mirror field-specific shifts from the prevalence of conceptional towards empirical contributions. According to Weinberg and Galenson (2005), conceptional innovative creativity is based rather on new theoretical knowledge than on experience and should be especially high in the early years of an inventor's career as younger scientists can benefit from up-to-date knowledge attained during their more recent educational training. In contrast, experimental creativity should be particularly high in later stages of life when scientists have already gained considerable experience.

economic growth. However, these studies can give only indirect insights regarding the impact of demographic change on innovative performance given that economic growth is not only driven by innovation, but also by other factors. Other macroeconomic studies focus on the relationship between workforce demographics and overall aggregate productivity. For instance, Feyrer (2007) suggests that changes in the age structure of the workforce are significantly correlated with changes in aggregate productivity for a broad country sample. But similar to economic growth, productivity in general may only be a weak proxy for innovative performance. Even though innovation and technological change are assumed to be main determinants of changes in productivity, factors such as investment in human capital may play a significant role, too.

One of the few studies that come very close to the issue regarding the impact of demographic change on innovative performance at the macroeconomic level is the study from Bönte et al. (2007). The authors examine the relationship between the demographic age structure of individuals in working age and the number of innovative startups within German regions. The level of entrepreneurial activities can be seen as an indirect measure for innovative output in the sense that innovation constitutes itself not only by the creation of new knowledge but also by the ability and willingness of innovative entrepreneurs to use this knowledge in order to develop and commercialize new products and services. Bönte et al. (2007) find that the number of startups in knowledge-based industries is affected by changes in a region's age distribution whereas the number of new firms in other industries is not. In detail, age groups in the range of 20-30 years and 40-50 years have a positive effect on the number of high-tech startups. In another study, Izmirlioglu (2008) examines the effect of the population's age-distribution on economic growth through technological progress within the framework of a multi-sector economy model that is calibrated for the United States for the period 1950-2050. He shows that the size and share in employment in R&D sectors may continue to rise and that technological progress may be sustainable despite population aging. In a similar study, Noda (2011) analyzes the relationship between population aging and technical change by using an economic growth model with quality-improving innovation. Contrary to the findings of Izmirlioglu (2008), Noda (2011) suggests that the progress of population aging causes the rate of innovation to decline. It is important to mention that the works of Izmirlioglu (2008) and Noda (2011) are rather theoretical and do not use any direct measure for research output, thus giving no direct empirical insights on the age-innovative performance relation. Finally, a recent study on workforce aging and innovative capacity from an aggregated perspective is given by Frosch (2011a). She analyzes the relationship between the regional workforce age composition and patent activity per worker for a panel of 164 European regions between 1992 and 2006. Thereby, Frosch (2011a) distinguishes between different qualities of knowledge within the workforce and comes to the conclusion that specific age patterns prevail within each of the knowledge fields and that these age patterns vary considerably between the different fields.

3.4 Model

While the previously mentioned studies give valuable insights on age-innovation dynamics at the individual, firm and regional level as well as for single countries, the following sections describe the estimation strategy in order to analyze the consequences of population and workforce aging on aggregated innovative performance for a panel of advanced countries.

3.4.1 Dataset and Econometric Model

Dataset

The data sample used in the study comprises a set of 22 OECD countries as listed in Appendix 1. Besides the general macroeconomic interest in countries as units of analysis in this study, using a sample at country level has a number of advantages. In contrast to smaller units such as firms, countries (especially in the OECD group) are rather stable entities and there is time series data available over long time periods and for many variables. Furthermore, an analysis at the country level is less subject to endogeneity bias arising from simultaneous causality compared to data on regional or even firm level. While there are good reasons to assume that innovative firms and regions can attract in particular younger people who are more mobile and that there is considerable cross-firm and cross-regional fluctuation, that should be less the case for countries where legal, cultural and spatial barriers still limit migration flows across countries. Finally, countries have the critical mass in terms of output of patents and trademarks to produce significant inference. In order to analyze demographic effects on patent output, time series for each country over the period 1985-2008 are used. Even though one might argue that a period of 24 years is not very long in demographic terms, the OECD countries in the sample experienced substantial changes in their age structures during that period. Due to the lack of long-term time series, the analysis based on trademarks covers only the period 1994-2008. Data are taken from various sources including the OECD statistics database, the World Bank's World Development Indicators (WDI), the World Population Prospects (WPP) database from the United Nations as well as databases from the International Labour Organization (ILO) and the World Intellectual Property Organization (WIPO). The dataset is not fully balanced due to missing data for some countries during some time periods. When appropriate, missing data points are interpolated for individual variables.

Static Baseline Model

In order to analyze the link between population respectively workforce aging on the one side and innovative performance on the other side, I use a panel data approach with cross-sectional time series at the country level. This methodology makes it possible to analyze the variation across countries as well as the variation over time within countries and allows to control for unobserved heterogeneity. Similar to the theoretical Romer model, the model to be estimated is build-up around a knowledge production framework of Cobb-Douglas style with a limited number of knowledge producing inputs. The baseline econometric model can be written as:

$$\ln y_{it} = \beta \ln v_{it-1} + \sum_j \beta_j \ln x_{jit-1} + \sum_k \beta_k \ln w_{kit-1} + \delta_t + c_i + \varepsilon_{it} \tag{3.6}$$

where y_{it} is the dependent variable in country i at time t. As dependent variable, two different indicators for innovative performance are used: triadic patents as a proxy for measuring technological innovation and cross-border trademarks to capture marketing and product innovations. v_{it} is the existing stock of knowledge which is, following Furman et al. (2002), proxied by GDP per capita.[5] x_{it} is a vector of demographic variables that capture via j different age share groups the age distribution of the total population respectively the age distribution of the workforce. w_{it} is a vector of k other, non-demographic control variables, δ_t controls for time-specific effects, c_i denotes country-specific effects, and ε_{it} is the idiosyncratic error term. Along with the other regressors the individual age share groups are regarded as classical input factors that provide human and physical capital and enter the model in a multiplicative way with each age group having its own specific elasticity.[6] The dependent and the independent variables follow a natural logarithm form in the model. Using a log-log specification is a widely used approach in empirical studies on innovation output and allows to linearize the Cobb-Douglas functional form and to interpret the estimation results for the parameters in terms of elasticities.[7] Furthermore, it has the advantage that it is less sensitive to outliers and that all age share groups can be included in the model at the same time without facing perfect multicollinearity. However, in order to assess whether the functional form drives the results, I test an alternative specification where the age share groups enter the model in an additive, non-logarithmic form, too. All explanatory variables in the model are lagged by one time period following the assumption that changes in the demographic age structure and other determinants do not translate into changes in the innovation indicators immediately, but with a time delay.

The country fixed effects model used in this study makes it possible to control for unobserved, time-invariant effects by allowing for different intercept terms across countries while the slope coefficients are regarded as common for the whole country-sample. This procedure deals with omitting variable bias because country-specific effects that remain constant over time such

[5]From a theoretical perspective the link between the stock of existing knowledge and the creation of new ideas is not unambiguous and depends on the sign of the elasticity factor ϕ in the knowledge production function of the Romer model described in equation (3.1) in Section 3.2. If $\phi > 0$, there is a so-called positive *standing on shoulders* effect, while if $\phi < 0$ there is a negative *fishing out* effect.

[6]This assumes that the inputs of individual age groups in the knowledge production function cannot be perfectly substituted by each other and that there are diminishing returns in the knowledge generation for each additional increase in the share of a specific age group.

[7]Instead of treating the dependent variables as continuous within a log-linear specification, some authors have suggested the use of count data models with an exponential form (see, for instance, Bosch et al., 2005). This specification addresses problems arising from a high number of observations where the dependent variable is equal to zero. However, while this may be a serious problem for studies based on firm level data or on samples incorporating a large number of smaller developing countries, there is no reason to worry about zero value observations for patents or trademarks in the OECD country sample used in this study.

as cultural, legal or institutional differences are controlled for. Beside country fixed effects, the usage of time dummies in the model controls for unobserved time-specific effects such as business cycles, long time trends or other events that affect all countries in the sample at the same point of time. The fixed effects model used in the baseline regression specification is often regarded as the preferred choice for macroeconomic studies. Even though the random effects model produces more efficient estimates than the fixed effects model, it is more strict in its assumptions and requires the country-specific effects c_i to be random variables that are not correlated with the explanatory variables. This reflects the postulate that any variations across countries are random in the sample. In contrast, the fixed effects model allows the country-specific effects to correlate with the explanatory variables, which is - as mentioned also by Judson and Owen (1999) - highly likely for typical macroeconomic datasets if the individual effect represents omitted variables. Judson and Owen (1999) further remark correctly that commonly macro samples contain most of the countries of interest thus making it less likely to be a random sample from a much larger universe of countries. Given these points the fixed effects model seems more appropriate than a random effects specification for the OECD dataset used in this study.[8]

However, the baseline model described above encounters two challenges. First, a static framework may neglect crucial dynamic feedback effects. It is widely assumed that the production of innovation is a dynamic process. For instance, the knowledge production function of the Romer model described in section 3.2 assumes that the existing stock of knowledge plays a crucial role in the creation of new knowledge. Using GDP per capita as a proxy for the stock of knowledge as described in equation (3.6) may be a rather imperfect measure to capture these dynamics in sufficient detail. Secondly, and closely related to the existence of potential dynamic feedback effects, there remains the risk that the model suffers from endogeneity bias. Some of the regressors in the model may not be strictly exogenous in the sense that causality may run not only from the right to the left in the model equation but also vice versa. This may be especially the case for some covariates in the model such as the number of researchers or R&D expenditures. Even though our demographic variables should be less subject to reverse causation, they still may not be immune against endogeneity problems. For instance, in the medium-term age structure may be affected by migration flows due to better job market and income perspectives resulting from innovation-driven growth. In the long run, innovation-driven growth may have an impact on family planning and fertility rates as women opt for better education and more participation in the labor force. Similarly, innovations in health care may drive demographic developments. Any reverse causation may result in overall biased estimation results as the explanatory variables are not any longer independent from the error term. While the conventional fixed effects model addresses endogeneity problems resulting from omitted time-invariant variables, it cannot deal adequately with potential simultaneity bias (nor with bias resulting from omitted time-varying variables). The problem of endogeneity is somewhat alleviated in our models as all explanatory variables are lagged by one period thus assuming that they are predetermined. However, as remarked by de la Croix et al. (2009), demographic

[8]This view is also supported by the more formal Hausman test.

variables using age shares are highly persistent thus even with lagged regressors endogeneity may remain an issue.

Augmented Linear Dynamic Panel Model

In order to address the issues of dynamic feedback and endogeneity more accurately and to test the robustness of the results attained from the baseline model, in an alternative specification the static fixed effects model is enhanced to a dynamic linear panel model with instrumented variables:

$$\ln y_{it} = \alpha \ln y_{it-1} + \sum_j \beta_j \ln x_{jit-1} + \sum_k \beta_k \ln w_{kit-1} + \sum_h \beta_h \ln z_{kit-1} + \delta_t + c_i + \varepsilon_{it} \qquad (3.7)$$

The proxy for the stock of knowledge, v_{it}, is replaced by a lagged version of the dependent variable, y_{it-1}. Therefore, this specification allows to model any potential dynamics arising from existing knowledge more directly than by using a proxy variable for the stock of knowledge. Although the effects of existing knowledge lie not in the primary interest of this study, including dynamics may be important for gaining consistent estimates for the coefficients of the demographic variables in the model.[9] However, adding dynamics to the model causes direct endogeneity problems as the regressor of the lagged dependent variable and the country fixed effect, c_i, are correlated with each other, thus making standard estimators such as the ordinary least squares (OLS) or the least squares dummy variable (LSDV) estimator inconsistent. Even though Nickell (1981) finds that the bias of the LSDV estimator diminishes as the time dimension of the panel gets larger and converges to zero as $T \to \infty$, Judson and Owen (1999) demonstrate in Monte Carlo simulations that even for large T=20 the bias can be sizeable. Hence, a generalized method of moments (GMM) procedure as developed by Arellano and Bover (1995) and Blundell and Bond (1998) is used for the dynamic panel model. The GMM estimator is derived from a system of two simultaneous equations where levels are instrumented by lagged first differences and first differences are instrumented by lagged levels. This system GMM procedure allows to use more instruments compared to the difference GMM estimator proposed by Arellano and Bond (1991), thus making the estimates more efficient. Furthermore, according to Blundell and Bond (1998) and Bond et al. (2001), the system GMM procedure is the first choice when there is high persistency in the dependent variable. However, the system GMM estimator is more strictly by assuming that the first differences of the instruments are not correlated with the individual country effects. A specific advantage of the GMM procedure is that it allows to control for endogeneity not only for the lagged dependent variable but also for potential endogeneity bias arising from the remaining variables in the model. Therefore, beside a vector of strictly exogenous regressors, w_{it}, also a vector z_{it} for instrumented endogenous regressors is added to the model. As the performance of the estimations depends strongly on the quality of the instruments, tests regarding their validity are conducted in order to examine

[9]Bond (2002) shows in an example of a Cobb-Douglas production function that adopting a dynamic econometric specification is sometimes essential for identifying parameters of interest, even in case that the dynamics themselves are not in the focus of attention.

whether they are highly correlated with the potential endogenous variables but orthogonal to the error term.

The GMM technique derives its estimations from its asymptotic properties and is typically tested and used in classical micro settings with panels consisting of large N and small T. Therefore, a main concern is that these estimators might perform only poorly within the macroeconomic environment of this study with small N and rather large T. This concern is further strengthened by the fact that the number of instruments increases strongly as T gets larger. As outlined by Roodman (2009a,b), a large number of instruments can overfit the endogenous variables in the model, thus provoking instruments to fail to filter out the endogenous components within the variables which leads to biased estimates similar to those from non-instrumenting estimators. In order to verify the appropriateness of GMM estimators for typical macro settings, a number of studies have conducted Monte Carlo simulation tests with differing T and N dimensions. For instance, Judson and Owen (1999) find that the GMM approach performs well in typical macro panels. Similar results are found by Buddelmeyer et al. (2008) and Soto (2009). In some panel settings the corrected least squares dummy variable (LSDVC) estimator first proposed by Kiviet (1995) - and later further developed by Bruno (2005) to fit unbalanced panel datasets - produces superior results compared to the difference GMM approach from Arellano and Bond (1991). Yet, the LSDVC estimator has the major drawback that, with exception of the autoregressive term, it assumes strictly exogenous regressors in the model. Thus, assuming a high degree of persistence in the times series and given the possibility of reverse causation in some of the used variables, the system GMM approach is the first choice for this study. Nevertheless, I will also publish the results obtained from the difference GMM estimator from Arellano and Bond (1991) as well as the LSDVC estimator[10] suggested by Bruno (2005) for comparability purposes. As already stated before, the OLS and LSDV estimators are inconsistent for linear dynamic panel models. While Hsiao (1986) finds the OLS estimator to be upward biased, Nickell (1981) shows that the LSDV estimator is expected to suffer from downward bias. I use these findings as a consistency check by comparing the results of the system GMM regressions with the estimates of the dynamic model specifications ran by pooled OLS and LSDV.

The results for the difference and system GMM are based on one-step estimations. Even though the one-step estimations assume homoscedastic errors and there is a more complex two-step procedure available that produces heteroscedasticity-consistent standard errors, the latter procedure may be problematic given the small N in this study. In addition, Soto (2009) shows that there are no gains in accuracy and efficiency using two-step estimators compared to one-step estimations, even when the two-step estimators are corrected for finite samples as proposed by Windmeijer (2005).

[10] The LSDVC procedure requires a consistent estimator for initializing the bias correction. I report the results for the LSDVC estimations by using the system GMM estimator to initialize the correction procedure. Using alternatively the difference GMM estimator or a more simple estimator proposed by Anderson and Hsiao (1982) does not change the results significantly.

3.4.2 Indicators for Measuring Innovative Performance

The econometric model in this study uses two measures of innovative performance as dependent variables. As innovation and innovative performance are not tangible concepts and thus not directly measurable, an application of accurate proxies is needed to capture indirectly this phenomenon. While there are plenty of indicators that focus on the input side of research,[11] these indicators offer no information about how successfully these inputs are used in the production of innovation. Thus, indicators that are based on research output are preferable as they proxy innovative performance more directly. Among the few available output-oriented measures for inventive performance there are indicators based on patent counts, the number of scientific publications and, more recently, the number of trademarks. The following section introduces the indicators used in this study: triadic patents and cross-border trademarks.

Triadic Patents

Since the pioneering work of Schmookler (1966), patent-based indicators are frequently used in literature to measure inventive activity. Due to their specific characteristics, a number of authors have suggested patents counts as reliable predictors for (macroeconomic) inventive output and innovative performance (Griliches, 1990; Hagedoorn and Cloodt, 2003; de Rassenfosse and van Pottelsberghe de la Potterie, 2009). Patents are regarded to have a close link to inventive activity and cover a wide range of technologies and sectors. Furthermore, detailed data is broadly available for a large number of countries over a long time period.

However, using patents counts as a measure for innovative performance also has some major drawbacks.[12] First, even though patents cover a wide range of technologies, not all inventions are patented due to economic and legal reasons. From an economic standpoint, patenting an invention makes just sense if the expected future revenue from the invention covers at least the costs of patenting the invention. Thus, inventions with a low economic value or inventions stemming from basic research with no direct commercial use are more likely to be not captured by patent-based indicators. From a legal standpoint, not all inventions are patentable as they do not fulfill the legal requirements. Especially non-technological innovations are often excluded from patent data as they do not fit in the classical patent requirements of novelty and non-obviousness. Furthermore, there are alternative options for intellectual property protection beside patenting such as secrecy.[13] Second, even when inventions are captured by patents, the economic value of the invention may vary significantly across patents. A number of studies such as Lanjouw et al. (1998), Harhoff et al. (1999) or the Patval survey

[11]Input-oriented indicators usually analyze data on research inputs that are readily available such as R&D expenditure, the number of researchers engaged in R&D, specific education measures, etc.

[12]For a detailed discussion of the advantages and disadvantages of patents as statistical indicators see Griliches (1990), Popp (2005) and OECD (2009).

[13]According to Popp (2005), inventions that result in new products are more likely to be patented while research that results in new processes is rather kept secret. The rationale behind this pattern is that new products will be publicly available in the market, thus making the loss of secrecy that comes with a patent for products less a concern than for an innovative process.

(2005) by the European Commission suggest a highly skewed distribution of patent values. While there are some few patents with a very high value, a large share of filed patents are of no or little economic value as they are not used for commercial purposes or industrial application. Thus, patents counts on its own give no information about the value of innovations. Third, the comparability of patent data across countries and over time may be limited. There is some evidence that patent-based indicators are not only affected by research productivity but also by the propensity to file a patent application. This propensity may be influenced by various factors such as the patent system's legal and administrative framework that may differ significantly across countries, sectors and time. Using an econometric model, de Rassenfosse and van Pottelsberghe de la Potterie (2009) show that beside the research performance also the propensity to patent significantly affects the number of patent registrations across countries. Thus, not only differences in innovative performance but also differences in patent practices may lead to differences in patent counts across countries and over time.[14] As the effects of research performance cannot be disentangled easily from the effect of country-specific patent practices, the comparability of patent counts from different national patent offices is rather limited.

Using homogenous patent data from a single major patent office such as the European Patent Office (EPO) or the United States Patent and Trademark Office (USPTO) in order to compare cross-country innovative performance is no real option, because the data may be biased towards the home-country as domestic inventors tend to file more patents at their home-country's patent office compared to applicants from abroad.[15] However, a solution to diminish this home bias problem is to use patent families where the same invention is filed in several patent offices. In this study a triadic patent family as defined by the OECD is used, analyzing patents that are filed in three major patent offices, the EPO, the USPTO and the Japan Patent Office (JPO), to protect the same invention. Triadic patents have been suggested by several authors such as Dernis and Khan (2004) as a reliable indicator to analyze research activity across countries as this patent family allows to use a data set within a homogenous legal context and at the same time controls for any home bias. Furthermore, triadic patents improve the quality of the dataset by selecting only inventions with a similar value. As the costs of registering triadic patents are rather high, inventors should go this step only for more valuable inventions. Furthermore, as applicants have a time period of one year between their first filing (commonly referred to as priority filing) and further applications at other patent offices, inventors have

[14] Dernis and Khan (2004) and Popp (2005) note that the content of patents differs significantly due to the intricacies of individual patent offices. For instance, patents filed in the Japanese Patent Office (JPO) are commonly narrower and contain fewer claims than comparable patents filed in offices of other countries. Thus, more patents are needed in Japan to protect the same invention.

[15] One may argue that this home bias can be controlled for by restricting the sample on a set of homogenous countries that have a similar propensity to file patents at a given patent office, for example by restricting a sample for an EPO-based patent indicator on European countries. But even in this case there might be still a significant heterogeneity regarding the propensity to patent at the EPO due to factors such as a high diversity in bilateral trade relations among European countries. For instance, let us assume that the United Kingdom has close bilateral trade relations to the United States and a higher propensity to file patents at the USPTO relative to EPO filings compared to France and Germany. Thus, only using an indicator based on EPO applications would in this case underestimate the innovative performance of the United Kingdom.

the opportunity to gain more accurate information about the value of their patent within this time frame. Altogether, this suggests that a data set based on triadic patents in combination with an econometric model controlling for country and time fixed effects gives a reliable basis to compare inventive performance across a set of OECD countries over time.

The data for triadic patents are taken from the OECD Patent Database and based on priority filings which are closest to the date of invention. However, there is a timeliness problem as patent information is not available immediately after the date of the priority filing but with a time lag, mainly due to legal rules involving delays in the patent application process. As this delay can last up to several years in the case of the USPTO, now-casts are used for the latest years as described by Dernis (2007). Patents counts are calculated in per capita terms in order to adjust for population or workforce size.

Cross-border Trademarks

While the usage of patents counts as an indicator for innovative performance has a long tradition in the literature on innovation and technological change, trademarks have not been in the focus of innovation studies until recently. According to the OECD (2009, 2010), trademarks are, similar to patents, a form of legal intellectual property protection and enable the identification and differentiation of goods and services by protecting distinctive signs, such as words, symbols and designs. As trademarks are often used to signal novelty and to promote new products and services by advertising, the registration of trademarks is assumed to be closely associated with the introduction of new products and services in the market. Due to these characteristics, the OECD (2009, 2010) proposes the number of new trademarks as an indicator of product and marketing innovations as well as a measurement of non-technological innovation and innovations in the service sector that cannot be captured accurately by patent-based indicators. Thus, trademarks counts may be seen complementary to patent counts in order to indicate innovative performance across countries. And indeed, there is some empirical evidence that there is a close relation between the number of trademarks and the level of innovation at the firm as well as the country level.[16]

In general, indicators based on trademark counts face similar problems as patent-based indicators. For instance, not all trademark registrations are directly associated to the introduction of new products and services as some trademarks are never used directly in the market. Millot (2009) remarks that trademarks may be filed for strategic reasons such as protecting several options for a future product or blocking competitors of using certain names or signs. Furthermore,

[16]By analyzing a sample of German firms in the knowledge-intensive service sector, Schmoch (2003) finds a significant correlation between trademarks and innovative activity. As the link between patents and innovation in his sample is much weaker, Schmoch (2003) suggests trademarks to be a good indicator for innovation in the service sector. Mendonca et al. (2004) also suggest that trademark analysis can capture relevant aspects of innovation phenomena by empirically studying the key patterns of Community Trademarks for 15 countries within the European Union. These findings are complemented by an in-depth study of the Portuguese case. In a micro study for a sample of Swedish companies, Malmberg (2005) finds the relation between trademarks registrations and the introduction of new products to vary considerably across different sectors thus suggesting that the use of trademarks as innovation indicator has to be made selectively, probably on per industry basis.

trademark indicators are also subject to challenges such as strongly skewed value distributions or a limited comparability across countries due to heterogeneity in national trademark legislation and a home bias in the propensity to register towards domestic trademark offices. Thus, similar to patents, the usage of trademark-based indicators across countries requires an appropriate selection and modification of the raw data from various trademark offices.[17] However, according to Millot (2009), building an indicator based on trademarks that are filed in different offices at the same time (in analogy to triadic patents) may detain important information. Unlike patents, trademarks often are strongly associated with specific national markets and have a strong link to local aspects such as language and culture. Furthermore, there may be different trademarks across countries for the same product. In order to account for these idiosyncratic characteristics of trademarks, in this study I use so-called "cross-border" trademarks which are defined by the OECD (2010) as applications at the USPTO except for the United States and countries with a high propensity to file trademarks in the United States such as Australia, Canada, Mexico and New Zealand. For these countries, the indicator uses adjusted counts that are based on the relative share of their filings at the JPO and the European Office for Harmonization in the Internal Market (OHIM).

3.4.3 Specification of Age Effects

The set of demographic variables measuring the age distribution constitute the main explanatory variables of interest in our econometric model. In order to incorporate these variables in the regressions, I use two different specifications. The first specification maps the age distribution of the population of each country. Analyzing the age structure of the total population allows to capture any life cycle dynamics and dependency effects stemming from non-working young and old aged population groups as well as effects resulting from age-related shifts in the productivity level within the workforce.[18] In a second specification, the age distribution of the workforce is analyzed by skipping non-working groups from the model. While this approach excludes any macroeconomic dependency effects from the analysis, productivity changes in producing innovation within the workforce can be studied in more detail. Demographic data for the overall population are drawn from the United Nations World Population Prospects (WPP) database, workforce age data is taken from the International Labour Organization (ILO).

As stated by Higgins (1998), Lindh and Malmberg (1999a) and Bloom and Canning (2001), a basic problem in using regression models for the analysis of age effects is that due to the high dimension not all age groups of a distribution can be included in the regressions because of

[17] An indicator based on international registrations at the World Intellectual Property Organization (WIPO) is not used in this study because some important OECD countries have not been member in the Madrid System for a long time, thus making an analysis over time not possible (see also Millot, 2009; Schmoch and Gauch, 2009).

[18] It is important to keep in mind that while dependency and productivity effects are captured by this specification, any mere size effects resulting from population shrinkage are excluded from the analysis by using per capita measures. Of course, this assumes that there are no scale effects through which changes in the size of the total population affect innovation output on a per capita basis.

multicollinearity and degree-of-freedom problems. In order to address this problem, age effects are often represented in a parsimonious form by imposing restrictions on the coefficients of the various age share groups. Thereby, the main purpose is to reduce the number of variables in the model without losing too much relevant information. A common way is to use broad, aggregated measures for the population structure, mostly youth and old dependency rates or even only the total dependency rate. While the main benefit from using these broad measures is that multicollinearity and the reduction of degrees of freedom is less a problem than when more detailed age shares are included in the model, this comes at the costs of neglecting potentially relevant parts of the total age variation in the analysis of age effects. Another way to estimate age effects is to restrict age profiles to low-order polynomials as shown by Fair and Dominguez (1991) and also applied by Higgins (1998), Luehrmann (2003) and Bosworth and Chodorow-Reich (2007). This allows using the information of the entire age distribution while keeping the model rather simple and addressing multicollinearity problems. The age share coefficients are commonly restricted to lie on a third or fourth-order polynomial. A third option is to specify age effects by including shares for a limited number of aggregated age groups and assuming that the age effects are identical within each of the age groups but may vary between the different age groups. This approach is used, for instance, by Lindh and Malmberg (1999a,b), Feyrer (2007) and Frosch (2011a).

In order to model the age distributions in the main regressions of this study, I rely on the last of the three procedures described above. According to Lindh and Malmberg (1999a), using age share groups may be seen as a compromise between the other two methods by capturing age structures in some detail while being more direct and flexible than the polynomial approach. However, collinearity may still be an issue and it may be problematic to identify the most relevant age phases within an agent's individual economic life cycle thus making the definition of boundaries between the specific age share groups somehow arbitrary. Regarding the estimation of age effects within the total population, I follow the classification used by Lindh and Malmberg (1999a,b) and de la Croix et al. (2009) and divide the population into five sub groups: children (0-14 years), young adults (15-29 years), mature adults (30-49 years), middle aged (50-64 years) and retirees (65 years and above).[19] According to the authors, this aggregation of age groups is a pragmatic approximation that works well for growth equations for the OECD countries without running into collinearity problems. The age structure of the workforce is modeled in a similar manner, whereby I orientate on Frosch (2011a) regarding the classification of the working age groups and differentiate between three sub groups: young professionals (20-34 years), prime-age workers (35-49 years) and older workers (50-64 years). However, while these classifications allow to estimate any population and workforce effects across the age dimension, the age share group approach comes to its limits when a second dimension is introduced to the models in some detail. Therefore, I will use the polynomial approach when estimating alternative regression models using age specific educational attainment measures, that is, when age and educational attainment data are crossed.

[19]Lindh and Malmberg (1999a) further divide the oldest age group in young retirees (65-74 years) and old retirees (75 years and above).

3.4.4 Non-demographic Control Variables

As demographic factors by their own may only explain a minor part of the overall variation in innovative performance across countries and time, it is important to control for other confounding factors in the regression model. This section introduces the set of non-demographic control variables used in the models. These variables rest upon theoretical and empirical considerations and are typically described in literature to affect innovative activity. Due to the fixed effects specification, variables with only little variation over time (e.g. country size) are excluded from the model. An overview of all variables used in the models and their measurements is also given in Table 3.1.

R&D employment [RES]: The number of knowledge workers and researchers that are occupied in research-related activities is critical to the output of ideas and innovation. The variable *RES* is operationalized by the number of researchers per thousand workforce and controls for shifts in the allocation of labor resources from other sectors towards the R&D sector and vice versa.

R&D expenditure [EXP]: Expenditure in R&D is an essential driver of innovation as it directly captures how much firms and the public sector invest in R&D efforts. R&D expenditure covers expenditures for various R&D related issues including hiring R&D staff or investment in physical capital. The variable *EXP* is measured as the share of gross domestic R&D expenditure in percent of total capital formation (formerly gross domestic investment).

Education [EDU]: There is some empirical evidence that the quality of human capital has an impact on innovative performance. High human capital investment in the sense of a well-established and efficient education system provides not only highly-skilled workers to the R&D sector (and thus may be correlated with the variable *RES*) but also may affect their productivity. The variable *EDU* is measured by the average years of total schooling of the population aged 25 years or above. Alternatively, in a further analysis more detailed age-specific education profiles are used.

Openness [OPE]: Openness to trade is critical to innovation as it enables countries to benefit from each other's research efforts. According to Kiriyama (2012), there are three main transmission channels through which trade may affect innovation. First, imports and foreign direct investment (FDI) can give access to foreign knowledge and serve as vehicles of technology diffusion. Second, imports and FDI as well as technology licensing contribute to intensifying competition, thereby indirectly giving incentives to innovate. Third, exports can affect innovation by serving as a learning opportunity as well as by giving incentives for innovative activities. The variable *OPE* is proxied by the ratio of cross-border trade to GDP by calculating the sum of the values of imported and exported goods and services divided by GDP.

Access to computers [COM]: Computers constitute a special form of physical capital available to the R&D sector. It is widely recognized that the spread of computers and information technology has a positive impact on overall productivity at the firm and country level. As research activities are often characterized by the production of a lot of information that has to be processed, stored and analyzed, access to computers and software should especially in the R&D sector enhance productivity. The variable *COM* is measured by the number of computers per 1'000 population.

It is important to be aware of some special characteristics of our data regarding the control variables described above when it comes to the interpretation of estimation results. First, there might be collinearity between the control variables. In particular, there are good reasons to think that the variables RES and EXP are highly correlated with each other.[20] While collinearity in the control variables should neither affect the explanatory power of the model as a whole nor the consistency of the coefficients for the demographic variables (which lie in the primary focus of this study), the coefficients of single control variables should be interpreted with some caution. Second, some of the control variables might be correlated with the demographic variables in the model, too. For instance, R&D firms could extent their expenditures in physical capital to a higher degree than other sectors in order to counteract the effects of a shrinking workforce due to demographic effects. Similarly, individuals might opt for more years of schooling when they anticipate longer life times following from decreasing mortality rates. In both cases at least one of the control variables is correlated with the demographic variables in the model with the consequence that some of the variation due to age effects is filtered out by the control variables.

3.5 Estimation Results

The empirical results of the regression analysis in this study are represented in six sections. In the first two sections, the main results regarding the macroeconomic analysis of the age-innovation link are presented for the age structure of the total population (section 3.5.1) respectively the age structure of the workforce (section 3.5.2). The subsequent four sections report results for various robustness checks. Section 3.5.3 replaces the vector of population age shares by a matrix of age-education shares in order to control for differing levels of education across age cohorts of the total population. Section 3.5.4 estimates models with an alternative functional form while Section 3.5.5 re-estimates the system GMM estimates by stepwise limiting the maximum number of lags used as instruments. Finally, in the last section I present the results of a number of further tests and robustness checks.

3.5.1 Population Age Effects

This section concentrates on the estimation of age effects stemming from changes in the age distribution of the total population - that is, the aggregated age structure of both active and

[20] Indeed, there is a rather high positive correlation factor of 0.7 for the two variables.

non-active population parts. Therefore, the dependent variables in the models are standardized by the size of total population. Using per capita rates instead of levels for the innovation indicators ensures that results are not driven by simple size effects that result from changes in total population size. Table 3.3 shows the regression results regarding the link between the population age structure and the number of new applications for triadic patents per million capita by using various estimators. As there is some evidence for heteroscedasticity and autocorrelation in the the data, results are presented with robust standard errors. The first column presents the results for the static baseline model with country and time fixed effects. The coefficients for the various age groups show the typical hump-shaped pattern of the age-innovation relationship that also has been found in previous micro-based studies at the individual and firm level. While there is a weak relation between the number of patent registrations and the share of age groups of children and young adults, the link becomes more pronounced and statistically significant for the mature adults and middle aged age groups. Especially the group of individuals aged 30-49 years is strongly positive associated with the number of per capita patents. Then, the effect gets weaker again for the group of older individuals aged 65 or above.[21] The stock of knowledge, proxied by GDP per capita, seems not to play a crucial role in the generation of new patents. Furthermore, looking at the control variables reveals that only the variables measuring the number of researchers and R&D expenditures are statistically and economically significant in the model and have - as expected - positive signs.

Columns (2) to (6) in Table 3.3 show the results for the dynamic specifications with differing estimators. The autoregressive term is highly significant, statistically and economically, for all specifications thus suggesting that dynamic feedback effects play a crucial role in the generation of new patent applications. The model in column (2) uses the pooled OLS estimator while column (3) relies - similar to the baseline model - on the LSDV estimator and controls for country-specific effects. As already mentioned in the section before, in the presence of dynamics both estimators are biased in differing directions regarding the parameters for the lagged dependent variable in the models and are therefore used as a consistency check. Thus, a consistent estimator should produce an autoregressive coefficient α that lies within the range of 0.861 and 0.458. Looking at the remaining specifications in columns (4)-(6), one can see that this is the case for the corrected LSDVC as well as the system GMM estimator, but not for the difference GMM estimator. With an α of 0.427, there is the indication that the difference GMM estimator suffers from weak instruments, presumably due to the high persistency in the data series. Both GMM techniques are used to control for potential endogeneity by using lags as instruments for the autoregressive term as well as for the two control variables measuring the number of researchers and the expenditures in R&D. I choose these variables to be instrumented because I assume that potential reverse causation may be present especially here.[22] While the LSDVC estimator would be the first choice if one expects no endogeneity problems,

[21] One has to keep in mind that the individual age shares are parts of the entire age distribution and hence only relative effects can be interpreted; we will come to this point in more detail in section 3.5.4.

[22] As an experiment, I instrumented each of the demographic variables, too. Doing so, the qualitative findings remained rather stable even though the point estimates became less pronounced. However, at the same time the number of instruments got very high, so I did not further persue this approach in the study.

the system GMM estimator is the preferred estimator in this study.

The results of the system GMM estimations are presented in column (6). Compared to the results of the static baseline model, the hump-shape of the age effects becomes flatter and less pronounced when adding dynamics and instruments to the model. Nevertheless, the general pattern of the age-innovation relationship remains, again with a statistically significant peak for the 30-49 year old age group. In contrast to the baseline model, the control variable measuring education becomes now highly significant while the effect of the instrumented variable RES which measures the number of researchers disappears. However, due to potential collinearity between some control variables, the estimation results for the parameters of the single control variables should be interpreted with caution. In general, Table 3.3 shows that the typical inverse U-shaped age-innovation pattern is quite stable over the different specifications using triadic patents as an indicator, even though the magnitude of the pattern differs and is quite small in the case of the (biased) pooled OLS estimator. Figure 3.1 gives a visual overview of the age effects pattern on patenting for all used specifications.

Table 3.4 shows the results when triadic patents are replaced by the number of new cross-border trademark applications per million capita. The static baseline model in column (1) shows again the typical hump-shaped pattern for the age parameters. As in the case of triadic patents, the age effects peak again for the age group of the mature adults (30-49 years), suggesting that a large share of this age group has a positive affect on the number of newly filed trademarks. However, the effect of the mature adults is only statistically significant at the nine percent level while the remaining age coefficients are statistically not different from zero at common levels. The parameter GDP per capita turns now negative, thus suggesting an negative pooling out effect if the variable is interpreted as an an indicator for the stock of knowledge. But as already mentioned, GDP per capita may be only a weak proxy for the stock of knowledge (especially when it comes to trademarks), and the estimates are not statistically significant at common measures. Again, the columns (2) to (6) show the results for the dynamic specifications. The LSDVC and system GMM estimations produce coefficients for the lagged dependent variable that lie within the consistent range ($0.942 > \alpha > 0.563$) that is determined by the OLS and LSDV estimators. In contrast, with a value of 0.265, the difference GMM estimator again fails to produce a consistent estimate for the lagged dependent variable. The hump-shaped age pattern on trademarks that peaks with the mature adults remains stable when dynamics are included to the model, even though the mid-aged group (50-64 years) diverges somehow from this classical pattern. The results of the system GMM estimator are statistically significant for all age groups with exception of the (diverging) mid-aged group, but the estimated age curve is in general quite flat, especially when compared to the static baseline model. Figure 3.2 illustrates the relationship of age and cross-border trademark filings for the full set of model specifications.

3.5.2 Workforce Age Effects

In this section age effects are analyzed by focusing solely on the age structure of the working population in order to empirically study potential changes in the inventive productivity across different age groups within the workforce in more detail. Again, the several indicators of innovation are standardized by the size of the total workforce. Looking at the relationship of innovation and age patterns within the active workforce, Table 3.5 reveals the results of the regression analysis when the number of triadic patent registrations per million workers is the dependent variable. The results of the static baseline model suggests that especially the young professionals (20-34 years) and prime-age workers (35-49 years) contribute positively to the generation of new patents compared to older workers (50-64 years). However, the results are not statistically significant at common levels. The control variables education and openness to trade have an unexpected negative sign, while the number of researchers within the workforce and R&D expenditures contribute positively to the number of filed patents. When using the system GMM procedure with instruments for the lagged dependent variable as well as for R&D expenditures and the number of researchers in the workforce, the overall age pattern on patent registrations remains robust but is still statistically insignificant. Furthermore, the education variable changes to the expected positive sign. Looking at the full set of models, only the difference GMM estimator produces both economically and statistically significant results for the two age groups of the young professionals and prime-age workers. However, its autoregressive coefficient misses to be within the consistent boundaries given by the upward-biased autoregressive coefficient of the OLS estimates and the downward-biased autoregressive coefficient of the LSDV estimates ($0.870 > \alpha > 0.437$) thus suggesting that lagged levels on their own are only weak instruments. Overall, the results cannot give clear evidence that the age structure of the workforce matters regarding the number of triadic patent applications, given the fact that most coefficients of the age variables are statistically not different from zero.

Finally, Table 3.6 reports the results regarding workforce age effects and the number of cross-border trademark registrations per million workers. The static fixed effects model in column (1) shows a weak downward trend in trademark output as workforce age increases. However, only the coefficient of old workers is statistically significant at the 8 percent level. When using GMM techniques in order to implement a linear dynamic panel structure and to control for endogeneity, the downward trend remains but all age variables become statistically insignificant. Thus, similar to the patents regressions, there is no overall evidence in the given data that the age distribution of the workforce on its own has a crucial effect on the number of registered trademarks in per workers terms.

3.5.3 The Role of Age-specific Education Levels

As stated before, the quality of human capital might have a critical impact on innovative performance. Until now the level of educational attainment entered the model by a single control variable based on the widely used indicator of Barro and Lee (2012) which measures the average years of total schooling within the population aged 25 and older. However, more detailed information about the age distribution of human capital is desirable as there is the risk of spurious correlation in the age-innovation relation due to unequally distributed education levels across age cohorts. In order to study whether the age effects found in the previous sections are mainly driven by age-specific differences in human capital endowment, the variable EDU is replaced by age-specific education indicators. Population age and education data is based on the dataset from the International Institute for Applied Systems Analysis (IIASA) and the Vienna Institute of Demography (VID). This dataset contains educational attainment distributions by age group which are constructed on the base of back-and forward projections using education data from the reference year 2000 and considering the fact that individuals with different levels of schooling tend to have varying rates of mortality.[23] Unfortunately, comparable long-term time series data are not available for the workforce, so this section concentrates solely on age-education effects originating from the whole population.

As a first exercise, in order to test for qualitative differences between the two datasets, the measure of Barro and Lee (2012) is replaced by the same measure (average years of total schooling within the population aged 25+) form the IIASA/VID dataset. Alternatively, EDU is replaced by a more detailed (but still age-unspecific) differentiation of educational attainment including four variables that measure the shares of people aged 25+ or older with different levels of educational attainment: no education, primary education, secondary education and tertiary education. In both exercises the age effects attained in the previous regressions models remain stable, indicating that the two datasets contain rather similar information.

In order to analyze both the age and education dimensions simultaneously, in a second exercise the age share groups and education variables are replaced by population aggregates along a two-dimensional age-education matrix. Due to the high dimensionality and in order to avoid the proliferation of variables and an overly absorption of degrees of freedom, the population is divided rather broadly across both the age dimension (young aged between 15-39 years, mid-aged between 40-64 years and old individuals with an age of 65 years and above) and the education dimension (low educated with no or primary education and high educated with secondary or tertiary education), thus resulting in 6 parameters to be estimated.[24] For space reasons, I focus on the modified regression estimates from the baseline static fixed effects setting as well as the dynamic system GMM specification. Table 3.7a as well as Figures 3.5 and 3.6 in Appendix 3 report the results. After controlling for age-specific education levels, the baseline fixed effects model shows still age effects on the number of patents and trademarks applications, with peaks for the mid-aged groups. However, the estimated effects are of lower magnitude than the coefficients found on pure age effects in section 3.5.1. Interestingly, both low and high educated mid-aged groups have a positive correlation of similar magnitude with

[23]For a detailed description of the methodology and the underlying assumptions see Lutz et al. (2007) for back-projections and KC et al. (2010) for forward-projections.

[24]The age group of 0-14 year old individuals is not included in the IIASA/VID dataset, but due to its young age this group would fall per definition in the low education category.

the two innovation measures, even though only the results in the low educated group are statistically significant. In contrast, when using the system GMM approach, any effects from the low educated groups disappear while there remains a strong and statistically significant positive relation between the highly educated mid-aged group and the number of filed patent applications. The system GMM estimates indicate also differing age effects within the high educated group on trademark filings but the results remain statistically insignificant.

While the broad categorization of age-education shares keeps the number of regressors at a reasonable level, it may detract too much information from the data. Hence, in an alternative specification I use the full range of information available in the IIASA/VID dataset and incorporate all 11 age groups (15-19, 20-24,..., 60-64 and 65+) and break-up the education categories into more detailed sub-groups (low educated with no or primary education, medium educated with secondary education and high educated with tertiary education). Yet, as the sheer number of variables and potential multicollinearity prevents us from separating the individual effects and drawing inference from the total set of aggregates with 11*3 age-education combinations, I impose a cubic polynomial curve across the age dimension for each educational attainment sub group. This allows each age-education share to have an effect, but restricts these effects to lie on education-specific polynomial curves.[25] Table 3.7b reports the estimation results with the nine compounded polynomial terms (which have no direct interpretation) while Figure 3.7 visualizes the implied age profiles for each educational category. The results suggest that there are no age effects in the low educated sub-group while there are some age dynamics with differing patterns and peaks in the medium and high educated groups. Even though not all estimated polynomial coefficients are individually statistically significant at common levels, the Wald test indicates that most of them are jointly significantly different from zero within the various educational categories. However, despite their significance in statistical terms, the magnitudes of the implied age effects on the education-specific polynomial curves are rather small. Surprisingly, though the polynomial approach is intended to mitigate multicollinearity problems, I find strong evidence that the polynomial variables suffer from serious multicollinearity.[26] With partial correlation values around 0.99, the compounded polynomial terms within each of the education categories are highly correlated with each other. This derogates the reliability of the estimates for the individual polynomial variables which in turn affects the accuracy of the implied age profiles.

3.5.4 Functional Form and Interpretation

From a theoretical perspective the process of innovation generation can be represented in the form of a knowledge production function of Cobb-Douglas style that regards the various age share groups as classical input factors that enter in the production in a multiplicative manner.

[25] For a detailed description of the approach using polynomial restricted coefficients see Appendix 2.

[26] Lindh and Malmberg (1999a) find similar multicollinearity issues for their OECD sample when restricting age effects on saving and investment to lie on a cubic polynomial curve.

The log-log specification allows to estimate the elasticities in a simple linear manner. But using the log-specification has a further convenient side effect. Due to the compositional data nature of the age shares, they are subject to the constant sum constraint $\sum_j x_j = 1$, that is, the full set of j age share groups have to sum up to 1 for a given time period and country. While using their non-log form in the regression models requires to skip one group from the equation due to collinearity with the constant, the logarithmic form releases the exact linear relationship between the intercept and the full set of demographic age groups (see also de la Croix et al., 2009). Therefore, it comes not surprisingly that some studies have followed this path and included the full set of variables representing the age share distribution in logarithmic form into their growth or knowledge regression models. However, when it comes to the interpretation of the estimated coefficients, such an approach is not without problems. Even though the specification is statistically feasible in the sense that it can be estimated by standard estimation approaches, including the full set of age shares into a single regression model makes classical interpretation of the coefficients difficult as it would implicitly need to assume that the proportion of one age cohort can be altered without changing the proportion of one or more other cohorts which is, of course, not possible.[27] In fact, Lindh and Malmberg (2009) remark that the net effect of a change in a single age share group cannot be directly inferred by looking at its coefficient, but the net effect will also depend on corresponding changes in the other age shares and thus needs to be interpreted in terms of changes in the whole age distribution.

In order to test whether the decision to include the full set of age shares into our regression equations has a major impact on the results, the youngest age group (0-14 years) is dropped from the specification and taken as reference group. Doing so proves to have no qualitative impact on our results. As a second experiment to get further insights whether our results are driven in general by the log-linear functional form, the logarithms are abandoned from the demographic age share groups (see Table 3.8 in the appendix). This assumes that the age share groups enter not multiplicatively into the knowledge production function, but additively. For completeness, I also replace the logs from the other independent variables in order to attain a log-lin (or semi-log) specification, but robustness tests show that it literally does not matter whether the control variables enter the model in their logarithmic or non-logarithmic form. One has to keep in mind that due to the semi-log functional form the coefficients have now to be interpreted in terms of semi-elasticities, that is, the percentage change of the dependent variable following an unit change in an independent variable. As Table 3.8a shows, the hump-shaped population age-innovation pattern remains remarkably stable and again the strongest age effects can be found for the age group of the 30-49 year old individuals for both patent and trademark filings. Overall, the age effects tend to be more significant in the semi-log specifications, both in statistical and economical sense, thus suggesting that our previously attained log-log estimates are comparatively conservative. Only for the system GMM regression on trademarks the effects are quite small and statistically not different from zero. The workforce age-innovation relation follows a similar form as the previously attained results from the log-log specification, too. In the static fixed effects models we find a significant negative association between patents and

[27] See also Aitchison and Bacon-Shone (1984) for a early discussion of the problem.

trademark filings and older workers, but this relation becomes statistically insignificant in the system GMM model. Overall, the results show that our previously attained results remain robust to the tested differences in the functional form.

3.5.5 The Case of Too Many Instruments

As mentioned before, the GMM models in this analysis might be unreliable due to the high number of used internal instruments in relation to the small number of cross-sectional units. While there is neither a formal test for instrumental proliferation nor a clear guidance in the literature at which point the number of instruments should be regarded as too large relative to the number of units and time periods, Roodman (2009a) suggests as a rule of thumb that the number of instruments should not exceed the number of cross-sectional units in order to reliably capture the endogenous parts from the instrumented regressors. As we can see the number of instruments in our system GMM models for population age effects exceeds by far our small number of cross-sectional units (22 countries) with 494 instruments in the patents regression (first column in Table 3.9a, Appendix 3) respectively 338 instruments in the trademarks regression (first column in Table 3.9b). In order to test whether the results remain robust when less instruments enter the equations, I stepwise restrict the maximum number of lags in the instrument matrix that is used in the system GMM specification. Columns 2 and 3 in Tables 3.9a,b show the results for population age effects on patents and trademarks when a maximum of 5 respectively 2 lags are used as instruments. The overall hump-shaped age pattern remains quite stable for both patent and trademark GMM regressions when the number of instruments is reduced. However, the number of instruments remains further quite above the rule of thumb stated by Roodman (2009a). As a further step to reduce the number of instruments, the data is aggregated to non-overlapping 3-year averages which reduces the number of T.[28] The general hump-shaped pattern still remains for patents and trademarks (last columns in Table 3.9a,b), but even though the procedure drops the number of instruments significantly, it still remains quite high.

Whether our unrestricted and restricted GMM regressions produce reliable estimates depends critically on the strength and validity of the used instruments. Appropriate instruments should be highly correlated with the instrumented endogenous variable but at the same time need to be uncorrelated with the error term. Unfortunately, the typical test procedures for weak instruments developed for linear IV regression models cannot be used in our context and there is no standard test for instrumental strength available when using the difference and system GMM regressions (Stock et al., 2002; Bazzi and Clemens, 2009). Even though the instruments of the system GMM estimator are supposed to be stronger than the instruments of the difference GMM approach (especially when time series are persistent), Bun and Windmeijer (2010)

[28] An optional way to reduce the number of instruments beside restricting the maximum number of lags and aggregating upon the time dimension to reduce T is given by Roodman (2009a). He proposes to “collapse” the instrument matrix in the sense that it includes not one instrument for each lag and time period of the instrumenting variables but only one instrument for each lag.

show that there is no guarantee that system GMM instruments do not suffer from weakness. In contrast, there are widely accepted direct and indirect test procedures available for the validity of GMM instruments. First, I use the Arellano-Bond test for serial correlation in the first-differenced residuals, which is also regarded to examine the validity of the used instruments. While first-order autocorrelation is common due to the typical construction of the GMM procedure and does not imply that the model suffers from misspecification, serial correlation of higher order may compromise instrumental validity. The second to last rows in Tables 3.9a and 3.9b report the test results. I find no evidence for autocorrelation problems in the system GMM estimations for triadic patents. However, in the cross-border regressions the null of no second-order autocorrelation is rejected at the 9 percent level when restricting the instrumental to a maximum of two lags. Interestingly, the AB test shows no signs of higher order serial correlation when using 3-year averages in the trademark regression.

Similar to testing for autocorrelation, the Sargan test of over-identifying restrictions as discussed by Arellano and Bond (1991) allows to test the overall validity of the used instruments for the system GMM estimations. There is no evidence of non-exogenous instruments for the unrestricted system GMM models as the null hypothesis that the over-identifying restrictions are valid cannot be rejected (see last rows in Tables 3.9a,b). However, when the number of instruments is stepwise reduced, the null is clearly rejected in the patent regressions. The results should be interpreted with some caution. Even though the Sargan test is according to Roodman (2009b) not so vulnerable to instrument proliferation compared to the alternative Hansen test, the high number of instruments used in our system GMM models might still weaken the explanatory power of the test. Roodman (2009b) argues that not only low, but also high p-values of the Sargan test might be seen as an indication for invalid instruments. For instance, with a value of 0.97 the obtained p-value of the test in the unrestricted trademark regression is close to unity. Given that the one-step Sargan test tends to overreject the null hypothesis in presence of heteroscedasticity, real p-values might even be higher. Overall, the results suggest the system GMM regression might still suffer from endogeneity due to the numerous and potentially non-exogenous instruments.

3.5.6 Further Tests and Robustness Checks

In the previous sections the age-innovation relationship was analyzed in static and dynamic settings using various estimators and testing different specifications and functional forms. In order to examine the robustness of the obtained results further, the models undergo in this section additional tests and robustness checks. For space reasons, I do not report all numerical results in detail, but focus on a brief description of the main findings. Detailed estimation and test results are available from the author upon request.

Robustness Checks

The robustness of the models is further tested to various alternative specifications and sample sub-groups. In a first step, sensitivity tests are applied with different age boundaries for the age share groups in order to test whether results critically depend on the aggregation of age structure information. Experimenting with alternative aggregates shows that the age effects are rather robust to changes in the age group specifications. In another experiment, the impact of life expectancy on age structure effects is tested. There is the possibility that decreasing mortality rates and better old age health may have effects on factors such as investment in education, the length of the working period, life cycle dynamics as well as productivity levels which in turn change the age-innovation relationship. In order to capture such crossover-effects, I include a variable measuring life expectancy at birth in years as well as interaction terms between life expectancy and each age share group in the model. The estimation results give some hints that indeed there are interdependencies between age effects and life expectancy and that age effect profiles get flatter with rising life expectancy. Unfortunately, there is also strong evidence that the extended model suffers from serious multicollinearity between the age share group variables and the interaction terms, thus making statistical inference difficult.[29]

In another series of experiments, the configuration of the control variables is changed. For instance, including the number of computers per 1'000 people (COM) to the model does not change the coefficients of the other variables in the model significantly. The coefficients for the variable itself mostly remain rather small and statistically insignificant. In another check, the variable controlling for the number of researchers is skipped from the specification while at the same time Israel is included to the sample (for which no data on the number of researchers are available) thus increasing the sample from 22 to 23 countries. The age effects change only slightly and the overall results remain stable. Finally, all control variables (RES, EXP, EDU, OPE) are skipped from the models. As mentioned before, some of these control variables might correlate with the age variables and filter out some of the effects that are induced by demographic change. As expected, the link between the population age distribution and patenting remains and is sometimes even more pronounced when the control variables are removed. The same is true for the relationship between age and the number of filed trademarks.

Finally, I test a specification where each variable is aggregated to non-overlapping 3-year averages. As showed in the previous section, this procedure is an efficient way to reduce the number of instruments in the system GMM regressions. But it also lessens potential problems arising from noisy data and country-specific short-term fluctuations and is therefore conducted for the full set of models, too. Given the rather short time series in our sample, I decide to use 3-years averages instead of 5-year averages (the latter are often used in literature), as it is a good compromise between filtering out short term noise and keeping the number of observations at a sufficient level. The estimation results for population age effects with the aggregated data remain rather robust and previously attained general propositions are confirmed, thus suggesting

[29]For instance, the correlation between the age group of the young (0-14 years) and its interaction term with life expectancy is with 0.99 close to perfect.

that short-term noise is no serious problem in our population regressions. Similarly, the results for workforce age effects keep their pattern but remain statistically insignificant. Hence, even after smoothing out potential heterogeneous short-term fluctuations by data aggregation, there so no clear evidence that changes in the age distribution of the workforce have an impact on patent and trademark filings.

Tests

While autocorrelation tests for the system GMM estimates were already reported in the context of instrument validity, I also test the baseline fixed effects models for heteroscedasticity and serial correlation. Following Baum (2001) and Greene (2003), a modified Wald statistic for groupwise heteroscedasticity in the residuals of the fixed-effect regression models is computed. The null hypothesis of homoscedasticity is rejected for all models. In order to test for autocorrelation in the static panel data models, the procedure described by Wooldridge (2002) and Drukker (2003) is used which is applicable for random or fixed effects models. While autocorrelation seems to be no problem for the baseline model looking at age effects on triadic patent output, static models with cross-border trademarks as dependent variable may be affected by autocorrelation. Therefore, the decision to use heteroscedasticity and autocorrelation robust standard errors seems to be the right choice in our models.

I also apply tests regarding cross-sectional dependence for the static panel models, which arises when the error terms of individual cross-sectional units are correlated which each other because of factors such as interdependency effects, spatial dependence and the presence of common shocks. In the case of innovation, an increasingly macroeconomic integration and closer ties and interactions between international R&D efforts may foster spill-over effects across the various national innovation systems. According to Hoyos and Sarafidis (2006) and Sarafidis and Robertson (2009), the consequences of cross-sectional dependence on estimation results depend on a number of factors and may in severe cases cause estimators used in static and dynamic panel data models to be biased and inconsistent. Even though the time fixed effects component inherent to all model specifications in this study captures universal shocks and thus lessens problems of potential contemporaneous correlation, there might still be heterogeneous cross-sectional dependence in the error terms. Using different statistical measures (Pesaran, Friedman and Frees) as described by Hoyos and Sarafidis (2006), I detect no clear evidence for cross-sectional dependencies in the error terms for the static specifications. However, these test results might be unreliable as they rely on panels with a high number of cross-sectional units and a low number of time series observations.[30] I refrain from testing the dynamic panel models with difference and system GMM estimations as procedures such as suggested by Sarafidis et al. (2009) require a larger N than available in this study in order to produce reliable results. Thus, cross-sectional dependence might still be an issue in our dataset.

[30]Similarly, the broadly used Lagrange Multiplier (LM) test proposed by Breusch and Pagan (1980) cannot be conducted at this point as it needs the time dimension to be considerably larger then the cross-sectional dimension, a requirement that is not given for the used dataset.

Finally, I test for unit roots. Non-stationary in the sense that the mean and the variance of the underlying processes are not constant over time can cause spurious correlation. Therefore, the testing procedure for panel data described by Levin et al. (2002) is applied.[31] In general, as remarked by Lindh and Malmberg (2009), the age share variables in our models should by definition not be unit root processes in the long run due to their natural boundaries. However, the inertia and persistence of the demographic variables might nevertheless cause spurious regression results. I find no evidence for the existence of unit roots in the tested data with exception of the time series for the variable of the middle aged group between 50-64 years, where the null hypothesis of non-stationary cannot be rejected at common significance levels. This variable is integrated of order one, I(1), as stationarity seems to be established by taking the first difference. As only one variable in our models is tested to be integrated (which implicitly also rules out any cointegration in our model), using the middle aged cohort variable as level data might cause some bias.[32] However, Phillips and Moon (1999) show that spurious correlation resulting from integrated variables is less a concern in panel data sets than in pure time series regressions due to the cross-sectional heterogeneity nature.

3.6 Conclusion

The object of this paper has been to examine the impact of population and workforce aging on innovative performance. While previous studies have mainly analyzed the relationship between age and innovation at the individual or firm level, this paper has taken a macroeconomic perspective at the country level. In its analysis the paper has focused on OECD countries which rely heavily on innovation and technological progress as the key drivers of their economic growth. Therefore, it provides not only insights about the macroeconomic age-innovation link in general but gives also a better understanding through which channels demographic change may affect economic growth.

In concordance with findings of previous studies, the results of the regression analysis in this paper suggest that there is an inversely U-shaped relation between the population age distribution and the output of innovation in form of triadic patent filings for the sample of 22 OECD countries. While the contribution of young and old age groups to the innovation generation process seems to be relatively small, middle aged groups appear to be a crucial driver of innovation. Especially the relation between the share of the mature adults (30-49 years) within the total population and the number of new patent applications per capita is strongly positive. The findings are robust in static and dynamic panel settings using various estimators. Further, there is evidence that the estimation results do not solely emanate from different levels

[31] As the LLC test requires strongly balanced data, time series for trademarks, the workforce age groups as well for the control variables regarding R&D expenditure and the number of researchers cannot be tested for unit roots.

[32] Transforming the integrated variable in the first difference form (as sometimes suggested in literature) would reestablish stationarity, but at the same time aggravate interpretation given that the remaining age shares are stationary and remain in levels.

of educational attainment across age cohorts. Similarly, the link between the population age composition and cross-border trademark filings follows a hump-shaped pattern, even though the age-trademark link is statistically less significant in most models compared to the patent regressions. The relation becomes statistically more significant when the system GMM estimator with instrumented variables is used. However, at the same time the age effect profiles get flatter and less pronounced. Furthermore, age effects on trademarks tend to diminish for the system GMM estimates when controlling for cohort-specific educational attainment levels and are in general less robust to changes in the functional form.

The link between the workforce age distribution and innovation is not conclusive. The patent regressions give some evidence that high shares of young and prime age workers may have a positive impact on the number of patent filings per worker, but the coefficients are found to be statistically not different from zero. Similar, I find some evidence for a negative relationship between the share of old workers within the workforce and the number of newly filed trademarks. Nevertheless, the statistically weak results suggest that the main driving force behind the identified macroeconomic population age effects on innovative output is not any variance in productivity levels across worker groups of different ages but rather dependency effects and interdependencies between active and non-active population groups.

Even though numerous robustness tests were conducted in order to test the stability of the findings over a wide set of specifications including varying indicators, estimators and functional forms, there should be some cautiousness about the interpretation of the results. Measuring innovation is not a trivial task, and although a number of steps were applied in this study to overcome some of the main drawbacks of proxying innovation, they may remain rather imperfect indicators for innovation. In addition, despite treating all explanatory variables as predetermined by using lagged values, due to the high persistency - especially of the demographic variables - endogeneity may still be an issue in our dataset. Furthermore, the small number of cross-sectional units in the study limits the use of system GMM regressions with internal instruments in order to control for endogeneity. Even after restricting the maximum number of lags used as instruments, the number of instruments in the regressions remained high and there is the risk of overfitted endogenous variables.

Overall, this study provides empirical evidence that demographic change and population aging have a significant impact on aggregated national innovative performance, but future research, preferably with larger samples and using external instruments, will be needed to shed further light on the macroeconomic age-innovation link.

Table 3.1: List of Variables

Dependent variables	Description	Source
Triadic patents [PAT]	Patents per million capita resp. worker filed at the EPO, USPTO and JPO to protect same invention	OECD
Cross-border trademarks [TRM]	Foreign trademarks filings per million capita resp. worker at the USPTO, resp. OHIM or JPO	WIPO

Demographic variables	Description	Source
Population age groups [AGE]	Age share group size relative to overall popoluation size (in percent)	WPP
Workforce age groups [AGE]	Age share group size relative to overall workforce size (in percent)	ILO
Population age-education groups	Age share group size subdivided by education level relative to overall population size (in percent)	IIASA/VID

Other variables	Description	Source
GDP per capita [GDP]	GDP per capita in thsd. USD (constant USD, year 2000)	WDI
R+D employment [RES]	Number of researchers per thousand workforce	OECD
R+D expenditure [EXP]	Gross domestic R+D expenditure (public and private) in percent of gross domestic investment	OECD
Openess [OPE]	Imports + exports of goods and services in percent of GDP	WDI
Education [EDU]	Average years of total schooling of population aged 25+	Barro/Lee
Computers [COM]	Number of computers per thousand population	WDI

Abreviations: EPO = European Patent Office, USPTO = United States Patent and Trademark Office, JPO = Japan Patent Office, OECD = Organisation for Economic Co-operation and Development, OHIM= Office of Harmonization for the Internal Market, WIPO = World Intellectual Property Organization, WPP = World Population Prospects (United Nations), ILO = International Labour Organization, IIASA= International Institute for Applied Systems Analysis, VID = Vienna Institute of Demography, WDI = World Development Indicators (World Bank).

Table 3.2: Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Dependent variables				
Patents per mill. capita	35.44	30.96	0.02	129.24
Trademarks per mill. capita	49.16	46.37	1.38	315.22
Patents per mill. worker	74.13	59.20	0.06	243.61
Trademarks per mill worker	97.15	79.09	3.70	603.27
Population age shares				
Age group 0-14	18.56	2.62	13.44	29.24
Age group 15-29	21.21	2.30	15.96	27.94
Age group 30-49	28.96	1.88	23.01	34.51
Age group 50-64	16.68	2.01	12.22	21.62
Age group 65+	14.59	2.49	5.91	22.12
Workforce age shares				
Age group 20-34	37.98	4.52	29.05	50.70
Age group 35-49	39.86	3.10	30.40	57.98
Age group 50-64	22.21	4.05	13.83	32.72
Population education-age shares				
Low edu. group 15-39	4.04	4.99	0.01	24.97
Low edu. group 40-64	7.39	6.90	0.01	26.42
Low edu. group 65+	6.75	5.08	0.01	16.51
Medium edu. group 15-39	25.62	5.02	9.72	35.02
Medium edu. group 40-64	17.30	6.06	2.69	29.40
Medium edu. group 65+	6.52	4.62	0.21	16.51
High edu. group 15-39	6.67	2.72	1.24	13.81
High edu. group 40-64	5.95	2.62	0.73	13.84
High edu. group 65+	1.32	0.78	0.05	3.36
Control variables				
GDP per capita	22.19	7.90	6.63	41.90
R&D expenditure	8.97	4.36	1.23	23.70
R&D employment	5.98	2.60	1.13	15.93
Education	9.89	1.70	5.53	13.22
Openness	68.98	33.06	16.01	182.88
Computers	355.29	255.78	0.01	909.49

Note: All variables in their orginial (non-log) unit measures as described in Table 3.1.

Table 3.3: Population Age Effects on Patenting

	(1) LSDV	(2) D-OLS	(3) D-LSDV	(4) D-LSDVC	(5) diff. GMM	(6) sys. GMM
$PAT_{(t-1)}$		0.861***	0.458***	0.553***	0.427***	0.618***
		(19.09)	(5.02)	(6.65)	(4.89)	(7.48)
$GDP_{(t-1)}$	-0.0106					
	(-0.03)					
AGE $0\text{-}14_{(t-1)}$	0.549	-0.192	0.420	0.490	0.0729	0.776
	(0.36)	(-0.91)	(0.50)	(0.64)	(0.07)	(1.11)
AGE $15\text{-}29_{(t-1)}$	1.189	-0.0403	0.861	0.837***	0.507	0.805
	(0.76)	(-0.12)	(1.09)	(213.44)	(0.51)	(1.34)
AGE $30\text{-}49_{(t-1)}$	4.292**	0.331	2.603***	2.480***	2.680***	2.238**
	(2.78)	(0.91)	(3.43)	(7.59)	(3.36)	(2.38)
AGE $50\text{-}64_{(t-1)}$	2.204***	0.306	1.260***	1.148***	1.259***	1.329***
	(3.51)	(0.83)	(3.69)	(8.60)	(3.58)	(3.32)
AGE $65+_{(t-1)}$	1.723*	-0.162	0.940*	0.897**	0.818	0.473
	(1.73)	(-1.03)	(1.87)	(2.07)	(1.25)	(1.09)
$EDU_{(t-1)}$	0.298	0.245*	0.226	0.173	0.167	0.897***
	(1.10)	(1.78)	(1.47)	(0.32)	(0.75)	(2.95)
$EXP_{(t-1)}$	0.571*	0.271***	0.387*	0.356***	0.389*	0.699***
	(2.03)	(3.33)	(1.85)	(3.83)	(1.68)	(3.04)
$RES_{(t-1)}$	0.461***	-0.0273	0.159	0.0993***	0.146	-0.0560
	(3.33)	(-0.55)	(1.37)	(6.95)	(1.28)	(-0.66)
$OPE_{(t-1)}$	-0.444	0.0379**	-0.235	-0.250***	-0.266	-0.0837
	(-1.48)	(2.21)	(-1.19)	(-13.92)	(-1.56)	(-0.67)
N	497	497	497	497	473	497

Note: All variables in natural logarithm form. Robust t statistics in parentheses. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 3.4: Population Age Effects on Trademarks

	(1) LSDV	(2) D-OLS	(3) D-LSDV	(4) D-LSDVC	(5) diff. GMM	(6) sys. GMM
$TRM_{(t-1)}$		0.942***	0.563***	0.715***	0.265***	0.727***
		(35.09)	(6.91)	(33.21)	(3.61)	(11.32)
$GDP_{(t-1)}$	-0.848					
	(-0.98)					
AGE 0-14$_{(t-1)}$	-3.586	0.338	-0.926	-0.494	-2.543	1.207**
	(-1.62)	(1.03)	(-0.80)	(-0.93)	(-1.31)	(2.16)
AGE 15-29$_{(t-1)}$	-0.623	0.191	-0.0714	0.0359	-0.869	1.131**
	(-0.37)	(0.43)	(-0.10)	(0.08)	(-0.71)	(2.12)
AGE 30-49$_{(t-1)}$	2.539*	0.466	1.070*	0.843***	1.390	1.628***
	(1.76)	(0.86)	(1.76)	(12.84)	(1.36)	(2.70)
AGE 50-64$_{(t-1)}$	1.130	0.0305	0.0528	-0.134	-0.0638	0.127
	(1.08)	(0.08)	(0.09)	(-1.38)	(-0.09)	(0.33)
AGE 65+$_{(t-1)}$	-0.768	0.207	0.108	0.261	-0.336	1.042**
	(-0.72)	(0.90)	(0.18)	(1.27)	(-0.41)	(2.57)
$EDU_{(t-1)}$	-0.104	0.0341	0.00240	-0.0299	0.458	0.444**
	(-0.13)	(0.30)	(0.01)	(-0.05)	(0.52)	(2.28)
$EXP_{(t-1)}$	0.217	0.0143	0.0424	-0.0158	-0.0430	0.223*
	(1.17)	(0.28)	(0.43)	(-0.11)	(-0.28)	(1.93)
$RES_{(t-1)}$	0.463**	0.00996	0.240*	0.209***	0.347	0.0645
	(2.09)	(0.14)	(1.81)	(12.00)	(1.45)	(0.59)
$OPE_{(t-1)}$	-0.179	-0.0144	0.00129	0.0266***	-0.394	-0.113
	(-0.53)	(-0.59)	(0.01)	(41.71)	(-1.05)	(-0.99)
N	336	315	315	315	293	315

Note: All variables in natural logarithm form. Robust t statistics in parentheses. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Figure 3.1: Population Age Effects on Patenting

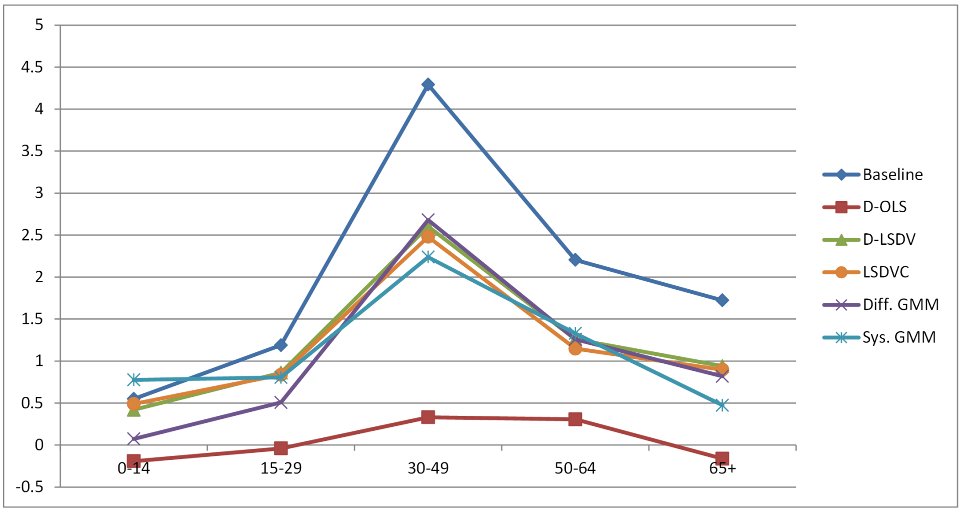


Figure 3.2: Population Age Effects on Trademarks

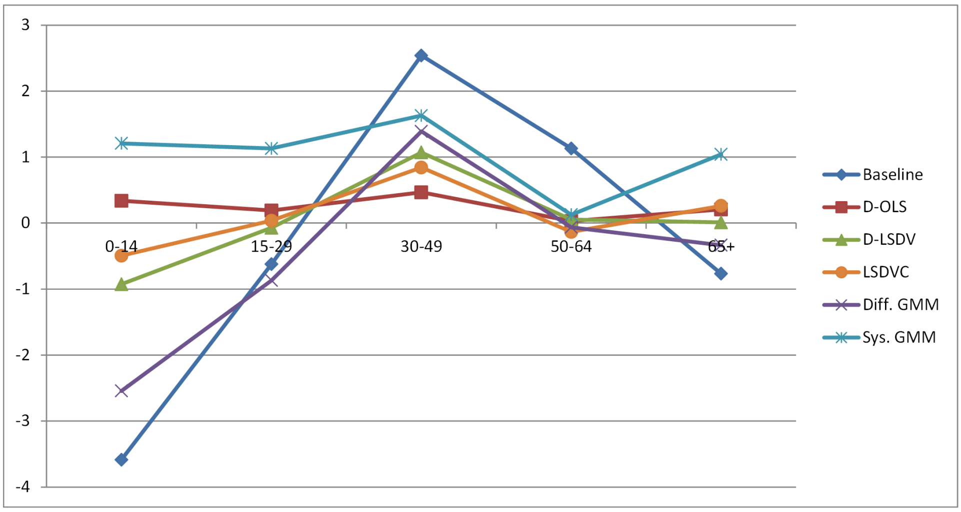


Table 3.5: Workforce Age Effects on Patenting

	(1) LSDV	(2) D-OLS	(3) D-LSDV	(4) D-LSDVC	(5) diff. GMM	(6) sys. GMM
$PAT_{(t-1)}$		0.870***	0.437***	0.540***	0.398***	0.581***
		(22.89)	(3.77)	(12.70)	(3.64)	(5.96)
$GDP_{(t-1)}$	-0.264					
	(-0.91)					
AGE 20-34$_{(t-1)}$	2.220	-0.414	1.443	1.699	2.027**	1.592
	(1.24)	(-0.67)	(1.37)	(0.84)	(2.04)	(1.14)
AGE 35-49$_{(t-1)}$	2.009	-0.344	1.418	1.757	2.209**	1.695
	(1.25)	(-0.71)	(1.47)	(1.14)	(2.39)	(1.43)
AGE 50-64$_{(t-1)}$	-0.158	-0.324	0.0263	0.268	0.249	0.606
	(-0.13)	(-1.14)	(0.04)	(0.31)	(0.39)	(0.80)
$EDU_{(t-1)}$	-0.760*	0.0904	-0.354	-0.325***	-0.596*	0.501
	(-1.84)	(1.10)	(-1.43)	(-16.78)	(-1.74)	(1.23)
$EXP_{(t-1)}$	0.598*	0.259***	0.458*	0.426***	0.508*	0.752***
	(1.96)	(3.81)	(1.91)	(12.91)	(1.90)	(3.04)
$RES_{(t-1)}$	0.525***	0.00448	0.203*	0.130	0.250**	0.130
	(3.83)	(0.09)	(1.79)	(1.53)	(2.01)	(1.27)
$OPE_{(t-1)}$	-0.615**	0.00355	-0.397**	-0.423	-0.368**	-0.262
	(-2.38)	(0.15)	(-2.20)	(-1.53)	(-2.23)	(-1.46)
N	417	417	417	417	392	417

Note: All variables in natural logarithm form. Robust t statistics in parentheses. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 3.6: Workforce Age Effects on Trademarks

	(1) LSDV	(2) D-OLS	(3) D-LSDV	(4) D-LSDVC	(5) diff. GMM	(6) sys. GMM
$TRM_{(t-1)}$		0.942***	0.483***	0.659***	0.293***	0.681***
		(34.25)	(6.73)	(16.63)	(4.65)	(11.63)
$GDP_{(t-1)}$	-0.795					
	(-1.33)					
AGE $20\text{-}34_{(t-1)}$	-2.059	0.520	-1.529	-1.199	-0.686	-0.419
	(-0.73)	(0.62)	(-0.87)	(-0.63)	(-0.28)	(-0.31)
AGE $35\text{-}49_{(t-1)}$	-2.760	0.460	-1.682	-1.166	-1.267	-0.881
	(-0.99)	(0.58)	(-0.92)	(-1.07)	(-0.53)	(-0.66)
AGE $50\text{-}64_{(t-1)}$	-3.091*	0.260	-1.996*	-1.598	-2.154	-0.895
	(-1.87)	(0.57)	(-1.83)	(-1.58)	(-1.57)	(-1.32)
$EDU_{(t-1)}$	-0.00617	0.0703	-0.0516	-0.0681	0.418	0.513*
	(-0.01)	(0.68)	(-0.12)	(-0.09)	(0.57)	(1.80)
$EXP_{(t-1)}$	0.184	0.0111	0.0855	0.0223	0.0367	0.153
	(0.85)	(0.18)	(0.59)	(0.08)	(0.21)	(1.25)
$RES_{(t-1)}$	0.638***	0.0301	0.312**	0.278***	0.640***	0.231*
	(3.03)	(0.49)	(2.34)	(12.40)	(4.15)	(1.74)
$OPE_{(t-1)}$	-0.664***	-0.00550	-0.187	-0.0708	-0.291	-0.153
	(-2.85)	(-0.20)	(-1.18)	(-0.75)	(-1.41)	(-0.98)
N	299	282	282	282	260	282

Note: All variables in natural logarithm form. Robust t statistics in parentheses. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Figure 3.3: Workforce Age Effects on Patenting

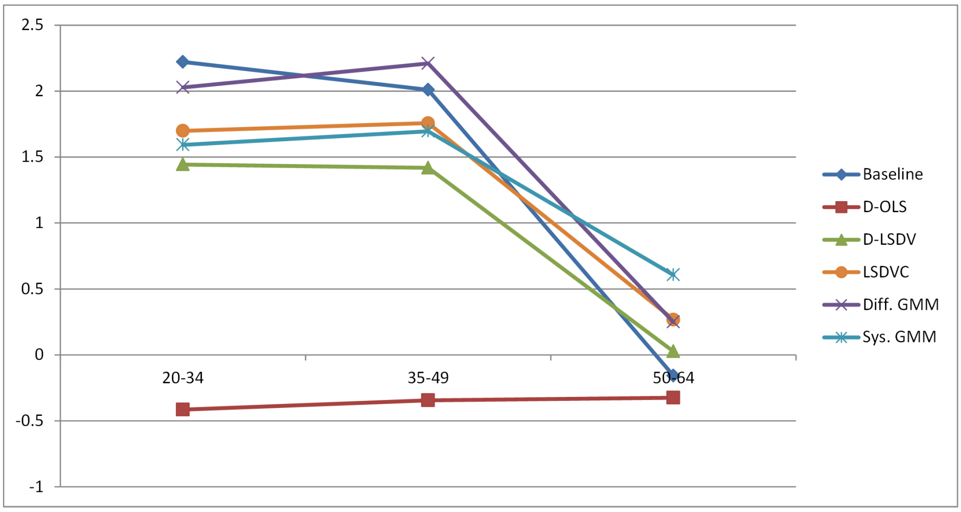
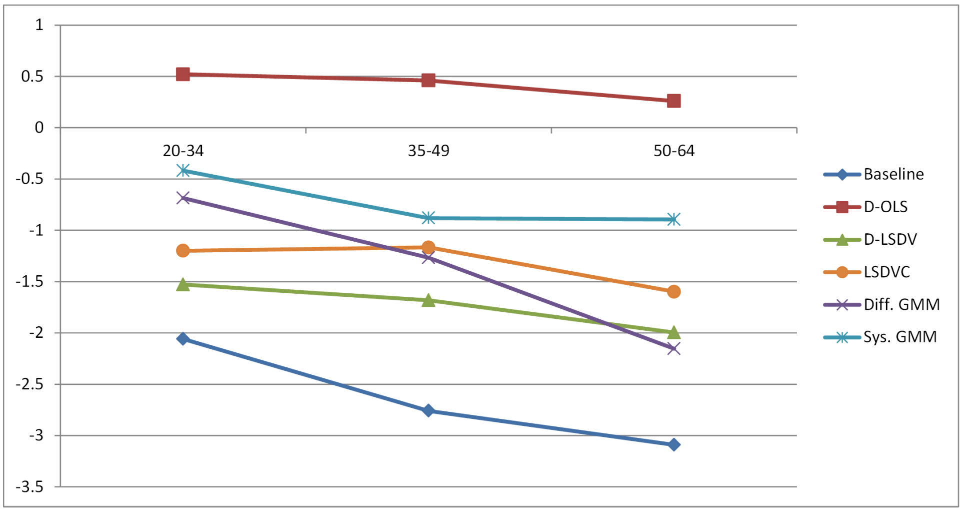


Figure 3.4: Workforce Age Effects on Trademarks



3.7 Appendix

Appendix 1: List of Countries

The country sample includes the following OECD countries:

Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, South Korea, Sweden, Switzerland, United Kingdom and the United States.

For a robustness check also Israel is included to the sample.

Appendix 2: Polynomial Restriction Methodology

In the following the approach of estimating education level-specific age effects under a polynomial restriction is briefly described. I build upon Fair and Dominguez (1991) and Higgins (1998) and extent their framwork to a two-dimensional setting in order to estimate age effects by controlling for differing levels of education. Let us assume a log-lin version of the baseline econometric model outlined by equation (3.6) in section 3.4.1 where the population age shares as regressors are replaced by shares that are subdivided by $m = 3$ educational attainment level groups (low, medium, high) and $n = 11$ age groups (15-19, 20-24,..., 60-64, 65+), so that the sum of all age-education effects is $\sum_{l=1}^{m}\sum_{j=1}^{n}\beta_{lj}x_{ljit}$. The linear regression specification to estimate is then:

$$\ln y_{it} = \alpha + \sum_{l=1}^{m}\sum_{j=1}^{n}\beta_{lj}x_{ljit-1} + \mu$$

where x_{ljit} is the population share for the cohort in country i at time period t that has an education level of l and an age of j. μ is defined as $\mu = \beta v_{it-1} + \sum_k \beta_k w_{kit-1} + \delta_t + c_i + \varepsilon_{it}$ in analogy to equation (3.6) in section 3.4.1. As it is difficult to separate out any individual effects and draw inference by estimating the full set of $m * n$ age-education combinations in a single regression model, for each education level l, a constraint is imposed on the share coefficients, β_{jl}, assuming that they fit a polynomial curve of a given order, in our case of third-order:

$$\beta_{low,j} = \gamma_{low,0} + \gamma_{low,1}j + \gamma_{low,2}j^2 + \gamma_{low,3}j^3$$

$$\beta_{med,j} = \gamma_{med,0} + \gamma_{med,1}j + \gamma_{med,2}j^2 + \gamma_{med,3}j^3$$

$$\beta_{high,j} = \gamma_{high,0} + \gamma_{high,1}j + \gamma_{high,2}j^2 + \gamma_{high,3}j^3$$

For simplicity and space reason let us now concentrate only on the group of low educated individuals, but of course the following steps apply to the other two education categories within l in an analog way. Given that all age group shares sum up to 1 within each category, the sum of the age effects within the category of low educated becomes:

$$\begin{aligned}\sum_{j=1}^{n}\beta_{low,j}x_{low,jit} &= \sum_{j=1}^{n}(\gamma_{low,0} + \gamma_{low,1}j + \gamma_{low,2}j^2 + \gamma_{low,3}j^3)x_{low,jit} \\ &= \gamma_{low,0} + \sum_{j=1}^{n}(\gamma_{low,1}j + \gamma_{low,2}j^2 + \gamma_{low,3}j^3)x_{low,jit}\end{aligned}$$

In order to avoid multicollinearity, a restriction is imposed on the age effects within each education category to sum up to zero which presumes that for an uniform age distribution the single age effects net out each other and have in sum no net effect. This eliminates the constant

γ_{l0} thus making the interpretation of the age share coefficients more straightforward. Again, showing the case for the low educated group:

$$\sum_{j=1}^{n} \beta_{low,j} = 0 \Rightarrow \gamma_{low,0} = -\frac{\gamma_{low,1}}{n} \sum_{j=1}^{n} j - \frac{\gamma_{low,2}}{n} \sum_{j=1}^{n} j^2 - \frac{\gamma_{low,3}}{n} \sum_{j=1}^{n} j^3$$

Finally, the following transformed regression specification can be estimated that includes three compounded polynomial terms for each of the three education categories:

$$\ln y_{it} = \alpha + \gamma_{low,1} \underbrace{\sum_{j=1}^{n} j(x_{low,jit-1} - \frac{1}{n})}_{D1_{low}} + \gamma_{low,2} \underbrace{\sum_{j=1}^{n} j^2(x_{low,jit-1} - \frac{1}{n})}_{D2_{low}} +$$

$$\gamma_{low,3} \underbrace{\sum_{j=1}^{n} j^3(x_{low,jit-1} - \frac{1}{n})}_{D3_{low}} + ... + \gamma_{high,3} \underbrace{\sum_{j=1}^{n} j^3(x_{high,jit-1} - \frac{1}{n})}_{D3_{high}} + \mu$$

Then, the specific effect of each age group j within a specific education category l can be easily calculated with the formula $\beta_{lj} = \gamma_{l0} + \gamma_{l1} j + \gamma_{l2} j^2 + \gamma_{l3} j^3$.

Appendix 3: Robustness Tests - Tables and Figures

Table 3.7: Population Age Effects on Patenting and Trademarks - Age-specific Education

(a) Education-specific Age Groups

	(1) Patents LSDV		(2) Patents sys. GMM		(3) Tradem. LSDV		(4) Tradem. sys. GMM	
LAG			0.603***	(7.73)			0.702***	(12.88)
$GDP_{(t-1)}$	0.878***	(6.20)			0.657	(1.12)		
YNG $LOW_{(t-1)}$	0.0225*	(1.97)	0.0157	(1.45)	-0.0713***	(-3.76)	-0.00604	(-0.74)
MID $LOW_{(t-1)}$	0.342**	(2.72)	-0.0282	(-1.23)	0.504**	(2.10)	-0.0118	(-0.39)
OLD $LOW_{(t-1)}$	0.0927***	(3.61)	0.0190	(1.17)	0.0713*	(1.76)	0.0332	(1.03)
YNG $HIGH_{(t-1)}$	-0.0972	(-0.32)	-0.389	(-1.51)	0.140	(0.17)	0.393	(1.12)
MID $HIGH_{(t-1)}$	0.417	(1.29)	0.553***	(3.29)	0.462	(0.64)	0.106	(0.34)
OLD $HIGH_{(t-1)}$	0.295***	(2.85)	-0.00352	(-0.05)	0.253	(1.01)	0.0980	(0.73)
$EXP_{(t-1)}$	0.652**	(2.50)	0.589***	(3.14)	0.296	(1.41)	0.0373	(0.43)
$RES_{(t-1)}$	0.454***	(4.49)	0.108	(1.40)	0.455*	(2.02)	0.188	(1.62)
$OPE_{(t-1)}$	-0.0499	(-0.19)	-0.124	(-0.99)	-0.0896	(-0.38)	0.0149	(0.13)
N	479		479		321		301	

(b) Education-specific Age Polynomials (third-order)

	(1) Patents LSDV		(2) Patents sys. GMM		(3) Tradem. LSDV		(4) Tradem. sys. GMM	
LAG			0.661***	(8.71)			0.734***	(12.42)
$GDP_{(t-1)}$	-0.0126	(-0.83)			0.0156	(0.79)		
D1 $LOW_{(t-1)}$	-0.00116	(-0.33)	-0.00259	(-1.42)	-0.0124**	(-2.41)	-0.00758	(-0.96)
D2 $LOW_{(t-1)}$	0.000316	(0.33)	0.000709	(1.38)	0.00317**	(2.28)	0.00132	(0.87)
D3 $LOW_{(t-1)}$	-0.0000192	(-0.33)	-0.0000425	(-1.35)	-0.000184**	(-2.17)	-0.0000652	(-0.81)
D1 $MED_{(t-1)}$	0.114***	(3.10)	0.0296	(1.31)	0.104***	(2.94)	0.0278*	(1.66)
D2 $MED_{(t-1)}$	-0.0194**	(-2.52)	-0.00299	(-0.72)	-0.0151**	(-2.09)	-0.00331	(-1.04)
D3 $MED_{(t-1)}$	0.000963**	(2.19)	0.0000703	(0.32)	0.000642	(1.60)	0.000103	(0.59)
D1 $HIGH_{(t-1)}$	-0.104***	(-3.30)	-0.0360	(-1.15)	-0.0983	(-1.39)	-0.0710***	(-2.91)
D2 $HIGH_{(t-1)}$	0.0185***	(3.05)	0.00645	(1.14)	0.0165	(1.28)	0.0126***	(2.92)
D3 $HIGH_{(t-1)}$	-0.000968***	(-2.89)	-0.000325	(-1.10)	-0.000790	(-1.17)	-0.000639***	(-2.88)
$EXP_{(t-1)}$	0.00185	(0.17)	0.0282**	(2.13)	0.00795	(0.32)	-0.00494	(-0.62)
$RES_{(t-1)}$	0.130***	(2.83)	0.0287*	(1.66)	0.0630	(1.17)	0.0272	(1.51)
$OPE_{(t-1)}$	0.00239	(1.05)	0.000626	(0.45)	-0.00459	(-1.06)	0.00120	(0.74)
N	479		479		321		301	

Note: All variables in natural logarithms in table (a) while age shares and control variables in non-logarithmic form in table (b). Robust t statistics in parentheses. LAG defines coefficients for lagged dependent variable. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Figure 3.5: Education-specific Population Age Effects on Patenting

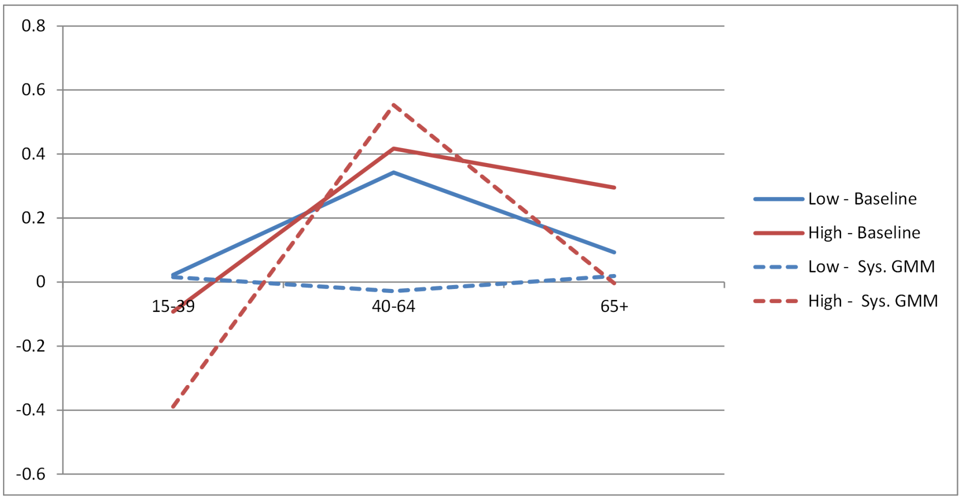


Figure 3.6: Education-specific Population Age Effects on Trademarks

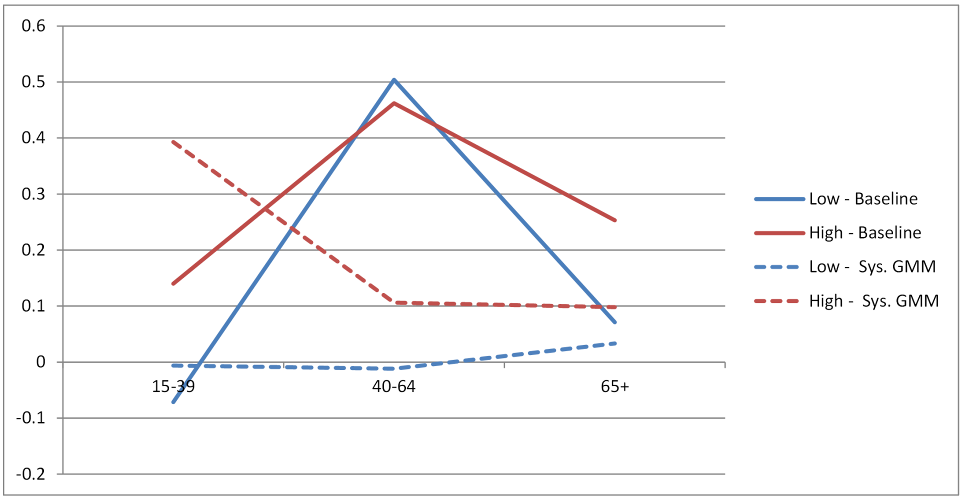


Figure 3.7: Education-specific Population Age Effects on Patents and Trademarks - Third-order Polynomials

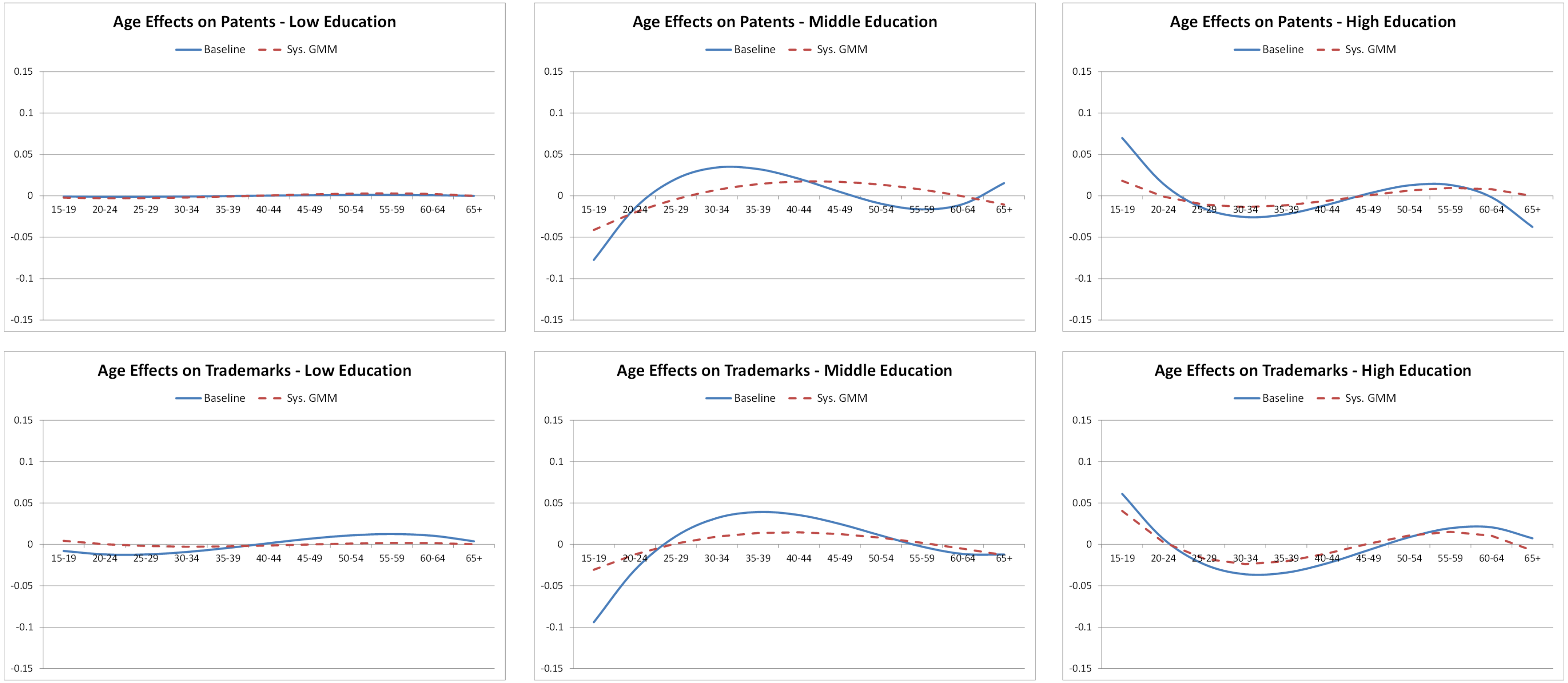


Table 3.8: Age Effects on Patenting and Trademarks - Semi-Log

(a) Population

	(1) Patents LSDV		(2) Patents sys. GMM		(3) Tradem. LSDV		(4) Tradem. sys. GMM	
LAG			0.749***	(22.23)			0.798***	(18.41)
$GDP_{(t-1)}$	-0.0345	(-1.35)			-0.0370	(-1.18)		
AGE 15-29$_{(t-1)}$	0.113***	(2.99)	0.00499	(0.42)	0.142*	(1.80)	-0.0324**	(-1.98)
AGE 30-49$_{(t-1)}$	0.253***	(4.37)	0.0687***	(3.03)	0.242***	(3.54)	0.00726	(0.37)
AGE 50-64$_{(t-1)}$	0.221***	(3.79)	0.0634***	(3.24)	0.168**	(2.23)	-0.0136	(-0.52)
AGE 65+$_{(t-1)}$	0.108***	(3.10)	0.0155	(1.53)	0.103*	(1.75)	-0.00106	(-0.08)
$EDU_{(t-1)}$	-0.0255	(-0.51)	0.0587***	(2.70)	-0.0252	(-0.27)	0.0246	(1.11)
$EXP_{(t-1)}$	0.0380**	(2.70)	0.0358***	(2.73)	0.0260	(1.26)	0.00688	(0.74)
$RES_{(t-1)}$	0.0662*	(2.01)	0.00428	(0.33)	0.0403	(1.29)	0.00561	(0.42)
$OPE_{(t-1)}$	-0.00537	(-1.53)	-0.000274	(-0.20)	-0.00590	(-1.10)	-0.000801	(-0.54)
N	497		497		336		315	

(b) Workforce

	(1) Patents LSDV		(2) Patents sys. GMM		(3) Tradem. LSDV		(4) Tradem. sys. GMM	
LAG			0.753***	(16.49)			0.754***	(18.40)
$GDP_{(t-1)}$	-0.0338	(-1.50)			-0.0339	(-1.18)		
AGE 35-49$_{(t-1)}$	-0.0135	(-1.30)	0.00812	(1.00)	-0.0217	(-1.69)	-0.00135	(-0.20)
AGE 50-64$_{(t-1)}$	-0.0921***	(-4.63)	-0.0198	(-1.52)	-0.0913***	(-4.07)	-0.0225	(-1.59)
$EDU_{(t-1)}$	-0.202***	(-3.11)	0.0151	(0.67)	-0.0290	(-0.34)	0.0359	(1.57)
$EXP_{(t-1)}$	0.0176	(1.40)	0.0394***	(2.77)	0.0128	(0.67)	0.0167	(1.42)
$RES_{(t-1)}$	0.0726*	(1.93)	0.0196	(0.87)	0.0643*	(1.83)	0.0128	(0.77)
$OPE_{(t-1)}$	-0.00388	(-1.19)	-0.00258	(-1.17)	-0.00801	(-1.68)	-0.00219	(-1.17)
N	417		417		299		282	

Note: Age shares and control variables in non-logarithmic form. Robust t statistics in parentheses. LAG defines coefficients for lagged dependent variable. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

Table 3.9: Population Age Effects on Patenting and Trademarks - Restricted GMM

(a) Patents

	(1) unrestricted annual		(2) max. 5 lags annual		(3) max. 2 lags annual		(4) max. 2 lags 3year avg.	
$PAT_{(t-1)}$	0.618***	(7.48)	0.581***	(6.94)	0.566***	(7.25)	0.301	(1.04)
AGE 0-14$_{(t-1)}$	0.776	(1.11)	1.227	(1.48)	1.621	(1.45)	1.518	(1.30)
AGE 15-29$_{(t-1)}$	0.805	(1.34)	1.508*	(1.92)	1.923*	(1.84)	2.873*	(1.66)
AGE 30-49$_{(t-1)}$	2.238**	(2.38)	3.189***	(2.62)	3.771**	(2.32)	6.000**	(2.01)
AGE 50-64$_{(t-1)}$	1.329***	(3.32)	1.850***	(3.15)	2.115***	(2.82)	2.820**	(2.08)
AGE 65+$_{(t-1)}$	0.473	(1.09)	0.805	(1.60)	1.006	(1.50)	0.709	(0.86)
$EDU_{(t-1)}$	0.897***	(2.95)	1.117***	(3.01)	1.071***	(2.90)	1.555**	(2.49)
$EXP_{(t-1)}$	0.699***	(3.04)	0.817***	(3.33)	0.938***	(3.41)	1.617**	(2.13)
$RES_{(t-1)}$	-0.0560	(-0.66)	-0.124	(-1.15)	-0.210	(-1.19)	-0.270	(-0.88)
$OPE_{(t-1)}$	-0.0837	(-0.67)	-0.0396	(-0.29)	0.00749	(0.05)	-0.107	(-0.38)
N	497		497		497		147	
No. instruments	494		367		187		51	
AB test (AR2)	0.12		0.12		0.12		0.10	
Sargan test	0.21		0.00		0.00		0.00	

(b) Trademarks

	(1) unrestricted annual		(2) max. 5 lags annual		(3) max. 2 lags annual		(4) max. 2 lags 3year avg.	
$TRM_{(t-1)}$	0.727***	(11.32)	0.687***	(9.48)	0.740***	(8.74)	0.751***	(6.09)
AGE 0-14$_{(t-1)}$	1.207**	(2.16)	1.612**	(2.29)	1.680**	(1.99)	0.881	(0.68)
AGE 15-29$_{(t-1)}$	1.131**	(2.12)	1.889***	(2.75)	1.722**	(2.32)	1.621	(1.03)
AGE 30-49$_{(t-1)}$	1.628***	(2.70)	2.238***	(2.61)	2.207**	(2.03)	2.533***	(2.75)
AGE 50-64$_{(t-1)}$	0.127	(0.33)	0.284	(0.61)	0.307	(0.58)	-0.337	(-0.26)
AGE 65+$_{(t-1)}$	1.042**	(2.57)	1.444***	(2.83)	1.359**	(2.20)	1.415**	(2.09)
$EDU_{(t-1)}$	0.444**	(2.28)	0.550**	(2.27)	0.348	(1.19)	-0.548	(-0.64)
$EXP_{(t-1)}$	0.223*	(1.93)	0.339**	(2.29)	0.365**	(2.06)	0.255	(0.72)
$RES_{(t-1)}$	0.0645	(0.59)	0.00346	(0.02)	-0.114	(-0.69)	-0.0802	(-0.14)
$OPE_{(t-1)}$	-0.113	(-0.99)	-0.131	(-0.97)	-0.119	(-0.89)	-0.137	(-0.40)
N	315		315		315		87	
No. instruments	338		238		121		33	
AB test (AR2)	0.11		0.11		0.09		0.78	
Sargan test	0.97		0.45		0.09		0.54	

Note: All variables in natural logarithm form. Robust t statistics in parentheses. Time dummies included, but coefficients not reported. GMM estimations treat the autoregressive term as well as the control variables $EXP_{(t-1)}$ and $RES_{(t-1)}$ as endogenous. Bottom lines show p-values for Arellano-Bond test (H0: no second-order autocorrelation) and Sargan test (H0: overidentifying restrictions are valid). ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively.

4. Long-term electricity consumption forecasting using heterogeneous panels with age structure information

Abstract

Long-term electricity demand and consumption forecasts play a crucial role in the strategic energy planning process and are integral for both management decision-making in utility companies as well as for energy policy formulation of governmental authorities. This paper presents a panel data regression approach for forecasting long-term electricity consumption by using demographic projections of population size and age composition. Employing a panel of 22 OECD countries over the period 1960-2010 and various homogeneous and heterogeneous estimation procedures, out-of-sample tests suggest that a simple reduced-form forecasting model using age shares as regressors performs well both compared to an alternative GDP-based model as well as to naïve forecasts. The demographic model is used to generate forecasts up to the year 2025, predicting still rising final electricity consumption for all countries in the sample over the next years. However, the predicted growth rates of electricity consumption slow down significantly over time.

Keywords: electricity consumption, age structure, forecasting, demography, panel data

4.1 Introduction

Electricity demand and consumption forecasts play a crucial role in the energy planning process. While short-term electricity forecasts focus in particular on the prediction of daily and weekly load profiles for scheduling and dispatching purposes, long-term forecasting of aggregated annual consumption (respectively peak-loads) is integral for strategic planning and management decision-making in utility companies. Due to the long construction times for new power generation facilities as well as transmission and distribution systems, long-term forecasts require lead times of at least several years in order to guarantee accurate infrastructure planning and to avoid electricity shortage respectively overinvestment in the long-run. Similarly, regulatory authorities have to build their energy policy formulation and policy adjustments on the basis of long-term forecasts.

A basic challenge in this context is the high degree of uncertainty that is associated with long forecast horizons in general. Especially for the case that methods require a number of explanatory factors as input variables, forecasters are confronted with uncertainties because the reliability of their forecasts critically depends on the assumptions and preliminary predictions they make about the future evolution for each of the independent variables. In order to limit this uncertainty, recently the use of disaggregated demographic data has been proposed in several forecasting applications covering various fields. The main appeal of using demographic age structure information as a device for long-term forecasting is that - unlike most other explanatory variables - it can be predicted with rather high precision and over long time horizons into the future.

Given that there is some evidence for a link between energy consumption and demographic age structure, this paper analyzes to which extent demographic age structure data can enhance the accuracy of long-term forecasts of electricity consumption. Thereby, the main purpose of this paper is to formulate a simple and easy-to-implement long-term dynamic forecast model for annual electricity consumption that includes publicly available demographic information on population size and age composition as the only explanatory variables. The forecast performance of the regression model is evaluated with ex ante out-of-sample experiments based on historical demographic projections for a heterogeneous panel dataset of OECD countries. Thereby, various homogeneous and heterogeneous estimators are applied. The results are compared with naïve forecasts as well as with the results of an alternative simple dynamic electricity demand model which is based on GDP projections and was recently described in literature.

The remainder of the paper is organized as follows. The next section gives a brief literature-based overview on forecasting with demographic data and the link between age and energy consumption behavior. Section 4.3 describes the dataset and the econometric methodology, including a brief description of the used models and estimators. Section 4.4 presents the estimation results and reports the findings of the out-of-sample forecasts, followed by forecasts of future final electricity consumption for all countries of the sample up to the year 2025. Finally, the last section concludes.

4.2 Long-term Forecasting, Age Structure and Electricity Consumption

There is a broad set of methods described in literature in order to conduct long-term electricity forecasts. These methods include univariate time series approaches using techniques such as the autoregressive integrated moving average (ARIMA) model (Erdogdu, 2007) or multivariate regression models (Mohamed and Bodger, 2005; Bianco et al., 2009). Besides, simulation approaches (Akhwanzada and Tahar, 2012) as well as computational intelligence based methods such as genetic algorithms and artificial neural networks (Azadeha et al., 2007; Hamzacebi, 2007) have gained increasing popularity for predicting electricity consumption.

While some of these methods are atheoretical and purely technical in the sense that only historical information for the variable of interest is required in order to forecast future trends, others build upon theoretical and empirical founded relations and require to make assumptions about the future development of the input variables in the model. In recent years, a number of regression-based studies have suggested to use age structure information as a device for mid- and long-term forecasting. A main argument in favor of using demographic data is the fact that they can be easily measured, are widely available and - of particular relevance for forecasting purposes - can be relatively reliably projected over long time horizons. For instance, Lindh (2004) finds age structure information to produce reliable forecasts for potential GDP and, to a lesser extent, for inflation. Using a similar methodology, Andersson and Österholm (2005) show that a model with age shares as regressors performs well in forecasting trends in real exchange rates. Bloom et al. (2007) give empirical evidence that the accuracy of long-term economic growth forecasts significantly improves when age structure data are added to the growth models. Similar results are found by Lindh and Malmberg (2007, 2009) who suggest that a pure demographic model compares favorably with other methods for long-term forecasts of GDP per capita. Finally, Koegst et al. (2008) analyze whether age structure data can be used as a forecasting device for future water demand. Yet in contrast to the previously mentioned studies they find no clear evidence that age structure effects can contribute to the prediction of future water demand in metropolitan areas.

Even though there are some few applications of demography-based projections in the context of energy use and green house emissions (York, 2007; Kronenberg, 2009; Brounen et al., 2012), rather little is known about the quality of such projections, especially when the focus is on final electricity consumption. However, analyzing the application of age structure information for energy forecasts in more detail is a promising path at least for two reasons. First, there is large consensus in literature that energy and electricity consumption is closely related to GDP and income which are measures of economic activity and the standard of living.[1] Yet, as shown in some of the previously stated studies, the age composition is a good forecasting device for GDP and income and thus should comprise a considerable part of the information that is included in GDP and income variables, too. Second, there is some empirical evidence at both the micro- and macroeconomic level that age structure directly affects energy consumption. For instance, age effects have been found for Japan (Yamasaki and Tominaga, 1997), the United States (O'Neill and Chen, 2002; Tonn and Eisenberg, 2007), Germany (Kronenberg, 2009), the United Kingdom (Hamza and Gilroy, 2011), the Netherlands (Brounen et al., 2012) and Italy (Garaua et al., 2013). Furthermore, York (2007), Liddle and Lung (2010) as well as Kim and

[1]The review of Bhattacharyya and Timilsina (2009) reveals that GDP or income are widely used as main driver variables in energy demand models.

Seo (2012) have identified a relationship between aging and energy consumption for differing multi-country samples.

Most of these studies focus on residential energy demand and suggest that elderly persons consume more energy in per capita terms than younger individuals. The common explanations given for this pattern are as follows: First, older people tend to spend more time at home and for that reason consume more energy for space- and water-heating, lighting and electrical consumer products such as televisions. Second, they often live alone or as couples in large and energy-inefficient old houses once designed for families with children. These houses are in general more energy-intensive. Finally, old persons have a stronger preference for well tempered rooms than younger individuals thus driving up energy consumption for space heating and air conditioning. In contrast to residential consumption, the relation between industrial energy consumption and age structure is less intensively analyzed in literature. Kim and Seo (2012) argue that industrial energy demand decreases as the population ages due to the break-away of labor force caused by aging and retirement. The accompanied decreases in productivity lead to a slow-down in industrial activity. Thus, the overall age effects on energy consumption depend critically on the interaction of the sub-effects on residential as well as industrial energy demand.

It is important to mention that the previous stated studies mainly focus on energy consumption in general and that age-specific consumption behavior for electricity may differ from these patterns considerably. In general, age structure effects should depend critically on the energy system in place but also on other specific factors, including climate and the socioeconomic structure. For instance, the individual effects in a country may be determined by the country-specific energy-mix (electricity, gas, oil, etc.) that is used for heating-systems.[2] As these factors differ across countries and regions, one should expect age effects on electricity consumption to be rather heterogeneous across countries, too.

4.3 Method

4.3.1 Dataset

The dataset used in this study comprises a panel of 22 OECD countries (see Appendix 1) with annual times series observations from 1960-2010. I focus on this group of developed countries because they share rather common economic and institutional features. Although the units in this sample are still supposed to differ significantly from each other in many energy-related aspects, the OECD sample should be less subject to heterogeneity than a broader sample that includes emerging and developing countries, too. This study focuses on a country-level

[2]For instance, according to statistics from the German Association of Energy and Water Industries (BDEW) for the year 2008, German residential heating is mainly based on natural gas while heating with electricity is only used in 6% of all dwellings. In contrast, in New Zealand electricity is the main fuel used for domestic heating according to a 2004 survey from the New Zeland Ministry of Environment.

analysis, but it could also be conducted on smaller spatial units such as regions, cities or specific electricity supply areas (of course, provided that the required data are available). Electricity consumption data are taken form the Electricity Information Statistics of the International Energy Agency (IEA), while GDP data were derived from the eighth version of the World Penn Table (Feenstra et al., 2013). The demographic information covering population size and age composition data is obtained from the World Population Prospects database of the United Nations (2013).

4.3.2 Model Specification

The analysis uses a dynamic linear regression model following a reduced form. Single equation reduced form approaches are widely used in both studies related to energy demand and studies analyzing the impact of age structure variables. In contrast to more complex structural, simultaneous equation models this approach has the advantage that fewer variables are required in the model.

Following traditional economic theory, most electricity demand models in literature include income respectively output and the electricity price as the main explanatory variables. While simple models are often limited to these two variables (and even sometimes omit prices from their analysis), more sophisticated studies on long-term electricity consumption are modeled with additional sets of explanatory variables including, among others, the price levels for alternative substitutes of electricity (e.g. natural gas), the number of customers, the population size as well as weather and climatic conditions. In addition, studies that focus on a single country analysis sometimes include region-specific factors[3] to their models, too. A main advantage of such comprehensive sets of general and idiosyncratic variables is that they allow to consider in some detail the region's specific conditions and the intrinsic characteristics of the energy system in place. However, for forecasting purposes such an approach is not without difficulties. Not only have reliable historical data to be available for each single variable, but also assumptions about the future development of these variables have to be made. Yet the latter is often a hard task given that many of the used variables are associated with large uncertainties in the future, especially when assumptions have to be made for long forecast horizons. Tashman et al. (2000) show that uncertainty in the forecasts of the regressors increases the forecast uncertainty of the overall regression model substantially. Thus, a simple model may be preferable over a more complex and sophisticated one even if the latter better fits the data but its input variables can only be predicted with high uncertainty.

Therefore, the forecasts in this paper are focused on a more parsimonious approach following a reduced form that includes a very limited set of explanatory variables. As a benchmark I use a simple GDP-based electricity demand model whereby I orientate on the forecasting model

[3]For instance, Egelioglua et al. (2001) find the number of visiting tourists to have good explanatory power for electricity consumption in Northern Cyprus.

proposed by Bianco et al. (2009). The latter is parsimonious in its structure and - even though it is used by the authors to forecast electricity demand of Italy - due to its generic form it also should be applicable to other OECD countries. The forecasting model follows the specification:

$$E_{it} = \alpha + \beta_{1i}E_{it-1} + \beta_{2i}(GDP_{it}/POP_{it}) + \varepsilon_{it} \tag{4.1}$$

where E is the annual electricity consumption measured in GWh, GDP is the real GDP adjusted for purchasing power parity (PPP) and measured in million US dollars, POP is the population size in thousands and ε is the error term. The subscript i denotes the country while t is the time period. The dependent variable E measures total final electricity consumption[4] which seems most relevant for the purpose of this study given that strategic energy planning processes are based in particular on projections of total use. Nevertheless, I also run additional regressions for the residential and industrial sector (which make up a large share of overall electricity consumption) in order to provide further insights. Since the forecasting model of Bianco et al. (2009) is designed for a single country analysis while we want to generate forecasts for multiple countries of different sizes, I modify the model and scale the dependent variable by population size:

$$E_{it}/POP_{it} = \alpha + \beta_{1i}(E_{it-1}/POP_{it-1}) + \beta_{2i}(GDP_{it}/POP_{it}) + \varepsilon_{it} \tag{4.2}$$

In a first step estimates and forecasts for per capita electricity consumption are computed which are then, in a second step, multiplied with population projections in order to gain aggregated consumption levels. Hence, GDP and population size are the main determinants in the model. Obviously, the model does not include any prices as independent variables. Bianco et al. (2009) justify this step by the low price elasticities they found for the demand of electricity in Italy. Similarly, Liu (2004) found also rather low short- and long-term price elasticities for electricity demand in a sample of OECD countries. Indeed, an analysis with our data set and an alternative model that includes the total prices or real prices for household and industrial clients did not increase the explanatory power of the model measured in adjusted R^2 terms. But even if prices would significantly contribute to the explanation of energy demand, the benefits of including these variables as regressors into the forecasting model would be questionable given that future electricity prices - as stated by Zachariadis (2010) - are characterized by large uncertainties and depend highly on unknown developments at the national level as well as on international markets.

The GDP-based benchmark model is compared with a model that relies beside an autoregressive term only on demographic variables as explanatory factors:

[4] (Total) final electricity consumption covers consumption of end-users from households, industry, agriculture, services, transport, etc. while the own-use of electricity producers and utilities as well as transmission and distribution losses are not included.

$$E_{it}/POP_{it} = \alpha + \beta_{1i}(E_{it-1}/POP_{it-1}) + \sum_k \beta_{ki} AGE_{kit} + \varepsilon_{it} \tag{4.3}$$

where AGE are k variables that capture the age structure of the population in country i at period t. Similar to the benchmark model I include a lagged dependent variable on the right hand side of the equation since there are good reasons to assume electricity consumption to be persistent to some degree (e.g. due to habit formation of consumers). Furthermore, there are also practical arguments for a dynamic specification such as handling potential autocorrelation issues but also improving the overall forecast performance.

The specification of AGE depends critically on the level of detail in which age structure information is available. For instance, the 2012 Revision of the World Population Prospects offers population age data for at least 17 age groups, subdivided into 5-year intervals (0-4, 5-9, ..., 75-79, 80+). A common challenge when incorporating time series for such detailed age structure data into an econometric model is the high degree of collinearity across age groups that makes inference difficult. In order to extenuate multicollinearity issues and preserve degrees-of-freedom, different approaches for more parsimonious specifications have been suggested in literature (see e.g. Bloom and Canning, 2001). The main intention is to reduce the parameters to estimate and at the same time to preserve as much relevant age information as possible in the reduced set of variables. A simple but effective way to establish such a parsimonious form is to define a smaller set of aggregated age share groups under the assumption that the age effects differ across these groups but are homogeneous within the groups. I follow in this study Lindh (2004) and subdivide the age distribution into six age groups: 0-14, 15-29, 30-49, 50-64 and 65+. The age group of the 0-14 year old individuals had to be skipped from the model due to the perfect collinearity with the error term. Besides, I use an alternative specification by further aggregating the age information into three groups: young (0-14), working age (15-64) and retirees (65+) and skipping once again the youngest group. This broad classification does not only reduce the number of parameters to be estimated, but also has the advantage that the age groups can be easily transformed from youth and old age dependency ratios. The latter point is of particular relevance for our out-of-sample tests where historical age structure projections are only available in form of youth and old age dependency ratios. Beside using aggregated age shares, I tried also a more sophisticated method that builds upon a low order polynomial restriction approach. This econometric procedure, pioneered by Fair and Dominguez (1991), has the advantage that the full set of age information available in the dataset can be incorporated into the regression model, but at the same time constrains the age effects to fit a polynomial curve. However, the approach proved not practical in this study neither for cubic nor quartic polynomials because collinearity still seemed to be highly present among the various compounded polynomial terms.

4.3.3 Estimators

A basic issue from a methodological standpoint is whether the panel structure of our dataset should be exploited and pooled for forecasting purposes. While there is a myriad of studies in literature that use time series forecasts, forecasting with panel data has not been very common until recently. Thus, it is not surprising that in the context of energy forecasting pure time series approaches prevail. One of the few exceptions (if not the only one) is Baltagi et al. (2002) who analyze the accuracy of forecasting electricity and natural gas consumption with panel estimators for a sample of 49 US states.

In general, panel data approaches have several advantageous features over pure cross-sectional and time series data (Hsiao, 2007). Most obviously, the additional gain of observations by exploiting both the time and cross-sectional dimension of the dataset allows for more accurate inference and increased efficiency of estimations. Further, a main advantage of using panel data is the capability to control for unobserved heterogeneity across units and time. This builds on the common assumption that the error terms in equations (4.1)-(4.3) are specified as a two-way error component model of the form:

$$\varepsilon_{it} = \mu_i + \lambda_t + v_{it} \tag{4.4}$$

where μ_i is an unobserved and time-invariant unit-specific effect, λ_t denotes a time-specific disturbance term that stays constant over the cross-section and v_{it} is the remaining idiosyncratic error term or white noise. In our particular case of electricity consumption, μ_i may include country-specific factors such as climatic conditions, the socioeconomic structure, or peculiarities of the energy system. In contrast, λ_t may include global technological trends or international oil shocks. Pooled estimators can explicitly deal with these factors, whereas pure cross-sectional data cannot control for the unobserved effects of μ_i and pure time series data cannot control for λ_t. However, the approach of pooling data builds on the restrictive assumption that the slope parameters to be estimated are homogeneous across the cross-sectional units:

$$\beta_i = \beta, \forall i = 1, ..., N \tag{4.5}$$

Authors such as Pesaran and Smith (1995) have questioned this assumption, especially when the time dimension is large, and noted that the pooling of heterogeneous data might lead to biased estimation results. Yet, in the context of forecasting a number of studies have shown that using panel data approaches can improve forecasting accuracy even when the assumption of homogeneous parameter slopes is rejected by the data.[5] A common interpretation is that the benefits of pooling are able to outweigh the disadvantages resulting from the heterogeneity bias. Trapani and Urga (2009) show via a series of Monte Carlo simulations that the forecast

[5] See Baltagi (2008) for a review of studies using panel data for forecasting.

performance of panel estimators strongly depends on the degree of heterogeneity in the dataset and pooling produces superior results especially when the level of heterogeneity is rather mild.

Since it is difficult to evaluate a priori whether data pooling enhances the forecast accuracy for a given dataset, I follow the procedure of previous studies such as Baltagi et al. (2002), Baltagi et al. (2004) or Brücker and Siliverstovs (2006) and estimate the demographic model as well as the benchmark model with different estimators. I first consider a set of pooled estimators that treat the effects for the panels as homogeneous. The most restrictive estimator in this group is the pooled ordinary least squares approach (pOLS) which assumes both the intercept and the slope parameters to be identical over the whole sample. Therefore, the error term is not split as in equation (4.4) but only the overall error (that is, the sum of μ_i, λ_t and v_{it}) is considered. In contrast, also two versions of the fixed effects model are used which assume the slope coefficients to be homogeneous for all units, too, but allow the intercepts to vary across countries. In detail, the two fixed effects models include a one-way version (FE1) which controls for the country-fixed effects (μ_i) and a two-way version (FE2) where the disturbance term follows equation (4.4) and also considers time dummies (λ_t) in order to control for external shocks and trends that affect all countries in the sample at the same point in time. In order to conduct forecasts with the two-way fixed effect model, future time dummies are predicted by a simple linear time-trend regression:

$$\lambda_t = \alpha + \delta t + \varepsilon \tag{4.6}$$

Even though it is well known that the described dynamic panel models are asymptotically biased in the presence of a lagged dependent variable for finite T (Nickell, 1981), the bias should be negligible in the view of the long time series used in this study. Hence, I refrain from taking correcting measures, e.g. applying instrumented estimation techniques based on generalized method of moments (GMM) approaches. Finally, the last estimator used in the group of homogeneous estimators is the random effects model (RE) which regards the country-specific effects as random and uncorrelated with the explanatory variables in the regression. The random effects model is estimated by maximum likelihood.

The results of the pooled estimators are compared to estimates that regard the effects for each country as heterogeneous. Therefore, the parameters of the energy models are estimated for each country individually by standard ordinary least squares (iOLS) regressions. This approach gives the largest degree of flexibility as intercepts and slopes are allowed to differ for each country. While the iOLS estimations ignore the panel structure of the dataset at all, in addition two heterogeneous panel estimators are used that also estimate the parameters for each country separately but then average the parameter estimates over the whole sample. First, the Mean Group (MG) estimator proposed by Pesaran and Smith (1995) is applied which computes the unweighted averages of all individually estimated parameters. In addition, I compute the so-called Common Correlated Effects Mean Group (CCEMG) estimator which is suggested by Pesaran (2006). This estimator is similar to the MG estimator but in order to allow for potential cross-sectional dependence the individual regressions are augmented by regressors computed as the cross-sectional means of the dependent and independent variables.[6]

Finally, the Pooled Mean Group (PMG) estimator is employed which can be regarded as an intermediate alternative between the previous two groups of homogeneous and heterogeneous estimators. This in-between estimator was developed by Pesaran et al. (1999) and assumes homogeneity of the long-run coefficients but allows the intercepts and short-run effects to differ across countries. The model includes a country-specific error-correcting parameter measuring the responsiveness and speed of adjustment for any deviations from a presumed long-term equilibrium. In order to apply the PMG estimator in this study the model equations (4.2) and (4.3) have to be transformed into an autoregressive distributed lag (ARDL) form (see Appendix 2).

4.4 Empirical Analysis

4.4.1 Unit Roots and Cointegration

As a first step of the empirical analysis, the time series are tested for unit roots and cointegration.[7] It is widely known in time series econometrics that non-stationarity manifesting in non-constant means and variances over time can cause spurious correlation among the variables. I start with running unit root tests for the time series of each country separately applying the widely used augmented Dickey-Fuller (ADF) test as well as a modified and more powerful version of this test suggested by Elliott et al. (1996). In addition, three panel test approaches are applied that make advance of the dataset's panel structure and have – as shown for instance by Levin et al. (2002) - much higher power compared to the single time series ADF-type test procedures: the panel unit root test introduced by Levin et al. (2002), the test procedure proposed by Im et al. (2003) as well as the the approach of Pesaran (2007) which allows for cross-sectional dependence. The tests are run with differing lag structures (e.g. following the Akaike Information Criterion) as well as with and without including time trends. The results reveal that the time series of GDP per capita are likely to contain unit roots and are integrated of order I(1), that is, the time series become stationary after taking first differences. There is also some support that electricity consumption follows an I(1) process. In contrast, there is no clear evidence of non-stationarity in the age structure variables. This is not unexpected, given that due to their nature of being ratios within fixed boundaries, these variables cannot be non-stationary in the long run (Lindh and Malmberg, 2009).

[6]It is important to mention that I had to modify the CCEMG estimator for the forecasting exercises in this study because in its original form the mean of the present values of the dependent variable enters the right hand side of the equation. Given the fact that these values are not available in advance, I use instead the values of the first-order lag of the averaged dependent variables which are known.

[7]Detailed quantitative results of all tests are available from the author upon request.

In the light of the evidence that, at least in the benchmark model, all variables seem to be integrated at the same order, there is the possibility that they share similar non-stationary properties and follow a long-run relationship. In this case variables form a cointegrated set and spurious correlation should not be a problem. However, applying the augmented version of the Enger-Granger (1987) test for cointegration on the time series of each country cannot reject the null that there is no cointegration. Similarly, the panel cointegration tests proposed by Westerlund (2007) give no support for a long-term equilibrium by analyzing the significance of the error correction term in the underlying error correction model of the tests. When time series models are found to be non-stationary and non-cointegrated, a common strategy in applied econometrics is to differentiate the data in order to transform the time series into stationarity. Even though this approach mitigates issues arising from spurious correlation, it is important to mention that using the (stationary) first derivatives is not without cost and may neglect relevant long-run relationship information. As tests of transforming the models in equations (4.2) and (4.3) from levels into first differences revealed rather similar estimation results, I decided to keep the variables in their non-differenced form.

In general, we should not be too much concerned about non-stationarity and spurious correlation within this study insofar as pooled data models are used. Phillips and Moon (1999) have shown that the problem is quite less serious in panel structure settings due to the additional cross-sectional information. In addition, as remarked by Lindh and Malmberg (2007), out-of-sample forecasts as applied in this study provide an indirect test of this issue for both time series and panel models because regressions producing spurious results cannot generate reasonable forecasts.

4.4.2 Estimation Results

As a second step before starting the forecasting experiments, in this section the age effects on electricity consumption are analyzed by simply regressing electricity per capita consumption on the age share groups previously defined: 15-29, 30-49, 50-54 and 65+.[8] The results for the various estimation procedures are reported in Table 4.1. It is important to bear in mind that the coefficients of the single share groups have to be interpreted in relative terms because the absolute age effects on per capita energy consumption critically depend on how the overall age profile changes. Even though estimations were conducted on a sector basis, for the sake of brevity I concentrate on the age effects on total final electricity consumption (sub-Table 4.1a) which lie - as explained before - in the primary interest of this study. As one can see in the first two columns, the individual OLS estimations by conducting regressions for each

[8] I refrained from including the lag of the dependent variable in this exercise due to the concern that it could “dominate” the regression results and suppress the age effects. This happens according to Achen (2000) when there is autocorrelation and the explanatory variables follow a trend. In fact, tests showed that the estimated age effects became substantially smaller when an autoregressive term was added to the estimations; but nevertheless the coefficients remained still statistically significant and the main pattern proofed rather stable. For the forecasting excercises I include a lagged dependent variable in the equations as it contributes to the model fit and at the same time still allows the age variables to have significant effects on the forecasts.

country separately produce rather heterogeneous coefficients ranging from significantly positive to significantly negative for most age groups. This suggests that age effects differ considerably across the sample countries and confirms the proposition that regional electricity consumption patterns depend on country-specific factors such as consumer habits, the economic and industrial structure, climatic conditions as well as which sources of energy (electricity, gas, oil, etc.) are used for domestic cooking and heating-systems. However, despite the heterogeneity in the individual OLS regressions, the MG estimator produces statistically significant estimates for all age group coefficients. This may be seen as a hint that the heterogeneity across OECD countries is manageable to some degree. The averaged point estimates of the MG estimator suggests that especially the oldest age group contributes significantly to higher final electricity consumption. This is what we would expect following the previously stated assumptions that old people boost residential electricity demand. Beside the old, also the age group of the 30-49 year old individuals is (in relative terms compared to its neighboring age groups) positively associated to electricity consumption. An explanation for this pattern may be that this group contributes in particular to a country's productivity level and boosts industrial output and energy demand. Finally, the CCMEG estimator confirms the finding that a large share of old individuals has a positive impact on final electricity consumption.[9]

The homogeneous estimators yield results that do not differ too much from the averaged heterogeneous estimates. The pooled OLS as well as the one-way fixed and random effects models produce relative positive age effects for the age group of the 30-49 year old individuals which are more pronounced compared to the averaged estimators, but the effects of the retirees above the age of 65 still remain dominant. In contrast, the two-way fixed effects estimator yields a much flatter age effects profile suggesting that time effects absorb some of the age effects. Finally, the long-run effects of the PMG estimator supports the previous findings that old individuals have a relative positive impact on final electricity consumption. However, similar to the individual OLS estimates the country-specific short-run coefficients differ significantly across countries. The country-specific convergence terms which imply the speed of adjustment from a shock to long-term equilibrium have the expected negative sign for 21 out of the 22 countries where again 13 out of the 21 are statistically significant at usual confidence levels.[10] This suggests that variables return to a common long-term equilibrium and that there is indeed a long-term relationship between final energy consumption and the age structure.

4.4.3 Forecasting Performance

After having analyzed the effects of age structure on electricity consumption, this section evaluates the forecast ability of the demographic age structure model and the benchmark model using out-of-sample tests. Therefore, the dynamic models described in equations (4.2) and

[9]In order to conserve space, the augmented cross-sectional means of the CCMEG estimator are not reported in Table 4.1.

[10]Again, for space reasons, the individual short-term effects and error-correcting speed parameters of the PMG are not reported in Table 4.1, but available upon request.

(4.3) are estimated for a truncated dataset covering the period 1960-1995 and forecasts are computed over a time horizon h of 15 years (1996-2010) for evaluation purposes. As the sample comprises a set of $N = 22$ countries, in total $N \times h = 330$ point forecasts are computed for each model. Given that the age structure model as well as the GDP-based benchmark model follow a dynamic specification and include the lagged dependent variable as a regressor on the right hand side of the equation, all forecasts have to be predicted stepwise and recursively by using previous forecasts in order to predict the value of the dependent variable. The out-of-sample tests are based on an ex ante approach (sometimes also referred to as unconditional forecasts), that is, only the information is used that would have been available at the point in time when the forecast was conducted. This reflects not only the typical situation a practical forecaster is confronted with, but also allows to evaluate both the effectiveness of the forecasting model and the effects of any projection errors in the independent variables. Consequently, only data that were available before 1996 (the starting point of our forecasts) are incorporated into the models. Demographic data regarding projections of population size and age structure are taken from the medium variant of the 1994 revision of the World Population Prospects. Since these historical data contain only projections on youth and old age dependency ratios, the parsimonious specification has to be used including working age (15-64 years) and retirees (65 years and above) shares in the model. Assumptions about GDP growth rates are based on the baseline scenario projections of the World Energy Outlook 1995 from the IEA.

The models are compared with naïve forecasts which are defined in this study as simple linear time-trend regression models that are estimated for each country individually:

$$E_{it} = \alpha_i + \beta_i t + \varepsilon_{it} \tag{4.7}$$

In order to measure the forecast accuracy, the mean absolute percentage error (MAPE) is computed for the various models and estimators. This traditional measure of forecasting accuracy is defined as:

$$MAPE = \frac{100}{n} \times \sum_{n} \mid (P_n - A_n)/A_n \mid \tag{4.8}$$

where P_n and A_n are the nth predicted and actual values while n is the total number of predictions. As an alternative measure, I use Theil's U statistic which provides a direct comparison between the forecasts of the respective models and the naïve forecasts:

$$U = \sqrt{\frac{\sum_n ((P_n - A_n)/A_n)^2}{\sum_n ((F_n - A_n)/A_n)^2}} \tag{4.9}$$

where F_n is the nth prediction of the naïve forecast. Theil's U statistic is a relative measure. Values of U smaller than 1 indicate that the predictions of the tested model outperform the naïve forecast while values over 1 indicate that the forecasting performance of the model is doing worse than the naïve forecast. As the errors are squared in equation (4.9), Theil's U places more weight on large forecast errors. In general, I assume the practical costs resulting from forecasting errors to be fairly identical for under- and overpredictions, and therefore, equal weights are placed on both kinds of errors.[11]

Tables 4.2-4.4 report the accuracy measures for the different models and estimators. Again, I concentrate here on the total final consumption (Table 4.2) estimates which are of primary interest. The results for each model (AGE, GDP) and estimator combination are ranked by the MAPE that measures the averaged accuracy of all 330 forecasts covering the full forecasting horizon and country set. In addition, also the MAPE for the 5th and the 15th year of the forecasting period is reported in order to analyze whether the forecast accuracy changes with increasing forecast horizon. Several main findings stand out. First, the age structure models dominate the top of the ranking list. Second, the three best performing models in the list use estimators that allow for heterogeneous intercepts but restrict the slopes of the estimates to be homogeneous: the one-way (AGE-FE1) and two-way (AGE-FE2) fixed effects estimators as well as the random effects model (AGE-RE) are in the top field of the list. This supports previous findings such as Baltagi et al. (2002) or Brücker and Siliverstovs (2006), who attest this class of estimators a good forecasting performance. Third, the age structure model also performs relatively well when individual OLS regressions are conducted (AGE-iOLS), especially when the results are directly compared with the benchmark model (GDP-iOLS). In contrast, the forecasts of the pooled OLS estimates perform comparatively well for the GDP-based benchmark model (GDP-pOLS) but only poorly for the age model (AGE-pOLS). This suggests that income effects are rather similar across the OECD sample and the forecasts of the benchmark model can benefit considerably from strict data pooling while age effects differ significantly across units and do not fulfill the restrictive assumption of both intercepts and slopes being homogeneous. The fact that the AGE-iOLS model clearly outperforms the individual OLS predictions of the benchmark model (especially when the forecast horizon is long) suggests age structure based models to be the first choice when limitations in cross-sectional data availability do not allow an application of panel techniques. Fourth, the forecasting performance of the mean group estimators (PMG, CCEMG and MG) is only mediocre to poor. Similar results were represented by Baltagi et al. (2002), Baltagi et al. (2004) and Brücker and Siliverstovs (2006) who have reported a poor performance for the averaged heterogeneous estimators, too. Fifth, a look at Theil's U statistic reveals that all models with exception of the AGE-MG model outperform the naïve forecast. However, when focusing on the MAPE of the 15th year forecasts the simple linear trend regression model outperforms some models (GDP-CCEMG, GDP-PMG, GDP-iOLS and AGE-pOLS). Finally, the forecast errors increase significantly for almost all models as uncertainty rises with longer forecast horizons. However, the error increases are in general less pronounced for the age structure models. While the MAPE of the 5th year forecasts mostly

[11] Small and Wong (2002) remark that the MAPE has a bias of favoring underestimates because these can never exceed a MAPE value of 100 for nonnegative forecasts while there are no such limits for errors resulting from overpredictions. However, this bias remains rather theoretic in this study.

lies in rather similar ranges for the benchmark and the demographic models, the errors of the former are in general significantly larger for the 15th year forecasts. These findings corroborate the proposition that age structure variables are well suited especially for long-term forecasts due to the stability of demographic projections. However, even though the age models perform comparably well, the long-term forecasting errors are still considerable with a MAPE for the 15th year forecasts that is around 10 in the case of the best ranked model (AGE-FE2). This reveals the high degree of certainty that is inherent to long-term forecasting.

Even though the focus of this paper lies primarily on total final consumption, it is worthwhile to mention that the forecasting performance is less accurate for residential and industrial electricity consumption using both GDP and age structure based models. This is especially true for the long-term forecasts (MAPE of 15th year), and here again, for industrial consumption. The latter is, however, not surprising given that the financial crisis and the accompanied slowdown in industrial activity at the end of our forecasting horizon were not foreseeable in 1995 (the starting point of the forecast) by using GDP or age structure based projections. Indeed, for 17 out of the 22 countries the 15th year forecasts overpredicted industrial electricity consumption using the AGE-FE model. Nevertheless, the age models show still a good performance in comparative terms. This is especially true when the age structure model is applied in combination with the fixed effects estimator, which performs well in all three consumption categories.

4.4.4 Forecasts up to 2025

After having analyzed the forecast performance of demographically based models with unconditional out-of-sample tests, in this section forecasts for all 22 OECD countries are made up to the year 2025 (see Table 4.5). The forecasts are based on the one-way fixed effects specification (AGE-FE) which is easy-to-implement and performed well in the previous tests. Demographic projections are taken from the medium variant of the 2012 revision of the World Population Prospects database. The forecasts predict a growth of final electricity consumption for all 22 countries over the period 2011-2025 with the highest average annual growth rate projections for Ireland (2.30%), Canada (2.25%), Australia (2.23 %) and New Zealand (2.22%). The main demographic drivers of growth in final electricity consumption in these countries can be found in continuing rises in population size (mainly due to immigration) as well as increases in per capita consumption due to higher shares of old individuals with an electricity-intensive consumption pattern. In contrast, the lowest average annual growth rates of electricity consumption are predicted for Finland (0.58%), Belgium (0.82%), Japan (0.90%) and Germany (0.97%). These countries have stagnating or shrinking population sizes, but age structural effects still drive overall electricity consumption. For instance, in the case of Japan the population is assumed to decrease by 3.2% over the projected period while at the same time the share of individuals above the age of 64 years with high per capita residential electricity demand is expected to increase by around 6.1%. The overall final electricity consumption for the full OECD sample is expected to grow annually on average by 1.43% over the prediction period. However, there is a trend of diminishing growth rates both in absolute and relative terms over time.

Of course, these forecasts (as well as the previous out-of-sample forecasts) do neither consider the potential impact of policies nor technological developments.[12] But policies and political initiatives as well as the spread of new technologies such as battery-driven cars are likely to have a considerable impact on future consumption patterns. Therefore, the model predictions in this study should be viewed rather as a status quo baseline scenario assuming no crucial changes in the surrounding political, economical and technological framework. Given the simple structure and good performance of the demographic age structure model it seems to be well-suited as an easy-to-implement first step in a more complex forecasting and planning process where in subsequent steps differing assumptions and scenarios about future developments are built around the baseline projections.

4.5 Conclusion

This paper has analyzed the forecasting performance of a demographically based model for long-term electricity consumption. Using demographic information as a forecasting device has attractive features given that population and age structure data are widely available and can be projected rather reliable even far into the future. An analysis with a heterogeneous panel dataset of 22 OECD countries over the time period 1960-2010 finds that age structure information has significant explanatory power on per capita electricity consumption. Subsequent out-of-sample experiments with unconditional forecasts that are based on historical demographic projections show that a simple reduced-form forecasting model including age shares as regressors performs well both compared to an alternative GDP-based model as well as to naïve forecasts. Especially in the case when single time series regressions are run separately for each country or when data are pooled but allowed to have county-fixed effects, the age structure model clearly outperforms the GDP-based benchmark model. In contrast, strictly pooling data by assuming slopes and intercepts to be identical for the whole sample worsens the accuracy of the demographically based forecasts significantly. This suggests that there is considerable heterogeneity across countries and the intercepts should be allowed to vary from country to country. The quality of the demographically based forecasts is superior to the benchmark forecasts especially for total final electricity consumption, and there in particular for long forecasting horizons. The advantage of the age models is less pronounced for residential and industrial consumption (where forecasts are in general less accurate for both demographically and GDP-based models). Forecasts over the period 2011-2025 using demographic projections predict positive but diminishing future growth rates of final electricity consumption for the OECD sample.

Overall, this paper suggests simple and easy-to-implement demographically based models to

[12]The two-way fixed effects model may consider some of these effects by controlling for time fixed effects which may include OECD-wide trends such as technological progress.

be a promising forecasting device for long-term electricity consumption. The forecasts of these models are particularly well-suited to serve as baseline scenarios and starting point for more complex forecasting and planning process where in subsequent steps differing policy assumptions can be built around the baseline projections.

Table 4.1: Estimation Results for Age Effects on per Capita Electricity Consumption (MWh)

(a) Total Final Consumption

	Heterogeneous				Homogeneous				In-Between
	iOLS		MG	CCEMG[1]	pOLS	FE1	FE2	RE	PMG[2]
	max	min							
AGE15-29	0.772***	-1.302***	0.175*	0.0407	0.0809	0.214***	-0.0570*	0.213***	0.0926**
	(0.143)	(0.383)	(0.0983)	(0.0435)	(0.0775)	(0.0274)	(0.0299)	(0.0273)	(0.0399)
AGE30-49	1.129***	-0.363	0.366***	0.0117	0.409***	0.441***	0.132***	0.442***	0.0545
	(0.267)	(0.263)	(0.0818)	(0.0473)	(0.0543)	(0.0225)	(0.0294)	(0.0225)	(0.0387)
AGE50-64	0.967***	-0.271***	0.321***	0.0424	-0.245***	0.100***	-0.00332	0.0991***	0.0989**
	(0.317)	(0.0832)	(0.0791)	(0.0506)	(0.0943)	(0.0349)	(0.0345)	(0.0349)	(0.0426)
AGE65+	4.038***	-0.694***	0.702***	0.198**	0.538***	0.628***	0.0850**	0.627***	0.442***
	(0.194)	(0.213)	(0.191)	(0.0887)	(0.0637)	(0.0254)	(0.0349)	(0.0253)	(0.0203)

(b) Residential

	Heterogeneous				Homogeneous				In-Between
	iOLS		MG	CCEMG[1]	pOLS	FE1	FE2	RE	PMG[2]
	max	min							
AGE15-29	0.263***	-0.316**	0.0662**	-0.0108	-0.000783	0.0681***	-0.0465***	0.0679***	0.0422**
	(0.0217)	(0.123)	(0.0325)	(0.0143)	(0.0252)	(0.0107)	(0.0116)	(0.0107)	(0.0186)
AGE30-49	0.285***	-0.0924***	0.112***	-0.0269	0.0816***	0.122***	-0.0243**	0.122***	0.182***
	(0.0723)	(0.0159)	(0.0228)	(0.0337)	(0.0177)	(0.00884)	(0.0113)	(0.00881)	(0.0225)
AGE50-64	0.350***	-0.0486	0.0943***	0.0550**	-0.161***	-0.0192	-0.0815***	-0.0199	0.0195
	(0.0519)	(0.0646)	(0.0242)	(0.0267)	(0.0308)	(0.0137)	(0.0133)	(0.0137)	(0.0256)
AGE65+	1.289***	-0.376***	0.234***	0.0377	0.217***	0.229***	0.00441	0.229***	-0.0350
	(0.0613)	(0.105)	(0.0652)	(0.0445)	(0.0208)	(0.0100)	(0.0134)	(0.00999)	(0.0337)

Note: Standard errors in parentheses. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively. [1]Augmented cross-section means effects of CCEMG estimator and [2]short-term effects form PGM estimator included, but coefficients not reported.

Table 4.1: Estimation Results for Age Effects on per Capita Electricity Consumption (MWh) *(continued)*

(a) Industry

	Heterogeneous				Homogeneous				In-Between
	iOLS		MG	CCEMG[1]	pOLS	FE1	FE2	RE	PMG[2]
	max	min							
AGE15-29	0.389***	-0.600	0.0818*	0.0503*	0.0442	0.0853***	-0.0150	0.0852***	0.161***
	(0.0331)	(0.376)	(0.0441)	(0.0296)	(0.0381)	(0.0116)	(0.0134)	(0.0116)	(0.0215)
AGE30-49	0.838***	-0.438	0.153**	-0.0286	0.145***	0.163***	0.105***	0.163***	0.190***
	(0.115)	(0.267)	(0.0612)	(0.0310)	(0.0267)	(0.00958)	(0.0132)	(0.00956)	(0.0220)
AGE50-64	0.737***	-0.211***	0.112**	-0.0306	-0.0505	0.0306**	0.0476***	0.0304**	-0.145***
	(0.145)	(0.0587)	(0.0553)	(0.0443)	(0.0464)	(0.0149)	(0.0155)	(0.0148)	(0.0268)
AGE65+	1.429***	-1.180***	0.192**	0.0703	0.185***	0.204***	0.0531***	0.204***	0.116***
	(0.148)	(0.273)	(0.0976)	(0.0518)	(0.0313)	(0.0108)	(0.0157)	(0.0108)	(0.0182)

Note: Standard errors in parentheses. ***, ** and * indicate statistically significant coefficients at the 1, 5, and 10 percent levels, respectively. [1]Augmented cross-section means effects of CCEMG estimator and [2]short-term effects form PGM estimator included, but coefficients not reported.

Table 4.2: Out-of-Sample Forecasting Performance - Annual Final Electricity Consumption

		MAPE			
Rank	Model/Estimator	**15 year average**	5th year	15th year	Theil's U
1	AGE-FE2	**6.789**	5.515	10.275	0.577
2	AGE-FE1	**6.932**	5.465	11.049	0.594
3	AGE-RE	**7.579**	5.923	11.971	0.655
4	AGE-iOLS	**8.190**	6.000	11.757	0.700
5	GDP-pOLS	**8.261**	5.713	14.710	0.704
6	GDP-RE	**8.924**	6.153	16.132	0.725
7	GDP-FE1	**9.252**	6.237	16.925	0.730
8	GDP-FE2	**9.444**	6.659	17.185	0.758
9	AGE-PMG	**9.795**	6.169	16.812	0.978
10	GDP-MG	**9.969**	9.544	12.913	0.721
11	GDP-CCEMG	**10.103**	5.802	19.734	0.857
12	AGE-pOLS	**10.594**	6.424	20.386	0.833
13	GDP-iOLS	**10.766**	6.121	21.376	0.901
14	AGE-CCEMG	**10.920**	9.001	14.924	0.826
15	GDP-PMG	**11.464**	6.974	21.510	0.981
16	Naive	**12.018**	10.035	17.851	1.000
17	AGE-MG	**16.419**	17.486	17.099	1.171

Table 4.3: Out-of-Sample Forecasting Performance - Annual Residential Electricity Consumption

		MAPE			
Rank	Model/Estimator	**15 year average**	5th year	15th year	Theil's U
1	AGE-iOLS	**9.587**	6.151	16.401	0.702
2	AGE-FE1	**9.751**	6.300	17.481	0.681
3	AGE-CCEMG	**9.770**	6.294	17.518	0.786
4	GDP-pOLS	**10.180**	6.870	18.944	0.742
5	GDP-RE	**10.181**	6.723	18.435	0.717
6	GDP-FE1	**10.376**	6.838	19.119	0.702
7	GDP-CCEMG	**10.562**	6.948	19.238	0.723
8	AGE-FE2	**10.706**	6.840	16.656	0.722
9	GDP-MG	**10.766**	10.692	11.937	0.710
10	AGE-RE	**10.836**	7.176	18.871	0.779
11	AGE-PMG	**11.591**	6.771	20.876	0.878
12	GDP-FE2	**11.626**	7.526	21.515	0.827
13	GDP-iOLS	**12.298**	8.107	22.250	0.899
14	AGE-pOLS	**12.373**	7.473	23.700	0.858
15	Naive	**14.228**	11.133	21.364	1.000
16	AGE-MG	**16.440**	17.942	16.232	1.064
17	GDP-PMG	**16.909**	9.321	34.014	1.350

Table 4.4: Out-of-Sample Forecasting Performance - Annual Industrial Electricity Consumption

		MAPE			
Rank	Model/Estimator	**15 year average**	5th year	15th year	Theil's U
1	GDP-pOLS	**8.968**	5.692	17.883	0.661
2	AGE-FE1	**9.740**	7.262	19.676	0.751
3	GDP-RE	**11.221**	6.919	21.517	0.798
4	AGE-FE2	**11.542**	6.552	25.762	0.866
5	AGE-pOLS	**11.600**	6.015	25.521	0.874
6	AGE-RE	**11.965**	6.366	26.484	0.898
7	GDP-FE2	**12.033**	7.479	24.899	0.874
8	AGE-iOLS	**12.415**	9.161	23.098	0.888
9	GDP-FE1	**12.562**	7.385	28.348	0.955
10	AGE-CCEMG	**14.199**	12.604	22.936	0.981
11	Naive	**14.506**	9.922	27.814	1.000
12	GDP-iOLS	**14.547**	6.796	34.909	1.099
13	AGE-PMG	**17.366**	11.841	31.448	1.512
14	GDP-CCEMG	**19.482**	8.504	47.321	1.787
15	GDP-PMG	**20.263**	10.623	47.924	1.575
16	GDP-MG	**25.288**	21.503	35.469	1.561
17	AGE-MG	**30.987**	29.953	37.604	2.071

Table 4.5: Forecasts Final Electricity Consumption (GWh) up to 2025

	2010	2018	2025	Average annual growth (%)
Australia	201'221	238'735	268'618	2.23
Austria	61'333	67'582	71'805	1.14
Belgium	83'311	89'638	93'515	0.82
Canada	469'948	561'428	628'557	2.25
Denmark	32'065	35'968	39'016	1.45
Finland	83'479	87'919	90'706	0.58
France	444'089	485'520	516'376	1.09
Germany	528'958	580'887	605'978	0.97
Greece	53'120	58'735	62'179	1.14
Ireland	25'156	29'962	33'848	2.30
Italy	299'313	339'154	362'819	1.41
Japan	1'001'837	1'094'658	1'136'731	0.90
South Korea	449'345	519'818	568'741	1.77
Netherlands	106'865	119'304	128'646	1.36
New Zealand	39'304	46'608	52'404	2.22
Norway	114'682	129'944	141'440	1.56
Portugal	49'888	57'119	62'653	1.71
Spain	260'578	294'433	316'449	1.43
Sweden	131'217	144'773	155'043	1.21
Switzerland	59'772	69'695	77'314	1.96
United Kingdom	328'318	374'431	406'650	1.59
United States	3'801'921	4'274'346	4'657'630	1.50
Total	8'625'720	9'700'655	10'477'118	1.43

4.6 Appendix

Appendix 1: List of Countries

The country sample includes the following OECD countries:

Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Portugal, Spain, South Korea, Sweden, Switzerland, United Kingdom and the United States.

Appendix 2: Pooled Mean Group (PMG) Specification

In order to apply the Pooled Mean Group (PMG) estimator, I follow Pesaran et al. (1999) and transform the dynamic panel models in equations (4.2) and (4.3) into a first-order autoregressive distributed lag (ARDL) form. In the following the transformation is described for the age structure model, but applies analogously for the benchmark model:

$$E_{it}/POP_{it} = \lambda_i(E_{it-1}/POP_{it-1}) + \sum_k \theta_{k0i} AGE_{kit} + \sum_k \theta_{k1i} AGE_{kit-1} + \varepsilon_{it} \tag{4.10}$$

with an one-way error component $\varepsilon_{it} = \mu_i + v_{it}$. The error correction is specified as:

$$\triangle(E_{it}/POP_{it}) = \phi_i(E_{it-1}/POP_{it-1} - \beta_{0i} - \sum_k \beta_{ki} AGE_{kit}) - \sum_k \theta_{k1i} \triangle AGE_{kit} + \varepsilon_{it} \tag{4.11}$$

where ϕ_i is the speed of adjustment to the long-run equilibrium, defined as $\phi_i = -(1 - \lambda_i)$. The long-term coefficients for each age share group k follow the form $\beta_{ki} = \frac{\theta_{k0i}+\theta_{k1i}}{1-\lambda_i}$. Finally, the inclusion of the term $\beta_{0i} = \frac{\mu_i}{(1-\lambda_i)}$ allows the mean of the cointegration relationship to be nonzero.

5. Conclusion

This cumulative dissertation consisting of three self-contained essays has empirically analyzed the impact of demography and the age structure on different economic aspects. The first essay has dealt with the question whether and to what extent demographic factors can explain the build-up of large and persistent current account surplus positions in some OECD countries since the mid-1990s. In order to analyze this issue, the study has taken a saving-investment perspective and examined the relationship between the present age distribution as well as anticipated future demographic change on the one side and real domestic saving, investment and the current account on the other side. Expectations of agents were captured by aggregated anticipation measures that are based on a series of historical population projections dating back up to the 1960s. Using data from a broad country panel sample, the study provides evidence for substantial demographic effects on real domestic saving rates and, to a lesser extent, on investment rates that seem to translate into demographic induced movements in the current account balance. An increase in present old age dependency rates significantly lowers domestic saving and investment rates and the current account. This confirms the theoretical proposition of life cycle dynamics in saving and investment behavior. Similarly, projected changes in the future age distribution show to have an impact on present saving and investment behavior. A projected future increase in old age dependency seems to induce precautionary saving behavior and provoke a negative impact on investment rates. This positive effect on saving rates in combination with the negative impact on investment translates into an upward pressure on the current account. The results are very similar for a closed economy and extended open economy framework suggesting that domestic factors prevail in the determination of saving and investment rates. The estimated demographic effects are rather strong for some OECD surplus countries and can explain to some extent the saving and investment pattern which could be observed since the early 1990s.

The second essay has analyzed the link between population and workforce aging on the one side and innovation on the other side. Thereby, triadic patent data has been used as an indicator for technological innovation and the number of cross-border trademarks as a measure for marketing and product innovation. The results of the regression analysis with a sample of 22 OECD countries suggest that there is an inversely U-shaped relation between the population age distribution and the output of innovation in form of triadic patent filings. While the contribution of young and old age groups to the innovation generation process seems to be relatively small, middle aged groups appear to be a crucial driver of innovation. Especially the relation between the share of the mature adults (30-49 years) within the total population and the number of new patent applications per capita is strongly positive. A further analysis reveals that the estimation results do not solely emanate from different levels of educational attainment across age cohorts. Similarly, the link between the population age composition and cross-border trademark filings follows a hump-shaped pattern, even though the age-trademark link is statistically less significant. Finally, the link between the workforce age distribution and innovation is not conclusive. Even though there are some hints for workforce age effects, the statistically weak results suggest that the main driving force behind the identified macroeconomic population age effects on innovative output is not any variance in productivity levels across worker groups of different ages but rather dependency effects and interdependencies between active and non-active population groups.

Finally, the third and last essay has examined the forecasting performance of a demographically based model for long-term electricity consumption. Using a heterogeneous panel dataset of OECD countries, the study finds age structure information to have significant explanatory power on per capita electricity consumption. Subsequent out-of-sample experiments with unconditional forecasts based on historical demographic projections have shown that a simple reduced-form forecasting model including age shares as regressors performs well both compared to an alternative GDP-based model as well as to naïve forecasts. Especially when the models are pooled but allowed to have differing intercepts, the age structure model clearly outperforms the alternative models. This suggests simple and easy-to-implement demographically based models a promising forecasting device for long-term electricity consumption. Forecasts over the period 2011-2025 using demographic projections predict positive but diminishing growth rates of final electricity consumption for the OECD sample.

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Curriculum Vitae

Andreas Tusch

Research & Education

2010–14 University of St. Gallen, Switzerland
Ph.D. in International Affairs and Political Economy

2001–07 University of St. Gallen, Switzerland
Bachelor of Arts & Master of Arts in International Affairs

Exchange & Visiting Research Terms

2012–13 Stockholm School of Economics (SSE), Sweden

2007 University of Auckland, New Zealand

2003 Singapore Management University (SMU), Singapore

Professional Experience

2014– Inhouse Consultant, Unicredit Management Consultancy, Munich

2008–10 Strategy Consultant, The Advisory House, Munich

2005 Internship Corporate Finance, DaimlerChrysler Argentina, Buenos Aires