Inequality in Germany

The Role of Household Context and the Concept of Economic Resources

Inauguraldissertation

zur

Erlangung des Doktorgrades

der

Wirtschafts- und Sozialwissenschaftlichen Fakultät

der

Universität zu Köln

2012

vorgelegt

von

Dipl.-Volksw. Nico Pestel

aus

Goch

Referent: Prof. Dr. Clemens Fuest

Korreferent: Prof. Dr. Felix Bierbrauer

Tag der Promotion: 17. Januar 2013

Acknowledgements

This dissertation is the result of my research work over a period of more than three years and its completion would not have been possible without the help and guidance of many others. I am very grateful for the support from the Institute for the Study of Labor (IZA) in Bonn, where I have been working as a Resident Research Affiliate under the IZA Scholarship Program since 2009. I greatly benefited from a range of resources provided by IZA as well as from the excellent working environment there. I am grateful to Clemens Fuest for supervising my doctoral studies at the University of Cologne despite the physical distance to Oxford, where he is Research Director of the Oxford University Centre for Business Taxation. In addition, I would like to thank Felix Bierbrauer, who is Professor of Public Economics at the University of Cologne, for being the second supervisor of my dissertation. In particular, I am truly indebted and thankful to Andreas Peichl for his excellent and continuous support during the last years. His assistance, guidance, encouragement and friendship have been a great source of inspiration and motivation for my work. He is also a co-author of three chapters (2, 4 and 5) of this dissertation. Of course, I am also obliged to my other co-authors: Hilmar Schneider, my supervisor at IZA, co-authored chapter 4. My colleague Sebastian Siegloch is a co-author of chapter 2. A special thank goes to him for the friendly and productive working environment while sharing an office with me. Moreover, I wish to acknowledge many helpful comments and suggestions that I received from numerous colleagues at seminars, workshops and conferences. Finally, I would like to express my gratitude to my parents and my family who have always and unconditionally supported me in pursuing my goals. Above all, I am particularly grateful to my beloved wife Elena for all the support and encouragement that I receive from her on every single day of our life.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Motivation and Contribution

Economic inequality has increased considerably in many Western countries over the past decades.[1] The growing gap between rich and poor is now one of the main issues on the policy agendas around the world. The recent period of economic crisis in the aftermath of the 2008 financial market collapse in the United States has rendered issues concerning the distribution of economic resources, in general, and questions of the appropriateness of extremely high earnings, in particular, even more urgent (OECD, 2011, p. 17). Austerity measures in the context of the euro crisis have recently triggered social unrest in countries like Greece and Spain where these measures are perceived to affect the poor disproportionally. The "*Occupy Wallstreet*" movement, which presses policy makers for steps against growing social and economic inequality, has popularized the catchphrase "*We are the 99%*". Interestingly, this slogan directly refers to academic research on the increasing income share of the richest 1% of the US population, which is nowadays back to historically high levels.[2] The latter example especially shows that the *distribution* of economic resources across the population is not just a matter for

[1]For extensive overviews, see Gottschalk and Smeeding (1997); Atkinson and Piketty (2007); OECD (2008, 2011); Atkinson (2008b); Salverda et al. (2009).

[2]Figures of this trend over the last century (e.g., Piketty and Saez, 2007b, pp. 147 ff.) have become widespread not only in academic journals but also in leading newspapers (New York Times, Oct. 26, 2011: "*It's Official: The Rich Get Richer*", Frankfurter Allgemeine Sonntagszeitung, Oct. 14, 2012: "*Amerika entdeckt den Klassenkampf*").

public debate and policy making. On the contrary, the analysis of distribution is long since "*back in from the cold*" (Atkinson, 1997) and has turned from "*watching the grass grow*" (Aaron, 1978) to an active and relevant area of research in public economics. This dissertation contributes to the literature on economic inequality with a special focus on Germany. In the remainder of this section, I will outline why the study of economic inequality, in general, is a relevant area of research with important implications for policy making and public debate. In the next section, I will give an overview of the specific research questions that are addressed in the single chapters and briefly present the main results.

Why should economists care? In addition to public and policy makers' interest in issues concerning economic inequality, there is also *scientific* interest in this topic. Salverda et al. (2009) argue that there are mainly three reasons for being interested in economic inequality. First, the distribution of economic resources and factors that influence this distribution "*were central concerns at the outset of market economics*" (p. 6). In addition, according to Musgrave (1959), income redistribution is one of three functions of government activity alongside the efficient allocation of resources and macroeconomic stabilization. Hence, the distribution of resources is a key component of economic research whereby the focus of the literature has shifted from functional to personal distributions over the last decades (Goldfarb and Leonard, 2005). Second, both citizens and policy makers have strong normative feelings about inequality. Economists should, therefore, be able to provide answers to economic phenomena that are of such vital concern for agents in the political process (Atkinson and Bourguignon, 2000, p. 4). Indeed, scientific interest in income distribution has increased alongside increases in inequality (Jenkins and Micklewright, 2007a). Finally, even if inequality itself were not of great interest, there are a number of important implications that come with it. For example, many economists argue that inequality is not a bad thing per se. On the contrary, inequalities in relative factor prices are fundamental to the functioning of market economies. With a special focus on labor markets, Welch (1999) emphasizes that inequalities in wages are "good" since they signal scarcities, provide incentives for investments in human capital and compensate for different job attributes. However, Welch himself states that inequality becomes "destructive" when society does not view effort as worthwhile and upward mobility is perceived unlikely or even impossible. In general, public opinion in market economies shares economists' view that absolute equality in economic outcomes is not desirable and that inequalities are, to a certain degree, not only inevitable but even necessary (Salverda et al., 2009, p. 7). However, if income differences are viewed as insurmountable, social cohesion as well as acceptance of market economy and even democracy are challenged (Stiglitz, 2012).

So, is inequality "good" or "bad" at the end of the day? Atkinson (1997) argues that the normative assessment of *equity* is rather concerned with *mobility* over the lifecycle or across generations and not with cross-sectional income differences. However, there is evidence that economies with greater levels of inequality also show lower levels of mobility (Björklund and Jäntti, 1997; OECD, 2008) which can hamper equality of opportunity (Roemer, 1998) and, hence, justice. In addition, a recent strand in the literature shows that relative income positions matter for subjective well-being of individuals (Luttmer, 2005; Senik, 2005; Clark et al., 2008). Moreover, Bartels (2008) and Gilens (2012) show for the US that increasing levels of economic polarization can lead to *political* polarization. Governments seem to become more responsive to preferences of the affluent population while preferences of low and middle income earners – the majority of the electorate – are less or even not at all represented when a small fraction of the population commands a large share of economic resources (Atkinson and Piketty, 2007).[3]

To sum up, in light of these direct and indirect effects of economic inequality on various dimensions, there are good reasons why economists should carry out sound analyses of the distribution of resources across households and individuals. This should serve as a basis for explaining causes and consequences to policy makers and the wider public. Given that there is no consensus on an "optimal level of inequality", it is very difficult for decision makers to judge whether a society experiences levels of inequality that actually harm public welfare or not. An objective basis for decision making should, therefore, consider the specific causes and implications of inequality, since it is usually the result of a complex

[3]Murray (2012) cites the former US Supreme Court Justice Louis D. Brandeis (1856–1941): "*We can have democracy in this country, or we can have great wealth concentrated in the hands of a few, but we cannot have both*" (p. 1).

interaction of various contributions and determinants that are discussed in the following. Speaking with Jenkins (1995), one should know "*whodunnit*" (p. 29).

Inequality of what among whom? When dealing with economic inequality as a research subject the question "*inequality of what among whom*" arises (Goldfarb and Leonard, 2005). The answer to the part "*among whom*" is straightforward for economists. The term *economics* dates back to the ancient Greek word *oikos* which means *household*. Hence, the essence of the economics discipline is the study of the smallest unit of individuals within an economy jointly carrying out production and consumption activities. The question of "*what*" is related to the underlying concept of economic resources and is much more complex. Analyses of inequality are typically concerned with the distribution of wages, earnings or income.[4] However, there are "*several steps between relative factor prices and [...] disposable income among households*" (Atkinson, 2003a, p. 23). The most important steps in this process are the creation of *gross market income* from various sources and all household members, the design of the government's *tax and transfer system* as well as patterns of *household formation and composition*.

Firstly, gross labor earnings make up the largest share of total household incomes and are an important driver of income inequality (Atkinson, 2008b). A vast literature in labor economics deals with rising wage and earnings dispersion. Common explanations are changes in the supply and demand for skills and tasks as well as changing labor market institutions and policies.[5] In addition, differences in wages and earnings are affected by pay differentials across gender, race, occupations or sectors.[6] Other market incomes, from self-employment and private pensions as well as from capital and property, have also gained importance as

[4]In addition, there are some studies on consumption inequality (see, e.g., Fuchs-Schündeln et al., 2010; Heathcote et al., 2010; Meyer and Sullivan, 2010, 2011).

[5]See Autor et al. (1998); Katz and Autor (1999); Card and Lemieux (2001); Goldin and Katz (2008); Autor et al. (2008); Acemoglu and Autor (2011) for studies on the effects of skill-biased technological change and increasing international trade with low-wage countries. The role of the minimum wage and trends of de-unionization have, among others, been investigated by DiNardo et al. (1996); Fortin and Lemieux (1997); Card and DiNardo (2002); Lemieux (2006).

[6]See Altonji and Blanc (1999); Blau and Kahn (2000, 2006); Kunze (2005); Arulampalam et al. (2007) for an overview of the literature on gender and racial wage gaps and Ehrenberg and Schwarz (1987); Pederson et al. (1990); Hundley (1991) for pay differentials across the private and public sector. Chapter 2 deals with a related issue.

sources of both income and inequality (Frick and Grabka, 2003, 2010; OECD, 2011). A recent strand in the literature deals with the contribution of top incomes to overall inequality and shows that large shares of total pre-tax income are increasingly concentrated among the rich (Piketty and Saez, 2003; Atkinson and Piketty, 2007; Atkinson et al., 2011).

Secondly, another important determinant of household income is the tax and transfer system.[7] Governments redistribute market incomes via income and payroll taxes as well as cash and in-kind benefits. The level of redistribution, i.e., the difference between inequality of market and disposable income, is determined by the institutional setting of the economy as well as voters' and policy makers' perceptions and preferences for redistribution from rich to poor (see McCarty and Pontusson, 2009, for an overview of the political economy of redistribution).[8]

Finally, total disposable household income depends on the household context, i.e., the number, composition and characteristics of individuals actually forming households. For given wages and labor market conditions, gross earnings depend on the number of hours worked, while taxes paid and cash benefits received are determined by the characteristics of and the family relationships within households. Hence, the household context, which has changed tremendously over the past decades, determines the distribution of resources both within and across households in the economy.[9] The observed distribution of disposable income is not simply a matter of mechanically applying the tax and transfer schedule to gross incomes for a given household composition, but the result of complex interactions between the market production of gross income (joint decisions on labor supply and savings) and the formation of households (marriage, cohabitation and fertility decisions,

[7]See, among others, Slemrod (1992); Poterba (2007); Piketty and Saez (2007a); Bargain and Callan (2010); Peichl and Doerrenberg (2012) for analyses of the (re)distributional effect of tax and transfer policies.

[8]For example, Bargain et al. (2011) decompose the change in after-tax income inequality in the US over a period of 30 years and isolate the direct policy effect on inequality. They find that tax reforms implemented under Democrat (Republican) administrations had an equalizing (disequalizing) effect. As a consequence of partisan politics, the overall policy effect almost cancels out over the whole time period.

[9]See Jenkins (1995); Cancian and Reed (1998, 1999); Burtless (1999, 2009); Hyslop and Mare (2005); Daly and Valletta (2006); Martin (2006); Bover (2010); Schwartz (2010) for studies addressing the role of changing household and family structures for inequality. Chapters 3 and 4 contribute to this literature.

ageing and retirement), which might, in turn, be affected by incentives from the tax and transfer system. Therefore, it is an enormous challenge to formulate "*models of the household income distribution, incorporating not only models of labour market earnings [...] and the demographic factors affecting who lives with whom*" (Jenkins and Micklewright, 2007a, p. 19). This issue is beyond the scope of this thesis and, instead, the analysis is restricted to particular aspects and "building blocks" (Atkinson and Bourguignon, 2000, p. 5).

The discussion of different concepts of economic resources has so far been restricted to either gross or disposable income and, hence, to the *flow dimension* of economic resources. However, recently interest in the *stock dimension*, the accumulation of assets commanded by households and individuals, has increased. Stiglitz et al. (2009) recommend including the analysis of wealth when assessing the well-being of the population, which is important for the analysis of economic inequality for several reasons. First, wealth is typically much more unequally distributed than income (Davies et al., 2011) and should therefore complement the analysis of inequality. Second, wealth fulfils several important economic functions. It serves as a source of income, utility and power as well as social status and helps to stabilize consumption over time (Wolff and Zacharias, 2009; Michelangeli et al., 2011). Finally, especially with regard to the analysis of inequality at the top of the distribution, the composition of the rich subpopulation is very heterogenous in terms of income and wealth (Atkinson, 2008a; Waldenström, 2009). In fact, inequality in wealth can differ substantially from inequality in income (OECD, 2008; Jäntti et al., 2008; Roine and Waldenström, 2009).[10]

The case of Germany. Germany has long been a country with comparatively low levels of income inequality among the OECD world. Although still exhibiting average levels of inequality, the growth in the income gap has been considerably fast since the turn of the millennium (OECD, 2008, 2011). Therefore, empirical results in the academic literature relating to inequality in Germany differ substantially, depending on the specific period under consideration. After World War II, the distribution of income was quite stable until the 1980s, inequality started growing slowly in the 1990s and growth accelerated around 2000 (Dell, 2005, 2007;

[10] Chapter 5 analyzes the joint distribution of income and wealth at the top.

Atkinson, 2007b). Drivers of this trend have mainly been gross incomes, especially at the top of the distribution (Bach et al., 2009; Fuchs-Schündeln et al., 2010).

Special attention has been paid to the development of wage inequality and the effects of globalization, technological change and changes in wage bargaining on the labor market (Dustmann et al., 2009; Antonczyk et al., 2010). In addition and in line with similar experiences in other countries, capital and property have become more important income sources, which are very unequally distributed and increasingly contribute to overall inequality (Frick and Grabka, 2003; Frässdorf et al., 2011). This is also reflected in the growth of wealth inequality in Germany (Hauser, 2003; Frick et al., 2010). The reunification of East and West Germany in 1990 and the transition process of the former East afterwards has also rendered the overall distribution more unequal (Schwarze, 1996; Grabka et al., 1999; Biewen, 2005; Fuchs-Schündeln et al., 2010).

Moreover, household composition has changed considerably. For example, German household size is now the second lowest among OECD countries (OECD, 2008), which has important implications for the distribution of income. While market income inequality is relatively high in Germany, inequality in disposable income after taxes and transfers is average in international comparisons (OECD, 2008, 2011). This is mainly due to the progressive system of income taxation. Although there is some evidence that a series of reforms after 2000 have reduced the redistributive effect of the income tax, it is still characterized by a high level of progression (Corneo, 2005; Bach et al., 2011).

In a series of reports on *poverty and richness* in Germany (Bundesregierung, 2001–2012) the German federal government regularly monitors the development of inequality across various dimensions and gives an overview of the population's attitude to distributional issues. Moreover, the government states its general assessment of the current level and future development of inequality and how it intends to address this. According to these reports, policy makers and the public in Germany are, generally, very concerned with inequality and preferences for redistribution are quite high (Alesina and Angeletos, 2005).

Hence, Germany is an interesting case for the study of inequality, since every component determining the overall distribution of economic resources described above plays an important role in this country: Market income inequality has increased substantially over the past decades, the tax and transfer system is strongly redistributive and reduces market inequality. Moreover, the population structure has distinctly changed and inequality is an important issue on the policy agenda.

1.2 Agenda and Summary of Results

The aim of this dissertation is to contribute to the empirical literature on economic inequality in Germany. The studies presented in the following chapters differ with respect to both "*inequality of what*" as well as "*among whom*". More precisely, the underlying concept of economic resources varies between earnings, gross and net household income as well as household wealth. At the same time, the extent to which the household context is involved in the analysis ranges from individuals to couples to the entire household. In the remainder of this section, I will first briefly outline the overall agenda of the thesis and then summarize the proceedings as well as the main results of each chapter separately.

Agenda. The agenda is as follows. Chapter 2 addresses the literature on the dispersion of *individual earnings* and deals with a very specific case of a wage gap by testing for an earnings premium for German members of parliament. Chapter 3 extends the analysis of earnings inequality beyond the individual level and considers the household context and studies the role of marital sorting on inequality of *couple earnings* while taking into account labor supply behavior of spouses. Whereas chapters 2 and 3 are confined to the analysis of the distribution of gross labor earnings, chapter 4 is concerned with the distribution of *total household income* (gross and net) and examines the role of changing household structure. Finally, while the previous chapters analyze the flow of earnings and incomes, chapter 5 extends the analysis to the stock dimension of economic resources and looks at the joint distribution of *household income and wealth* at the top. Chapter 6 concludes.

Chapter 2. Individual Earnings: The Politicians' Wage Gap. A vast literature in (labor) economics deals with the dispersion of individual gross wages and earnings. As discussed before, labor earnings make up a large share of total household income and, therefore, earnings inequality is a "*subject of real significance for everyone*" (Atkinson, 2008b, p. 3). While a large portion of differences in remuneration of workers can be explained by differences in human capital as well as labor market conditions and policies, there is still a significant share that remains unexplained. A number of analyses have shown that compensating wage differentials, rent-seeking behavior and discrimination also play an important role in explaining pay differences. Moreover, the current economic crisis has rendered issues concerning the *appropriateness* of high earnings an important topic in public debate. Hence, for the assessment of whether earnings inequalities are equitable, it is crucial to determine whether they can be justified or not.

Chapter 2 deals with a very specific case of a wage gap and tests whether there is an earnings premium for German members of parliament (MPs). Of course, the pay of a tiny number of MPs (in comparison to the total population) cannot noticeably affect the entire distribution of earnings in Germany. However, politicians' earnings attract wide media attention and, therefore, have a strong impact on the public's attitudes towards equitable pay, particularly since members of parliament command legislative power that can be used for regulative and/or redistributive purposes. Hence, with respect to the assessment of pay adequacy, German MPs are of special interest.

There are, however, arguments in favor of a positive wage gap for politicians. The citizen candidate framework suggests an income premium in the form of a compensating wage differential for the uncertainty of (re)election as well as for campaigning costs. Moreover, a wage premium for MPs could be beneficial for society if it attracted more able individuals to run for office and, as a consequence, yielded a more efficient provision of public goods.

Using a unique dataset of German MPs, this chapter analyzes the politicians' wage gap (PWG). After controlling for observable characteristics as well as accounting for election probabilities and campaigning costs, we find a positive earnings premium for MPs which is statistically and economically significant. The results are consistent with the citizen candidate model when comparing MPs to citizens occupying executive positions. However, it shrinks to zero when restricting the control group to top level executives.

Chapter 3. Couple Earnings: Marital Sorting and Labor Supply. Studies on pay differentials like chapter 2 are mainly concerned with the adequacy of and inequalities in individual earnings. However, earned income is not only determined by a worker's productivity (the wage rate) but also by the number of hours worked, which results from labor supply coordination within households.

Chapter 3 extends the analysis beyond the distribution of pay across individuals to the investigation of joint couple earnings. Increases in the correlation of spouses' earnings in couple households has been interpreted as an increasing similarity of spouses in terms of earnings-related characteristics (assortative mating), which has an amplifying effect on inequality since it reduces the level of redistribution within households. Previous studies on this issue can largely be classified as accounting approaches since observed earnings distributions are compared to counterfactuals by manipulating the correlation between male and female earnings. However, the role of labor supply behavior has so far not been taken into account.

In this chapter, I measure the effect of non-random sorting of spouses on inequality across couple households in West Germany from 1986 to 2010 by matching couples randomly to each other and predicting counterfactual labor supply choices. This allows me to quantify the pure effect of sorting in *earnings potential* rather than observed earnings. Using German microdata as well as a behavioral microsimulation model, I find that the impact of observed sorting on earnings inequality among couples turned from slightly equalizing to slightly disequalizing in recent years, but is generally rather neutral. However, after adjusting for the effect of labor supply choices, I find that sorting in productivity has a much stronger impact on earnings inequality.

Chapter 4. Income Inequality, Household Size and the Welfare State. Increasing correlation of spouses' earnings is only one aspect of changing living arrangements and household contexts in many Western countries. More generally, structural shifts in household composition are linked to rising inequality, since the number and characteristics of individuals living together affect the distribution of economic resources due to income sharing within households.

Chapter 4, therefore, addresses the effect of changing household compositions on inequality in pre and post government income (after subtracting income and payroll taxes and adding benefit payments to market incomes) and, hence, pays special attention to the role of the tax and transfer system in Germany. Moreover, while the previous chapters deal with the important role of gross income inequality, economic well-being depends on resources that are available for current and future consumption, i.e., disposable income. The aim of this chapter is to quantify the effect of changes in household composition that are accompanied by changes in employment patterns on the income distribution. The case of Germany is of special interest in this respect since the demographic development is not only characterized by an ageing population, but also by a sharp fall in average household size.

Using German microdata, we find that the growth of the income gap between 1991 and 2007 is indeed strongly related to changes in household composition. The result for income inequality before taxes and transfers is much larger than the result for inequality in disposable incomes. This means, that the welfare state has largely compensated for inequality induced by changes in household structure.

Chapter 5. Multidimensional Affluence: Income and Wealth. In line with many other analyses of economic inequality, chapters 2–4 apply concepts of economic resources that exclusively deal with the *flow dimension*. However, well-being is usually not perceived as an one-dimensional phenomenon and, recently, there is also an increasing interest in the *stock dimension*. In addition, top income and wealth shares of very rich households have been identified as important drivers of overall economic inequality.

Chapter 5 contributes to both strands of the literature and extends the analysis beyond income, introducing a family of multidimensional measures of affluence. The analysis is concerned with the role of both income and wealth for the top of the distribution and compares Germany to the US. Since "the rich" are an important source of both economic growth and economic inequality, it is important to know who the rich in society are, how much they have and what kind of resources they command. When determining who belongs to the top, the literature has so far only been concerned with a single dimension and has mainly focused on the shares of top fractiles.

However, neither a headcount ratio nor top shares are satisfying measures for (inequality of) economic well-being at the top because they do not account for changes in the composition or in the distribution among the top. Moreover, analyzing top income and wealth shares separately does not reveal insights about their *joint* distribution. In contrast to commonly used top income shares, the proposed multidimensional affluence measures allow for the analysis of the extent, intensity and breadth of affluence within a common framework.

We illustrate this by analyzing the role of income and wealth as dimensions of multidimensional well-being in Germany and the US in 2007, as well as for the US over the period 1989–2007. We find distinct country differences with the country ranking depending on the measure. While in Germany wealth predominantly contributes to the intensity of affluence, income is more important in the US.

Chapter 2

Individual Earnings: The Politicians' Wage Gap*

2.1 Introduction

The remuneration of politicians is widely debated in many countries. In particular, the fact that politicians can set their own salary frequently triggers public criticism whenever their wages increase. This might be one of the reasons why ever-larger fractions of the populations of Western democracies perceive that the political class has separated itself from the electorate, forming an elitist circle of substantive political power and little accountability (Hay, 2007). In addition, rising economic inequalities have amplified the general discontent with politicians, since the political elite belongs to the top of the income distribution, removed from the average citizen (Gilens, 2005; Solt, 2008).[1] There are, however, also arguments for a positive wage gap. From a positive point of view, the citizen candidate framework suggests an income premium for politicians as a form of compensation for the uncertainty of (re)election as well as for campaigning costs (Osborne and Slivinski, 1996; Besley and Coate, 1997). Moreover, a larger salary could raise the cost of

*This chapter is based on the paper *The Politicians' Wage Gap: Insights from German Members of Parliament* (joint with Andreas Peichl and Sebastian Siegloch, see Peichl et al., 2012).

[1] The German case is of special interest as the reputation of politicians in Germany seems to be lower than the reputation of most other occupations and has been decreasing for many years (Allensbacher Archiv, 2008). In addition, trust in German politicians is rather low compared to several other European countries (European Social Survey, 2007).

abusing political office (Becker and Stigler, 1974). From a normative perspective, a wage premium for politicians could be beneficial for society if it attracted more able individuals to run for office and as a consequence yielded a more efficient provision of public goods (Caselli and Morelli, 2004; Messner and Polborn, 2004).

In this chapter we empirically test whether there is a politicians' wage gap (PWG) for German members of parliament (MPs) conditional on qualification as well as election probabilities and campaigning costs.[2] To the best of our knowledge, this has not been investigated before. We make use of a unique microdata set of personal and professional information on German MPs, providing detailed insight into their earnings (including remuneration from public office and outside earnings) as well as their occupation before entering parliament (Becker et al., 2009). We combine these data with the German Socio-Economic Panel Study (SOEP), a microdata set which is representative for the German population and thus for the electorate. We estimate election probabilities as well as campaigning costs for candidates running for the German parliament in order to calculate MPs' expected income. The empirical analysis then proceeds in two steps in order to estimate the PWG. First, we employ a standard ordinary least squares (OLS) regression to account for observable characteristics that affect earnings. Second, we make use of semi-parametric matching techniques in order to further increase comparability between MPs and voters.

Our results show that both the sign and the size of the wage gap depend on the definition of the control group and the MPs' income. On average, politicians earn more than citizens in executive positions after controlling for observed characteristics, most importantly qualification. Using a broad definition of executives, the PWG varies between 35% and 65% depending on the specification (corresponding to 20,000–36,000 euros per year). Robustness checks suggest that these results are unlikely to be biased by positive selection into politics. When defining the control group more narrowly, the wage gap shrinks and is statistically indistinguishable from zero for "top level" executives, suggesting that German politicians' pay is

[2]Previous research has only examined income differentials between public and private sector employees. See Ehrenberg and Schwarz (1987); Bender (1998) and Gregory and Borland (1999) for overviews. Although most studies concentrate on US data, similar results are obtained for other countries (e.g., Pederson et al., 1990; Hartog and Oosterbeek, 1993; Melly, 2005; Gorodnichenko and Peter, 2007).

not excessive in this case. These findings are consistent with the citizen candidate framework, which stipulates a non-negative wage gap. The wage gap mechanically decreases when excluding politicians' outside earnings, while it increases considerably when neglecting election probabilities and campaigning costs.

The chapter is structured as follows. In section 2.2 we discuss the theoretical concept underlying our empirical analysis. Section 2.3 describes the institutional background and the data. In section 2.4 we lay out our empirical strategy and present the results. Section 2.5 concludes.

2.2 Theoretical Background

In this section we use the citizen candidate framework (Osborne and Slivinski, 1996; Besley and Coate, 1997) to provide a theoretical explanation for a non-negative income differential for members of parliament when compared to the electorate. All citizens initially find themselves in a situation of political competition and have to decide whether to run for office (Cadigan, 2005). Citizens weigh the costs of running for office against the uncertain individual benefits of winning the election.[3] Typically, the necessary condition for a rational citizen to decide to run for political office takes the form (Caselli and Morelli, 2004):

$$p \cdot (W^{office} - W^{private}) \geq CC. \tag{2.2.1}$$

Hence, the difference between income from public office (W^{office}) and market income in the private sector ($W^{private}$) weighted by the election probability (p) has to compensate for the direct campaigning costs (CC) associated with candidacy. From expression (2.2.1) it follows directly that the pay of politicians should exceed in the long run the incomes of comparable citizen in order to compensate for the uncertainty of (re)election and for the sunk costs of candidacy.

The model has implications for the selection of candidates with regard to qualification. The effect of ability on participation is mixed. On the one hand, high-

[3]See Besley (2004); Mattozzi and Merlo (2008); Gersbach (2009); Braendle and Stutzer (2010) and De Paola and Scoppa (2011). For empirical applications, see Ferraz and Finan (2009); Gagliarducci et al. (2010) and Gagliarducci and Nannicini (2012).

ability citizens have a larger expected income in the private sector and therefore face a smaller (perhaps negative) wage premium when running for office. On the other hand, if voters prefer competent citizens in political office, better qualified candidates are more likely to win the election and might face lower costs due to more efficient campaigning.

The politicians' wage gap. The main purpose of this study is to empirically test whether there is a wage premium for German MPs which can neither be explained by advantageous characteristics of politicians, such as qualification, nor by a compensation for uncertainties and campaigning costs stemming from electoral competition. In order to specify what we refer to as the politicians' wage gap (PWG), we define a binary indicator R_i, which equals 1 if individual i decides to run for office and 0 otherwise. Individual income Y_i is defined as:

$$Y_i(X_i, p_i) = \begin{cases} p_i \cdot W_i^{MP}(X_i) + (1 - p_i) \cdot W_i^{cit}(X_i) - CC_i & \text{if } R_i = 1 \\ W_i^{cit}(X_i) & \text{if } R_i = 0, \end{cases} \tag{2.2.2}$$

where X_i denotes individual characteristics and $p_i \in [0, 1]$ is the probability of being elected. When running for office, income is the probability weighted sum of remuneration from public office W_i^{MP} and potential income in the private labor market W_i^{cit} net of campaigning costs CC_i. When not running for office, income simply equals the market income of a citizen given characteristics Y_i^{cit}. Comparing the incomes of two individuals i (a candidate) and j (a citizen) with identical characteristics $X_i = X_j = \widetilde{X}$ yields a definition of the relative wage gap:

$$PWG^{\,unc}\left(\widetilde{X}, p_i\right) = p_i \cdot \left(\frac{W^{MP}(\widetilde{X})}{W^{cit}(\widetilde{X})} - 1\right) - \frac{CC_i}{W^{cit}(\widetilde{X})}. \tag{2.2.3}$$

Expression (2.2.3) defines the *unconditional* PWG, taking into account the uncertainty of candidate i being (re)elected as well as the requirement of investing in the election campaign.[4] From the perspective of the citizen candidate framework,

[4] We also estimate the *conditional* wage gap, defined as $PWG^{\,cond}(\widetilde{X}) = \frac{W^{MP}(\widetilde{X})}{W^{cit}(\widetilde{X})} - 1$. It neglects election probabilities and campaigning costs and is nested in (2.2.3). This wage gap is observed by the electorate and thus relevant for the perception of the political elite's pay.

the unconditional PWG of an elected *MP* should in general be weakly greater than zero, assuming that candidates form realistic expectations regarding election probabilities and campaigning costs, otherwise they would not have decided to run for office. Alternatively, a positive wage premium for politicians could be interpreted as a prize for winning the political tournament.

2.3 Institutional Background and Data

The Bundestag is the lower house of the German parliament and its members are elected to four-year terms. Each eligible voter has two votes. The first one is directly attributed to a candidate representing the electoral district. This part of the election has the features of a majority-rule voting system. The second vote is for a party which may then, according to its share of party votes, send candidates from predefined electoral lists to the Bundestag. This part of the election has the feature of proportional representation. While each directly elected candidate represents one of the 299 electoral districts, candidates on the party lists capture the remaining 299 seats in accordance with their party's overall share of second votes. Due to 16 additional surplus mandates, the Bundestag comprised a total number of 614 seats in its 16^{th} legislative period (Oct. 2005–Sept. 2009).

Data. The empirical analysis is based on a unique dataset comprising personal and professional information on German MPs, which is an extended and updated version of the data used by Becker et al. (2009). We include only MPs who have been members of the Bundestag for the entire period under consideration. Hence, 599 MPs remain in the sample for the year 2006. We extract all available data, including biographical and socio-demographic information as well as data on previous occupations and political offices, from the MPs' individual Bundestag websites (see table 2.6.1 in the appendix).

We calculate the annual gross earnings as the sum of basic remuneration from public office, payments for cabinet members, pensions, interim allowances and outside earnings. Each MP receives a remuneration which is determined by the Bundestag itself (7,009 euros per month in 2006, see Bundestag, 2009). Furthermore, MPs who are both members of the Bundestag and the Federal Government are paid extra. When a member of the government resigns, she receives interim payments for the number of months served as a member of the cabinet – a total of at least six months but not more than three years (Bundesministergesetz, 2008). After resigning from office the former minister is entitled to a public pension if the position was held for at least two years.

In order to improve accountability, German MPs have been obliged by law to disclose information on outside employment since 2005 (Bundestag, 2010). All MPs have to report professional activities and sources of income which they pursue outside their political mandates. The level of transparency is fairly high compared to many other countries (Djankov et al., 2010). For each payment, it is indicated whether it is received on a regular (annual or monthly) basis or one-off (Bundestag, 2011b). Outside earnings are published according to four categories: (1) below 1,000 euros, (2) 1,000–3,500 euros, (3) 3,500–7,000 euros and (4) more than 7,000 euros. The highest category has no upper bound. In order to obtain a measure of outside earnings in this category, we follow Becker et al. (2009) and assume a maximum of $12,000$ euros, which yields a linearly increasing difference between the category means.[5] Finally, we calculate the amount of outside earnings for each MP by using average values for each category.

All earnings are before taxes and are likely to underestimate an MP's total income. First, we do not include capital income due to a lack of data. Second, we do not consider the (partly tax-free) allowances for office-related expenses, as they are not necessarily part of the individual's earnings. Third, we do not include additional incomes paid to (vice-)chairmen of the parties' parliamentary groups, as this information is not publicly available for all parties and MPs.[6]

We combine the politicians' data with representative survey data for the electorate taken from the SOEP (Wagner et al., 2007) and construct the same socio-

[5]As this choice may induce distortions, we experiment with several alternatives – including the categories' lower bounds. The results do not change qualitatively. In terms of quantitative effects, note that the chosen upper bound level is a conservative assumption (Becker et al., 2009). Hence, if the estimated effects are biased, they will be underestimated. We check the information on outside earnings with other data sources, such as newspaper reports and MPs' personal statements.

[6]Office-related allowances mainly cover expenses at the constituency level (about 3,700 euros per month), staff costs (more than 14,000 euros) and travel costs. Party salaries can be quite substantial. For example, a vice-chairman of the Social Democratic Party (SPD) receives 3,451 euros per month.

demographic variables for the electorate in 2006. Total gross earnings are calculated at the individual level by accumulating labor earnings, fringe benefits, pensions and bonus payments. Education is based on the CASMIN classification (Comparative Analysis of Social Mobility in Industrial Nations), the sector of employment on the ISCO-88 classification (International Standard Classification of Occupations). Non-German individuals younger than 18 years are excluded since they are not eligible to vote. Note that in many datasets, larger incomes are not very well covered. To tackle this issue, the SOEP includes a special high-income sample to increase the representativeness of the upper tail of the income distribution, which has been validated against administrative data (Frick et al., 2007; Bach et al., 2009). Therefore, the SOEP is the main data source for the German government's reports on poverty and affluence. We use the SOEP's population weights to make the data representative.

Samples. MPs in the German Bundestag are the top politicians in Germany. They face a relatively heavy workload and have personnel responsibility, which certainly distinguishes them both from an average employee and from an average (local) politician. For these reasons we consider MPs as holding executive positions in terms of occupation and only compare them to citizens working in similar jobs. As a baseline, we start with a rather broad comparison group which follows the SOEP definition and includes individuals in leadership positions across various occupational sectors working full-time. The sample, which we refer to as "all executives", comprises master craftsmen, self-employed people, members of the liberal professions (e.g., medical doctors, lawyers or architects), managers (of both for-profit and not-for-profit organizations) as well as public sector executives and high-level civil servants. To check the sensitivity with respect to the control group, we narrow down the definition in two steps by excluding certain professions from the "all executives" sample. Firstly, we drop master craftsmen as well as self-employed persons and liberal professionals without employees from the baseline and refer to this sample as "white collar executives". Secondly, we define the "top level executive" sample as managers as well as liberal professionals and the self-employed with ten or more employees.

Descriptive statistics. Table 2.3.1 summarizes the distribution of characteristics among the German population eligible to vote, our three executive samples and the MPs. Despite efforts to increase the number of women in professional leadership positions, female politicians are clearly under-represented in the Bundestag. The share of females is even smaller among executives (17%–22%). Both executives and MPs turn out to be older and much better educated than the electorate as a whole. More than 40% of the executives are classified as high-skilled and the proportion among MPs can be as much as twice this. Furthermore, MPs often exhibit occupational backgrounds in the public sector, while many executives are self-employed. Regarding our research question, we are especially interested in the comparability of MPs and executives in terms of annual gross earnings. With a median of 24,000 euros (in 2006), the center of the electorate's distribution is far below the center of the distributions of "all executives" and of MPs', which exhibit median values of 42,000 and 86,100 euros. MP earnings average at 106,000 euros, while the mean among the electorate is 28,100 euros and 56,100 euros in the "all executive" sample. Comparing the three executive samples, the narrowing of the definition becomes apparent in the rising mean and median earnings.

Election probabilities. Due to its mixed-member electoral system (see above), there are two ways to enter the Bundestag: either by winning the majority of votes in an electoral district or by being ranked sufficiently high on a party list. We quantify the probabilities of being elected for both channels separately. We first turn to the probability of being elected directly in one of the 299 electoral districts.

For decades districts have been won only by candidates from the two major parties with Christian (Social) Democrats being more successful in the South and West (North and East) as well as in rural and Catholic (urban and protestant) areas.[7] Hence, the party's share of first votes in the previous election (2002) can be regarded as a meaningful predictor of the 2005 vote share and implicitly the probability of winning a majority in the district. In fact, the data show that an

[7]Exceptions are the three districts in the East of Berlin where the Left Party's candidates received the majority of first votes several times. In 2005 a candidate running for the Green Party was successful in another Berlin district for the first time.

Table 2.3.1: Characteristics of the German electorate and MPs (2006, in %)

		Electorate	All executives	White collar	Top level	MPs
Gender	Female	52.2	22.1	19.9	16.9	32.2
Age	18 – 29	16.7	4.9	4.3	4.8	1.2
	30 – 39	15.0	21.0	21.8	20.7	12.5
	40 – 49	20.1	35.9	35.3	39.6	24.2
	50 – 59	16.2	27.1	26.1	23.8	41.4
	60 – 69	15.3	9.9	10.8	7.3	19.9
	≥ 70	16.8	1.2	1.7	3.7	0.8
Education	Low-skilled	15.4	2.3	1.2	0.0	0.2
	Medium-skilled	68.0	56.5	47.1	48.0	17.0
	High-skilled	16.6	41.2	51.6	52.0	82.8
Region	West Germany	77.4	77.5	83.4	87.3	78.0
Occupational status	Not working	47.0	0.0	0.0	0.0	0.0
	Part-time	14.4	0.0	0.0	0.0	0.0
	Full-time	38.6	100.0	100.0	100.0	100.0
Sector	Private sector	36.2	18.2	20.0	68.3	40.1
	Public sector	8.3	15.1	24.7	3.7	53.4
	Self-employed	5.6	66.7	55.3	28.0	6.5
Annual earnings	Mean	28,135	56,110	70,036	88,536	105,698
(in euros)	Median	24,000	42,000	55,059	72,000	86,108
	Observations	20,836	1,505	985	299	599

Source: SOEP and Bundestag, own calculations.

individual candidate can influence the electoral outcome only marginally (e.g., by popularity or campaigning effort). To quantify the probability, we retrieve the 2002 first vote shares for each party in each of the 299 districts. We then run a logistic regression of the binary outcome variable *elected* (= 1 if the candidate is elected, 0 otherwise) on party and state dummy variables and on the 2002 first vote share.[8] We use the predicted values for the MPs in our dataset.

The election of party list candidates works as follows. In each of the 16 German states every party sets up a separate list (*Landesliste*). The total share of second votes determines a party's total number of seats in parliament. After subtracting each party's number of directly elected MPs, the remaining total is then allocated to the state party lists (net of the direct candidates) according to the share of

[8]The predicted probabilities for the major parties' candidates are displayed in figure 2.6.1 in the appendix. Note that there are two distinct curves with similar shapes for both major parties. The one more to the left (with fewer observations) represents Eastern German districts where the Left Party receives a much larger share of votes than in the West and the probability of winning the relative majority is greater for a given vote share.

second votes *in the respective state*. This number finally determines how many party list candidates enter parliament. Consequentially, a candidate's election probability on a party list is a function of the rank and the number of seats allocated to the party. To estimate these probabilities, we construct a dataset of all party list candidates running for the 2005 election of the Bundestag, based on information from the federal agency administrating elections (Bundeswahlleiter, 2011). We run a logistic regression of the binary outcome *elected* on a set of explanatory variables. These comprise state and party dummies, the rank on the respective party list, a binary indicator for the traditional, major parties (the Christian Democrats, the Social Democrats and the Left Party in the Eastern states) as well as several interaction terms. Moreover, we include a binary variable indicating whether the party list rank is "promising", i.e., if it had allowed the candidate to enter parliament in the previous election. Based on the estimated coefficients, we use the predicted values for the elected MPs in our dataset.[9] The overall probability of being elected is the maximum of the probabilities of being elected either through a party list or directly in an electoral district. In table 2.3.2 we present the estimated probabilities for all candidates and elected MPs.

Campaigning costs. Campaigning costs can be regarded as a necessary investment to be made before being (re)elected and hence reduce an MP's income. The amount of campaigning costs can be expected to vary across MPs, depending on various individual characteristics. Unfortunately, detailed information regarding campaigning expenses from the politicians under consideration is not available.[10] The only reliable source of information on campaigning expenses are the parties' annual statements of accounts (Bundestag, 2011a). In Germany political parties are legally obligated to report their financial situations to the President of the

[9]See figure 2.6.2 in the appendix. In some cases (especially for Christian and Social Democrats) predicted probabilities are rather low even for highly ranked candidates. This is due to the fact that in some federal states one of the major parties regularly wins almost every district (first vote) and hence the respective party does not send any list candidate to parliament.

[10]There are only very few MPs who provide information on individual campaigning costs (see, e.g., Martin Dörmann reporting personal expenses of 10,000 euros, `http://www.martin-doermann.de/live/wp-content/uploads/2008/02/glaeserne-taschen.pdf`, 10–19–2011). Moreover, neither party headquarters nor parliamentary groups were willing or able to provide detailed information upon request.

Table 2.3.2: Estimated election probabilities

	Obs.	Mean	Sd	Min	Max
Party list					
All candidates	1,843	0.208	0.360	0.000	1.000
Elected MPs	384	0.828	0.242	0.001	1.000
Elected MPs (major parties)	249	0.781	0.260	0.001	1.000
Electoral district					
All candidates	1,196	0.250	0.397	0.000	1.000
Elected MPs	299	0.880	0.226	0.021	1.000
Elected MPs (major parties)	295	0.881	0.225	0.021	1.000
Overall					
Christian Democrat	216	0.861	0.216	0.032	1.000
Social Democrat	221	0.863	0.217	0.107	1.000
Green Party	46	0.939	0.128	0.340	1.000
Liberal Party	61	0.918	0.173	0.380	1.000
Left Party	53	0.850	0.287	0.001	1.000
None	2	0.964	0.001	0.963	0.965
Elected MPs	599	0.873	0.215	0.001	1.000

Source: Bundeswahlleiter (2011), own calculations.

Bundestag on an annual basis and separately for each federal state. We collect data on the parties' expenses from the statements of accounts during the period 2004–2009. We subtract revenues (i.e., party donations and government subsidies) to calculate yearly net expenses by party and state. As in some states the Bundestag elections coincide with other elections, we need to subtract the effect of those other elections on expenses. We, therefore, run a state-party fixed effect regression of net expenses on federal, state, district and European election year dummies and predict the expenses for the year 2005 as if there had not been any other election.[11] Thus, we obtain the net expenses per electoral seat for the 2005 Bundestag election by state and party. We define these as campaigning costs that the individual candidates have to bear.

The results are displayed in table 2.3.3. On average, campaigning costs amount to 23,500 euros per seat and there is considerable variation not only across parties

[11]Regression outputs are available from the authors upon request.

Table 2.3.3: Estimated campaigning (in euros)

			Party			
State	Christ. Dem.	Social Dem.	Green	Liberal	Left	Total
BB	22,333	61,295	9,804	19,578	24,888	27,580
BE	21,892	35,157	12,333	22,542	25,420	23,469
BW	18,215	36,351	11,080	19,239	22,983	21,573
BY	-13,153	30,121	10,424	19,564	22,411	13,873
HB	52,756	21,886	692	18,950	23,898	23,636
HE	20,329	38,659	11,682	16,131	24,161	22,192
HH	-13,632	49,603	6,561	16,172	21,189	15,978
MV	15,811	36,783	10,364	18,368	23,014	20,868
NS	23,474	36,094	11,042	18,819	22,695	22,425
NW	36,787	49,789	14,411	23,443	22,848	29,455
RP	30,589	41,588	11,326	21,176	23,122	25,560
SA	21,487	35,899	12,881	17,898	21,674	21,968
SH	24,878	39,474	14,203	19,181	28,754	25,298
SL	14,302	40,092	9,647	19,144	23,170	21,271
SN	73,567	58,198	13,005	11,399	34,079	38,050
TH	19,764	40,900	12,787	17,925	25,850	23,445
Average	23,087	40,743	10,765	18,721	24,385	23,540

Source: Bundestag (2011a), own calculations. Estimated campaigning costs per seat by state and party.

but also across states. Interestingly, when comparing the two major parties, the campaigning costs for Social Democrats are on average much higher than for Christian Democrats (41,000 versus 23,000 euros), which is due to considerably larger donations for the latter. Note that the negative values in table 2.3.3 indicate that revenues, especially from donations, exceeded expenses. In those cases we set the individual campaigning costs of the candidate to zero. The estimated campaigning costs can be regarded as an upper bound from the individual candidate's perspective, since it is highly unlikely that the candidate has to bear personally all of the additional costs. Usually, candidates receive (financial) support from their local party as well.

2.4 Empirical Strategy and Results

2.4.1 Ordinary Least Squares

The model. In order to estimate the politicians' wage gap as defined in section 2, we enter an indicator variable P_i, which takes on the value 1 if individual i is an MP and 0 otherwise. Annual earnings Y_i for MPs and citizens are defined as follows:

$$Y_i = \begin{cases} \widehat{p_i} \cdot W_i^{MP} + (1 - \widehat{p_i}) \cdot \widehat{W_i} - \widehat{CC_i} & \text{if } P_i = 1 \\ W_i^{cit} & \text{if } P_i = 0. \end{cases} \tag{2.4.1}$$

For citizens we use the information on gross earnings W_i^{cit} from the SOEP. For MPs we use the information collected on earnings W_i^{MP} multiplied by the estimated election probabilities $\widehat{p_i}$. Potential earnings of an MP in the private sector $\widehat{W_i}$ are predicted values based on estimated coefficients from an OLS regression on the sample of citizens. Campaigning costs $\widehat{CC_i}$ are calculated as described above.

In order to operationalize equation (2.4.1), we employ a dummy variable approach which is standard for detecting wage differentials between subgroups in empirical labor economics (see, e.g., Pederson et al., 1990; Kunze, 2005). As is common, instead of estimating the model in levels, we use the log of Y_i, which yields the following Mincerian earnings equation (Mincer, 1974) to be estimated using ordinary least squares (OLS):

$$ln(Y_i) \ = \ \beta_0 \ + \ \beta_1 P_i \ + \ \boldsymbol{\beta}\mathbf{X}_i \ + \ \mu_i. \tag{2.4.2}$$

A positive and significant estimate of β_1 would provide empirical evidence in favor of a wage premium for politicians. Put another way, the coefficient on the politicians' dummy variable corresponds exactly to $PWG^{\,unc}(\widetilde{X}, p_i)$ from equation (2.2.3). In terms of the citizen candidate model $\widehat{\beta_1}$ measures by how much $p \cdot (W^{office} - W^{private})$ exceeds CC (cf. (2.2.1)). We control for a vector $\mathbf{X}_i$ of demographic characteristics which have been shown to be standard determinants of earnings, such as gender, qualification, age, tenure or number of children. The error term is denoted by μ_i. Depending on the specification of the model, we also include interaction terms between certain characteristics and the politician dummy in order to test for heterogeneous effects.

OLS results. Table 2.4.1 presents estimation results of equation (2.4.2) for the three different executive samples defined above.[12] Specification (1) shows a positive and significant (at the 0.01 level) coefficient on the dummy variable *politician* of 0.501. This suggests that MPs ceteris paribus earn 65% more than non-MP citizens.[13] The coefficients on the covariates have the expected signs: tenure and age, measuring specific and general human capital respectively, have a positive but decreasing effect on earnings. Education has a positive effect on annual earnings. Compared to the low-skilled, high-skilled (medium-skilled) individuals have a positive income differential of 149% (57%). The female dummy reveals the well-known gender wage gap (Oaxaca, 1973) – in our case of around 30%, which is comparable to previous estimates for Germany (Kunze, 2005; Arulampalam et al., 2007). The variables concerning party affiliation confirm that supporters of those parties which are said to promote more business friendly policies – Christian Democrats and Liberals – earn about 20–30% more than supporters of leftist parties (Social Democrats, Green Party, Left Party).[14] Living in East Germany reduces annual gross individual earnings considerably. Finally, private sector employees earn more than individuals in the public sector or self-employed.

In specification (2) we restrict the income of MPs to their remuneration from public office. The PWG decreases mechanically to 0.324 (38%), but remains statistically and economically significantly. In models (3)–(6) we compare the MPs to more narrowly defined executive samples. As expected, the estimated wage gap shrinks. When applying the "white collar" sample, the wage gap for total income is 0.428 (53%), while the coefficients on the covariates hardly change. Using the "top level executives", the coefficients for both income definitions are not significantly different from zero. This results is still in line with the citizen candidate

[12]In this section we focus on the results when applying the unconditional income concepts for MPs following definition (2.2.3). We also estimate the conditional wage gap. As expected PWG estimates shift upwards (see table 2.6.2 in the appendix).

[13]Note that $\widehat{\beta_1}$ can be interpreted only in percentage terms for small values. From (2.4.2) it follows that $ln(Y|P=1) - ln(Y|P=0) = \beta_1$ and thus $\frac{Y|P=1-Y|P=0}{Y|P=0} = exp(\beta_1) - 1$.

[14]Note that survey respondents in the SOEP report their party preferences. Hence, we are able to use information on party affiliation not only for MPs but also for the citizens in our sample.

Table 2.4.1: OLS – Unconditional wage gap: Baseline results

Executive sample	All		White collar		Top level	
MP income	Total (1)	Remun. only (2)	Total (3)	Remun. only (4)	Total (5)	Remun. only (6)
Politician	0.501***	0.324***	0.428***	0.251***	0.049	-0.127
	(0.086)	(0.085)	(0.084)	(0.083)	(0.158)	(0.158)
Tenure	0.006	0.006	-0.005	-0.005	0.007	0.007
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Tenure^2	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.050*	0.050*	0.064***	0.064***	0.005	0.005
	(0.027)	(0.027)	(0.023)	(0.023)	(0.034)	(0.034)
Age^2	-0.000	-0.000	-0.001**	-0.001**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Medium-skilled	0.453	0.453	0.255*	0.255*	0.145	0.144
	(0.314)	(0.314)	(0.144)	(0.144)	(0.153)	(0.153)
High-skilled	0.914***	0.914***	0.765***	0.765***	0.466***	0.466***
	(0.308)	(0.308)	(0.151)	(0.151)	(0.164)	(0.164)
Female	-0.284***	-0.284***	-0.247***	-0.247***	-0.263***	-0.263***
	(0.052)	(0.052)	(0.056)	(0.056)	(0.082)	(0.082)
Married	0.012	0.012	0.067	0.067	0.089	0.090
	(0.058)	(0.058)	(0.063)	(0.063)	(0.086)	(0.086)
Children	0.087	0.087	-0.014	-0.014	0.203**	0.203**
	(0.061)	(0.061)	(0.067)	(0.067)	(0.091)	(0.091)
Christ. Dem.	0.191***	0.191***	0.160***	0.160***	0.199***	0.199***
	(0.053)	(0.053)	(0.053)	(0.053)	(0.077)	(0.077)
Liberal	0.253***	0.253***	0.124	0.124	0.332***	0.332***
	(0.097)	(0.097)	(0.105)	(0.105)	(0.113)	(0.113)
East	-0.397***	-0.397***	-0.399***	-0.399***	-0.284***	-0.284***
	(0.053)	(0.053)	(0.063)	(0.063)	(0.100)	(0.100)
Self-employed	-0.234***	-0.234***	-0.184***	-0.184***	0.097	0.097
	(0.050)	(0.050)	(0.058)	(0.058)	(0.093)	(0.093)
Public sector	-0.241***	-0.241***	-0.444***	-0.444***	-0.054	-0.055
	(0.069)	(0.069)	(0.068)	(0.068)	(0.111)	(0.111)
Constant	8.763***	8.763***	8.794***	8.793***	10.089***	10.088***
	(0.893)	(0.893)	(0.508)	(0.508)	(0.769)	(0.769)
Adjusted R^2	0.331	0.331	0.376	0.376	0.436	0.436
Observations	2104	2104	1584	1584	898	898

Note: Robust standard errors in parentheses. Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

framework, which stipulates a non-negative wage gap.

Group-specific results. The results for the PWG in table 2.4.1 represent an average effect for all of the MPs under consideration. To provide further evidence of whether the wage gap differs for politicians from different socio-demographic backgrounds, we interact the *politicians'* dummy with other characteristics. We estimate the specifications on the "all executive" sample and include all covariates shown in table 2.4.1 (for total MP income).

The results displayed in table 2.4.2 suggest that we do not find additional returns to tenure. Specification (2) shows that the wage gap for high-skilled politicians is much lower ($0.815 - 0.381 = 0.434$) than for medium-skilled MPs (0.815), representing the omitted category. As far as gender is concerned, table 2.4.2 shows a positive and significant coefficient on the *Politician x Female* interaction term. This positive coefficient neutralizes the negative gender pay gap found in the full sample (cf. table 2.4.1), so that women in politics do not earn significantly less than male politicians. This is not surprising since male and female MPs receive the same basic pay from holding public office.[15] A similar logic applies to the PWG of East German politicians. While the baseline results in table 2.4.1 show that earnings in the East are much lower for the combined MP-citizen sample, the *Politician x East* interaction term yields a positive sign. This indicates that the East-West pay gap is significantly smaller among politicians.

Interestingly, as far as party affiliation is concerned, the results of specification (5) suggest that members of more leftist parties exhibit a substantially larger wage gap conditional on observable characteristics than members of right-wing parties. More precisely, the wage premium for Liberal and Christian Democrat MPs decreases to 0.289 and 0.354 respectively compared to 0.641 for leftist MPs. This is due to the fact that left-wing voters earn less on average (see table 2.4.1).[16] Hence,

[15] This might help to explain why Kotakorpi and Poutvaara (2011) find that generous remuneration for public office has stronger effects for female than for male candidates in Finland. Similarly, running the earnings regression on the MP sample yields an insignificant gender dummy estimate.

[16] Especially the Social Democrats as well as the Left Party traditionally are supported by blue-collar workers, with close ties to trade unions. The right-wing parties in Germany are historically more business-friendly, which might explain why they receive around 70% of total party donations (Bundestag, 2011a). These patterns can be expected to have an effect on MPs'

the wage gap is wider when comparing the incomes of an average left-wing MP and of a comparable left-wing voter. Finally, the PWG is not different for MPs who were self-employed before becoming politicians but larger for MPs who previously worked in the public sector. In specification (7) we control for all interaction terms simultaneously and the results do not change considerably. As a result, the group-specific results suggest that existing income differentials between socio-economic groups (male-female, West-East, left-right) in the overall population are mitigated or even neutralized in the politicians' sample. The earnings distribution among MPs seems to be much more homogenous than in the private labor market.

Table 2.4.2: OLS – Unconditional wage gap: Interaction effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Politician	0.514***	0.815***	0.392***	0.448***	0.641***	0.344***	0.602***
	(0.082)	(0.107)	(0.090)	(0.087)	(0.093)	(0.082)	(0.099)
Pol. x Tenure	-0.002						0.003
	(0.005)						(0.005)
Pol. x H-skill		-0.381***					-0.350***
		(0.073)					(0.070)
Pol. x L-skill		0.470					0.482
		(0.326)					(0.316)
Pol. x Female			0.336***				0.253***
			(0.064)				(0.063)
Pol. x East				0.238***			0.239***
				(0.069)			(0.067)
Pol. x Liberal					-0.352***		-0.160
					(0.101)		(0.108)
Pol. x Christ. Dem.					-0.287***		-0.164**
					(0.065)		(0.064)
Pol. x Self-empl.						0.091	0.047
						(0.085)	(0.072)
Pol. x Public sector						0.282***	0.199**
						(0.079)	(0.079)
Adjusted R^2	0.330	0.330	0.330	0.330	0.330	0.330	0.328
Observations	2104	2104	2104	2104	2104	2104	2104

Notes: Regressions estimated on sample of all executives. MP income is defined as total earnings. In addition to the interaction terms, all covariates from table 2.4.1 are included in each specification. Robust standard errors in parentheses. Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

earnings after retiring from politics (Eggers and Hainmueller, 2009; Querubin and Snyder, 2009).

Selection on unobservables. Like all empirical studies our analysis is subject to the well-known danger of omitted variable bias. If there is an unobserved confounder that affects both selection into politics and earnings, the estimates of our wage gap are biased. In the context of our study, such an unobserved confounder could be related to the politicians' personality. For instance, it might be that politicians have certain qualities, such as higher motivations, more competitiveness or better networking skills, that make them more likely to enter politics and at the same time have a positive effect on their earnings.

In order to assess the potential impact of such a positive selection, we make use of the 2005 wave of the SOEP, which contains information on the Big Five personality traits of respondents.[17] The Big Five is a theoretical measurement system stemming from psychology which has been shown to describe an individual's personality comprehensively along five dimensions: openness, conscientiousness, extraversion, agreeableness and neuroticism. Previous research has shown that neuroticism and (to some extent) agreeableness have a negative effect on earnings and job performance (see, e.g., Nyhus and Pons, 2005; Borghans et al., 2008, for surveys). We are able to replicate this relationship with our "all executive" sample.

As we do not have any information about the personality traits of MPs, we need to impute their Big Five values. In order to provide an upper bound for a positive selection into politics based on personal characteristics, we assume that MPs have average scores (compared to executives) on the dimensions that do not affect earnings (i.e., openness, conscientiousness and extraversion). For agreeableness and neuroticism we, however, assign them values that are one standard deviation lower than the average, which will have a positive effect on their earnings (due to the negative coefficient in the earning equation). The overestimation becomes apparent when looking at the mean values for agreeableness and neuroticism across samples. While the averages in the electorate are 5.40 and 3.88 respectively, the mean values in the "all" ("top level") executive sample are 5.26 and 3.70 (5.25 and 3.53). In contrast, the imputation method assigns politicians values of 4.38 and 2.43, which are considerably lower. Another reason for us to believe that this

[17]Previous research has shown that the Big Five are stable over time (Cobb-Clark and Schurer, 2012); hence we can use the panel structure of the data and link the personality information from 2005 to our 2006 data.

procedure leads to an upper bound is the fact that the scarce research on the Big Five in the political arena indicates that politicians are more extraverted and more agreeable than the average citizen (Caprara et al., 2003; Gerber et al., 2011). Note that the latter relationship would even suggest a negative selection into politics based on personal characteristics, i.e., lower wage premia for politicians.

Table 2.4.3: OLS – Unconditional wage gap including Big Five

Executive sample	All		White collar		Top level	
MP income	Total (1)	Remun. only (2)	Total (3)	Remun. only (4)	Total (5)	Remun. only (6)
Politician	0.380***	0.203**	0.318***	0.142	-0.154	-0.330
	(0.100)	(0.100)	(0.116)	(0.115)	(0.202)	(0.202)
Openness	-0.028	-0.028	0.010	0.010	-0.006	-0.006
	(0.030)	(0.030)	(0.020)	(0.020)	(0.043)	(0.043)
Conscientiousness	0.011	0.011	-0.004	-0.004	0.021	0.021
	(0.032)	(0.032)	(0.035)	(0.035)	(0.041)	(0.041)
Extraversion	0.037	0.037	0.014	0.014	0.054	0.054
	(0.036)	(0.036)	(0.030)	(0.030)	(0.039)	(0.039)
Agreeableness	-0.046	-0.046	-0.013	-0.013	-0.004	-0.004
	(0.031)	(0.031)	(0.031)	(0.031)	(0.037)	(0.037)
Neuroticism	-0.034*	-0.034*	-0.046**	-0.046**	-0.048	-0.048
	(0.019)	(0.019)	(0.022)	(0.022)	(0.031)	(0.031)
Adjusted R^2	0.354	0.354	0.404	0.404	0.469	0.469
Observations	1894	1894	1451	1451	860	860

Note: Robust standard errors in parentheses. In addition to Big Five, all covariates from table 2.4.1 are included in each specification. Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 2.4.3 shows that even if the selection into political careers based on personal traits is wholly positive (with respect to earnings) our estimates are quite robust. As expected, all coefficients decline, but the PWG remains positive for specification (1)–(3) and statistically indistinguishable from zero otherwise.[18]

[18]Based on the findings by Caprara et al. (2003), we also assign politicians an above average level of extraversion as a robustness check. The results do not change as extraversion does not significantly affect earnings.

2.4.2 Matching

The model. As table 2.3.1 shows, the MPs differ from the executives in several characteristics. Matching, an econometric technique popular in the field of labor economics (Caliendo and Kopeinig, 2008), is a method to further increase the comparability of politicians and executives. In general, matching is applicable if the population under consideration can be divided into one sub-population receiving a treatment (in our case being a politician) and another sub-population of untreated individuals (citizens). Matching is a way to tackle the problem that we cannot observe what politicians would have earned if they had not been elected, by finding the most appropriate match in terms of observable characteristics within the control group to calculate the counterfactual outcome. Hence, matching ensures that only the nearest neighbors in terms of characteristics are used to estimate the PWG (Imbens, 2004; Imbens and Wooldridge, 2009).[19] Furthermore, the matching framework allows us to assess the relevance of potential unobserved factors influencing the PWG. As discussed in section 2.4.1, this might be especially important as unobserved motivation or assertiveness could explain at least some of the PWG.

We define a binary "treatment" indicator $P_i \in \{0, 1\}$ that takes the value 1 if an individual is an MP and 0 otherwise. Again, the outcome variable $Y_i(P_i)$ is annual gross earnings. We are interested in estimating the *average treatment effect on the treated* (ATT), which is defined as:

$$\tau_{ATT} = E[Y(1)|P = 1] - E[Y(0)|P = 1], \tag{2.4.3}$$

with $E[.]$ standing for expectation. The ATT is equal to the potential income differential if it were possible to draw an individual i randomly from the *sample of MPs* and allow the simultaneous pursuit of a career as a non-MP citizen in the regular labor market. In order to construct the counterfactual $E[Y(0)|P = 1]$, we identify a "statistical twin" among the non-treated in terms of observable characteristics. As matching on numerous characteristics X causes dimensionality

[19]In that sense, matching is comparable to non-parametric regression methods such as kernel estimation, since it allows identification without explicit assumptions regarding the (potentially non-linear) functional form of the association between dependent and independent variables.

problems, we follow standard practice and condition on the propensity score of being treated. That is, we estimate the probability of being a politician given X, $Pr(P = 1|X)$, with a standard probit model.[20] The covariates X control for self-selection into the treatment, which in the case of becoming a politician is certainly a very specific and individual decision (Belman and Heywood, 1989; Gregory and Borland, 1999).

Matching results. We estimate the propensity score of being a politician using a simple probit model, controlling for all the socio-demographic variables available in our data, such as age, tenure, qualification, gender, presence of children, marital status, occupational position (for politicians before becoming MPs) and region.[21]

As done in section 2.4.1, we estimate the PWG using three different definitions of the control group. Table 2.4.4 presents the results of the propensity score matching with the logarithmized annual earnings as the outcome variable. We employ a one-to-one nearest neighbor matching specification with replacement and a caliper of one-quarter of the standard deviation of the estimated propensity score (Rosenbaum and Rubin, 1985). The $\widehat{ATT}$ for full earnings and the "all executive" sample is significant (at the 0.01 level) and estimated at 0.312, which indicates that being a politician increases earnings by more than 35% on average. The t-statistics at the lower part of table 2.4.4 show that matching on the propensity score balances treatment and control groups well. The only exception is the *East* covariate, for which we, nevertheless, do not find large difference between the two. In addition, the mean standardized bias after matching (2.20) is very small and suggests that matching was successful (Caliendo and Kopeinig, 2008). The $\widehat{ATT}$ remains positive and significant, when using MPs' basic pay as the outcome variable for politicians – excluding outside earnings, payments for cabinet members, pensions and interim allowances.

Specifications (2) and (3) of table 2.4.4 show that narrowing the control group

[20] Rosenbaum and Rubin (1983) show that propensity score matching ensures independence of treatment from the potential outcome, which is one of the two identifying assumptions of the matching estimator – the other one being the common support assumption.

[21] Note that the interpretation of the coefficients of the propensity score estimation is not economically relevant. Neither is the purpose of the propensity score estimation to predict the selection into treatment, but to balance the covariates. For completeness, estimation results of the probit estimations are presented in table 2.6.3 in the appendix.

Table 2.4.4: Matching – Baseline results

	(1)	(2)	(3)
Executive Sample	All	White collar	Top level
Treated observations	599	599	599
Control observations	1,505	985	299
		Full earnings	
ATT	0.312 (0.061)***	0.221 (0.090)***	-0.270 (0.534)
Rosenbaum Γ	2.4	1.8	–
		Basic remuneration from public office	
ATT	0.135 (0.060)**	0.045 (0.089)	-0.447 (0.534)
Rosenbaum Γ	1.6	–	–
t-statistics / % bias reduction:			
Age	-0.03 / 99.5	0.20 / 96.3	6.93 / 12.5
High-skilled	-0.39 / 97.5	-4.03 / 67.2	-1.68 / 85.4
Medium-skilled	0.31 / 97.9	3.95 / 66.9	1.60 / 86.0
Children	-0.37 / 96.8	-0.49 / 95.5	1.44 / 84.7
Gender	0.12 / 96.5	0.37 / 91.5	0.06 / 99.1
East	1.96 / -103.4	0.00 / 100.0	-0.35 / 86.8
Married	0.06 / 91.1	0.56 / 75.3	-0.51 / 54.9
Public sector	-0.06 / 99.5	0.81 / 91.6	-0.12/ 99.3
Self-employed	1.12 / 97.3	2.09 / 94.3	-0.00 / 100.0
Standardized Bias	2.20	5.70	6.58

Note: Estimates are based on "psmatch2" by Leuven and Sianesi (2010) and "rbounds" by Gangl (2004). One-to-one nearest neighbor matching is conducted with replacement and a caliper of $0.25 \cdot \sigma_{prop.score}$. ATT refers to average treatment effect on the treated. Standard errors of ATT (shown in parentheses) are corrected following Abadie and Imbens (2006). Asterisks indicate the conventional significance levels. Rosenbaum Γ denotes the minimum influence (in terms of explanatory power of all observables) a potential unobserved confounder must have to render the PWG estimate insignificant (based on a 1% significance level). T-statistics under H0: *"no significant differences in mean characteristic between treated and control group"*. % bias reduction corresponds to reduced differences in observables between control and treatment group due to matching.

leads to a decline in the estimated PWG. While it remains positive and significant for full earnings and the "white collar" sample, it is statistically indistinguishable from zero in all other earning-sample combinations – similar to that of section 2.4.1. As the sample size decreases, it becomes more difficult to balance the covariates and the mean standard biased rises as a consequence.[22]

Furthermore, we conduct several robustness checks to make sure that our results are not driven by functional forms, the matching algorithm or choices made when estimating the propensity score. We find almost identical estimates when using Epanechnikov kernel matching. The results are also robust to using a simpler model to estimate the propensity score excluding all interaction terms. Yet in that case, the balancing property is not fulfilled for all covariates, which is precisely the reason why interaction terms should be used. Moreover, our results do not change when using a logit instead of a probit model to estimate the propensity score.

Selection on unobservables. Just as in the OLS analysis, we are faced with potential bias caused by omitted variables. So far we have assumed that the observable covariates X fully account for the self-selection of individuals into treatment and control groups. However, if there are unobserved factors that simultaneously affect selection into treatment and the outcome, the identifying assumption of unconfoundedness is violated and matching estimators are susceptible to a *hidden bias* (Caliendo and Kopeinig, 2008). In the case of politicians, unobserved characteristics such as motivation, competitiveness or networking skills, might determine self-selection into the treatment group, while simultaneously having a positive effect on earnings. To account for this potential bias, we conduct a Rosenbaum bounds sensitivity analysis (see Rosenbaum, 2002, for a technical presentation).[23] In a nutshell, the Rosenbaum bound analysis provides a value Γ, which indic-

[22]As was done for OLS, we also provide matching estimators for PWG based on the conditional income of the politicians. Ignoring campaigning costs and the probability of not being elected to office raises the politicians' earning and, thus, the PWG. Table 2.6.2 in the appendix shows that the $\widehat{ATT}$ varies between zero and 0.5 depending on the income definition and the sample used.

[23]Another estimation technique to account for unobserved heterogeneity is the application of a fixed-effects regression (see Diermeier et al., 2005, for an application to US Congress members). However, this would require a panel dataset of MPs, and we have data only for one legislative period. Moreover, there is no variation in the dummy variable identifying MPs.

ates how sensitive the results are with respect to an unobserved confounder. A value of $\Gamma = 1.6$ would imply that an unobserved confounder with an explanatory power of at least 1.6 times the explanatory power of *all* observables X is needed to render the estimated effect statistically insignificant (at the 1% significance level). Thus, a low value of Γ indicates that results are quite sensitive to unobserved confounders; high values of Γ (greater than 2) suggest that it is extremely unlikely that confounding factors alter statistical inferences. The values of Γ in table 2.4.4 show that it is quite unlikely that personality traits of politicians could render the positive PWG found in specifications (1) and (2) for full earnings insignificant. Thus, the positive wage gap based on the basic pay of German MPs for the "all executive" sample is quite robust to omitted variable bias.

2.5 Conclusions

In this chapter we test whether there is a wage gap for German MPs. Building on a unique dataset and relying on the citizen candidate framework, we calculate the expected earnings of MPs taking into account election probabilities and campaigning expenses. We estimate the politicians' wage gap by comparing the MPs to a representative sample of German executives using both OLS and matching techniques.

We find that both the sign and the size of wage gap depend on the definition of the control group and the MPs' income. Using the broadest sample of executives, the PWG varies between 35% and 65% depending on the estimation method (corresponding to 20,000–36,000 euros per year). Robustness checks suggest that these baseline results are unlikely to suffer from omitted variable bias due to positive selection into politics. When defining the control group more narrowly, the wage gap shrinks and is statistically indistinguishable from zero for "top level" executives. In this case the data suggest that the pay of politicians is not excessive. However, while MPs may compare themselves with top-managers, this association might not be shared by the public, which in turn might have consequences for the perception of the adequacy of politicians' pay. The wage gap also mechanically decreases when we exclude politicians' outside earnings and restrict their income to the basic remuneration from holding public office. On the contrary, the income premium increases considerably when estimating the *conditional* wage gap, i.e., neglecting election probabilities and campaigning costs.

Thus, our empirical results are well in line with the theoretical predictions of the citizen candidate framework, which predicts a non-negative wage gap for politicians. From a normative perspective, a positive PWG could be beneficial for society if it attracted more able individuals to run for office or raised the costs of abusing political office. Yet recent theoretical and empirical studies show that higher earnings need not necessarily lead to better politicians (Poutvaara and Takalo, 2007; Kotakorpi and Poutvaara, 2011). We contribute to this literature by showing that becoming a politician is financially attractive for the average executive (and even more so for the average citizen) but not for top level managers and business owners. In addition, our analysis shows that the outside earnings constitute a substantial share of the income premium. Therefore, it is important to hold politicians accountable for their (outside) activities, which calls for a greater level of transparency (Besley and Case, 1995; Ferraz and Finan, 2008). While this seems to be the case in Germany (Djankov et al., 2010), the amount of outside earnings of MPs is not limited by law. This could be problematic, as moonlighting politicians might not only face a conflict of time regarding their legislative effort but also a conflict of interests (Gagliarducci et al., 2010).

Several qualifications have to be made with respect to the magnitude of our empirical results. First, in general, higher pay can be justified by a heavier workload. Unfortunately, we do not observe politicians' working hours.[24] Second, we probably underestimate the PWG, as we assume a conservative upper bound of outside earnings and overestimate individual campaigning costs. Third, it is likely that there is a positive selection bias for jobs in the political sector. Although we show that the baseline estimates are robust with respect to an unobserved confounder, their exact magnitudes might change. Finally, we are able to compare politicians and citizens only at one particular point in time. However, politicians who follow *political careers* (as opposed to *career politicians*; see Mattozzi and Merlo, 2008) might leave public office in order to work in the private sector and benefit from building their political networks. It would therefore be worthwhile to estimate the

[24]There is evidence collected from the MPs' websites that their working times vary between 50 and 70 hours a week. We find similar values for the executive samples.

PWG using lifetime income (see, e.g., Eggers and Hainmueller, 2009; Querubin and Snyder, 2009). Moreover, our findings for Germany should be complemented with (comparative) studies on other countries with different institutional details and regulations to flesh out the picture.

2.6 Appendix

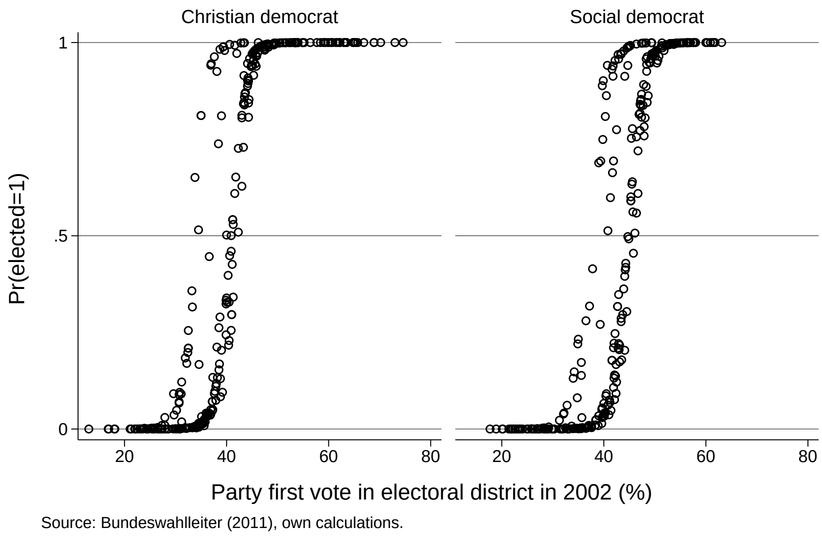


Figure 2.6.1: Election probabilities: Electoral districts

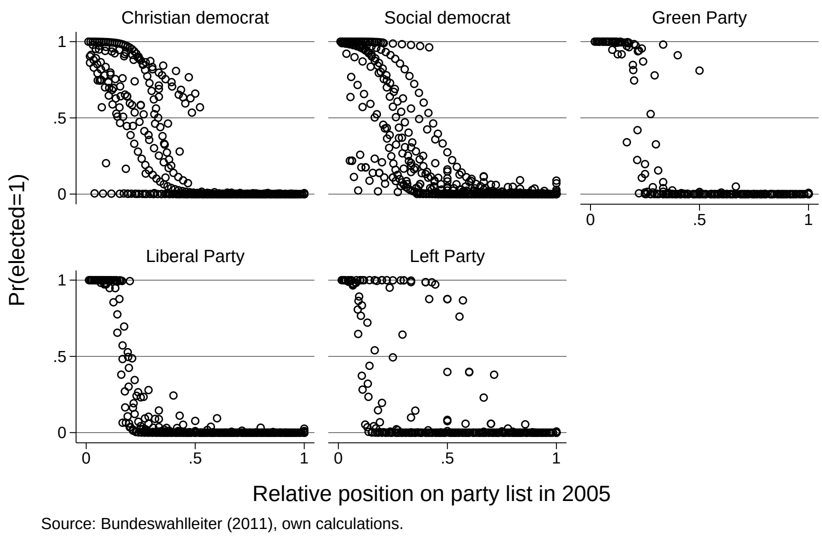


Figure 2.6.2: Election probabilities: Party lists

Note: The "relative position on party list" is the rank on the respective list (with rank 1 being the most promising) divided by the total number of candidates on that list. Hence, the first candidate on the list is assigned a value close to zero, while the last candidate receives a one.

Table 2.6.1: Characteristics of MPs by party affiliation

	Christian Democrat	Social Democrat	Green Party	Liberal Party	Left Party	None	Total
Number	217	220	46	61	53	2	599
Age (years)	51.8	52.4	48.6	49.9	50.6	49.5	51.5
Female (%)	0.2	0.4	0.6	0.2	0.5	0.0	0.3
East (%)	16.1	20.9	19.6	18.0	56.6	50.0	22.0
Direct (%)	66.4	65.0	2.2	0.0	5.7	50.0	48.7
Low skilled (%)	0.0	0.0	0.0	0.0	1.9	0.0	0.2
Medium skilled (%)	17.1	20.5	13.0	4.9	18.9	50.0	17.0
High skilled (%)	82.9	79.5	87.0	95.1	79.2	50.0	82.8
Employee (%)	51.6	25.9	39.1	55.7	34.0	50.0	40.1
Civil servant (%)	43.8	71.4	50.0	24.6	54.7	50.0	53.4
Self-employed (%)	4.6	2.7	10.9	19.7	11.3	0.0	6.5
Unconditional earnings (euros)	82,510	76,380	67,535	74,496	56,591	53,585	75,902
Conditional earnings (euros)	109,274	108,387	96,020	102,776	91,925	98,608	105,698

Source: SOEP and Bundestag, own calculations.

Table 2.6.2: OLS and Matching – Conditional wage gap

Executive sample	All		White collar		Top level	
MP income	Total (1)	Remun. only (2)	Total (3)	Remun. only (4)	Total (5)	Remun. only (6)
OLS	0.667***	0.493***	0.595***	0.421***	0.216	0.042
Matching	0.498***	0.324***	0.396***	0.222***	-0.101	-0.275
Observations	2104	2104	1584	1584	898	898

Note: Estimates derived from same specifications as in baseline models (see tables 2.4.1 and 2.4.4). Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 2.6.3: Propensity score estimation

Executive sample	All		White collar		Top level	
	coeff.	s.e.	coeff.	s.e.	coeff.	s.e.
Age	-0.004	35.804	0.072	36.050	0.019	0.006
High-skilled	-4.983	0.000	5.975	.	0.825	1.309
Medium-skilled	-7.671	0.540	4.011	0.600	-0.065	1.307
Children	-5.721	0.568	-6.251	0.626	0.268	0.254
Female	0.575	0.537	0.292	0.573	0.677	0.153
East	0.674	0.583	1.079	0.662	0.184	0.155
Married	2.040	0.559	0.251	.	-0.686	0.158
Public sector	0.070	0.559	10.870	0.198	2.553	0.407
Self-employed	-12.700	0.000	-2.378	0.727	-0.598	0.208
Age x H-skill	-0.004	35.804	-0.069	36.050		
Age x M-skill	0.029	35.804	-0.046	36.050		
Age x Children	0.138	0.011	0.144	0.012		
Age x Female	0.001	0.011	0.005	0.011		
Age x East	-0.011	0.012	-0.017	0.013		
Age x Married	-0.059	0.011	-0.060	0.012		
Age x Public sector	0.023	0.011				
Age x Self-empl.	0.018	0.013	0.007	0.013		
H-skill x Children	-0.404	0.246	-0.390	0.269		
H-skill x Female	-0.273	0.248	-0.169	0.265		
H-skill x East	0.074	0.252	-0.072	0.291		
H-skill x Married	0.306	0.262	2.118	0.589		
H-skill x Public sector	-1.355	0.248	-11.073	0.000	-0.718	0.420
H-skill x Self-empl.	10.059	0.620	0.558	0.332		
M-skill x Self-empl.	9.873	0.670				
Children x Female	0.493	0.211	0.416	0.223		
Children x Public sector	0.168	0.213	0.152	0.218		
Children x Self-empl.	-0.061	0.265	-0.083	0.281	0.128	0.296
Female x East	-0.141	0.216	-0.093	0.239		
Female x Married	-0.096	0.220	-0.268	0.231		
Female x Public sector	-0.144	0.199			-0.759	0.367
East x Married	0.163	0.221	-0.001	0.258		
East x Public sector	-0.133	0.207	-0.157	0.249		
Married x Public sector	-0.164	0.245	-0.119	0.243		
Married x Self-empl.	0.193	0.283	0.179	0.302		
M-skill x Married			1.947	0.610		
M-skill x Public sector			-9.735	0.274		
Children x East			0.320	0.231		
Children x Married			0.193	0.265	0.541	0.284
Female x Self-empl..			0.258	0.242		
East x Self-empl.			-0.032	0.294		
M-skill x East					0.202	0.329
Constant	5.594	0.481	-5.844	0.442	-1.495	1.332
Pseudo R^2	0.490		0.437		0.375	
χ^2	1231		918		428	
Observations	2104		1584		898	

Chapter 3

Couple Earnings: Marital Sorting and Labor Supply

3.1 Introduction

Increasing correlation of spouses' earnings is typically interpreted as increasing similarity of spouses in terms of earnings-related characteristics (assortative mating, see Mare and Schwartz, 2005). Moreover, marital sorting has an amplifying effect on inequality across households since it reduces the level of redistribution within families (Burtless, 1999, 2009; Schwartz, 2010). When the share of couples where both partners are either high or low wage earners grows, inequality across couple households will be higher compared to a situation where couples with one high and one low wage earner dominate. Since the population living in couple households makes up a large part of the total population, this affects the overall distribution of economic resources. The trend towards more positive sorting is also related to increasing female labor force participation, since the number of single-earner families has been decreasing in many countries (Blau and Kahn, 2007; Heim, 2007; Blundell et al., 2011a,b). More generally, changes in household demographics affecting "who lives with whom" (Jenkins and Micklewright, 2007b, p. 19) have been found to contribute to income inequality (see, e.g., Jenkins, 1995; Daly and Valletta, 2006; Martin, 2006; Peichl et al., 2012). Hence, with regard to economic inequality, trends of widening earnings gaps cannot be assessed independently of changes in the socio-demographic composition of the population of interest.[1]

Previous studies on the effect of an increasing association of female and male earnings on inequality can largely be classified as accounting approaches. The observed distribution of income or earnings is typically compared to a number of counterfactual distributions by manipulating female earnings or the correlation between spouses' earnings (e.g., Karoly and Burtless, 1995; Burtless, 1999; Aslaksen et al., 2005). Cancian and Reed (1998, 1999) emphasize that the question of whether female earnings contribute to income inequality can only be meaningfully assessed when the observed distribution of household income is compared to an appropriate reference distribution. However, when constructing such a counterfactual, the role of behavioral effects (labor supply) has so far not been taken into account. This is important, since earnings do not only reflect a worker's productivity (the wage rate) but also depend on the number of hours worked, which is determined by the allocation of partners' time on paid work, household production and leisure (Juhn and Murphy, 1997; Devereux, 2004; Gottschalk and Danziger, 2005). This depends on the household context and, therefore, changes in household characteristics are reflected in changing labor supply behavior. That is why the assessment of the effect of marital sorting on earnings inequality should explicitly adjust for labor supply behavior in order to disentangle the pure effect of sorting compared to the observed (non-random) sorting of spouses' earnings.

In this chapter, I measure the effect of the association of female and male earnings on total earnings inequality across couple households in West Germany over a 25-year period from 1986 to 2010 and adjust for labor supply choices. Using data from the German Socio-Economic Panel Study (SOEP) and a behavioral microsimulation model for Germany (IZAΨMOD, see Peichl et al., 2010), I estimate a discrete choice model of labor supply for couples for each year separately. This provides estimates on preferences for income, leisure as well as various interactions with household characteristics. Then, I create a sample of hypothetical couples by

[1]Labor earnings have become much more dispersed (see Katz and Autor, 1999, for an overview). Numerous studies analyze issues related to increases in inequality of hourly wages: skill-biased technological change and globalization (Juhn et al., 1993; Autor et al., 1998, 2008), changes in labor market institutions (DiNardo et al., 1996; Card and DiNardo, 2002; Lemieux, 2006) and the gender wage gap (Blau and Kahn, 2006; Arulampalam et al., 2007).

randomly matching individual earnings and characteristics of females and males from couple households. This serves as a counterfactual benchmark to assess the effect of non-random sorting on inequality. Spousal characteristics, which constitute a key part of the household context, affect individual labor supply decisions and, therefore, individuals would respond to a counterfactual environment. In order to capture labor supply adjustments, I use the estimated coefficients, predict labor supply behavior of the hypothetical couples and calculate the respective earnings of randomly matched individuals and, hence, total household earnings. Differences in earnings inequality between the distributions of observed and hypothetical couples after labor supply adjustment allow me to quantify the pure effect of marital sorting on inequality by applying an index measuring the effect of the association between spouses' earnings on inequality (the "flocking index", see Aslaksen et al., 2005).

I find that the observed pattern of sorting in earnings has a fairly weak impact on earnings inequality among couple households. The trend over time suggests that the effect of sorting has turned from slightly equalizing to slightly disequalizing in recent years. However, after adjusting for labor supply choices based on the hypothetical household context, I find that sorting in productivity has a large impact on earnings inequality. This result is driven by two factors: First, women with high (low) earnings potential tend to couple with high (low) earning men. Second, participation and working hours of women living in couples with high earning men were low in the 1980s, but increased disproportionally over the period under consideration. Taken together, this indicates that increasing earnings correlation between females and males results to a large extent from increasing labor force attachment of women rather than from changes in couple formation.

From a policy maker's perspective, this result implies a trade-off between policy measures promoting female labor force participation and redistributive policies. Achieving the objective of higher female employment apparently comes at the price of higher inequality. The policy implications are ambiguous. On the one hand, one could argue that government intervention is not justified, since the observed trend of increasing female labor force participation is the result of couples' choices. On the other hand, the growing share of dual earner couples implies a declining importance of intra family redistribution, which could potentially be substituted by government redistribution.

The chapter is organized as follows: Section 3.2 introduces the methodology before the empirical application and the data are described in section 3.3. Results are presented in section 3.4. Section 3.5 concludes.

3.2 Methodology

In order to quantify the extent of marital sorting on couple earnings inequality, I use an index introduced by Aslaksen et al. (2005), which is derived from a decomposition of the Gini coefficient. The "flocking index" quantifies both the extent and the sign of the effect of the association of female and male labor earnings ("flocking together"[2]) on inequality across couples. It is calculated based on the observed as well as a hypothetical distribution of couple earnings. The hypothetical distribution is constructed by matching spouses' individual earnings randomly to each other. However, it has to be noted that a shortcoming of previous applications of this index is that the difference between the observed and the counterfactual distribution does not reflect changes due to labor supply behavior. Hence, taking into account labor supply coordination requires a simulation of counterfactual choices given the randomly matched household context. In the following, I will first introduce the unadjusted "flocking index" and then suggest an extension that adjusts for labor supply choices.

The flocking index. Consider a population of n couple households indexed $i \in \{1, \dots, n\}$ and a distribution of household earnings $Y = (Y_1, \dots, Y_n)$, where household i's total earnings are simply the sum of both the female and the male spouse's individual earnings: $Y_i = Y_i^f + Y_i^m$. The cumulative distribution of total earnings, F_Y, is a function of the gender-specific marginal earnings distributions $F_Y = F_Y(F_Y^m, F_Y^f)$.[3] Each distribution is associated with mean earnings (μ_Y, μ_Y^f and μ_Y^m) and a level of earnings inequality, represented by the Gini coefficient $G(\cdot)$.

[2]The earliest citation of this proverb dates back to Minsheu (1599): "*Birdes of a feather will flocke togither*". This means that those with similar taste tend to congregate in groups. A modern version refers to "*doctors marrying doctors rather than nurses*" (OECD, 2011).

[3]See Decancq et al. (2012) for a copula-based decomposition of couple earnings inequality.

The Gini coefficient of the distribution of total couple earnings Y reads

$$G(Y) = \frac{2}{\mu_Y} \cdot Cov[Y, F_Y] = \frac{\mu_Y^f}{\mu_Y} \cdot \gamma^f + \frac{\mu_Y^m}{\mu_Y} \cdot \gamma^m, \tag{3.2.1}$$

where $\gamma^s = 2/\mu_Y^s \cdot Cov[Y^s, F_Y]$ for $s \in \{m, f\}$, which is a measure of the association between female or male earnings respectively and total earnings (see Aslaksen et al., 2005, p. 503). It depends on the covariance of gender-specific earnings Y^s and the couple's position in the total earnings distribution F_Y, which does not necessarily coincide with spouses' individual positions in the gender-specific distributions F_Y^s.

Taken the distributions of Y^f, Y^m and, hence, Y as given, the level of inequality in total household earnings $G(Y)$ is bounded between an upper and a lower level, i.e., $G(Y) \in [G^{min}(Y), G^{max}(Y)]$. These bounds depend on the spouses' positions in the gender-specific earnings distributions relative to the household's position in the total distribution. With $s, -s \in \{m, f\}$ and $s \neq -s$ these are defined as

$$\text{G(Y)} = \begin{cases} G^{max}(Y) & if \ F_Y^s(Y_i^s) = F_Y^{-s}(Y_i^{-s}) \\ G^{min}(Y) & if \ F_Y^s(Y_i^s) = 1 - F_Y^{-s}(Y_i^{-s}) \end{cases} \tag{3.2.2}$$

This means that the level of total couple earnings inequality is highest (lowest) if the highest earning woman is married to the man with the highest (lowest) earnings within the male distribution, the second highest earning woman with the second highest (lowest) man and so on. Hence, the pattern of marital sorting has the most (dis)equalizing effect on earnings inequality across couple households in a situation where sorting of spouses is perfectly negative (positive) with respect to individual earnings.

A way to assess to what extent the observed inequality in the distribution of couple earnings is affected by non-random sorting of spouses is to compare the observed distribution with a hypothetical one where partners' earnings are randomly matched to each other. Consider as a counterfactual a distribution of randomly matched couples indexed $\tilde{i} \in \{1, \ldots, n\}$ with total earnings $Y_{\tilde{i}} = Y_{\tilde{i}}^f + Y_{\tilde{i}}^m$. Note that without any adjustments the levels of inequality in the gender-specific marginal distributions do not change, i.e., $G(\widetilde{Y}^s) = G(Y^s)$ for $s \in \{m, f\}$.

However, inequality of total earnings is affected, i.e., in general $G(\widetilde{Y}) \neq G(Y)$. Normalizing the difference between observed and hypothetical inequality by the distance between random inequality and the upper or lower bound yields an index of the extent of "flocking together" (Aslaksen et al., 2005):

$$V(Y, \widetilde{Y}, Y^f, Y^m) = \begin{cases} \frac{G(Y)-G(\widetilde{Y})}{G^{max}(Y)-G(\widetilde{Y})} & if\ G(Y) > G(\widetilde{Y}), \\ \frac{G(Y)-G(\widetilde{Y})}{G(\widetilde{Y})-G^{min}(Y)} & if\ G(Y) < G(\widetilde{Y}), \end{cases} \tag{3.2.3}$$

where $V \in [-1, 1]$. Positive values of V imply that $G(Y) > G(\widetilde{Y})$, i.e., observed inequality of couple earnings is greater than inequality of the distribution of random matches. This reflects a disequalizing pattern of sorting, while negative values of V indicate a sorting pattern that is equalizing compared to random sorting. Note that the extreme cases of either perfect positive, i.e., $G(Y) = G^{max}(Y)$ (negative sorting, i.e., $G(Y) = G^{min}(Y)$) imply the maximum (minimum) values of $V = 1$ ($V = -1$). Finally, the case of $V = 0$ represents a situation where observed and random sorting pattern coincide.[4]

Household context and the adjusted flocking index. Previous studies assessing the effect of female earnings or the correlation of spouses' earnings on total inequality have constructed various counterfactuals from observed income or earnings distributions. The fact that observed household earnings and incomes and their distribution across the population do not only reflect couple formation but are also determined by income-producing choices, in particular spouses' (joint) decisions on labor supply, has so far been neglected.[5] Hence, the observation of increasing correlation of spouses' earnings does not necessarily only reflect changes in the assortativeness in couple formation but is also affected by changes in the coordination of labor market behavior of existing couples.

Consider, for example, a perfectly negative sorting pattern where the best earning woman and the least earning man form a couple and vice versa. This would indicate that sorting with respect to earnings is most equalizing, since resources

[4]Note that the interpretation of the flocking index is similar to a measure of correlation between two stochastic variables. Aslaksen et al. (2005) show that the flocking index is equal to the correlation coefficient when the Gini coefficient is replaced by the squared coefficient of variation.

[5]See Bargain et al. (2012) for a comprehensive documentation of significant cross-wage elasticities.

are redistributed within the household. However, since earnings are a function of earnings *potential* (the wage rate) and supply of working time on the labor market (hours), it is not clear whether this sorting pattern reflects assortative mating in traits like ability or education (doctors marry nurses) rather than patterns of labor market behavior of couples (female doctors work less when married to a male doctor).

The latter example reflects a situation where the number of hours supplied on the labor market is negatively associated with partner income, e.g., the higher the male earnings the lower the number of hours worked by the female spouse (and vice versa). This implies that the extent of "flocking together" with respect to earnings is influenced by labor supply choices of couples. That is why one has to take into account the dependency of individual earnings, in particular both the extensive and the intensive margin of labor supply, on the household context which comprises the earnings potential and other characteristics of the partner when constructing a counterfactual distribution of couple earnings.

Randomly matching individual earnings instead of using the observed earnings Y_i^s, which is a function of observed couple characteristics X_i, requires an imputation of hypothetical earnings $Y_{\tilde{i}}^s$ based on the hypothetical setting $X_{\tilde{i}}$. I define the *adjusted flocking index* $\widehat{V}$ based on predicted counterfactual distributions for both female and male earnings. In order to do so, I make explicit that hypothetical individual earnings would adjust their behavior given the counterfactual couple characteristics, i.e., $\widehat{Y}_{\tilde{i}}^s = \widehat{Y}_{\tilde{i}}^s(X_{\tilde{i}})$, where a hat indicates a random match and labor supply adjustment. The nature of this relationship can be predicted based on the relationship of observed earnings and household characteristics $Y_i^s = Y_i^s(X_i)$ (see below). The adjusted flocking index is constructed using the adjusted distributions of female and male as well as total earnings:

$$\widehat{V} = \widehat{V}(Y, \widehat{Y}, \widehat{Y}^f, \widehat{Y}^m). \tag{3.2.4}$$

The interpretation of the adjusted flocking index is the same as for the unadjusted: Positive values indicate a disequalizing and negative values an equalizing sorting pattern. The main difference is that labor supply coordination given the household context is explicitly taken into account and, hence, the adjusted index gives an indication of the pure effect of partner sorting on earnings inequality across couple households.

Modeling household labor supply. In order to predict the relationship between household and partner characteristics and individual labor supply decisions, I make use of microsimulation techniques and apply a structural model of household labor supply (Aaberge et al., 1995; Van Soest, 1995; Blundell et al., 2000). I assume that couple households have a utility function $U_i = U_i(D_i, h_i^f, h_i^m; X_i)$, where the arguments are household disposable income D_i and leisure time of the female and male partner respectively (h_i^f and h_i^m) given household characteristics X_i. Moreover, I assume that utility is maximized by jointly deciding on (h_i^f, h_i^m) and disposable income is given by $D_i = d(w_i^f h_i^f, w_i^m h_i^m, I_i; X_i)$, where w_i^f and w_i^m are the fixed individual wage rates and I_i is non-labor income. The tax-benefit function $d(\cdot)$ transforms labor earnings and other gross income into disposable income given household characteristics. Furthermore, it is assumed that couple households can choose among a fixed choice set of combinations of net income and leisure time. This is reflected by a finite set of m working time categories for each individual, which gives a total of $m^2 = J$ choices of (h_{ij}^f, h_{ij}^m) per couple.

Utility U_{ij} of household i in choice j comprises the systematic influence of the arguments as well as observable heterogeneity captured by characteristics X_i and its interactions with the arguments. Unobserved heterogeneity in preferences is captured by adding a stochastic term (random utility maximization, see McFadden, 1974). Hence, total household utility is $V_{ij} = U_{ij} + \epsilon_{ij}$. Assuming that the error terms follow a Gumbel (extreme value) distribution and are independently and identically distributed across choices $j \in \{1, ..., J\}$ as well as the assumption of utility maximizing behavior imply that the probability of household i choosing category k over all other available categories $l \in \{1, ..., J\} \backslash k$ is

$$P_{ik} = P(V_{ik} > V_{il}) = P(U_{ik} - U_{il} > \epsilon_{il} - \epsilon_{ik}) = \frac{\exp(U_{ik})}{\sum_{l=1}^{J} \exp(U_{il})}. \tag{3.2.5}$$

The set of coefficients β of the systematic part of the utility function $U_i(D_i, h_i^f, h_i^m; X_i)$ can be estimated empirically on the sample of observed couple households (see Creedy and Kalb, 2006, for a detailed overview of microsimulation models of labor supply). The estimates $\hat{\beta}$ can be interpreted as population averages of preferences for income and leisure given observed heterogeneity in household characteristics. Hence, after having estimated the labor supply model, I can use $\hat{\beta}$ to predict the probability distribution across choices $\widehat{P}_{\tilde{i}j}$ for each hypothetical couple household. This is the basis for calculating labor supply choices $\hat{h}^s_{\tilde{i}}$, which gives hypothetical individual earnings $\widehat{Y}^s_{\tilde{i}}$ for $s \in \{m, f\}$ and total earnings $\widehat{Y}_{\tilde{i}}$ as well as the resulting levels of inequality which are required for calculating the adjusted flocking index according to equations (3.2.3) and (3.2.4).

3.3 Empirical Application

3.3.1 Microsimulation model

The analysis presented in this chapter is based on the microsimulation model IZAΨMOD of the Institute for the Study of Labor (IZA), which comprises a static tax-benefit calculator for Germany as well as a random utility model of labor supply as described in the previous section (see Peichl et al., 2010, for a documentation of the model). In order to predict labor supply choices, I have to impute income levels for counterfactual choices of working time.[6] It is straightforward to calculate gross labor earnings for categories that are not actually chosen by multiplying the individual hourly wage rates with the number of working hours.[7] However, since labor supply decisions are based on the trade-off between leisure time and disposable income it is necessary to subtract counterfactual income and payroll taxes and add benefit payments. Since the model's tax-benefit calculator is currently only available for recent years (since 2005) and not yet fully extended to the period from the mid-1980s onwards, I do not make use of IZAΨMOD's standard tax-benefit calculator. Instead, I apply a reduced-form regression methodology to calculate disposable income from gross incomes and run the following ordinary

[6] The model comprises seven working time categories for each individual with 10, 20,...,60 hours of work per week as well as the non-work category of zero hours. Therefore, couple households have a choice set of 7x7=49 categories.

[7] Wage rates are not observed for individuals currently not in employment and are estimated on observed wages using a Heckman correction for sample selection (Heckman, 1976, 1979). I use predicted wages for the entire sample.

least squares (OLS) regression model for each year $t = 1986, ..., 2010$ separately:[8]

$$D_{it} = \alpha_t^0 + X_{it}\alpha_t^x + Z_{it}\alpha_t^z + (X'Z)_{it}\alpha_t^{xz} + u_{it}, \tag{3.3.1}$$

where D_{it} is observed disposable income, Z_{it} is a vector of gross incomes (from labor, assets, private pensions and other gross income) including the squared values and X_{it} is a set of household characteristics that are relevant for various tax-benefit policies (marital status, age, age squared and hours worked of both spouses, number of children and number of working-age adults as well as dummies for civil servants and self-employed). The vector $(X'Z)_{it}$ comprises interactions of gross incomes and household characteristics. The regression results yield values for R^2 very close to one (0.97–0.99), which means that this fairly simple regression model captures almost the entire observed variation in disposable household incomes and, therefore, has sufficient predictive power to calculate tax liabilities and benefit payments in both observed and counterfactual choice categories.[9]

Using predicted disposable incomes as an input, I estimate the conditional logit model with the observed choice of working hours category as dependent variable as described in equation (3.2.5).[10] For the systematic part of the household utility function U_{ij}, I use a translog specification, i.e., the main arguments income and leisure as well as the interactions of income with female and male leisure enter the utility function in natural logarithms (see Peichl et al., 2010). In the conditional logit estimation, I use the squared arguments as well as several interactions with household characteristics as additional explanatory variables of labor supply decisions. The interaction variables are age and age squared of both partners as well as dummy variables for skill levels (high and low education), the presence of children in various age groups and for working part-time (10–30 hours per week) following Van Soest (1995).[11]

[8]See Frenette et al. (2007); Biewen and Juhasz (2012); Peichl (2012); Bargain et al. (2012) for similar approaches.

[9]Regression results are presented in tables 3.6.1 and 3.6.2 in the appendix.

[10]See Bargain et al. (2012) for an extensive overview of this methodology.

[11]Results of the conditional logit estimations are presented in tables 3.6.3–3.6.8 in the appendix. The labor supply model is estimated separately for flexible couples and for flexible females and males in semi-flexible couples (see below).

Data and sample selection. The simulation model is based on microdata from the German Socio-Economic Panel Study (SOEP), which is a panel survey of households and individuals that has been conducted annually since 1984 and currently comprises 27 waves (Socio-Economic Panel, 2011). Population weights make the respondents' information representative for the German population. Issues concerning sampling and weighting methods or the imputation of information in case of item or unit non-response are well documented by the SOEP Service Group (see Haisken-DeNew and Frick, 2005; Wagner et al., 2007).

The sample is restricted to West Germany, since especially shortly after the reunification of Germany in 1990, labor supply behavior of East Germans differs substantially from that of West Germans. Moreover, income levels are still substantially different between East and West. The sample is further restricted to couples (both married and cohabiting) where both spouses are of prime working age (25–55) and at least one spouse can adjust labor supply flexibly. This means that I exclude couples where both spouses are in education, in military or community service, pensioners, on parental leave, civil servants, self-employed or have gross household income from capital that exceeds half of income from labor. Individual earnings comprise gross earnings from dependent work as well as from self-employment in the month prior to the survey interview. Household labor earnings are the sum of both partners' earnings.

3.3.2 Descriptives

Earnings inequality and correlation. The development of observed earnings inequality across couple households in West Germany over the period 1986–2010 is displayed in figures 3.6.1 and 3.6.2 in the appendix. The Gini coefficient of total couple earnings (figure 3.6.1) has increased quite strongly from 0.23 in the mid-1980s to around 0.3 at the end of the period under consideration. At the same time, the correlation coefficient of female and male earnings in the sample of couples has increased from around -0.13 in 1986/87 to 0.03 in 2009/10 and turned from a negative to a positive correlation in the mid-2000s. Correlation and inequality of wages follows a similar trend.

The trends of observed female and male earnings inequality are displayed in figure 3.6.2 in the appendix. While the Gini coefficient of male earnings displays both a similar level and upward trend as couple earnings inequality, female earnings inequality has substantially decreased over the past 25 years. Starting from a very high level (around 0.64 in 1986) it has decreased to around 0.5 in 2010, which is still quite high compared to male earnings inequality.

Employment and hours worked. The observation of decreasing earnings inequality among women is for a large part driven by advances in female labor force participation. In the mid-1980s less than 50% of women in couples were employed, while the employment rate has increased to more than 70% at the end of the last decade (figure 3.6.3 in the appendix). This development has particularly dampened female earnings inequality since the share of women with zero earnings has been constantly decreasing. At the same time, the employment rate of prime-aged men has remained fairly constant at a high level of 90–95%. In addition, men work on average full-time with at least 40 hours per week over the entire period, while the average number of hours worked by women is much lower due to lower participation rates and part-time work (see figure 3.6.4 in the appendix).

Previous research (e.g., Juhn and Murphy, 1997) has documented that changes in both labor force participation and hours worked of females are not uniformly distributed across the distribution of male earnings. Figures 3.3.1 and 3.3.2 show the changes in employment rates and hours of women by *male* earnings quintile and within 5-year subperiods.[12] Female labor force participation was below average especially for women living with men in the upper tail of the earnings distribution in the 1980s. For example, only 40% of women with men in the top quintile of the male earnings distribution were employed and worked on average about 13 hours per week, while 50–60% of women with non-working or low earning men (bottom quintile) were employed and worked 20–23 hours. This pattern has changed over time. Employment growth among women has been largest at the upper tail of the male distribution. In the recent period 2006–2010, there are almost no differences in employment rates and hours worked by women across the male distribution.

[12] Individuals are assigned to one of six groups. Individuals with zero earnings are assigned to the group “not in work”, individuals with positive earnings are assigned to their earnings quintile (based on positive earnings).

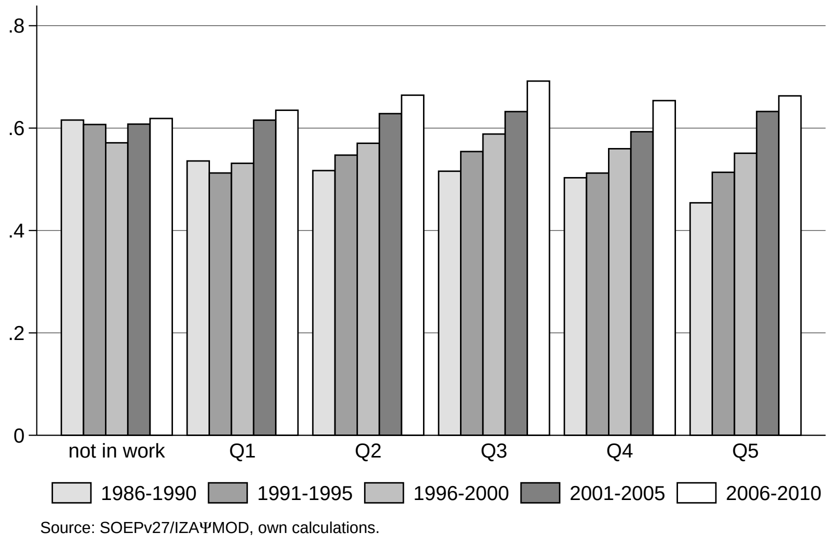


Figure 3.3.1: Female employment rates by male earnings quintile (1986–2010)

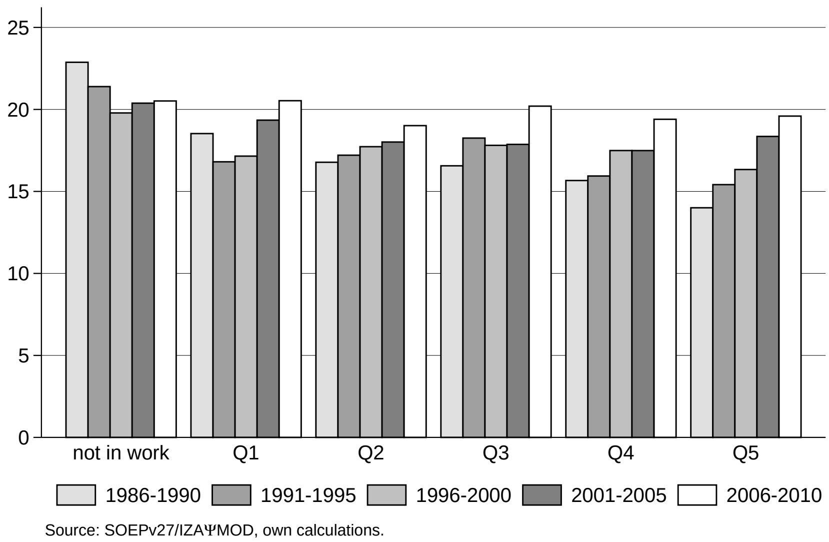


Figure 3.3.2: Female working hours by male earnings quintile (1986–2010)

3.4 Results

3.4.1 Unadjusted flocking index

The descriptive results suggest that earnings inequality has increased among couples and among men, while earnings inequality among women has decreased. At the same time, earnings correlation between females and males in couples has turned from negative to slightly positive over the period 1986 to 2010. In order to analyze whether increasing association of female and male earnings has contributed to overall inequality, I calculate the unadjusted flocking index following Aslaksen et al. (2005) as defined in equation (3.2.3) for each year separately. This means that spouses' earnings from observed couples are matched randomly to each other and earnings levels are not adjusted, but taken as given.

The resulting trend of the unadjusted flocking index over time is displayed in figure 3.4.1. The extent of "flocking together" remains fairly constant from the mid-1980s until the early 1990s. The resulting negative values, ranging from around -0.08 to -0.11, suggest that the pattern of sorting during this period has slightly dampened earnings inequality across couple households. However, the effect was not particularly strong.[13] From the mid-1990s until the mid-2000s, the unadjusted index remains mostly negative but values are closer to zero, which implies that the pattern of earnings sorting is rather neutral with respect to couple earnings inequality. I find positive values of the unadjusted flocking index only for the period 2006–2010. Ranging from 0.01 to 0.07, this result indicates a disequalizing pattern of sorting, which is however not very strong. Nevertheless, I find an upward trend of the extent of association between spouses' earnings on inequality over the period 1986–2010. In particular, this effect has switched signs in the 2000s turning from an equalizing to a disequalizing pattern of marital sorting in earnings.

3.4.2 Adjusted flocking index

As discussed in section 3.2, when measuring the effect of the association of spouses' earnings on inequality across couples using observed earnings, results might be

[13]Recall that the minimum and maximum values of the flocking index -1 and 1 respectively.

biased when earnings reflect both assortativeness of earnings potential in couple formation as well as labor supply behavior of households. Therefore, the adjusted flocking index explicitly takes into account labor supply. I use the estimated coefficients on preferences for income and leisure and several interactions with household and partner characteristics (see section 3.3) and predict labor supply behavior of the randomly matched hypothetical couples. This allows me to predict earnings levels after labor supply adjustment, which are used as an input to calculate the adjusted flocking index as defined in equation (3.2.4).

The results are presented in figure 3.4.1. I find that the level of the adjusted flocking index is positive throughout the entire period under consideration and considerably larger than the unadjusted flocking index. Note that the upper and lower bounds are the same as in equation (3.2.3) since the counterfactual distribution taking into account labor supply is compared to the observed distribution of couple earnings. The elements of both the unadjusted and the adjusted flocking index are displayed in figure 3.4.2. From the mid-1980s until the mid-1990s the level ranges between 0.3 and 0.4 and decreases somewhat afterwards, ranging from around 0.25 to 0.3 during the past 15 years. This means that the level of couple earnings inequality based on random sorting and adjusting for labor supply behavior is much lower compared to inequality of the observed pattern of sorting (figure 3.4.2).

The interpretation of this result is that, while the pattern of observed earnings sorting does not have a large impact on earnings inequality, the pattern of sorting in earnings *potential* does have a strong disequalizing impact. However, it is veiled by a particular pattern of labor market behavior of (potentially high earning) women in couples with high earning men who tend not to participate in the labor force in early years. This view is supported by a similar trend of the flocking index calculated for hourly wages only (figure 3.4.1), which only takes into account sorting in productivity. This corresponds to calculating earnings based on wage rates and assigning both females and males the same number of working hours. The difference between unadjusted and adjusted flocking index is particularly large at the beginning of the period under consideration in the 1980s but has decreased considerably since then due to increasing labor market attachment of women.

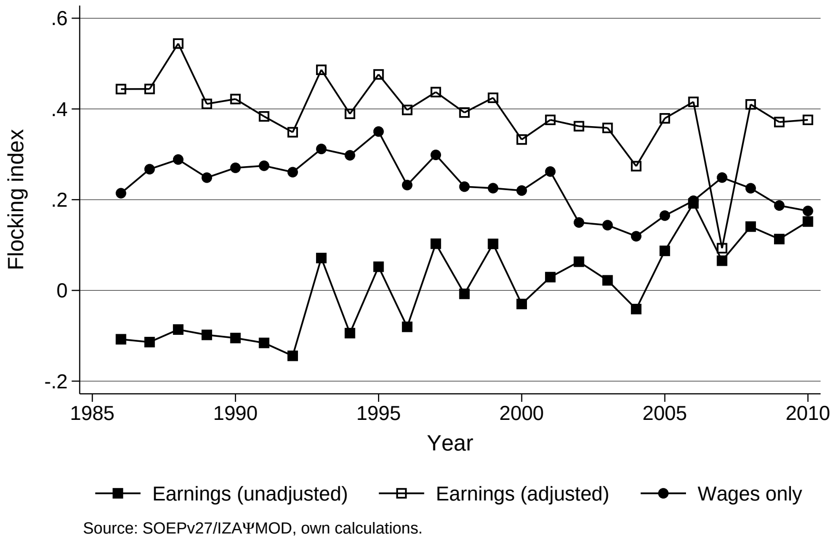


Figure 3.4.1: Unadjusted and adjusted flocking index flocking index (1986–2010)

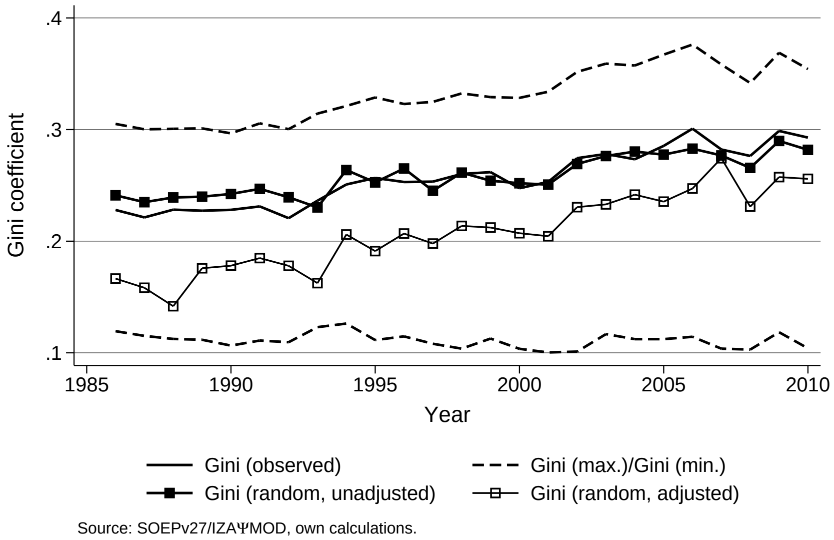


Figure 3.4.2: Elements of the unadjusted and adjusted flocking index (1986–2010)

Labor supply adjustments. In the following, I take a closer look at which parts of the female and male earnings distributions labor supply adjustments are most important when earnings are matched randomly to each other. The resulting labor market outcomes of adjusted employment and hours worked are presented in figures 3.6.3 and 3.6.4 in the appendix. Overall, employment rates and average hours slightly decrease compared to the observed outcomes, but the trends are very similar. I find that changes in male labor force participation are on average very small (see figures 3.4.3 and 3.4.4). Adjustments in participation are concentrated among men from lower quintiles of the observed earnings distribution, while hours would be slightly reduced in upper quintiles. Both participation and hours would increase for men not in work. However, note that this group makes up only about 5–10% of males due to the very high observed employment rates (see above).

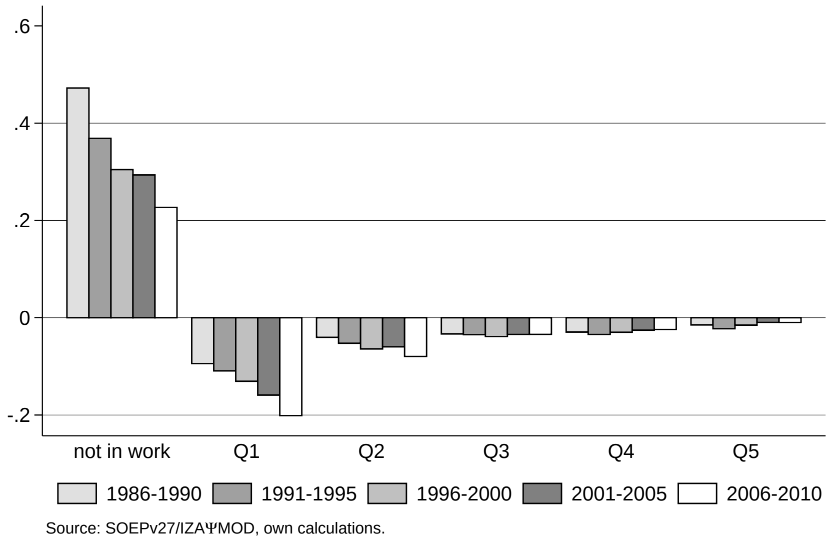


Figure 3.4.3: Male employment: adjustment by own earnings quintile

The small difference in overall employment rates between observed and random sorting masks considerable differences across the earnings distribution of women, which is shown in figures 3.4.5 and 3.4.6. Women who are observed to be not in employment would increase their participation considerably in the case of random matching by up to 40 percentage points and more than ten hours in the 1980s. Recall that women not in employment tend to couple with high earning men in

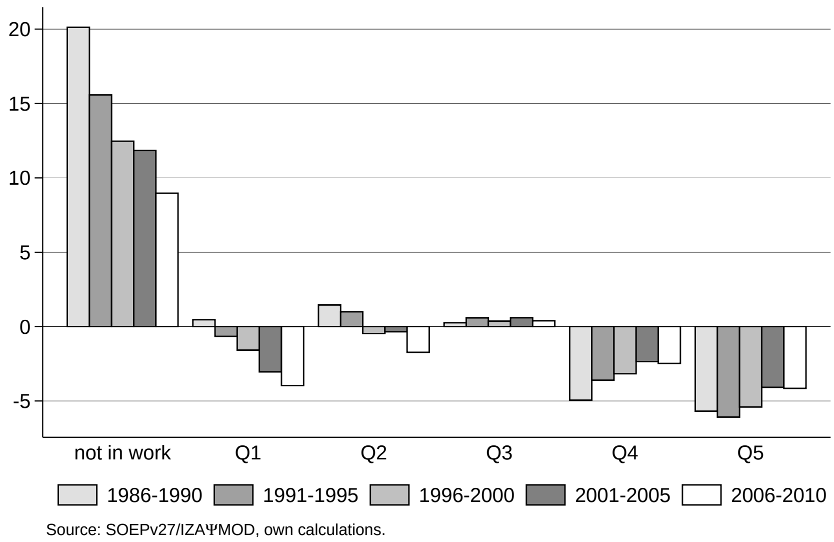


Figure 3.4.4: Male working hours: adjustment by own earnings quintile

earlier years. Hence, being matched to a man with lower earnings (potential) would apparently create incentives to participate in the labor force and/or work more hours, which is in line with negative cross-wage and income elasticities documented in the literature.[14] At the same time, women in employment would on average reduce their labor supply both at the extensive and the intensive margin. This pattern remains fairly similar over time, however the extent of the adjustments decreases between the 1980s and the 2000s. The responsiveness of women to other income has decreased over time (see Blau and Kahn, 2007; Heim, 2007) and is generally lower for women in upper deciles of the female earnings distribution.

Finally, figures 3.4.7 and 3.4.8 show the predicted labor supply adjustments of women across the earnings distribution of the men they are randomly matched to. I find that women who are matched to a non-working or low earning man would respond with an increase in labor supply, while women matched to men in upper quintiles would reduce participation and hours worked. This result is in line with the interpretation of male earnings having an "income effect" on labor supply of women (Reed and Cancian, 2009).

[14]See Aaberge et al. (1995, 1999); Devereux (2004); Blau and Kahn (2007); Bargain et al. (2012).

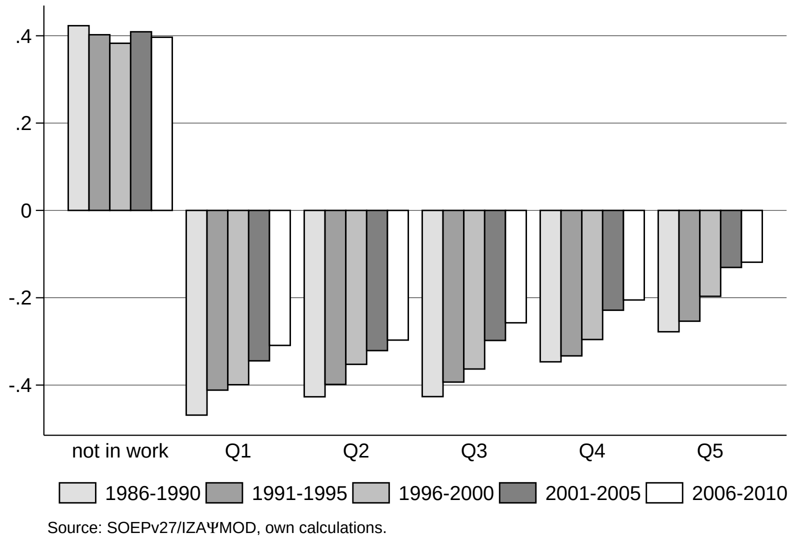


Figure 3.4.5: Female employment: adjustment by own earnings quintile

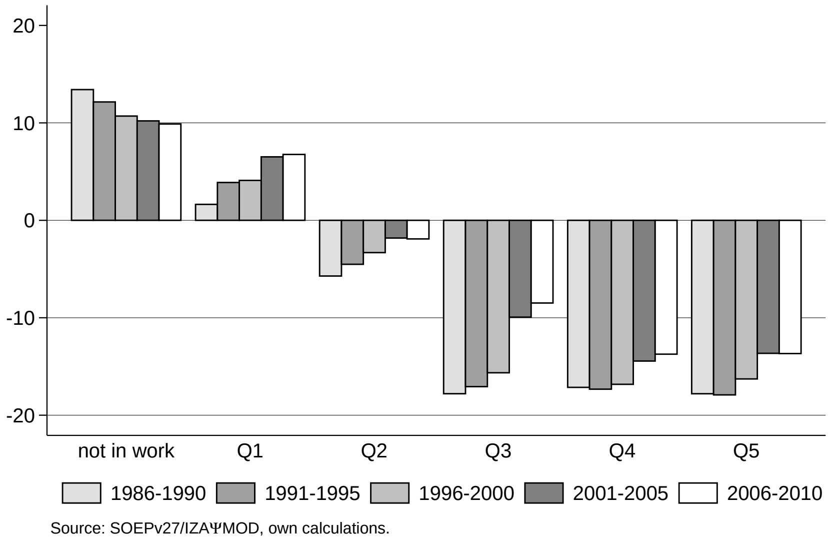


Figure 3.4.6: Female working hours: adjustment by own earnings quintile

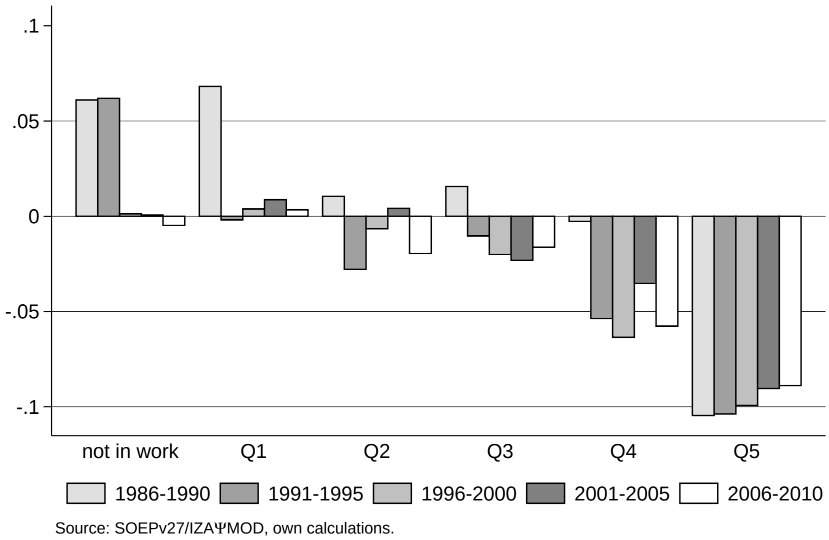


Figure 3.4.7: Female employment: adjustment by male earnings quintile

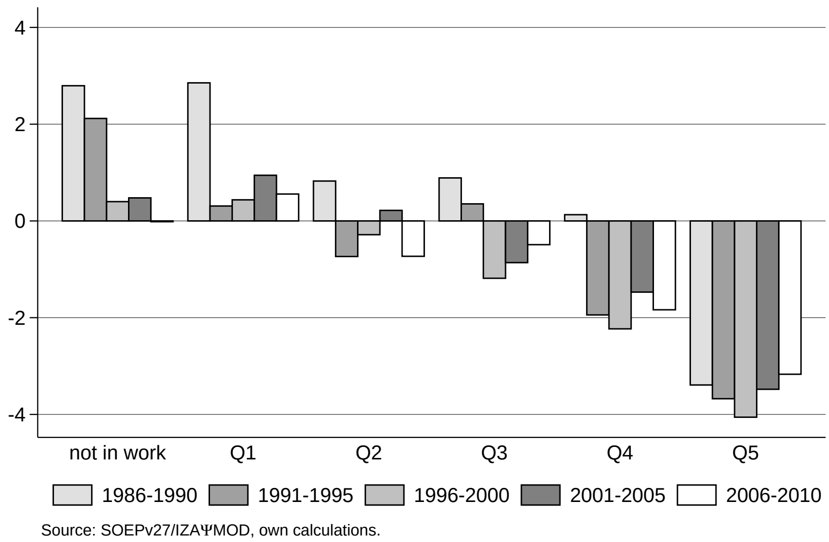


Figure 3.4.8: Female working hours: adjustment by male earnings quintile

3.5 Conclusions

In this chapter, I measure the effect of the association of female and earnings on total earnings inequality across couple households in West Germany over a 25-year period from 1986 to 2010. I match spouses randomly to each other and predict labor supply choices of hypothetical couples, which yields a counterfactual distribution of earnings and allows me to quantify the extent of marital sorting in earnings potential. Constructing counterfactuals based on observed earnings is misleading since labor supply choices are affected by both earnings potential as well as labor supply coordination in couple households

Using data from the German Socio-Economic Panel Study (SOEP) and a behavioral microsimulation model for Germany, I find that the observed pattern of sorting in earnings has a fairly weak impact on earnings inequality among couple households. However, the trend suggests that the pattern of sorting has turned from slightly equalizing to slightly disequalizing in recent years. After adjusting for labor supply choices based on the household context, I find that sorting in productivity has a much stronger positive impact on earnings inequality.

This result is mainly driven by two factors: First, women with high (low) earnings potential generally tend to couple with high (low) earning men. Second, women in couples with high earning men are more often not employed and work less in the 1980s, but increased labor supply above average over the period under consideration. Taken together, this suggests that increasing earnings correlation between females and males in couples results to a large extent from increasing labor force attachment of women, especially with high earnings potential, rather than from changes in couple formation.

Moreover, these results suggest that advances in the attachment of women to the labor market affect the distribution of earnings across couple households. For policy makers, this implies a trade-off, since measures supporting further increases in female labor force participation potentially amplify economic inequality across couple households, which make up a large, though diminishing, share of the total population. Higher female employment apparently comes at the price of higher inequality.

However, based on this study, there are no unambiguous policy implications.

On the one hand, one could argue that government intervention is not justified, since the observed trend of increasing female labor force participation is the result of couples' choices. On the other hand, the growing share of dual earner couples implies a declining importance of intra family redistribution, which could potentially be substituted by government redistribution. Future research should address the normative implications based on a theoretical framework of optimal taxation of couples.

3.6 Appendix

Figure 3.6.1: Couple earnings: correlation and inequality (1986–2010)

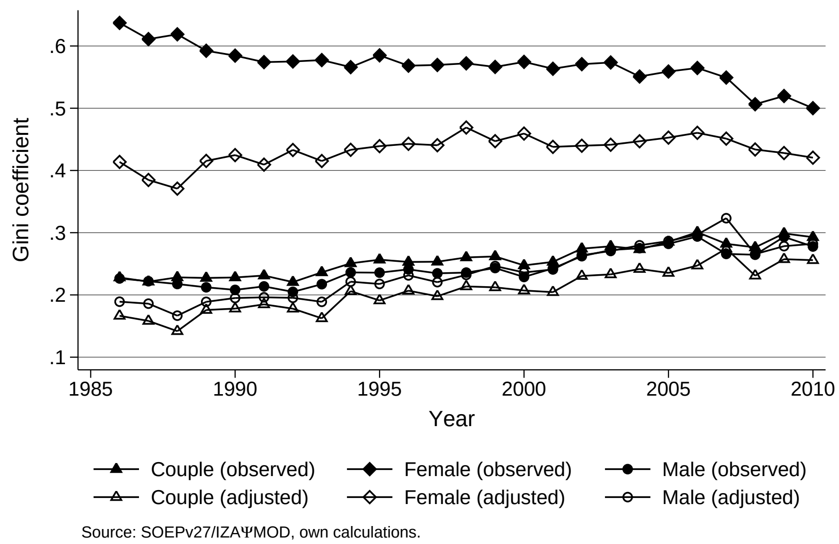


Figure 3.6.2: Individual and couple earnings: inequality (1986–2010)

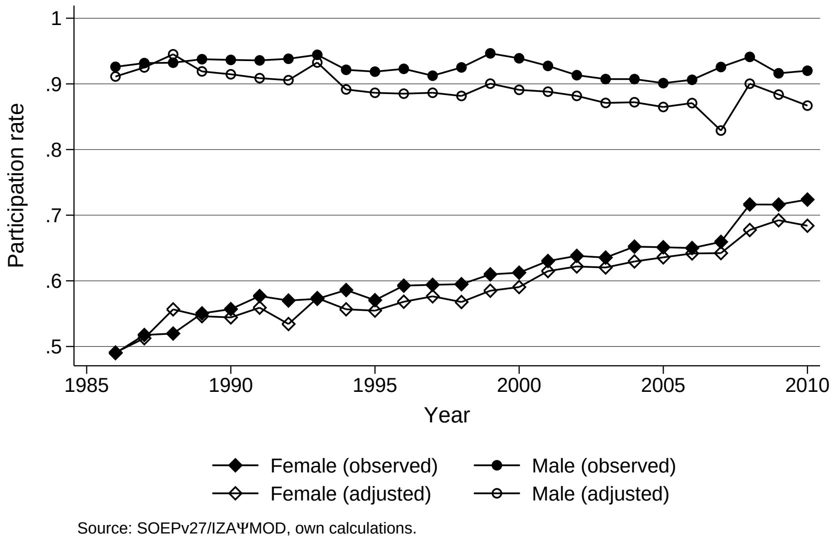


Figure 3.6.3: Employment rates: females and males (1986–2010)

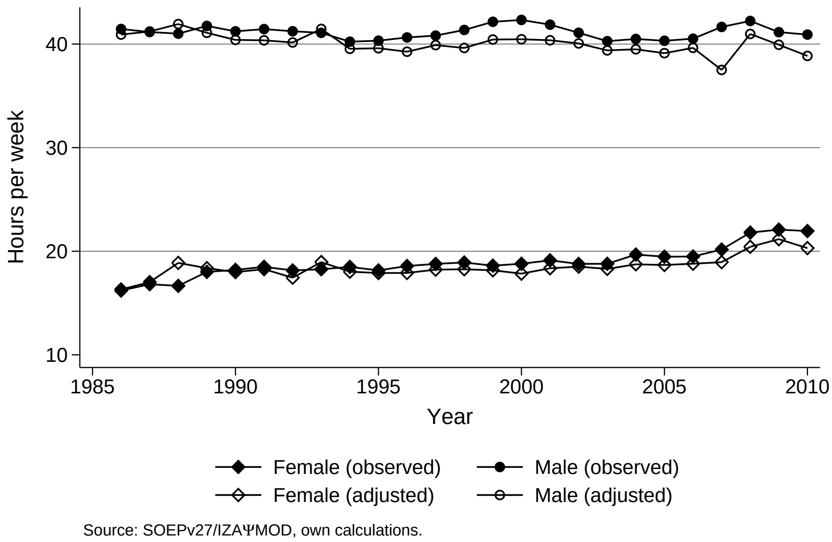


Figure 3.6.4: Working hours: females and males (1986–2010)

Table 3.6.1: OLS – Estimation of tax-benefit system (1986–1998)

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
married	25.797	8.292	-33.461	-122.350***	-88.548***	-144.553***	-66.463	52.429	61.470	-162.750***	-113.206**	57.533	-80.593
hours (male)	-5.027***	-5.213***	-3.479***	-4.710***	-3.990***	-3.709***	-8.366***	-7.256***	-8.608***	-5.942***	-6.151***	-4.744***	-4.442***
hours (female)	3.200***	1.110*	1.983***	1.497**	3.053***	0.553	2.723***	3.381***	3.517***	1.558*	2.110**	0.929	1.080
couple	-233.843***	-160.718***	-155.676***	-143.471**	-97.746*	-209.854***	-1.390	-205.542***	-64.509	67.085	-26.629	-71.962	-330.297***
age (male)	14.970***	12.411***	14.474***	22.128***	15.498***	14.569***	15.111***	13.821***	8.243**	10.053***	17.068***	7.185*	23.411***
age (female)	7.615***	6.051**	8.849***	13.633***	10.408***	10.014***	5.891**	8.541***	7.301**	3.664	9.604***	5.923*	16.726***
age sq. (male)	-16.589***	-15.233***	-17.729***	-27.125***	-17.724***	-14.633***	-20.022***	-16.188***	-11.109***	-10.748***	-18.674***	-7.261	-21.741***
age sq. (female)	-9.328***	-6.882**	-9.614***	-15.581***	-10.702***	-10.786***	-7.831**	-9.644***	-12.570***	-3.844	-10.751***	-7.005*	-14.891***
civil serv. (male)	96.192**	-43.547	-66.820	-54.054	-10.406	25.289	104.194	125.422	67.097	33.349	-51.481	-20.693	57.222
civil serv. (female)	-196.726*	28.376	-24.404	-7.601	-65.017	-63.425	-214.752**	0.261	-247.797*	-262.609*	-208.983**	-282.958**	-84.626
self-empl. (male)	95.349***	82.070**	-5.447	64.999	18.348	-14.928	13.164	90.941*	136.633**	-79.665	-103.666*	-88.310	-14.364
self-empl. (female)	-85.367**	-169.962***	-124.665***	-136.299**	106.774**	-112.357*	-138.551**	-132.798**	-37.626	-41.708	-64.853	-82.101	-139.419*
kids 0-2	120.752***	35.321	165.965***	153.498***	88.619***	181.102***	200.557***	405.496***	242.502***	317.665***	149.896***	129.479**	342.178***
kids 3-6	115.715***	166.031***	80.828***	67.945**	87.248***	140.659***	150.015***	250.597***	113.469***	87.696***	68.691**	254.082***	204.415***
kids 7-16	84.131***	103.957***	107.526***	108.820***	143.996***	166.384***	109.286***	116.827***	53.165**	80.097***	81.607***	55.449**	127.892***
kids 17-25	62.626*	33.487	-9.812	67.450*	85.637**	48.874	10.021	120.393**	187.741**	209.227***	-26.617	-47.151	-122.618*
adults	63.089***	91.199***	52.427**	24.849	70.122***	101.195***	119.646***	76.051**	101.728***	97.476***	124.294***	186.408***	209.504***
gross inc.	1.208*	2.380***	1.525***	2.276***	1.111**	1.097*	0.359	1.020*	-0.995*	0.165	1.366**	1.027**	0.943*
gross inc. sq./100	0.001	0.012*	0.013**	0.013**	0.004	0.002	-0.004	0.001	0.001	0.013***	0.002	0.003	-0.003
gross inc. x married	0.340	0.532**	0.203	0.419	0.015	0.135	0.213	0.251	0.121	0.097	0.137	-0.004	0.337*
gross inc. x hours (male)	-0.004	0.012**	0.002	0.006	0.007*	0.015***	0.003	-0.000	0.005	-0.005	0.012**	0.002	-0.006
gross inc. x hours (female)	-0.000	-0.009*	-0.006*	-0.008*	-0.007**	-0.012***	0.000	-0.001	0.008*	0.010**	0.004	-0.008	0.005
gross inc. x couple	0.877	1.749*	1.509**	2.109**	0.928*	0.916	0.348	0.365	-1.220*	-0.076	0.894*	0.905*	0.009
gross inc. x age (male)	-0.035	-0.079***	-0.070***	-0.088***	-0.026	-0.041*	-0.012	-0.017	0.044**	-0.007	-0.013	-0.043***	-0.024
gross inc. x age (female)	-0.051**	-0.039	-0.031*	-0.052**	-0.029*	-0.021	-0.010	-0.012	0.028*	0.017	-0.050***	-0.028*	-0.027*
gross inc. x age sq. (male)	0.028	0.065***	0.067***	0.076***	0.020	0.039**	0.006	0.013	-0.038**	0.012	-0.005	0.044***	0.025*
gross inc. x age sq. (female)	0.048**	0.011	0.013	0.030	0.016	0.009	0.009	-0.002	-0.017	-0.029*	0.049***	0.021*	0.023*
gross inc. x civil serv. (male)	-1.532	-1.185	-1.824**	-2.207	0.024	-1.721*	1.394	1.370	8.925	-0.503	-1.709	1.077	0.529
gross inc. x civil serv. (female)	0.592	1.567	-0.385	-0.117	-0.481	1.439	1.540	-0.907	-1.105	-15.835	-6.689	90.097	0.196
gross inc. x self-empl. (male)	0.247	0.012	-0.116	-0.334	0.048	0.170	0.286**	-0.055	-0.367***	0.090	-0.126	0.049	0.042
gross inc. x self-empl. (female)	0.131	0.325*	0.312*	0.393**	0.007	0.131	-0.109	-0.264*	0.288*	-0.430***	-0.074	0.257	0.008
gross inc. x kids 0-2	-0.103	-1.747	1.956*	1.153	-1.202	1.082	-0.853	1.409***	2.014	0.634	1.007	3.450	0.322
gross inc. x kids 3-6	1.551*	0.308	-0.423	-0.275	0.858	-0.634	-0.052	-0.189	-0.136	0.360	-2.672*	-0.167	-0.458
gross inc. x kids 7-16	-0.031	-0.403**	-0.077	0.431*	-0.097	0.458	0.278	0.475	0.728**	0.612	0.614***	0.393	-0.282
gross inc. x kids 17-25	0.095	-0.116	0.209*	0.051	0.176	-0.081	0.889***	0.310*	0.268	0.373	0.440	0.287	0.205
gross inc. x adults	-0.050	-0.225***	-0.116**	-0.191**	-0.043	-0.185***	-0.167**	-0.230***	-0.155*	-0.198**	-0.120	-0.022	0.075
gross inc. sq./100 x married	-0.001	-0.001	0.000	0.005	0.002	0.001	0.002	-0.003***	-0.003**	0.001	-0.002	0.002	-0.002
gross inc. sq./100 x hours (male)	-0.000	-0.000	-0.000*	-0.000*	-0.000***	-0.000	0.000	-0.000	-0.000	-0.000*	-0.000*	-0.000	0.000
gross inc. sq./100 x hours (female)	0.000	0.000*	0.000	-0.000*	0.000**	0.000	-0.000	-0.000	-0.000	0.000	0.000**	-0.000	-0.000
gross inc. sq./100 x couple	0.003	0.015**	0.018***	0.012*	-0.001	-0.003	-0.006	0.006	0.006	0.009**	0.008*	0.006*	-0.001
gross inc. sq./100 x age (male)	-0.000	-0.000*	-0.001***	-0.000**	0.000	0.000	0.000	-0.000	-0.000	-0.001***	0.000	-0.000	-0.000
gross inc. sq./100 x age (female)	0.000	-0.000*	-0.001***	-0.001**	-0.000	0.000	0.000*	-0.000	-0.000	-0.000**	-0.000	-0.000**	0.000
gross inc. sq./100 x age sq. (male)	0.000	0.000	0.000**	0.000	-0.000	-0.000	-0.000	0.000	0.000	0.001***	-0.000	0.000	0.000
gross inc. sq./100 x age sq. (female)	-0.000	0.000	0.001***	0.001**	0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000*	-0.000
gross inc. sq./100 x civil serv. (male)	-0.006	-0.001	0.007*	-0.001	0.000	-0.003	-0.002	0.001	-0.000	-0.001	0.001	0.001	-0.000
gross inc. sq./100 x civil serv. (female)	0.001	-0.005	-0.001	0.002	0.011	0.001	-0.008	0.001	-0.002	-0.004	-0.008	-0.000	0.001
gross inc. sq./100 x self-empl. (male)	-0.001	-0.000	-0.001	-0.000	0.001	0.001	-0.001	-0.000	0.001	-0.002*	-0.000	-0.001	-0.000
gross inc. sq./100 x self-empl. (female)	-0.003	-0.004*	-0.000	-0.001	-0.001	-0.004***	-0.001	-0.000	-0.001	-0.002	-0.000	-0.001	-0.001
gross inc. sq./100 x kids 0-2	0.002	0.002	-0.001	-0.007	0.001	0.007**	-0.008	-0.018***	-0.003*	-0.004	-0.003	0.004	-0.003
gross inc. sq./100 x kids 3-6	-0.000	0.001	-0.001	-0.003*	-0.002	-0.004**	0.002	0.006***	0.003	0.001	0.001	-0.005***	0.004***
gross inc. sq./100 x kids 7-16	-0.001	0.000	-0.000	-0.002**	-0.001	-0.001*	-0.002*	0.001	-0.000	-0.000	0.002*	-0.003***	-0.000
gross inc. sq./100 x kids 17-25	-0.000	-0.000	-0.003*	-0.004***	0.004**	-0.001	-0.002	-0.001	-0.004**	-0.002	-0.001	-0.002*	0.001
gross inc. sq./100 x adults	0.000	0.001	0.005***	0.003**	-0.002	0.001	-0.000	0.002*	0.002*	0.002*	-0.001	0.003**	0.001
labor inc.	-0.560	-1.708*	-0.883*	-1.602*	-0.430	-0.360	0.216	-0.314	1.606***	0.583	-0.643	-0.238	-0.091
labor inc. sq./100	-0.004	-0.014**	-0.014**	-0.016***	-0.005	-0.003	0.005	-0.002	-0.001	-0.015***	-0.003	-0.005	0.000
labor inc. x married	-0.368	-0.530**	-0.182	-0.342	0.034	-0.060	-0.194	-0.275*	-0.180	-0.014	-0.099	-0.044	-0.270
labor inc. x hours (male)	0.007	-0.009*	-0.001	-0.004	-0.006	-0.014***	0.001	0.003	-0.002	0.007*	-0.010*	-0.001	0.006
labor inc. x hours (female)	-0.002	0.008*	0.006	0.008*	0.006*	0.011***	-0.002	-0.001	-0.010*	-0.010**	-0.004	0.007	-0.005
labor inc. x couple	-0.596	-1.546*	-1.358**	-1.892**	-0.775	-0.702	-0.321	-0.160	1.414**	0.244	-0.722	-0.575	0.282
labor inc. x age (male)	0.023	0.069**	0.062***	0.073***	0.017	0.033*	0.007	0.007	-0.050**	-0.005	-0.001	0.030*	0.009
labor inc. x age (female)	0.045*	0.035	0.027*	0.043*	0.024	0.013	0.010	0.006	-0.035*	-0.024	0.043**	0.016	0.019
labor inc. x age sq. (male)	-0.014	-0.052**	-0.059***	-0.058***	-0.010	-0.032*	0.002	-0.000	0.046***	0.003	0.023	-0.028*	-0.008
labor inc. x age sq. (female)	-0.041*	-0.007	-0.008	-0.019	-0.013	0.001	-0.007	0.008	0.027*	0.037**	-0.042***	-0.008	-0.017
labor inc. x civil serv. (male)	1.555	1.316	1.982**	2.345	0.082	1.804*	-1.321	-1.316	-8.855	0.596	1.856	-0.961	-0.424
labor inc. x civil serv. (female)	-0.384	-1.522	0.468	0.206	0.606	-1.331	-1.357	0.977	1.247	15.997	6.797	-89.908	-0.115
labor inc. x self-empl. (male)	-0.160	0.083	0.288	0.469*	0.106	-0.003	-0.121	0.182*	0.502***	0.118	0.341**	0.199	0.180
labor inc. x self-empl. (female)	-0.057	-0.168	-0.191	-0.268	-0.011	0.000	0.236	0.378**	-0.229	0.511***	0.166	-0.146	0.140
labor inc. x kids 0-2	0.083	1.791	-1.974*	-1.168	1.239	-1.096	0.880	-1.567***	-2.056	-0.681	-0.977	-3.397	-0.385
labor inc. x kids 3-6	-1.592**	-0.358	0.425	0.289	-0.855	0.607	0.014	0.086	0.153	-0.338	2.715*	0.119	0.449
labor inc. x kids 7-16	0.025	0.391**	0.072	-0.440*	0.071	-0.509	-0.289*	-0.475	-0.704**	-0.597	-0.589***	-0.343	0.283
labor inc. x kids 17-25	-0.094	0.159	-0.138	-0.036	-0.140	0.119	-0.826***	-0.313*	-0.279	-0.428	-0.377	-0.176	-0.048
labor inc. x adults	0.018	0.170***	0.085	0.175**	0.001	0.133*	0.095	0.196**	0.108	0.151*	0.068	-0.074	-0.184*
labor inc. sq./100 x married	0.002	0.001	-0.000	-0.005	-0.002	-0.001	-0.002	0.003***	0.004***	-0.002	0.002	-0.001	0.001
labor inc. sq./100 x hours (male)	-0.000	0.000	0.000	0.000	0.000***	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000	-0.000
labor inc. sq./100 x hours (female)	-0.000	-0.000*	-0.000	0.000	-0.000**	-0.000	0.000	0.000	0.000	-0.000	-0.000**	0.000	-0.000
labor inc. sq./100 x couple	-0.006	-0.017**	-0.019***	-0.015**	0.001	0.001	0.007	-0.007*	-0.008	-0.010**	-0.009*	-0.009**	-0.001
labor inc. sq./100 x age (male)	0.001*	0.001**	0.001***	0.001***	-0.000	0.000	-0.000	0.000	0.000	0.001***	0.000	0.000	0.000
labor inc. sq./100 x age (female)	-0.000	0.000*	0.001***	0.001***	0.000	0.000	-0.000*	0.000	0.000	0.000**	0.000	0.000***	-0.000
labor inc. sq./100 x age sq. (male)	-0.001*	-0.001*	-0.001**	-0.000**	0.000	0.000	0.000*	-0.000	-0.000	-0.001***	0.000	-0.000	-0.000
labor inc. sq./100 x age sq. (female)	0.000	-0.000	-0.001***	-0.001***	-0.000	-0.000	0.000	-0.000	-0.000	-0.000*	-0.000	-0.000**	0.000
labor inc. sq./100 x civil serv. (male)	0.006	-0.001	-0.009*	-0.000	-0.001	0.002	0.001	-0.002	-0.000	0.000	-0.002	-0.002	-0.000
labor inc. sq./100 x civil serv. (female)	-0.004	0.005	0.001	-0.003	-0.013	-0.002	0.006	-0.001	0.001	0.003	0.008	-0.001	-0.001
labor inc. sq./100 x self-empl. (male)	0.001	-0.000	-0.001	-0.001	-0.002**	-0.002*	-0.000	-0.001	-0.002*	0.000	-0.001	-0.000	-0.001
labor inc. sq./100 x self-empl. (female)	0.003	0.002	-0.001	-0.000	0.001	0.002*	-0.000	-0.000	0.001	0.001	-0.000	0.000	-0.000
labor inc. sq./100 x kids 0-2	-0.002	-0.003	0.001	0.008	-0.002	-0.007**	0.008	0.021***	0.004*	0.004	0.003	-0.005	0.003
labor inc. sq./100 x kids 3-6	0.001	-0.000	0.001	0.003*	0.002	0.004**	-0.001	-0.005**	-0.004	-0.002	-0.002	0.005***	-0.005***
labor inc. sq./100 x kids 7-16	0.002	0.000	0.001	0.003**	0.001	0.002***	0.002*	-0.001	0.000	0.000	-0.002**	0.002**	0.000
labor inc. sq./100 x kids 17-25	0.001	0.000	0.003	0.004**	-0.004***	0.000	0.001	0.002	0.004*	0.003	0.000	0.002	-0.003*
labor inc. sq./100 x adults	-0.000	-0.000	-0.005***	-0.002**	0.002*	-0.000	0.001	-0.002*	-0.002*	-0.002	0.001	-0.002*	-0.000

continued on next page

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
asset inc.	-0.699	-2.682***	-1.503**	-2.355**	-0.085	-0.173	0.846*	-0.007	1.621**	0.127	-0.957	-1.133*	0.335
asset inc. sq./100	-0.006	-0.012	0.015	-0.028	-0.101***	-0.051**	-0.060**	-0.012	-0.010	0.001	0.042*	0.021	-0.022
asset inc. x married	0.334	-0.564*	-0.107	-0.701*	0.241	-0.094	-0.020	0.079	0.201	-0.261	0.074	0.074	0.003
asset inc. x hours (male)	-0.000	-0.012**	0.003	-0.002	0.001	-0.011**	-0.008*	0.003	-0.008	0.006	-0.010*	-0.004	0.005
asset inc. x hours (female)	-0.000	0.001	0.005	0.006	0.002	0.010***	-0.004	-0.001	-0.006	-0.012**	-0.012**	0.013**	-0.005
asset inc. x couple	-1.658*	-2.700***	-1.671**	-2.602***	-0.853	-0.765	-0.173	-0.625	0.385	-0.485	-1.651**	-2.037***	0.094
asset inc. x age (male)	0.052*	0.129***	0.095***	0.113***	-0.010	0.039*	0.008	0.014	-0.040*	0.030	0.026	0.081***	0.018
asset inc. x age (female)	0.044*	0.078***	0.046*	0.086***	0.018	0.015	-0.002	0.003	-0.025	-0.003	0.058***	0.063***	0.011
asset inc. x age sq. (male)	-0.044*	-0.114***	-0.096***	-0.093***	0.025	-0.037*	-0.004	-0.010	0.043*	-0.026	-0.001	-0.072***	-0.020
asset inc. x age sq. (female)	-0.036	-0.040*	-0.017	-0.057**	-0.004	-0.001	0.002	0.014	0.020	0.022	-0.051***	-0.048**	-0.004
asset inc. x civil serv. (male)	1.873	1.203	1.694**	2.145	-0.086	1.642*	-1.412	-1.547	-8.879	0.636	1.393	-1.339	-0.587
asset inc. x civil serv. (female)	-0.338	-1.229	0.182	-0.277	-1.107	-1.137	-1.405	0.840	1.296*	16.362	7.594	-89.751	0.229
asset inc. x self-empl. (male)	-0.316*	-0.122	0.024	0.195	-0.132	-0.301**	-0.345*	-0.041	0.303*	-0.138	0.055	-0.212	-0.253
asset inc. x self-empl. (female)	0.207	-0.265	-0.392*	-0.383*	-0.082	-0.094	0.078	0.105	-0.299*	0.399**	0.030	-0.385*	-0.284*
asset inc. x kids 0-2	.	1.320	-1.810*	-0.549	1.134	-1.076	1.499**	.	-1.235	-0.328	-1.118	-3.846	0.024
asset inc. x kids 3-6	-1.553*	-0.305	0.485	0.277	-0.848	0.880	0.082	-0.223	0.312	-0.162	2.824*	0.732	-0.027
asset inc. x kids 7-16	0.142	0.303	-0.011	-0.358	0.118	-0.480	-0.257	-0.522	-0.782**	-0.627*	-0.728***	-0.226	0.298
asset inc. x kids 17-25	-0.185	0.042	-0.230	0.165	-0.557**	0.107	-0.747**	-0.348*	0.033	-0.184	-0.589*	-0.226	-0.432*
asset inc. x adults	0.133	0.260***	-0.048	0.098	0.166	0.167	0.170	0.263**	0.258*	0.151	0.269*	-0.027	-0.102
asset inc. sq./100 x married	-0.037**	0.005	-0.004	-0.002	-0.001	0.007*	-0.007*	0.002	0.005	0.002	0.006	0.005	-0.004
asset inc. sq./100 x hours (male)	0.001***	0.000***	-0.000	-0.000	-0.000	0.000	0.000*	0.000*	0.000**	0.000*	0.000*	0.000	0.000
asset inc. sq./100 x hours (female)	-0.000*	0.000	0.000	0.000*	-0.000	0.000	0.000	0.000	-0.000	-0.000	-0.000	-0.000	0.000
asset inc. sq./100 x couple	0.037	-0.029	-0.080***	-0.040	-0.064**	-0.039*	-0.051*	-0.005	0.012	0.018	0.037	0.016	-0.009
asset inc. sq./100 x age (male)	0.000	-0.001*	0.001	0.001	0.005***	0.001	0.001	0.000	0.000	0.000	-0.003**	-0.001	0.001
asset inc. sq./100 x age (female)	-0.000	-0.000	0.002	0.001	0.003**	0.001	0.001	0.001	0.001	-0.000	-0.001	-0.000	0.001
asset inc. sq./100 x age sq. (male)	-0.000	0.002**	-0.000	-0.000	-0.005***	-0.001	-0.001	-0.000	-0.000	-0.000	0.004**	0.001	-0.001
asset inc. sq./100 x age sq. (female)	0.000	0.001	-0.003*	-0.000	-0.003*	-0.001	-0.000	-0.001*	-0.001	-0.000	0.001	0.000	-0.001
asset inc. sq./100 x civil serv. (male)	-0.004	0.002	-0.052***	0.010	0.001	0.009	0.003	0.004	-0.001	-0.004	0.012**	0.006	0.004
asset inc. sq./100 x civil serv. (female)	-0.008	-0.014	0.019	0.008	0.059	-0.011	0.055*	-0.003	0.002	0.002	0.011	-0.023	-0.031
asset inc. sq./100 x self-empl. (male)	0.009**	0.018**	0.014**	0.014**	-0.004	0.004	0.006	0.004	0.003	0.005	0.007*	0.014**	0.012*
asset inc. sq./100 x self-empl. (female)	0.002	-0.000	0.001	-0.000	0.019**	0.013*	0.006	0.007	0.007	0.009	0.000	0.002	0.015**
asset inc. sq./100 x kids 0-2	0.015	0.051*	-0.014	0.009	-0.008	-0.051***	0.033	-0.020	-0.021**	0.043	-0.003	-0.006	-0.014
asset inc. sq./100 x kids 3-6	-0.004	-0.011	-0.005	0.033*	0.015**	0.009	-0.008	-0.003	-0.032***	-0.024**	-0.014*	-0.007	-0.013
asset inc. sq./100 x kids 7-16	0.005	0.009*	0.010*	0.017**	0.008	0.010***	0.014**	-0.006	-0.004	-0.000	-0.008**	0.002	0.000
asset inc. sq./100 x kids 17-25	0.004	-0.002	0.007	0.007	0.015	0.014	-0.004	0.007	-0.001	-0.001	0.006	0.005	0.006
asset inc. sq./100 x adults	-0.006	-0.000	-0.006	-0.004	-0.016**	-0.000	0.001	-0.009*	-0.010*	-0.005	0.002	-0.007	-0.006
pensions (male)	0.383	2.184**	2.394***	2.582***	1.553***	0.548	1.239**	1.456**	-1.192**	0.689	0.850*	0.978**	0.712*
pensions (female)	0.499	1.552*	1.448**	2.428***	1.409**	0.596	0.955**	0.435	-0.346	0.129	1.157*	1.357**	0.602
pensions	-0.329	-1.369	-0.265	-1.654*	-0.513	-0.186	0.087	-0.356	1.312**	0.614	-0.640	-0.304	0.277
pensions sq./100	0.055***	0.007	-0.028	-0.004	-0.017	0.005	-0.045*	-0.014	0.004	-0.016	0.002	-0.018	-0.005
pensions (male) x married	0.142	0.467***	0.204	0.295	0.227***	0.355***	0.758***	0.729***	0.598***	0.197***	0.183*	0.097	0.206***
pensions (male) x hours (male)	0.001	0.009*	-0.003	0.001	-0.002	0.012***	0.008**	0.003	0.008**	-0.004	0.009**	-0.009***	-0.003
pensions (male) x hours (female)	0.003	0.001	-0.010***	-0.011***	-0.002	-0.010***	-0.003	-0.008***	0.002	0.005*	0.002	-0.004	0.003
pensions (male) x couple	0.263	1.423	1.292*	2.767***	0.774	0.529	0.586	0.152	-1.399**	0.437	1.724***	1.966***	0.072
pensions (male) x age (male)	0.013	-0.066**	-0.071***	-0.090***	-0.039*	-0.014	-0.027*	-0.026	0.054***	-0.020	0.008	-0.029*	0.002
pensions (male) x age (female)	-0.008	-0.029	-0.010	-0.079***	-0.035*	-0.018	-0.026*	-0.010	0.020	-0.006	-0.073***	-0.044**	-0.011
pensions (male) x age sq. (male)	-0.014	0.058***	0.061***	0.084***	0.036**	0.020	0.016	0.019	-0.042***	0.019	-0.026**	0.024*	-0.004
pensions (male) x age sq. (female)	0.005	0.008	-0.010	0.055***	0.031*	0.012	0.019	-0.002	-0.008	-0.003	0.071***	0.024	0.004
pensions (male) x civil serv. (male)	.	.	-2.257*	-1.955	1.087	-1.571*	0.078	-0.022	0.586	2.168*	0.021	1.411	-0.028
pensions (male) x civil serv. (female)	0.562*	0.748	.	0.173	-0.245	0.852	.	-0.044	-0.588	.	-2.106	.	.
pensions (male) x self-empl. (male)	-0.084	-0.251	0.035	0.035	-0.419***	0.098	0.241*	-0.360***	-0.493***	0.369***	0.358**	0.300*	0.042
pensions (male) x self-empl. (female)	-0.286*	-0.165	0.081	-0.080	0.050	-0.374*	-0.587*	0.257	-0.470***	-0.466***	-0.276	-0.015	-0.313***
pensions (male) x kids 0-2	-1.006	0.672	1.194*	-1.005	-0.980	1.497**	-1.463*	.	-0.344	0.392	0.428	3.116	0.823
pensions (male) x kids 3-6	1.162*	0.264	-0.648*	-0.410	0.619	-0.767	0.065	0.202	-0.028	-1.174*	-2.145***	-1.495	-0.569
pensions (male) x kids 7-16	-0.268	-0.710***	-0.204	0.074	-0.135	0.238	0.012	0.377	0.468	0.230	0.246**	-0.186	-0.275
pensions (male) x kids 17-25	0.167*	-0.302***	0.099	-0.057	0.078	-0.137	0.683***	0.268***	0.323***	0.139	0.337	0.181	0.339*
pensions (male) x adults	-0.331***	-0.186***	-0.284***	-0.146*	-0.111*	-0.167***	-0.331***	-0.332***	-0.130**	-0.154**	-0.180**	-0.153**	-0.155***
pensions (female) x married	0.194	0.415***	0.072	0.296	0.178	0.308***	0.647***	0.586***	0.362***	0.301***	-0.126	0.095	0.019
pensions (female) x hours (male)	-0.005	0.007	-0.000	0.002	0.001	0.006	-0.001	-0.001	0.007*	-0.004*	0.009*	-0.008*	-0.008*
pensions (female) x hours (female)	0.009**	0.001	-0.013***	-0.009**	-0.003	-0.010***	0.002	-0.005*	0.002	0.009***	0.003	-0.005	0.002
pensions (female) x couple	1.305	1.074	1.041	0.982	1.142*	0.209	1.124***	1.270	-2.129**	1.348	2.308***	1.729***	0.624
pensions (female) x age (male)	-0.019	-0.042	-0.034	-0.052*	-0.034*	-0.014	-0.031***	-0.041	0.065**	-0.047	-0.032*	-0.050***	-0.011
pensions (female) x age (female)	0.002	-0.010	-0.009	-0.055**	-0.048***	-0.004	-0.019	0.012	0.015	0.015	-0.046***	-0.028*	-0.006
pensions (female) x age sq. (male)	0.001	0.033	0.033*	0.052*	0.032*	0.013	0.013	0.025	-0.054**	0.032	-0.003	0.036**	0.002
pensions (female) x age sq. (female)	0.000	-0.003	-0.008	0.040*	0.044***	0.005	0.019	-0.015	-0.000	-0.017	0.057***	0.018	0.005
pensions (female) x civil serv. (male)	-1.601	-1.055	-1.871***	-2.551	0.181	-1.568*	0.267	.	24.014	-2.245	-1.644	2.131	0.107
pensions (female) x civil serv. (female)	.	0.602	-0.131	0.428	-0.138	1.228	0.911	0.090	5.837***	.	.	.	-0.116
pensions (female) x self-empl. (male)	1.121***	0.048	0.339	0.369	-0.314*	0.382**	0.258*	-0.366**	-0.502***	0.542***	0.422***	0.278	0.244
pensions (female) x self-empl. (female)	-0.174	-0.222	0.044	0.056	0.082	-0.331*	-0.454*	-0.008	-0.548***	-0.490***	-0.269	0.055	-0.267**
pensions (female) x kids 0-2	-0.074	-1.685	1.159	-0.690	-1.007	-0.246	-3.596	.	4.885	0.692	0.287	2.600	.
pensions (female) x kids 3-6	1.110	0.578	-0.988*	-0.917	0.164	-0.948	-0.257	-0.438	0.211	.	-1.118	-0.651	-0.298
pensions (female) x kids 7-16	-0.277	-0.591***	-0.242	0.168	-0.180	0.328	0.195	0.383	0.453	0.473	0.543***	0.106	-0.203
pensions (female) x kids 17-25	0.283**	-0.131	0.112	0.018	0.272*	0.199	0.626**	0.298**	0.134	-0.009	0.378	0.227	0.498**
pensions (female) x adults	-0.380***	-0.236***	-0.269***	-0.158*	-0.053	-0.176**	-0.337***	-0.326***	-0.141**	-0.147**	-0.164**	-0.074	-0.148**
pensions x married	-0.205	-0.517***	-0.183	-0.197	-0.251**	-0.182*	-0.545***	-0.602***	-0.483***	0.045	0.041	-0.085	-0.154*
pensions x hours (male)	0.007*	-0.001	0.002	0.002	0.003	-0.002	0.008**	0.003	0.004	0.005*	-0.003	0.010**	0.012***
pensions x hours (female)	-0.000	0.002	0.012***	0.009***	0.006*	0.013***	0.004	0.011***	0.000	-0.004	-0.001	0.010**	-0.001
pensions x couple	-0.250	-1.197	-0.676	-1.751*	-0.955*	-0.221	-0.104	-0.041	1.616**	0.240	-1.007*	-0.777*	0.460
pensions x age (male)	-0.009	0.046*	0.017	0.064**	0.020	0.010	-0.008	0.004	-0.049**	-0.004	-0.013	0.024*	-0.019
pensions x age (female)	0.004	0.021	-0.009	0.038	0.039**	0.006	0.006	0.001	-0.032*	-0.017	0.048***	0.010	-0.005
pensions x age sq. (male)	0.020	-0.031	-0.011	-0.051**	-0.013	-0.008	0.022*	0.005	0.047***	0.001	0.041***	-0.017	0.021*
pensions x age sq. (female)	0.005	0.001	0.026*	-0.019	-0.032**	0.002	-0.005	0.012	0.021	0.020	-0.054***	0.001	0.007
pensions x civil serv. (male)	2.419	1.268	2.122***	2.215	0.066	1.807**	-1.022	-1.404	-0.282	.	1.071	-0.518	-0.023
pensions x civil serv. (female)	-0.662	.	1.026	0.034	0.349	-1.108	-1.101	0.392	0.644	16.821	7.945	-96.855	0.181
pensions x self-empl. (male)	-0.239	0.053	-0.220	-0.204	0.486***	-0.181	-0.326**	0.255*	0.256	-0.438***	-0.378**	-0.254	-0.108
pensions x self-empl. (female)	0.001	0.551**	0.393*	0.180	-0.257	0.442**	0.606**	0.039	0.460***	0.514***	0.384*	0.149	0.543***
pensions x kids 0-2	-0.951	3.186	-1.927*	-0.750	1.520	0.350	0.674	-1.315*	-0.543	-0.633	-0.223	-2.358	0.180
pensions x kids 3-6	-1.357*	-0.470	0.134	0.772	-0.515	0.634	-0.098	-0.428	-0.177	.	3.535*	0.014	0.485
pensions x kids 7-16	0.512***	0.723***	0.293	-0.144	0.143	-0.407	-0.311*	-0.435	-0.383	-0.527	-0.584***	-0.153	0.264
pensions x kids 17-25	-0.169	0.319***	-0.002	0.086	-0.241	0.144	-0.444*	-0.368***	-0.122	-0.038	-0.233	-0.209	-0.389*
pensions x adults	0.281***	0.108	0.224***	0.158*	0.008	0.113	0.207***	0.285***	0.034	0.071	0.120	-0.010	0.019
pensions sq./100 x married	0.001	0.003	0.002	-0.001	0.006	-0.004*	-0.006***	-0.005*	-0.002	-0.009***	-0.004	-0.002	0.001
pensions sq./100 x hours (male)	-0.000	-0.000**	0.000	-0.000	-0.000	-0.000***	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000
pensions sq./100 x hours (female)	-0.000	0.000	0.000	0.000**	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
pensions sq./100 x couple	0.057***	0.007	-0.026	-0.003	-0.012	0.010	-0.035	-0.005	0.004	-0.010	0.009	-0.017	-0.003
pensions sq./100 x age (male)	-0.001***	0.000	0.001*	0.000	0.001	0.000	0.002**	0.001	0.000	0.001	0.000	0.001	0.000
pensions sq./100 x age (female)	-0.001**	-0.000	0.001	0.001	0.000	-0.000	0.001*	0.000	0.000	0.000	-0.000	0.001	0.000
pensions sq./100 x age sq. (male)	0.001**	-0.001	-0.001**	-0.001	-0.001**	-0.000	-0.001***	-0.001*	-0.000	-0.001	-0.001	-0.000	-0.000
pensions sq./100 x age sq. (female)	0.000	-0.000	-0.001*	-0.001	-0.000	-0.000	-0.001*	-0.000	-0.000	-0.000	0.000	-0.001*	-0.000
pensions sq./100 x civil serv. (male)	-0.098*	-0.023	-0.038	0.075	-0.020	0.004	0.028	0.085	-6.793	0.117	0.033	-0.100*	-0.002
pensions sq./100 x civil serv. (female)	0.076	-0.033	-0.077	-0.024	0.003	0.007	0.047	-0.009	-0.003	-0.212	-0.199	2.986	-0.013
pensions sq./100 x self-empl. (male)	0.008*	0.005*	0.006**	0.005	-0.005***	0.002	0.002	0.003	0.008***	0.002	0.004	0.000	0.000
pensions sq./100 x self-empl. (female)	0.013*	-0.019**	-0.025***	-0.013	0.009	-0.004	-0.004	0.008	0.000	0.000	-0.004	-0.008*	-0.009*
pensions sq./100 x kids 0-2	0.101	-0.233***	0.123	0.186	-0.027	-0.187***	0.069	0.042	-0.435	0.024	-0.047	-0.067	-0.050
pensions sq./100 x kids 3-6	0.021	-0.002	0.051	-0.024	-0.007	0.020	0.027	0.080***	0.005	-0.019	-0.175	0.049	-0.008
pensions sq./100 x kids 7-16	-0.038***	-0.012	-0.013	-0.009	-0.006	0.003	0.010**	0.000	-0.007**	0.008	0.013*	0.005	0.001
pensions sq./100 x kids 17-25	0.000	-0.001	-0.004	0.000	0.006*	-0.004	-0.010	0.001	-0.005	-0.003	-0.003	0.005	0.004
pensions sq./100 x adults	-0.000	0.002*	0.000	-0.001	0.003*	-0.000	0.003*	0.000	0.002	0.000	-0.002	0.002	0.001
Constant	31.159	45.031	-0.829	10.535	-70.615	-45.504	114.966**	43.675	229.439***	121.003*	10.971	148.419*	-261.887***
R^2	0.982	0.982	0.985	0.983	0.987	0.986	0.984	0.986	0.982	0.980	0.980	0.972	0.973
Observations	4198	4144	3942	3842	3788	3855	3859	3900	3888	4136	4074	4048	4733

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.2: OLS – Estimation of tax-benefit system (1999–2010)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
married	92.356*	-4.368	-118.132***	1.403	-56.411	32.925	-20.128	81.938**	57.659	-27.357	-81.721*	-57.398
hours (male)	-3.331***	-4.718***	-4.885***	-3.420***	-4.266***	-5.624***	-4.287***	-3.583***	-5.456***	-4.081***	-2.862***	-5.623***
hours (female)	1.030	1.845***	1.955***	2.108***	2.312***	4.241***	2.345***	1.974***	3.061***	2.207***	2.638***	3.323***
couple	-303.811***	-260.786***	-61.707	-80.419	-63.374	-122.185**	-201.529***	65.676	-183.243***	-166.001***	47.970	-152.572**
age (male)	18.555***	18.974***	17.668***	10.734***	15.435***	14.625***	16.145***	1.642	12.197***	9.506***	9.028***	16.564***
age (female)	12.088***	14.489***	12.806***	8.291***	9.081***	10.460***	14.731***	0.272	11.240***	8.868***	9.069***	11.301***
age sq. (male)	-19.709***	-19.371***	-20.097***	-10.548***	-18.584***	-15.658***	-16.918***	-3.152	-14.014***	-8.371**	-10.319***	-18.473***
age sq. (female)	-11.967***	-15.129***	-14.067***	-9.360***	-8.849***	-11.907***	-16.506***	-2.085	-12.800***	-9.344***	-11.759***	-11.189***
civil serv. (male)	-35.560	56.823	98.651	213.892***	125.946*	213.184*	53.754	81.161	145.260	73.847	-12.498	-331.073**
civil serv. (female)	-138.481	72.674	59.753	70.711	27.112	-24.363	76.935	61.111	71.574	-67.198	175.636**	136.619
self-empl. (male)	49.175	58.007*	72.936*	254.735***	156.888***	222.254***	165.393***	186.922***	257.199***	114.836***	128.366***	313.524***
self-empl. (female)	-6.710	23.140	105.759**	67.003*	169.432***	190.634***	6.635	52.219	33.993	45.269	83.833*	-46.790
kids 0-2	406.128***	356.962***	249.182***	205.184***	319.393***	281.520***	210.508***	248.210***	439.354***	364.299***	323.183***	363.670***
kids 3-6	236.786***	171.729***	177.005***	173.666***	238.344***	182.608***	184.465***	260.444***	247.491***	307.006***	186.116***	294.076***
kids 7-16	97.977***	146.694***	120.524***	149.797***	129.955***	148.602***	153.886***	159.435***	231.384***	205.343***	166.591***	221.954***
kids 17-25	-11.611	62.094	69.089	65.886*	73.368*	157.475***	91.810*	70.859	121.791**	79.783	178.193***	101.790*
adults	141.153***	137.425***	153.471***	135.529***	145.781***	135.108***	142.391***	162.271***	196.585***	204.884***	92.273***	148.589***
gross inc.	-0.262	0.413*	-0.050	-0.324	-0.568**	0.263	0.090	0.034	0.122	-0.866***	-0.518*	0.167
gross inc. sq./100	-0.002	0.001	-0.001	-0.002*	0.001	0.002*	-0.000	-0.000	0.001	0.004***	-0.000	0.006***
gross inc. x married	0.271	0.233**	-0.190	-0.208*	-0.204**	-0.013	0.067	0.121	-0.011	0.107	-0.195**	-0.039
gross inc. x hours (male)	-0.004	0.004*	0.007**	-0.004*	-0.003	0.001	-0.001	0.000	-0.001	-0.000	-0.000	-0.001
gross inc. x hours (female)	0.010***	-0.004*	-0.001	-0.006***	-0.001	0.001	0.000	-0.006***	-0.005**	0.003	0.003	0.002
gross inc. x couple	-0.522	0.029	0.390*	-0.476**	-0.730***	0.172	-0.081	0.040	0.075	-1.033***	-0.416*	-0.161
gross inc. x age (male)	0.003	-0.021**	-0.014*	0.027***	0.022***	0.002	0.015	0.006	-0.003	0.034***	0.026***	0.011*
gross inc. x age (female)	0.003	0.002	-0.007	0.013*	0.030***	-0.011	0.002	-0.001	-0.002	0.029***	0.013*	-0.001
gross inc. x age sq. (male)	0.005	0.024***	0.017*	-0.027***	-0.017**	-0.005	-0.019**	-0.009	0.004	-0.027***	-0.023***	-0.013**
gross inc. x age sq. (female)	0.001	-0.009	0.011	-0.007	-0.024***	0.011*	-0.003	0.002	0.000	-0.024***	-0.007	0.002
gross inc. x civil serv. (male)	6.364	-1.224	-0.953*	0.249	0.366	-0.564	-0.301	-0.875	-0.131	-0.053	-0.930	0.486
gross inc. x civil serv. (female)	-0.626	0.336	-0.065	0.234	0.177	-0.029	0.030	0.546*	-0.109	-0.023	-0.262	-0.468
gross inc. x self-empl. (male)	-0.171*	-0.216***	-0.066	0.040	0.012	0.010	0.043	0.022	0.100*	0.135***	-0.064	0.144***
gross inc. x self-empl. (female)	-0.157	-0.059	0.125	0.279***	-0.145	-0.038	0.221**	0.165**	-0.140	-0.156**	0.186**	-0.129
gross inc. x kids 0-2	5.148*	0.210	0.722	1.516***	-0.711	0.694	0.241	-0.824*	0.836*	0.958	0.266	0.360
gross inc. x kids 3-6	0.005	-0.153	0.837*	0.362	0.449*	0.176	0.071	-0.096	0.286	-0.615	0.443*	1.000
gross inc. x kids 7-16	0.330**	-0.012	-0.093	-0.110	0.393***	-0.005	0.175	0.002	0.020	0.008	0.269***	0.101
gross inc. x kids 17-25	-0.074	-0.176	-0.109	0.076	-0.175	-0.087	0.153	0.147	-0.014	0.312**	-0.173	0.037
gross inc. x adults	0.037	0.008	0.107**	0.089**	0.041	0.064	-0.090**	-0.011	0.059	-0.082**	-0.048	-0.103**
gross inc. sq./100 x married	-0.003**	0.000	-0.001	0.000	-0.000	0.001*	-0.002***	-0.000	0.001*	0.000	0.002***	0.002***
gross inc. sq./100 x hours (male)	-0.000	-0.000***	0.000	0.000	-0.000	0.000	0.000***	0.000**	-0.000*	-0.000	-0.000	-0.000
gross inc. sq./100 x hours (female)	-0.000	-0.000	0.000***	0.000***	0.000	0.000*	0.000	0.000	-0.000	-0.000	-0.000	0.000
gross inc. sq./100 x couple	0.002	0.004**	0.001	-0.001	0.002*	0.002*	0.003*	-0.002*	-0.000	0.003***	-0.002	0.002
gross inc. sq./100 x age (male)	0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***
gross inc. sq./100 x age (female)	0.000	-0.000***	0.000	0.000	-0.000*	-0.000**	-0.000**	0.000**	-0.000	-0.000***	0.000	-0.000**
gross inc. sq./100 x age sq. (male)	-0.000	-0.000*	-0.000	0.000	-0.000*	0.000	0.000	0.000***	0.000	0.000***	0.000	0.000*
gross inc. sq./100 x age sq. (female)	-0.000	0.000***	-0.000	-0.000	0.000	0.000*	0.000***	-0.000**	0.000	0.000**	-0.000	0.000*
gross inc. sq./100 x civil serv. (male)	-0.002	0.000	0.001	-0.001*	0.000	-0.000	-0.001	-0.001	0.002	0.000	0.002	0.001
gross inc. sq./100 x civil serv. (female)	0.011**	0.003***	0.001	-0.000	0.001*	-0.000	0.000	-0.002	-0.000	0.000	0.001	0.001
gross inc. sq./100 x self-empl. (male)	0.002***	0.000	-0.000	-0.000	-0.000*	0.000	0.000	0.000	0.000	0.000	0.001***	0.001*
gross inc. sq./100 x self-empl. (female)	-0.001	-0.000	-0.000	-0.000	-0.001***	0.000	-0.001**	-0.001***	-0.000	-0.001***	-0.000	-0.001*
gross inc. sq./100 x kids 0-2	-0.004	-0.003**	-0.002	0.000	-0.003**	-0.001	0.002	-0.004***	-0.001	-0.002	0.014***	0.001
gross inc. sq./100 x kids 3-6	-0.000	0.000	0.001	0.000	-0.000	-0.001**	0.000	0.001**	0.001**	-0.001*	-0.001	-0.003***
gross inc. sq./100 x kids 7-16	-0.003***	-0.000	0.000	0.000*	0.000**	-0.000	0.000	0.000	-0.000*	-0.001***	0.000	-0.001*
gross inc. sq./100 x kids 17-25	-0.002	0.001**	0.001*	0.000	0.001***	-0.000	-0.001***	-0.000	-0.001*	-0.001*	0.000	-0.000
gross inc. sq./100 x adults	0.001*	-0.000	-0.001*	0.000	-0.001***	-0.000	0.001***	0.000*	0.000***	0.001***	0.000	0.000
labor inc.	0.965***	0.333	0.753***	1.028***	1.246***	0.460*	0.582*	0.494*	0.481*	1.511***	1.125***	0.496**
labor inc. sq./100	0.002	-0.003*	-0.000	0.000	-0.003**	-0.003***	0.000	0.001	-0.001	-0.004***	0.001	-0.006***
labor inc. x married	-0.292	-0.221**	0.240*	0.226**	0.217**	0.013	-0.062	-0.146*	0.020	-0.096	0.229***	0.082
labor inc. x hours (male)	0.005	-0.003	-0.006**	0.004**	0.003*	0.000	0.001	0.000	0.002	0.001	0.001	0.002
labor inc. x hours (female)	-0.011***	0.002	0.001	0.005**	0.000	-0.003	-0.001	0.005**	0.004*	-0.004*	-0.004*	-0.003
labor inc. x couple	0.777**	0.246	-0.181	0.711***	0.911***	0.115	0.356	0.068	0.122	1.250***	0.557**	0.380*
labor inc. x age (male)	-0.014	0.011	0.005	-0.036***	-0.029***	-0.013	-0.023**	-0.008	-0.004	-0.038***	-0.031***	-0.018***
labor inc. x age (female)	-0.008	-0.012	0.000	-0.022***	-0.036***	0.001	-0.012	-0.000	-0.006	-0.035***	-0.020**	-0.006
labor inc. x age sq. (male)	0.010	-0.013	-0.005	0.036***	0.025***	0.017**	0.027***	0.011*	0.005	0.030***	0.029***	0.020***
labor inc. x age sq. (female)	0.002	0.020**	-0.004	0.017***	0.031***	-0.000	0.015*	0.000	0.008	0.031***	0.016**	0.005
labor inc. x civil serv. (male)	-6.235	1.316	1.040*	-0.202	-0.280	0.625	0.398	0.975*	0.202	0.139	1.051	-0.239
labor inc. x civil serv. (female)	0.796	-0.277	0.113	-0.188	-0.117	0.113	0.004	-0.491*	0.182	0.121	0.273	0.494
labor inc. x self-empl. (male)	0.337***	0.400***	0.235***	0.051	0.111**	0.106**	0.108*	0.109**	0.023	0.003	0.198***	-0.058
labor inc. x self-empl. (female)	0.274**	0.123	-0.088	-0.228***	0.170*	0.094	-0.116	-0.085	0.264**	0.214***	-0.134*	0.225***
labor inc. x kids 0-2	-5.271*	-0.285	-0.733	-1.511***	0.670	-0.700	-0.232	0.798	-0.913**	-1.008	-0.258	-0.339
labor inc. x kids 3-6	-0.052	0.154	-0.842*	-0.350	-0.448*	-0.172	-0.057	0.093	-0.269	0.587	-0.426*	-1.053
labor inc. x kids 7-16	-0.324**	0.007	0.110	0.122*	-0.367***	0.011	-0.161	0.010	-0.032	-0.012	-0.256***	-0.114
labor inc. x kids 17-25	0.155	0.228*	0.198	-0.023	0.230*	0.108	-0.104	-0.108	0.026	-0.244*	0.203	0.024
labor inc. x adults	-0.098	-0.048	-0.187***	-0.131***	-0.088**	-0.096**	0.045	-0.027	-0.084*	0.014	0.026	0.054
labor inc. sq./100 x married	0.003***	-0.000	0.000	-0.000	0.000	-0.001*	0.002***	0.001**	-0.001*	-0.000	-0.002***	-0.003***
labor inc. sq./100 x hours (male)	0.000	0.000**	-0.000	-0.000	0.000	-0.000	-0.000***	-0.000**	0.000	0.000	0.000*	0.000
labor inc. sq./100 x hours (female)	-0.000	0.000	-0.000***	-0.000***	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	-0.000
labor inc. sq./100 x couple	-0.003	-0.005***	-0.002	-0.000	-0.003**	-0.004***	-0.004**	0.001	-0.000	-0.004***	0.001	-0.003**
labor inc. sq./100 x age (male)	-0.000	-0.000	0.000	0.000	0.000	0.000***	0.000	0.000**	0.000	0.000***	0.000	0.000***
labor inc. sq./100 x age (female)	-0.000	0.000***	-0.000	0.000	0.000**	0.000***	0.000***	-0.000***	0.000	0.000***	0.000	0.000***
labor inc. sq./100 x age sq. (male)	0.000	0.000	-0.000	-0.000*	0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000***	-0.000	-0.000*
labor inc. sq./100 x age sq. (female)	0.000	-0.000***	0.000	-0.000	-0.000**	-0.000***	-0.000***	0.000**	-0.000	-0.000***	-0.000	-0.000**
labor inc. sq./100 x civil serv. (male)	0.001	-0.001	-0.001	0.001	-0.001	0.000	0.001	0.001	-0.002	-0.001	-0.003	-0.003
labor inc. sq./100 x civil serv. (female)	-0.013***	-0.004***	-0.001	-0.000	-0.001*	-0.000	-0.000	0.002	-0.000	-0.001	-0.001	-0.001
labor inc. sq./100 x self-empl. (male)	-0.003***	-0.001***	-0.000	-0.000	-0.000	-0.000*	-0.001**	-0.001***	-0.000**	-0.000*	-0.001***	-0.001***
labor inc. sq./100 x self-empl. (female)	0.000	-0.000	0.000	-0.000	0.001***	-0.000	0.000	0.001**	-0.000*	0.001**	0.000	0.000*
labor inc. sq./100 x kids 0-2	0.005*	0.003***	0.002	-0.000	0.003**	0.001	-0.002	0.004***	0.002	0.002	-0.014***	-0.001
labor inc. sq./100 x kids 3-6	0.001	-0.000	-0.001	-0.000	0.000	0.001*	-0.000	-0.001**	-0.002**	0.001*	0.001	0.004***
labor inc. sq./100 x kids 7-16	0.003***	0.000	-0.000	-0.000**	-0.001***	0.000	-0.000	-0.000*	0.000*	0.001***	-0.000	0.001**
labor inc. sq./100 x kids 17-25	0.001	-0.002***	-0.002***	-0.001	-0.001***	0.000	0.001**	-0.000	0.001*	0.000	-0.000	-0.000
labor inc. sq./100 x adults	-0.001	0.000	0.001***	0.000	0.001***	0.000	-0.001**	-0.000	-0.001**	-0.000*	0.000	0.000

continued on next page

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
asset inc.	1.127**	0.280	0.774***	1.227***	1.546***	0.309	0.635*	0.705***	0.645**	1.506***	1.367***	0.433*
asset inc. sq./100	-0.009	-0.007	0.004	0.001	-0.015***	-0.001	0.005	0.005*	0.004	-0.005**	-0.004	-0.025***
asset inc. x married	0.301	-0.126	0.361**	0.144	0.316***	-0.025	0.263**	-0.107	0.171*	-0.004	0.169*	-0.225
asset inc. x hours (male)	0.001	-0.003	-0.009***	0.003	0.003	-0.002	-0.002	-0.000	0.001	-0.001	0.004*	0.003
asset inc. x hours (female)	-0.010**	0.005*	-0.002	0.004*	-0.001	-0.003	0.000	0.006***	0.006***	-0.003	-0.003	-0.008***
asset inc. x couple	-0.262	-0.365	-0.903***	0.544**	0.749***	-0.374	-0.434	-0.107	-0.190	0.819***	0.495*	0.178
asset inc. x age (male)	0.008	0.020*	0.021*	-0.028***	-0.037***	0.002	-0.006	0.000	0.008	-0.032***	-0.033***	-0.008
asset inc. x age (female)	0.002	0.005	0.018*	-0.013	-0.032***	0.021**	0.008	-0.000	0.002	-0.022***	-0.004	0.012
asset inc. x age sq. (male)	-0.014	-0.017*	-0.023**	0.029***	0.034***	0.005	0.010	0.002	-0.010	0.027***	0.031***	0.014*
asset inc. x age sq. (female)	-0.004	0.006	-0.022**	0.006	0.027***	-0.017*	-0.005	0.004	0.002	0.018**	-0.004	-0.010
asset inc. x civil serv. (male)	-6.342	1.299	1.175**	-0.067	-0.312	0.562	0.456	1.041*	-0.011	0.164	0.581	-0.610
asset inc. x civil serv. (female)	-0.291	-0.864	-0.051	-0.267	-0.389*	0.024	-0.026	-0.213	0.024	-0.185	0.231	0.257
asset inc. x self-empl. (male)	0.017	0.104	0.089	-0.090*	-0.038	-0.116*	-0.109*	-0.122**	-0.104*	-0.150**	-0.001	-0.258***
asset inc. x self-empl. (female)	-0.029	-0.052	-0.216*	-0.337***	0.064	-0.096	-0.341***	-0.252***	-0.018	0.172**	-0.161*	0.060
asset inc. x kids 0-2	-4.443*	0.100	-0.441	-1.380**	1.271*	-0.345	-0.441	1.187**	-0.613	-1.018	-0.227	-0.550
asset inc. x kids 3-6	0.049	0.125	-0.750	-0.331	-0.498*	0.025	0.077	0.225	-0.516	0.763*	-0.394	-0.679
asset inc. x kids 7-16	-0.072	0.045	0.091	0.063	-0.470***	0.023	-0.188	-0.004	0.010	0.012	-0.313***	-0.103
asset inc. x kids 17-25	0.325	0.017	-0.088	-0.111	0.060	0.145	0.002	-0.023	0.127	-0.250*	0.280*	-0.100
asset inc. x adults	-0.087	0.019	-0.034	-0.097**	0.039	-0.048	0.054	0.007	-0.120**	0.046	-0.047	0.109*
asset inc. sq./100 x married	-0.006**	-0.000	0.001	0.000	-0.000	-0.000	-0.001	0.001*	-0.004***	-0.002*	-0.005***	-0.002
asset inc. sq./100 x hours (male)	0.000***	0.000***	0.000	0.000	0.000	0.000	-0.000	-0.000	0.000***	0.000***	-0.000	-0.000
asset inc. sq./100 x hours (female)	-0.000	0.000	0.000	-0.000	0.000	-0.000	-0.000*	-0.000***	-0.000***	-0.000	0.000	0.000**
asset inc. sq./100 x couple	0.007	-0.006	0.011	0.000	-0.011***	0.003	0.005*	0.009***	0.007*	-0.002	0.003	-0.018***
asset inc. sq./100 x age (male)	-0.001*	-0.000	-0.000	0.000	0.000**	-0.000	-0.000	-0.000	-0.000*	0.000***	0.000	0.001***
asset inc. sq./100 x age (female)	0.000	0.001**	-0.001*	-0.000	0.000***	-0.000	0.000	-0.000**	0.000	0.000***	-0.000	0.000***
asset inc. sq./100 x age sq. (male)	0.001*	0.000	0.000	-0.000	-0.000*	0.000	0.000	0.000	0.000**	-0.000***	-0.000*	-0.001***
asset inc. sq./100 x age sq. (female)	-0.000	-0.001***	0.001*	0.000	-0.000**	0.000	-0.000*	0.000	-0.000***	-0.000***	0.000*	-0.000*
asset inc. sq./100 x civil serv. (male)	0.011	-0.004	-0.013*	0.001	-0.002	0.001	0.003*	0.006	-0.003	-0.003	0.006	-0.001
asset inc. sq./100 x civil serv. (female)	-0.041*	-0.003	-0.006	0.000	-0.001	0.001	-0.002	-0.000	0.001	0.002	-0.010	0.000
asset inc. sq./100 x self-empl. (male)	0.004	0.000	-0.001	0.001**	0.001*	0.002***	0.001**	0.001***	-0.001**	-0.000	-0.002***	0.000
asset inc. sq./100 x self-empl. (female)	0.005*	0.001	0.002	0.000	0.002*	0.000	0.004***	0.003***	0.001**	0.001***	-0.001	0.002
asset inc. sq./100 x kids 0-2	-0.010	0.002	0.003	-0.015	0.001	-0.004*	-0.002	0.006	-0.003*	0.013	-0.098***	-0.003
asset inc. sq./100 x kids 3-6	-0.000	-0.001	-0.011*	-0.000	0.001	0.001	-0.002	-0.010**	-0.002	-0.001	0.001	0.005**
asset inc. sq./100 x kids 7-16	0.004*	-0.000	-0.000	-0.001	-0.000	0.000	-0.001	-0.001***	-0.000	0.001	-0.000	0.005***
asset inc. sq./100 x kids 17-25	-0.009*	-0.000	0.001	-0.000	-0.001*	-0.000	0.002*	-0.001***	0.001*	0.002***	-0.001	0.003
asset inc. sq./100 x adults	0.001	-0.000	0.000	-0.000	0.000	0.000	-0.002**	-0.001**	-0.001***	-0.001***	0.001*	-0.001
pensions (male)	0.654*	0.048	0.104	0.220	-0.080	1.524***	0.501	0.441	0.251	-0.745*	0.491	0.872*
pensions (female)	-0.082	0.064	0.441	0.401	0.129	0.809*	0.155	-0.184	0.586	-0.519	0.154	0.321
pensions	1.153***	0.482**	1.364***	0.628***	0.983***	0.112	0.724**	0.555**	0.419*	1.252***	0.859***	0.720***
pensions sq./100	-0.016	0.007	-0.026**	-0.010	-0.013	-0.010	-0.020*	-0.002	-0.003	0.001	0.001	-0.008
pensions (male) x married	0.285***	0.216***	0.001	0.081	0.054	0.138**	0.091	0.184***	0.257***	0.159**	0.082	0.110
pensions (male) x hours (male)	-0.002	0.004*	0.000	-0.003*	-0.004**	-0.002*	0.001	-0.004**	-0.004*	-0.000	-0.002	0.001
pensions (male) x hours (female)	0.003	0.001	-0.001	0.001	0.000	0.003**	-0.002	-0.004***	-0.004***	-0.000	0.001	-0.004**
pensions (male) x couple	-0.709***	0.371	-0.221	0.792**	-0.070	0.470	0.338	-0.222	0.401	-0.368	-0.595*	0.286
pensions (male) x age (male)	-0.003	0.005	0.018*	0.001	0.023**	-0.029**	0.010	-0.005	0.001	0.021*	-0.006	-0.016
pensions (male) x age (female)	0.011*	-0.017*	0.009	-0.039***	-0.002	-0.025***	-0.010	-0.000	-0.028**	-0.004	0.004	-0.023**
pensions (male) x age sq. (male)	0.002	-0.002	-0.027***	-0.000	-0.024***	0.017*	-0.016*	0.005	-0.001	-0.009	0.006	0.015
pensions (male) x age sq. (female)	-0.009	0.012	-0.006	0.036***	0.003	0.022***	0.004	0.000	0.028***	0.010	0.004	0.020**
pensions (male) x civil serv. (male)	0.909	0.824	0.825	-0.813**	0.302	-0.044	0.158	-0.012	-0.066	-0.041	-0.052	0.777
pensions (male) x civil serv. (female)	-0.649*	-0.696*	-0.087	-0.367***	-0.228*	-0.212*	-0.320**	0.061	-0.757***	-0.214	-0.215	-0.248*
pensions (male) x self-empl. (male)	-0.005	-0.082	0.159*	0.071	0.086	0.286***	0.213***	0.280***	-0.048	-0.005	0.307***	0.105
pensions (male) x self-empl. (female)	0.092	-0.148**	0.328***	0.115	-0.038	-0.015	-0.231**	0.062	-0.043	-0.089	-0.236***	-0.239***
pensions (male) x kids 0-2	.	.	.	0.147	-0.610	0.448	-0.999	-1.124*	-0.223	0.778	.	0.156
pensions (male) x kids 3-6	-0.319	-0.262	0.670	-0.075	0.183	0.456	0.226	-0.169	0.077	-0.759*	-0.012	0.377
pensions (male) x kids 7-16	0.048	0.011	-0.251**	-0.100*	0.295***	-0.173	-0.110	-0.083	-0.046	0.113	0.131*	-0.239
pensions (male) x kids 17-25	-0.025	-0.100	0.091	-0.006	0.142	0.032	0.291***	0.110	-0.352***	-0.045	-0.150	-0.238**
pensions (male) x adults	-0.139**	-0.074*	-0.079*	0.013	-0.206***	-0.155***	-0.247***	0.011	0.121***	0.040	0.000	0.018
pensions (female) x married	0.168*	0.249***	0.038	0.171**	-0.005	0.111	0.117	0.238***	0.307***	0.084	0.152*	0.131
pensions (female) x hours (male)	-0.003	0.001	0.001	-0.006***	-0.005**	-0.002	-0.001	-0.004*	-0.005**	-0.003*	-0.001	0.000
pensions (female) x hours (female)	-0.014***	-0.001	-0.005	-0.005*	-0.003	-0.004*	-0.000	-0.000	-0.002	-0.003	0.000	-0.006**
pensions (female) x couple	-0.981*	0.171	0.285	0.622*	0.306	0.814*	0.563	-0.298	0.407	-1.479***	-0.771*	-0.403**
pensions (female) x age (male)	0.032*	-0.008	0.011	-0.006	0.010	-0.016	0.004	0.012	-0.004	0.047***	0.026*	0.010
pensions (female) x age (female)	0.007	0.002	-0.005	-0.024**	0.003	-0.025**	0.003	0.002	-0.027*	0.002	-0.010	-0.011
pensions (female) x age sq. (male)	-0.024*	0.007	-0.022	-0.002	-0.019**	0.005	-0.017	-0.013	-0.006	-0.036***	-0.021*	-0.009
pensions (female) x age sq. (female)	-0.004	-0.000	0.004	0.027***	0.002	0.025***	-0.002	0.004	0.031***	0.010	0.016*	0.016*
pensions (female) x civil serv. (male)	5.475	-1.216	-0.646	-0.299	0.020	0.159	-0.003	-0.066	-0.091	0.175	-0.223	0.180
pensions (female) x civil serv. (female)	.	.	.	.	.	.	.	.	.	.	.	-0.308
pensions (female) x self-empl. (male)	0.030	0.209**	0.318***	0.202**	0.168*	0.311***	0.411***	0.334***	0.156*	0.094	0.318***	0.235**
pensions (female) x self-empl. (female)	0.057	-0.138**	0.261**	-0.000	-0.192**	-0.100	-0.407***	-0.013	-0.198**	-0.106	-0.237***	-0.236***
pensions (female) x kids 0-2	4.077	.	.	0.594*	-0.371	.	0.615	.	.	.	.	.
pensions (female) x kids 3-6	0.065	-0.038	1.162*	0.157	0.131	2.183	0.547	0.124	0.468	0.695	0.022	0.530
pensions (female) x kids 7-16	0.426**	0.070	-0.110	-0.226*	0.304**	-0.009	-0.228	-0.120	-0.108	-0.029	0.094	0.048
pensions (female) x kids 17-25	0.015	-0.043	0.050	-0.110	0.221*	0.086	0.408***	0.209*	-0.102	0.101	0.036	0.011
pensions (female) x adults	-0.107*	-0.063	-0.124***	0.015	-0.229***	-0.141***	-0.215***	0.023	0.077*	0.067*	-0.020	0.025
pensions x married	-0.351***	-0.260***	-0.013	-0.050	0.068	-0.098	-0.053	-0.198***	-0.311***	-0.090	-0.045	-0.005
pensions x hours (male)	0.006**	0.001	0.001	0.004**	0.005***	0.003*	0.004**	0.006***	0.008***	0.004**	0.002	0.003
pensions x hours (female)	-0.003	0.007***	0.005**	0.002	0.001	-0.002	0.002	0.004***	0.004**	0.001	0.000	0.004**
pensions x couple	1.068***	0.173	0.716***	0.062	0.563**	-0.165	0.486*	0.191	0.203	0.823***	0.545**	0.668***
pensions x age (male)	-0.036***	-0.007	-0.049***	-0.005	-0.034***	-0.005	-0.032***	-0.003	-0.006	-0.018***	-0.015**	-0.018***
pensions x age (female)	-0.024**	-0.006	-0.032***	0.010	-0.017**	0.013*	-0.018*	0.006	0.012	-0.007	-0.007	-0.002
pensions x age sq. (male)	0.031***	0.008	0.057***	0.003	0.037***	0.011	0.034***	0.002	0.009	0.009	0.011*	0.015**
pensions x age sq. (female)	0.021**	0.011	0.028***	-0.013*	0.011	-0.011*	0.020**	-0.008	-0.014*	-0.003	0.001	-0.004
pensions x civil serv. (male)	-5.445	1.781	1.122**	-0.062	0.006	-0.165	0.020	0.015	0.065	-0.142	0.237	-0.202
pensions x civil serv. (female)	-0.141	-0.023	0.050	0.369**	0.346*	0.195	0.367*	-0.267	0.950***	-0.000	0.251	0.468*
pensions x self-empl. (male)	0.056	0.112*	-0.167*	-0.143*	-0.113	-0.351***	-0.324***	-0.303***	-0.164**	-0.066	-0.300***	-0.247***
pensions x self-empl. (female)	-0.027	0.187**	-0.252*	-0.093	0.059	0.041	0.360***	0.005	0.256***	0.116	0.129*	0.260***
pensions x kids 0-2	-2.410	.	-0.188	-1.205*	0.287	-0.875	0.351	2.248**	0.071	-1.354	-0.902***	-0.548
pensions x kids 3-6	-0.016	0.000	-0.703	-0.020	-0.491*	0.742	0.025	0.365	-0.268	0.991**	-0.434*	-0.665
pensions x kids 7-16	-0.199	0.041	0.190	0.121*	-0.368***	0.187	-0.047	0.156*	0.084	0.060	0.093	0.016
pensions x kids 17-25	-0.078	0.244**	-0.034	0.132	-0.048	-0.001	-0.251**	-0.027	0.219*	-0.150	-0.035	0.126
pensions x adults	0.079	0.003	0.012	-0.097**	0.122***	0.073*	0.155***	-0.129***	-0.195***	-0.129***	-0.057	-0.135***
pensions sq./100 x married	0.002	0.000	0.001	-0.002**	-0.003*	-0.002	-0.002	-0.002	-0.000	-0.001	-0.001	-0.003*
pensions sq./100 x hours (male)	-0.000	-0.000***	-0.000	0.000**	0.000	-0.000	-0.000**	-0.000	-0.000	-0.000	0.000	0.000
pensions sq./100 x hours (female)	0.000**	-0.000***	-0.000**	-0.000	-0.000	0.000	0.000	0.000	0.000*	-0.000	-0.000	-0.000
pensions sq./100 x couple	-0.013	0.008	-0.022*	-0.006	-0.008	-0.007	-0.020*	0.002	-0.003	0.004	0.002	-0.004
pensions sq./100 x age (male)	0.000	-0.000	0.001***	0.000	0.000	0.000	0.001**	-0.000	0.000	-0.000	-0.000	0.000*
pensions sq./100 x age (female)	0.001	-0.000	0.001**	0.000	0.000	0.000	0.001**	-0.000	0.000	-0.000	0.000	0.000
pensions sq./100 x age sq. (male)	-0.000	-0.000	-0.001***	0.000	-0.000	-0.000*	-0.000*	0.000	-0.000	0.000	0.000	-0.000**
pensions sq./100 x age sq. (female)	-0.001**	-0.000	-0.001***	-0.000*	-0.000	-0.000*	-0.001**	0.000	-0.000	0.000	-0.000	0.000
pensions sq./100 x civil serv. (male)	-0.101	-0.044	-0.045*	0.014	-0.015	0.002	-0.002	-0.002	-0.003	-0.006	-0.003	-0.008
pensions sq./100 x civil serv. (female)	0.021	0.026	0.000	-0.002	-0.005	-0.000	0.000	0.006	-0.002	0.006	-0.003	-0.005
pensions sq./100 x self-empl. (male)	-0.002*	-0.002*	-0.000	-0.002**	-0.001*	-0.000	0.000	-0.001	0.001*	-0.001*	-0.001	-0.000
pensions sq./100 x self-empl. (female)	0.001	-0.001**	-0.001	0.000	0.001	-0.001	-0.001	-0.003**	-0.003**	-0.000	0.001	-0.000
pensions sq./100 x kids 0-2	-0.283***	0.008	-0.035	0.046	0.009	0.030	-0.037*	-0.214**	-0.029**	0.072	0.036**	0.034
pensions sq./100 x kids 3-6	0.014	0.007	0.001	-0.021	0.019	-0.106*	-0.006	-0.024	0.002	-0.021**	0.013	0.010
pensions sq./100 x kids 7-16	0.001	-0.002	0.001	-0.001	0.004*	-0.006	0.005	-0.001	0.000	-0.003*	-0.008***	0.003
pensions sq./100 x kids 17-25	0.009*	-0.004	-0.001	-0.002	-0.001	-0.001	0.000	-0.002	0.003	0.007*	0.006*	0.003
pensions sq./100 x adults	-0.001	0.000	0.001	0.001	0.001	0.000	0.002**	0.002**	-0.000	0.001	0.001*	0.002***
Constant	-45.926	-87.615*	-10.810	75.996*	32.376	57.878	56.331	344.918***	105.695**	106.270*	252.181***	109.323*
R^2	0.975	0.978	0.975	0.984	0.979	0.993	0.994	0.994	0.982	0.989	0.988	0.989
Observations	4545	8686	7767	8223	7932	7760	7519	8127	7507	7073	6589	6184

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.3: Labor supply estimation (flex. couple, 1986–1998)

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
log. income	-8.111	16.603*	34.888*	10.931	-67.155***	-22.396***	-34.762	39.057**	0.047	-13.028	-67.064***	-5.651	-29.699
log. income sq.	3.601***	1.823***	3.351***	2.924***	6.792***	3.196***	4.245***	1.661**	2.640***	3.169***	5.063***	3.187**	3.559***
log. leisure (m)	30.335*	50.449***	23.900	12.813	-30.358	7.571	49.299***	106.129***	48.724***	57.100***	-29.941*	39.001**	29.558*
log. leisure sq. (m)	-0.439	-1.785***	2.893***	1.195*	3.439***	0.207	-2.828***	-3.184***	-1.724***	-2.408***	1.695**	-0.854*	-0.843*
log. inc. x log. leis. (m)	-1.735	-2.722***	-3.310*	-0.557	2.121	0.303	-0.860	-6.716***	-2.810*	-3.540***	2.320*	-2.076	-2.167*
log. leisure (f)	103.969***	119.506***	150.759***	138.186***	90.954***	95.599***	82.046***	143.450***	92.568***	44.740***	52.320***	101.804***	56.260***
log. leisure sq. (f)	-4.012***	-6.208***	-3.438***	-5.011***	-3.187***	-5.789***	-4.146***	-5.573***	-4.301***	-2.100***	-3.205***	-3.913***	-2.603***
log. inc. x log. leis. (f)	-7.947***	-6.924***	-13.513***	-10.573***	-6.973***	-5.093***	-4.183***	-9.353***	-6.215***	-2.392*	-3.288**	-7.321***	-4.166***
log. leis. (m). x log. leis. (f)	-2.237***	-3.299***	-2.606**	-2.519***	0.050	-1.142*	-2.980***	-5.979***	-1.804*	-0.101	1.937**	-2.109**	0.215
log. inc. x kids 0-2	0.513	-0.921**	1.689***	0.520	-1.203***	0.651	0.834	3.861***	1.957***	0.979*	0.624	-0.088	2.004***
log. leis. (f) x kids 0-2	2.748***	2.912***	4.008***	5.282***	3.659***	4.453***	4.763***	5.688***	5.256***	3.184***	4.695***	4.457***	4.609***
log. inc. x kids 3-6	0.605*	1.534***	0.374	0.180	-0.109	0.460	0.657	1.659***	0.353	-0.219	-0.493	2.533***	0.341
log. leis. (f) x kids 3-6	2.108***	2.233***	2.019***	2.466***	2.208***	3.040***	2.465***	3.208***	2.287***	1.852***	2.366***	2.691***	2.836***
log. inc. x kids 7-16	0.626**	0.721***	1.227***	1.528***	2.095***	1.234***	0.684*	0.355	-0.077	-0.175	0.136	-0.262	0.268
log. leis. (f) x kids 7-16	0.965***	1.019***	1.379***	1.874***	1.334***	1.444***	1.209***	1.177***	1.106***	0.956***	1.311***	1.099***	1.020***
log. inc. x care	-3.672	3.704	0.666	-1.511	2.839	-2.982	5.000	-3.594	-1.094	0.034	1.899	-3.397	0.293
log. leis. (f) x care	-1.147	4.979	0.175	0.452	2.093	-1.347	4.745	-1.015	1.997	1.933	1.007	-2.647	-0.221
log. leis. (m) x care	-1.286	2.328	-0.183	0.333	2.328	-2.698	2.769	-3.394	-1.582	-0.419	-0.555	-1.697	-0.659
log. leis. (m) x age (m)	0.292*	0.274*	0.337*	0.245	0.161	0.079	-0.008	0.286*	0.210	-0.129	0.123	0.087	0.051
log. leis. (f) x age (f)	0.349***	0.136	0.285**	0.140	0.045	-0.001	0.130	0.305*	0.287*	-0.101	0.020	0.112	0.170
log. inc. x age (m)	0.001	0.243	0.050	0.356*	0.112	0.055	0.299	0.483**	0.302	0.017	0.514**	0.206	0.373*
log. inc. x age (f)	0.564***	0.188	0.332**	0.179	0.318*	0.259*	0.065	0.383**	0.388**	0.100	0.167	0.490**	0.500***
log. leis. (m) x age sq. (m)	-0.003*	-0.003	-0.003*	-0.003	-0.001	-0.000	0.001	-0.003	-0.003	0.002	-0.001	-0.001	-0.000
log. leis. (f) x age sq. (f)	-0.003*	-0.000	-0.002	-0.000	0.001	0.002	-0.000	-0.002	-0.002	0.002	0.001	0.000	-0.000
log. inc. x age sq. (m)	-0.000	-0.003	-0.001	-0.005**	-0.001	-0.000	-0.004	-0.005**	-0.004*	-0.001	-0.006**	-0.003	-0.004*
log. inc. x age sq. (f)	-0.007***	-0.002	-0.004**	-0.002	-0.004*	-0.003*	-0.001	-0.005**	-0.005**	-0.001	-0.001	-0.005*	-0.005**
log. leis. (m) x handicap (m)	3.223**	2.189***	1.930***	1.812***	.	3.052***	2.925***	.	2.682***	3.016***	1.783***	2.274***	2.328***
log. leis. (f) x handicap (f)	105.682	0.867	2.007**	1.743**	.	2.600***	1.705**	.	3.315***	2.546***	2.176**	2.797***	2.371***
log. inc. x handicap (m)	0.596	0.918	0.593	1.138*	.	1.465**	0.699	.	0.535	0.928*	0.034	-0.013	0.579
log. inc. x handicap (f)	0.012	-0.119	1.664*	-0.189	.	0.222	-0.004	.	0.554	0.580	0.032	0.669	0.283
log. leis. (m) x high-skill (m)	0.516	0.962	1.117*	-0.542	1.746**	0.148	0.141	1.105*	0.426	0.265	0.121	0.042	1.222**
log. leis. (f) x high-skill (f)	1.066*	1.363*	1.461**	2.246***	3.410***	0.369	-0.772	0.491	0.617	-0.492	0.333	0.166	-0.044
log. inc. x high-skill (m)	-3.134***	-1.286*	-2.694***	-2.809***	-0.517	-2.060***	-1.211*	-1.877***	-2.194***	-1.291**	-1.724**	-1.347*	-0.427
log. inc. x high-skill (f)	-0.705	0.348	-0.892	-0.776	-0.097	-1.013*	-3.310***	-1.039*	-0.343	-1.276***	-0.344	-1.484*	-0.807
log. leis. (m) x low-skill (m)	0.439	0.868**	-0.031	0.446	-0.361	0.710*	-0.418	-1.322***	-0.546	-0.051	-0.822*	0.288	-0.200
log. leis. (f) x low-skill (f)	-1.769***	-1.264***	-2.969***	-2.395***	-2.464***	-1.672***	-1.376***	-2.139***	-0.858**	-0.667*	-1.771***	-2.299***	-0.366
log. inc. x low-skill (m)	0.834*	0.867*	0.420	1.111**	0.770*	1.005**	0.504	-0.161	0.408	0.431	-0.207	0.878	-0.165
log. inc. x low-skill (f)	-0.089	0.358	-0.267	-0.890**	0.200	-0.444	-0.314	0.066	0.275	0.187	-0.658	-0.990*	-0.094
Part-time dummy (f)	-2.485***	-2.602***	-2.328***	-2.355***	-2.535***	-2.208***	-2.223***	-2.298***	-2.238***	-1.932***	-2.048***	-1.772***	-1.824***
Part-time dummy (m)	-3.684***	-4.212***	-4.054***	-4.326***	-4.356***	-4.392***	-3.878***	-4.192***	-4.017***	-3.749***	-4.092***	-3.998***	-3.441***
Observations	87808	86926	82516	80164	78841	75558	73402	71736	77175	81977	77812	76342	84329

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.4: Labor supply estimation (flex. couple, 1999–2010)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
log. income	-8.406	-19.991*	-44.780**	-13.659	-13.031	-26.645*	-68.550***	-39.794**	66.575***	-49.624**	-14.869	-33.155*
log. income sq.	1.483*	3.645***	4.867***	3.587***	3.714***	4.190***	5.872***	4.329***	-1.755*	4.622***	2.803***	3.386***
log. leisure (m)	47.205***	25.144**	-5.769	39.371***	25.825**	29.051**	-12.303	10.491	68.530***	-2.509	7.094	8.044
log. leisure sq. (m)	-2.336***	0.011	1.015**	-0.834**	-0.033	-0.363	1.319***	0.369	-2.191***	0.435	0.703	-0.614
log. inc. x log. leis. (m)	-4.191***	-1.854**	0.746	-2.489***	-2.258**	-2.693***	0.628	-0.694	-5.554***	0.220	-1.307*	-0.550
log. leisure (f)	40.734***	80.319***	75.645***	87.763***	78.071***	76.810***	39.352***	65.273***	93.061***	37.090***	61.491***	62.974***
log. leisure sq. (f)	-2.874***	-2.743***	-2.639***	-3.379***	-3.016***	-2.597***	-1.526***	-2.852***	-3.379***	-1.734***	-2.470***	-3.183***
log. inc. x log. leis. sq. (f)	-2.636**	-6.150***	-6.102***	-6.080***	-5.798***	-6.771***	-3.223***	-4.657***	-6.941***	-2.378**	-5.047***	-4.687***
log. leis. (m). x log. leis. (f)	0.166	-1.101**	-0.230	-1.477***	-0.989*	-0.926*	1.069*	-0.954	-2.717***	0.855	-0.248	-1.022
log. inc. x kids 0-2	2.618***	2.191***	1.345*	-0.058	1.254*	2.636***	-0.635	0.054	3.169***	1.550*	0.728	0.032
log. leis. (f) x kids 0-2	4.376***	5.160***	4.159***	3.280***	3.932***	4.704***	2.391***	3.616***	4.606***	4.894***	4.556***	2.575***
log. inc. x kids 3-6	1.318***	-0.139	-0.139	-0.575*	0.133	0.176	0.227	0.721*	0.104	0.830	-0.310	0.536
log. leis. (f) x kids 3-6	2.882***	2.591***	2.492***	2.572***	2.688***	2.850***	2.585***	2.283***	2.043***	2.521***	2.241***	2.413***
log. inc. x kids 7-16	0.178	0.539**	0.358	0.228	-0.083	0.001	0.284	0.321	0.941***	1.024***	0.427*	0.561*
log. leis. (f) x kids 7-16	1.272***	1.548***	1.312***	1.460***	1.178***	1.169***	1.158***	1.605***	1.621***	1.591***	1.663***	1.409***
log. inc. x care	3.895	-0.942	-3.138	-1.357	-1.418	-3.762	0.564	-2.089	-3.081	4.752	1.677	2.733
log. leis. (f) x care	0.997	0.810	-0.481	0.189	-0.450	-2.400	0.767	-0.639	-1.592	2.745	3.751	3.937
log. leis. (m) x care	3.794	-1.040	-2.664*	-2.452*	-2.697*	-3.441*	0.021	-1.354	-0.184	2.973	1.633	1.704
log. leis. (m) x age (m)	0.449***	0.171	0.142	0.030	0.256*	0.392***	0.151	0.217	0.395***	0.119	0.337**	0.550***
log. leis. (f) x age (f)	0.348**	0.022	0.066	-0.065	0.099	0.404***	0.115	0.149	0.154	-0.109	0.177	0.363**
log. inc. x age (m)	0.797***	0.451***	0.237	0.347*	0.032	0.526***	0.318	0.450**	0.642***	0.228	0.518**	0.447*
log. inc. x age (f)	0.514***	0.261*	0.344*	0.069	0.248*	0.401**	0.103	0.141	0.535***	-0.011	0.116	0.345*
log. leis. (m) x age sq. (m)	-0.005**	-0.002	-0.001	0.000	-0.002	-0.004**	-0.001	-0.002	-0.004**	-0.001	-0.003*	-0.006***
log. leis. (f) x age sq. (f)	-0.003	0.001	0.001	0.002*	0.000	-0.003*	-0.000	-0.000	-0.001	0.003	-0.000	-0.003*
log. inc. x age sq. (m)	-0.010***	-0.006***	-0.003	-0.004*	-0.001	-0.006***	-0.004*	-0.006**	-0.008***	-0.003	-0.006***	-0.005**
log. inc. x age sq. (f)	-0.005**	-0.002	-0.003*	-0.001	-0.003	-0.004**	-0.001	-0.001	-0.006**	0.001	-0.001	-0.004*
log. leis. (m) x handicap (m)	2.809***	2.325***	2.357***	3.108***	1.413***	2.181***	1.298**	2.007***	1.864***	1.404***	1.689***	2.124***
log. leis. (f) x handicap (f)	2.247***	2.489***	2.091***	2.188***	1.047*	1.626**	1.749**	2.109***	2.313***	1.670**	3.901***	2.788***
log. inc. x handicap (m)	0.171	0.259	-0.125	0.432	-0.033	0.423	-0.023	-0.386	-0.654	-0.566	-0.296	0.496
log. inc. x handicap (f)	-0.890	-0.314	0.382	-0.368	0.086	0.512	1.352*	0.648	0.082	-1.110*	-0.289	0.618
log. leis. (m) x high-skill (m)	1.135**	0.275	0.175	-0.062	0.573	0.975**	0.942**	0.777*	0.900**	1.013**	1.556***	1.228**
log. leis. (f) x high-skill (f)	0.058	0.816**	0.831**	0.579*	1.145***	0.777**	1.066***	1.560***	0.612*	0.465	0.787**	0.904**
log. inc. x high-skill (m)	-0.059	-2.086***	-1.423**	-2.332***	-1.585***	-1.344**	-1.277**	-1.235*	-0.495	-0.768	-0.538	-1.143*
log. inc. x high-skill (f)	-0.867	-0.656*	-1.283**	-1.268***	-0.266	-0.834*	-0.957*	-0.246	-0.392	-0.746	-0.694	0.147
log. leis. (m) x low-skill (m)	-0.431	-0.502	-0.066	0.112	-0.213	-0.681*	0.098	-0.935*	-1.161**	-0.148	-0.978**	-0.317
log. leis. (f) x low-skill (f)	0.086	-1.375***	-1.410***	-1.131***	-1.196***	-1.506***	-1.113***	-0.521	-0.235	-0.203	-0.790*	-0.035
log. inc. x low-skill (m)	-0.231	0.269	0.718	0.668	0.478	0.114	0.365	-0.310	-1.789***	0.068	-0.272	0.066
log. inc. x low-skill (f)	-0.054	-0.425	-0.981**	-0.574	-0.450	-0.781*	-0.419	-0.261	-0.338	-0.271	-0.683	0.094
Part-time dummy (f)	-1.585***	-1.411***	-1.297***	-1.222***	-1.220***	-1.234***	-1.141***	-1.082***	-1.079***	-0.979***	-1.009***	-0.987***
Part-time dummy (m)	-3.399***	-3.719***	-3.499***	-3.516***	-3.372***	-3.268***	-3.438***	-3.169***	-3.010***	-3.109***	-3.091***	-2.758***
Observations	78743	136955	119854	128576	119462	115101	105595	106036	95305	90503	96334	86142

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.5: Labor supply estimation (male in semi-flex. couple, 1986–1998)

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
log. income	8.845	1.946	26.267	61.148*	7.958	0.299	-20.236	-12.413	13.714	-27.041	-46.146**	-1.981	-31.979**
log. income sq.	2.587	-0.257	0.447	-2.161	0.672	1.444*	0.494	1.331	1.612	1.773	3.415***	1.676	3.155***
log. leisure (m)	68.344**	44.737*	76.839***	90.066***	44.428*	58.466***	37.957	51.567***	74.003***	30.327*	14.690	52.369***	32.035**
log. leisure sq. (m)	-2.275	-3.896***	-1.524	-2.581*	-1.072	-2.740**	-4.014***	-4.459***	-3.987***	-3.567***	-2.089**	-2.821***	-2.091***
log. inc. x log. leis. (m)	-3.392	-2.516	-11.661***	-10.611***	-4.500*	-4.064*	-1.049	-0.964	-2.387	-0.147	2.297	-1.824	0.235
log. inc. x care	230.357	5.619	76.058	-2.091	35.544	2.974	1.309	2.469	-4.332	211.425	22.963	25.276	8.424
log. leis. (m) x care	151.898	8.590	58.464	-0.572	-88.012	4.879	5.469	2.773	-1.033	125.623	23.266	22.924	2.273
log. leis. (m) x age (m)	-0.963	0.264	1.825**	1.058	0.321	0.021	0.114	-0.402	-1.223*	-0.025	-0.763	-0.674	-0.602
log. inc. x age (m)	-1.247	0.747	1.508**	1.526*	0.586	0.179	1.113	-0.002	-1.220*	0.237	-0.520	-0.412	-0.285
log. leis. (m) x age sq. (m)	0.012	-0.002	-0.020**	-0.012*	-0.003	0.000	-0.000	0.006	0.017**	0.001	0.010*	0.009	0.007
log. inc. x age sq. (m)	0.015	-0.008	-0.017**	-0.020*	-0.007	-0.002	-0.012	0.001	0.016*	-0.003	0.007	0.005	0.003
log. leis. (m) x handicap (m)	96.824	5.814	-3.354	5.091*	.	4.356	6.048	.	10.151**	8.912***	23.952**	2.929	0.616
log. inc. x handicap (m)	-11.481	2.796	-2.735	2.345	.	2.019	0.375	.	6.243	5.566	24.965**	-0.094	-4.001
log. leis. (m) x high-skill (m)	-0.888	0.370	3.688*	2.351	1.249	-1.626	-1.411	-3.318*	-0.973	-0.086	-2.517*	-2.944**	-2.428*
log. inc. x high-skill (m)	-3.104	-1.990	-0.905	0.255	-2.044	-3.508**	-3.152	-3.741**	-2.594	-0.109	-3.229*	-5.416***	-5.098***
log. leis. (m) x low-skill (m)	-2.198	-1.549	0.637	-1.488	-1.409	-2.019	-1.188	-0.254	-4.930***	3.860*	-1.036	0.298	4.388*
log. inc. x low-skill (m)	-2.940	-2.403	0.474	-1.581	-3.040	-1.983	-3.753	0.656	-5.269**	5.341*	-1.158	0.025	7.304*
Part-time dummy (m)	-3.421***	-3.185***	-4.348***	-3.269***	-2.974***	-3.706***	-4.009***	-4.303***	-3.904***	-3.201***	-4.390***	-4.274***	-4.206***
Observations	945	861	910	1008	1022	1652	1862	1841	2030	2373	2219	2324	2569

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.6: Labor supply estimation (male in semi-flex. couple, 1999–2010)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
log. income	-26.081*	-34.575**	-42.458**	-28.815*	-20.695	-23.139	-35.753**	-20.334	-30.899*	-40.855***	-30.315*	-54.853***
log. income sq.	1.716**	2.729***	3.753***	2.852***	2.575**	2.371*	3.087***	1.548	1.940*	3.375***	2.471**	3.697***
log. leisure (m)	35.481***	25.038**	33.752**	35.986***	46.279***	41.836***	34.417***	44.737***	26.734**	20.462	26.494**	7.207
log. leisure sq. (m)	-3.667***	-1.516***	-0.965	-1.251*	-2.373***	-1.629**	-1.219*	-2.169***	-2.282***	-1.818**	-1.367**	-0.977
log. inc. x log. leis. (m)	-0.692	-1.436	-2.032*	-1.381	-2.939**	-2.648*	-2.323*	-4.654***	-0.877	0.372	-1.593	-0.217
log. inc. x care	21.390	32.577	12.267	-0.710	-0.301	-5.864	-5.900	-7.272	4.370	11.079	2.193	-9.004*
log. leis. (m) x care	19.052	13.969	3.604	-0.977	-0.375	-4.020	-4.273	-4.719	3.343	7.465	-0.844	-6.294
log. leis. (m) x age (m)	-0.029	0.212	-0.175	-0.445	0.033	-0.022	0.073	0.781*	0.080	-0.189	0.269	0.398
log. inc. x age (m)	0.380	0.614	0.433	0.100	0.211	0.639	0.660	1.448**	0.737	-0.076	0.754	0.513
log. leis. (m) x age sq. (m)	0.000	-0.003	0.003	0.005	-0.000	0.000	-0.001	-0.009*	-0.001	0.002	-0.003	-0.004
log. inc. x age sq. (m)	-0.005	-0.009	-0.005	-0.002	-0.003	-0.008	-0.008	-0.017**	-0.009	0.000	-0.010	-0.006
log. leis. (m) x handicap (m)	9.173***	1.841	2.006	2.150	3.713	4.213*	3.254	4.678**	10.784***	7.645**	7.551***	8.389**
log. inc. x handicap (m)	7.732	-1.971	-1.365	-2.473	1.250	1.779	-0.122	1.490	8.584*	4.958	5.101	7.146
log. leis. (m) x high-skill (m)	-0.009	-0.966	-1.375	-0.063	0.147	-1.536	-1.241	-0.650	0.065	-1.471	-1.761	-0.310
log. inc. x high-skill (m)	0.073	-3.642**	-5.832***	-2.245*	-2.359*	-5.205***	-4.438***	-3.121**	-0.865	-2.560*	-4.938***	-2.397*
log. leis. (m) x low-skill (m)	0.702	2.144	3.403	2.778	4.480*	-1.769	-1.264	0.816	-0.757	2.093	-4.651**	-0.585
log. inc. x low-skill (m)	0.456	2.739	4.559	3.134	6.225*	-3.640	-2.787	0.164	-1.121	3.195	-6.823**	1.092
Part-time dummy (m)	-3.180***	-3.607***	-3.137***	-3.544***	-3.357***	-3.121***	-2.928***	-3.261***	-2.771***	-2.761***	-2.770***	-2.510***
Observations	2849	4592	4249	4515	4053	4039	3955	4067	3836	3486	3563	3360

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.7: Labor supply estimation (female in semi-flex. couple, 1986–1998)

	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
log. income	4.071	-9.389	-22.009	-5.529	-27.166**	-1.992	-13.990	-11.564	6.340	-13.931	-23.810***	-32.334*	-3.551
log. income sq.	3.515***	1.786**	3.853***	0.504	4.065***	0.987*	2.899**	2.665***	1.241*	1.598***	1.264**	2.915***	1.353**
log. leisure (f)	99.825***	40.914***	50.899***	45.812***	62.174***	31.813***	45.752***	55.973***	81.108***	41.658***	41.388***	39.576***	53.753***
log. leisure sq. (f)	-0.463	-1.022	0.115	-3.346***	-1.456	-2.817***	-0.399	-1.125	-3.590***	-3.108***	-5.099***	-1.722**	-3.325***
log. inc. x log. leis. sq. (f)	-11.637***	-4.436***	-6.214***	-3.351**	-4.722***	-0.990	-4.668***	-4.584***	-6.610***	-2.381*	-0.870	-3.245**	-3.029***
log. inc. x kids 0-2	-2.608	-2.634	-8.865**	-1.377	-4.602	-4.551	-11.013***	-0.601	1.418	-2.027	-0.536	8.150	8.410
log. leis. (f) x kids 0-2	1.769	0.700	-1.639	2.590	1.095	1.339	-2.201	1.773	4.710*	1.675	2.473	8.290	9.096*
log. inc. x kids 3-6	5.007*	-0.540	-3.038	-1.487	-7.222**	-2.393	-7.751***	-2.459	-4.413*	0.594	-0.542	3.105	-1.228
log. leis. (f) x kids 3-6	4.583***	1.131	0.434	1.608	-1.534	0.684	-1.547	0.548	0.666	3.483**	3.041**	3.726*	2.228*
log. inc. x kids 7-16	-0.494	-0.334	-3.259*	-2.348	-0.833	1.369	2.227	1.993	1.989	1.037	-0.263	-0.569	0.354
log. leis. (f) x kids 7-16	0.801	0.962	-0.380	0.444	0.827	1.707*	1.736	1.852**	2.229***	1.452*	0.930	0.845	1.177*
log. inc. x care	-9.804*	-1.741	-2.214	-6.068	-2.908	0.838	-0.196	-10.078	-3.393	-1.124	-1.762	-8.245	14.424
log. leis. (f) x care	-5.825*	-2.911	-2.340	-5.436*	-0.157	2.313	-2.742	-3.922	-2.422	-1.893	-2.188	-5.665*	9.422
log. leis. (f) x age (f)	0.473	0.620*	0.489	0.610*	-0.146	0.034	0.258	-0.131	0.214	0.197	0.355	0.249	-0.085
log. inc. x age (f)	0.916*	0.984*	0.505	1.161*	0.229	-0.199	0.497	0.155	0.675	0.313	0.734	0.638	0.158
log. leis. (f) x age sq. (f)	-0.004	-0.008*	-0.006	-0.007	0.002	-0.000	-0.003	0.002	-0.001	-0.001	-0.003	-0.001	0.003
log. inc. x age sq. (f)	-0.012*	-0.013*	-0.007	-0.014*	-0.004	0.002	-0.008	-0.002	-0.008	-0.004	-0.009	-0.006	-0.001
log. leis. (f) x handicap (f)	84.080	-2.615*	3.155	2.545	.	2.667	9.630	.	2.346	3.804*	9.603*	5.226*	3.467*
log. inc. x handicap (f)	-32.235	-4.610*	1.656	-0.817	.	0.055	2.843	.	-3.383	0.578	9.759	4.231	-0.349
log. leis. (f) x high-skill (f)	0.424	0.188	-0.217	0.129	0.397	-0.344	4.314*	0.203	3.798**	1.194	-1.332	-1.441	1.279
log. inc. x high-skill (f)	-4.112**	-3.323	-2.287	0.494	-1.470	-0.597	3.733	-1.445	5.047*	2.749	-2.195	-4.164*	0.832
log. leis. (f) x low-skill (f)	-0.619	1.386	0.066	-0.628	0.092	-0.510	-0.599	-2.144**	0.536	0.687	0.674	-0.890	-1.887
log. inc. x low-skill (f)	1.505	2.861	1.935	0.121	5.136*	0.562	-0.433	0.070	0.357	0.870	0.600	-1.412	-3.753*
Part-time dummy (f)	-2.316***	-2.144***	-2.057***	-2.108***	-1.948***	-1.501***	-1.642***	-1.684***	-1.754***	-1.566***	-1.662***	-1.496***	-1.603***
Observations	3094	2996	2695	2681	2625	2653	2681	2779	3045	3010	3178	3157	3486

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Table 3.6.8: Labor supply estimation (female in semi-flex. couple, 1999–2010)

	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
log. income	-6.917	-19.933**	-46.914***	-49.692***	-32.018***	-30.068***	-25.067***	-45.979***	-27.038***	-11.905	-16.205*	-23.577***
log. income sq.	0.580*	4.371***	4.793***	4.894***	5.012***	4.567***	3.971***	4.695***	3.557***	2.937***	2.662***	4.188***
log. leisure (f)	41.582***	69.313***	51.876***	47.724***	69.617***	73.951***	69.169***	41.866***	55.852***	62.938***	61.492***	72.060***
log. leisure sq. (f)	-3.176***	-1.506**	-1.503**	-1.636***	-0.607	-2.513***	-2.467***	-1.854***	-2.038***	-2.059***	-2.080***	-1.506**
log. inc. x log. leis. sq. (f)	-1.425*	-5.740***	-4.289***	-3.668***	-6.872***	-5.763***	-4.815***	-2.072***	-4.196***	-4.410***	-4.991***	-6.065***
log. inc. x kids 0-2	-6.086	3.142	-1.977	-1.956	-4.200	0.499	1.823	1.390	4.618	-2.491	-5.624**	-1.525
log. leis. (f) x kids 0-2	1.191	4.888	1.204	2.548*	-1.334	2.134	3.346	5.673*	4.380*	0.847	-1.416	1.806
log. inc. x kids 3-6	0.502	-1.190	0.794	0.618	0.977	-0.775	-0.221	5.132*	-3.563*	0.257	0.406	-0.311
log. leis. (f) x kids 3-6	2.248	2.494*	2.883**	2.451*	1.485	1.346*	2.118*	4.247**	0.299	1.983*	2.670**	1.924
log. inc. x kids 7-16	-0.982	0.647	0.233	0.415	-0.593	1.487	1.387	-1.288	1.080	1.035	0.298	2.950*
log. leis. (f) x kids 7-16	0.657	1.537**	1.268*	1.354**	0.497	1.034*	1.243**	0.563	1.499***	1.556**	1.448**	2.641***
log. inc. x care	35.657	-0.386	-1.377	13.003	-1.059	-7.064*	-6.461	-2.254	5.712	-2.085	0.109	1.197
log. leis. (f) x care	29.486	-1.875	-1.630	6.368	-1.757	-5.498**	-4.734*	-2.803	-0.295	-0.606	1.230	0.666
log. leis. (f) x age (f)	-0.215	-0.108	0.050	0.076	0.088	-0.038	-0.164	-0.149	0.054	-0.248	-0.010	-0.182
log. inc. x age (f)	0.479	-0.128	0.407	0.321	0.383	0.027	0.056	0.020	0.294	0.132	0.524*	0.151
log. leis. (f) x age sq. (f)	0.004	0.002	0.001	0.000	0.000	0.002	0.003	0.002	0.000	0.004	0.002	0.004
log. inc. x age sq. (f)	-0.005	0.001	-0.005	-0.004	-0.005	-0.000	-0.001	-0.001	-0.004	-0.002	-0.006*	-0.002
log. leis. (f) x handicap (f)	-0.146	1.477	3.508*	1.593	1.524	1.405	1.554	-0.226	0.535	2.275	4.688**	0.726
log. inc. x handicap (f)	-3.219	-2.576	2.960	-0.158	1.577	0.758	-0.627	-2.793	-1.616	-1.440	2.132	-1.130
log. leis. (f) x high-skill (f)	3.412*	0.811	0.348	1.405**	0.749	0.029	0.877	-1.067	-0.482	-1.386*	-0.355	-0.094
log. inc. x high-skill (f)	6.965*	-1.687*	-2.051*	-1.573	-4.445***	-2.684***	-2.669**	-4.817***	-3.401***	-4.784***	-3.071***	-2.981***
log. leis. (f) x low-skill (f)	-0.188	-2.226***	-1.185	-0.452	-0.577	1.664	1.249	0.887	-0.155	-1.332	-0.455	-0.117
log. inc. x low-skill (f)	-1.878	-0.624	0.010	0.525	-0.625	2.394	1.412	1.626	0.267	-1.850	-0.446	0.954
Part-time dummy (f)	-1.369***	-1.298***	-1.276***	-1.228***	-1.217***	-1.304***	-1.273***	-1.134***	-1.035***	-1.111***	-1.064***	-0.993***
Observations	3255	6097	5551	6440	5852	5943	5782	6146	5474	4732	5194	4711

Note: Significance levels are 0.1 (*), 0.05 (**), and 0.01 (***).

Chapter 4

Income Inequality, Household Size and the Welfare State*

4.1 Introduction

Since reunification in 1990, inequality as well as poverty and richness of the equivalent disposable income distribution in Germany have increased considerably (see OECD, 2008; Bach et al., 2009; Peichl et al., 2010, and figure 4.2.1). From a policy perspective it is important to understand the driving forces behind this widening income gap. One cause of this development, among others (e.g., changes in returns to education, skill-biased technological change, de-unionization or the weakening bargaining power of unions; also see Lemieux, 2010), could be structural shifts in household formation due to long-term societal trends. These might be linked to rising inequality, since a decrease in the number of individuals living together affects the income distribution because of income sharing within households. Furthermore, changing household structure is accompanied by changes in employment patterns, which also have an impact on the income distribution. Therefore, everything else equal, the income distribution is affected by household structure changes (Burtless, 1999, 2009).

The aim of this chapter is to quantify the effect of such changes on the income

*This chapter is based on the paper *Does Size Matter? The Impact of Changes in Household Structure on Income Distribution in Germany* (joint with Andreas Peichl and Hilmar Schneider, see Peichl et al., 2012).

distribution in Germany. The case of Germany is of special interest, as the demographic development is not only characterized by an ageing population, but also by a sharp fall in average household size. Despite this very pronounced development, there has not been much research that systematically analyzes these effects on income distribution for Germany.[1]

Two different methods can be used to assess the impact of changing household structure: subgroup decomposition and re-weighting. The first is an exact decomposition of the distributional change by population subgroups (Shorrocks, 1980; Mookherjee and Shorrocks, 1982; Shorrocks, 1984). This is the common approach in studies analyzing the effect of demographic change on inequality in the United Kingdom (Jenkins, 1995) and the United States (Martin, 2006). For Germany this decomposition technique has been applied to regional differences in income inequality after reunification (Schwarze, 1996) and to differences in poverty by region and household type (Bönke and Schröder, 2011). Bargain and Callan (2010) decompose the effects of tax-benefit reforms on income distribution. In addition to the subgroup decomposition, a re-weighting procedure in the tradition of the Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973) is applied in order to obtain counterfactual income distributions while keeping the marginal distributions of other characteristics fixed (DiNardo et al., 1996; Hyslop and Mare, 2005). These procedures have already been applied in the OECD (2008) study to assess the importance of demographic change on income inequality as well as to other contexts related to wage and wealth inequality (Lemieux, 2006; Bover, 2010).

In this study we contrast the results from both techniques. Due to the possible existence of non-linearities, and as a sensitivity analysis, we check whether both approaches lead to similar results. Note that both approaches remain descriptive, i.e., based on the results one cannot state that there is a *causal* relationship between household structure and income inequality. In addition to quantifying the impact of changing household structure on inequality, this chapter contributes to the existing literature by deriving analogous decomposition techniques for changes in poverty and richness measures. This enables us to conduct a more detailed ana-

[1] In a recent study on inequality, the OECD (2008) erroneously reports that a share of 88% of the total (absolute) change in the Gini coefficient of disposable incomes in West Germany from 1985 to 2005 is due to changing household structure. However, the authors have stated that this is a misprint. The true figure is 12%.

lysis of the tails of the income distribution. Our analysis is based on microdata from the German Socio-Economic Panel Study (SOEP).

We find that the growth of the income gap in Germany (East and West, from 1991–2007) is indeed strongly related to such changes. For inequality of incomes before taxes and transfers we find a fraction of 78%. However, the result for incomes after taxes and transfers is only 22%. This means that the welfare state has largely compensated for inequality induced by changes in household structure. The same holds for the change in poverty, but less for the change in richness measures. Similar results occur when using a counterfactual re-weighting procedure. The role of the welfare state is important, since it not only enables the pure existence of poor households by providing a minimum income, but it also affects the income situation of specific population groups. For example, the welfare state compensates low-income households with children but burdens double-earner couples with high marginal income tax rates.

The chapter is organized as follows: Section 4.2 provides an overview of the demographic trends in Germany, and section 4.3 reviews relevant definitions and methods. In section 4.4 these methods are applied to German survey data. The results are presented in section 4.5, and the chapter concludes in section 4.6.

4.2 Demographic Trends in Germany

The demographic development in Germany is not only characterized by an ageing population, but also by a sharp drop in average household size, which is now – together with Sweden – lowest among OECD countries (OECD, 2008). Especially the proportion of one- and two-person households has increased dramatically. The increase in the number of single households can be primarily explained by a higher rate of divorce and a lower rate of marriage. The increase in two-person households is related to two developments: first, the number of childless couples has increased, and second, the increase in life expectancy has led to a growing number of elderly two-person households. Figures 4.2.1 and 4.2.2 illustrate the demographic trend towards smaller households. According to data from the German Micro Census, the average number of individuals living together in a household decreased from 2.27 to 2.05 between 1991 and 2008. In East Germany this decrease was twice as

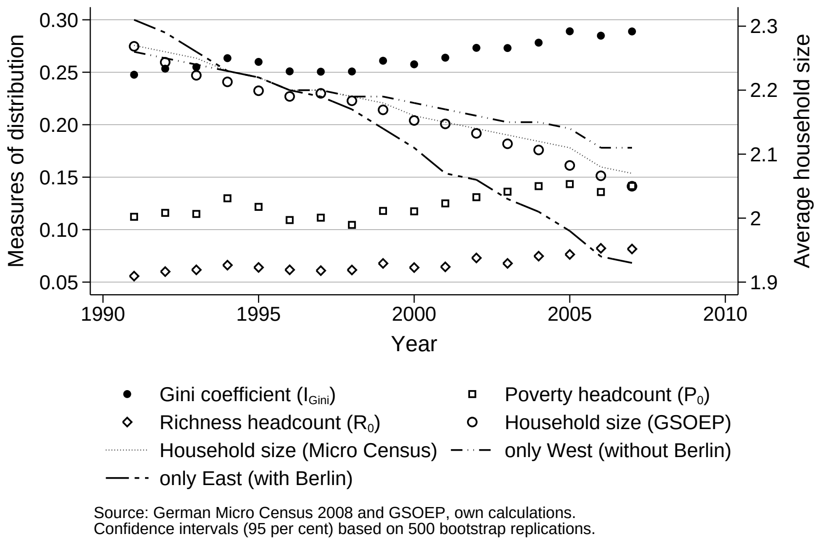


Figure 4.2.1: Household size, inequality, poverty and richness (1991–2007)

large: while the average household size was 2.31 in 1991, it was only 1.91 in 2008. Although Germany's population increased by 2.6% between 1991 and 2008 (from 80.2 to 82.3 million), the number of private households increased by 13.6% to 40.1 million. This was predominantly driven by the rising number of households with two persons at most. The number of one- and two-person households increased by 33.2% and 25.5% respectively, while the number of households with at least three persons has been decreasing (Statistisches Bundesamt, 2008b).[2] To a large extent, this development can be explained by the drastic and continual decline of Germany's birth rate, which decreased by 17.4% between 1991 and 2005 (Statistisches Bundesamt, 2008a). In addition, the trend towards individualization due to increasing relevance of modern life styles such as "living apart together" (see, e.g. Asendorpf, 2009) accounted for a large part of this observation.

With regard to causality, the described patterns may result from changes in mating behavior due to higher levels of education and more frequent labor market participation among women. This could lead to modifications in scope and

[2] Although according to the German Micro Census, the trend towards smaller households might be somewhat overstated due to statistical artifacts (see Statistisches Bundesamt, 2009, for details), the direction and magnitude of this trend nevertheless seem to be clear cut. Moreover, our calculations based on data from the SOEP are not significantly different (see figure 4.2.1).

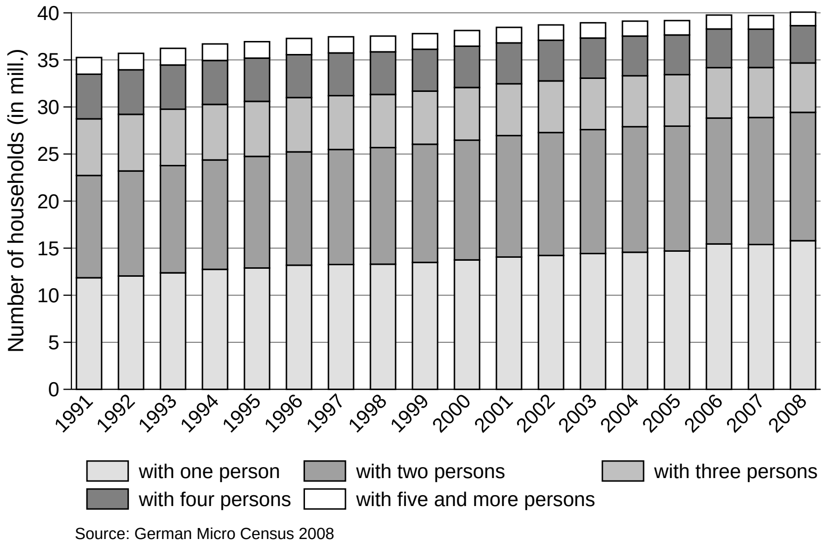


Figure 4.2.2: Number of different-sized households (1991–2008)

selectivity of fertility. Hence, it is conceivable that household formation in turn depends on one's position in the income distribution, i.e., there is some form of reverse causality. For instance, educated and employed women may be improving their income position, which again might coincide with remaining single for a longer time. In addition, demographic change can have different effects on pre and post fisc income distributions depending on how implicit equivalence scales are defined and compensate for different household behavior. Hence, the tax-benefit system can also provide incentives for a certain behavior, e.g., through a system of joint taxation which provides incentives for one-earner families.

As a result, it remains a priori unclear in which direction changes of household structure affect income distribution. The noticeable decline in the number of births, for example, means that couples nowadays tend to stay childless. This leaves them with higher equivalent incomes than in a situation with more children. In addition, this alleviates double-earnership, which makes them even better-off. Similarly, the increase in the number of single households results in a growing number of individuals with lower equivalent incomes, since they cannot share fixed costs of living expenses. This makes them worse-off than if they were cohabiting. Whether these effects lead to an increase or a decrease in inequality depends on the average income position of the respective household types.

4.3 Methodology

In this section we describe methods for the measurement and decomposition of inequality, poverty and richness. While re-weighting techniques seem to dominate traditional subgroup decompositions in labor economics literature, this is not true for the literature on income distribution. We employ both approaches here, since each has specific advantages. The re-weighting approach allows the calculation of different measures of distribution, since it is not restricted to a decomposable specific summary index, as is the case with the decomposition method. However, it is only possible to compare actually observed and counterfactual values to assess the importance of changes in the composition of the population. In contrast, using the decomposition approach allows the interpretation of each single component beyond simply within and between group inequality. Furthermore, using the subgroup decomposition approach allows our results to be compared to previous studies (Jenkins, 1995; Martin, 2006).

4.3.1 Decomposition Techniques

Inequality. There are several measures of inequality (see Atkinson and Bourguignon, 2000). In the context of our approach, the class of Generalized Entropy (GE) inequality measures (Shorrocks, 1980) is the most suitable one, as they can be decomposed so total inequality results from the sum of inequality *within* and *between* population subgroups. They are defined for an income distribution $Y = (y_1, \ldots, y_n)$, where y_i is the income of individual $i \in \{1, \ldots, n\}$, w_i is i's population weight and $\bar{y}$ the population mean.

For the purpose of this chapter we choose $I_0 = \sum_{i=1}^{n} \frac{w_i}{\sum_{i=1}^{n} w_i} \cdot ln\left(\frac{\bar{y}}{y_i}\right)$ from the GE family.[3] If one divides the total population into K disjoint and exhaustive

[3]According to Shorrocks, the features of this measure are best suitable for decomposition analysis, since total inequality can be exactly decomposed into within- and between-group inequality. Moreover, the weighting factors sum up to unity (Shorrocks, 1980, p. 625).

subgroups, denoted by $k \in \{1, \ldots, K\}$, the measure I_0 can be written as

$$I_0 = \underbrace{\sum_{k=1}^{K} v_k \cdot I_{0k}}_{within} + \underbrace{\sum_{k=1}^{K} v_k \cdot ln\left(\frac{\bar{y}}{\bar{y}_k}\right)}_{between}, \qquad (4.3.1)$$

where v_k denotes the weighted proportion of individuals belonging to population subgroup k. Hence, total inequality can be written as a weighted sum of inequality within and between population subgroups. This allows decomposing the *change* in total inequality over time into changes within subgroups and changes resulting from shifting population ratios, which can be written as

$$\begin{aligned}\Delta I_0 = I_0^{t+1} - I_0^t \approx & \underbrace{\sum_{k=1}^{K} \bar{v}_k \cdot \Delta I_{0k}}_{A} + \underbrace{\sum_{k=1}^{K} \bar{I}_{0k} \cdot \Delta v_k}_{B} \\ & + \underbrace{\sum_{k=1}^{K} \left[\bar{\lambda}_k - \overline{ln\left(\lambda_k\right)}\right] \cdot \Delta v_k}_{C} + \underbrace{\sum_{k=1}^{K} \left(\bar{\theta}_k - \bar{v}_k\right) \cdot \Delta ln\left(\bar{y}_k\right)}_{D}, \qquad (4.3.2)\end{aligned}$$

where Δ is the difference-operator; $\lambda_k = \bar{y}_k/\bar{y}$ denotes the ratio of population subgroup k's mean income to total population's mean income and $\theta_k = v_k \cdot \lambda_k$, which is the income ratio of group k. A symbol with a bar denotes the particular value averaged over time.[4] Thus, the total change in inequality can be decomposed into four components (Mookherjee and Shorrocks, 1982, p. 897). Summand A contains the contribution of inequality changes that result solely from changes *within* population subgroups (ΔI_{0k}) and abstracts from changes in composition by fixing population ratios to averaged values ($\bar{v}_k$). Accordingly, changes in inequality within groups with higher proportions would therefore be of greater importance. Summand B, on the other hand, contains the effect of changes in composition (Δv_k) on inequality *within* population subgroups. It analogously abstracts from changes in within-group inequality by fixing it on averaged values ($\bar{I}_{0k}$). If propor-

[4] Alternatively, it would be possible to use base or final period weights. However, Mookherjee and Shorrocks (1982) identify that this choice is unlikely to make a difference to the results. In addition, this corresponds to the weight that would be assigned by the Shapley value algorithm (Shorrocks, 1999; Jenkins and Van Kerm, 2005).

tions of groups with relatively high levels of inequality increase, total inequality will increase accordingly and vice versa. Summand C describes the effect of changes in composition (Δv_k) on inequality *between* population subgroups. Again, changes in population ratios are crucial for the direction of change. Summand C sums up the contribution to total inequality change that results when proportions of groups with relatively high (or low) mean incomes increase (or decrease). Summand D represents the contribution of changes in population subgroup mean incomes ($\Delta ln\,(\bar{y}_k)$). It fixes the difference between group proportions of total income and population respectively. The higher the income ratio of a group relative to its share, the greater the effect on total income inequality when the mean income of that group changes.

To summarize, summand A represents changes in inequality within population subgroups. Summands B and C both represent the contribution to inequality change resulting from demographic change, since they are based on shifting population ratios. Summand D represents the effect of changes in the distribution of population subgroup mean incomes. The relative importance of summands B and C compared to the total change in inequality ΔI_0 is of prior interest for our analysis.

Poverty and Richness. A well-known and widely used class of poverty measures which is decomposable by population subgroups was introduced by Foster et al. (1984). Total poverty P_α is defined as

$$P_\alpha(y;z) = \sum_{i=1}^{q} \frac{w_i}{\sum_{i=1}^{n} w_i} \cdot \left(\frac{g_i}{z}\right)^\alpha \text{ for } y_i \leq z, \tag{4.3.3}$$

where $\alpha \geq 0$ is a parameter of poverty aversion, and $g_i = z - y_i$ denotes the income shortfall between individual i's income y_i and a given poverty line z. The number of poor is denoted by q. They receive an income not exceeding the poverty line z. In order to assess how much of an observed change in poverty can be attributed to demographic changes, it is necessary to decompose the change into components accordingly. If one divides the population into K disjoint and exhaustive population subgroups, one can show that (Shorrocks, 1999, p. 13 f.)

$$\Delta P_\alpha = P_\alpha^{t+1} - P_\alpha^t = \underbrace{\sum_{k=1}^{K} \bar{v}_k \cdot \Delta P_{\alpha,k}}_{A} + \underbrace{\sum_{k=1}^{K} \bar{P}_{\alpha,k} \cdot \Delta v_k}_{B}, \tag{4.3.4}$$

where v_k denotes the population share. Subgroup k's income vector is denoted by y_k, and poverty is measured within each group by $P_{\alpha,k}(y_k; z) = \sum_{i=1}^{q_k}(w_i/\sum_{i\in k} w_i)\cdot (g_i/z)^\alpha$ for $y_{i\in k} \leq z$, where q_k denotes the number of poor individuals within group k. The change in poverty (ΔP_α) can be decomposed into the change in levels of group poverty (labeled A) and changes in the composition of the population (demographic change, labeled B). This decomposition of change also corresponds to the one that results from a Shapley value decomposition (Shorrocks, 1999).

Income richness is a less studied field than income poverty. Peichl et al. (2010) propose measures that are decomposable by population subgroups and allow for a consideration of the intensity of richness analogous to the Foster-Greer-Thorbecke (FGT) poverty measure. The richness index we employ is defined as

$$R_\beta(y; \rho) = \sum_{i=1}^{s} \frac{w_i}{\sum_{i=1}^{n} w_i} \cdot \left[1 - \left(\frac{\rho}{y_i}\right)^\beta\right] \text{ for } y_i \geq \rho, \tag{4.3.5}$$

where $\beta > 0$ is a parameter for the sensitivity to intensive richness. For greater values of β the richness measure puts more weight on the "very rich". The richness line is denoted by ρ, where individuals with an income above this line are defined as rich. As in the cases of inequality and poverty, it is possible to express richness as a weighted sum of richness within population subgroups $k \in \{1, \ldots, K\}$, where richness within each group k is denoted with $R_{\beta,k}(y_k; \rho) = \sum_{i=1}^{s_k}(w_i/\sum_{i\in k} w_i) \cdot \left(1 - (\rho/y_i)^\beta\right)$ for $y_{i\in k} \geq \rho$, and s_k denotes the number of rich within each group. Analogous to the decomposition of poverty change over time, it is straightforward to decompose the change in richness between periods t and $t+1$:

$$\Delta R_\beta = R_\beta^{t+1} - R_\beta^t = \underbrace{\sum_{k=1}^{K} \bar{v}_k \cdot \Delta R_{\beta,k}}_{A} + \underbrace{\sum_{k=1}^{K} \bar{R}_{\beta,k} \cdot \Delta v_k}_{B}. \tag{4.3.6}$$

The interpretation of this decomposition is the same as for poverty: summand B is the fraction of the overall change in richness that is related to demographic change.

4.3.2 Re-weighting Procedure

In order to assess the impact of the changing household structure between 1991 and 2007 by means of re-weighting, we need to compare the counterfactual distribution of 2007 incomes and 1991 household structure with the observed 2007 income distribution. In order to do so, we follow the approach suggested by DiNardo et al. (1996) and extended by Hyslop and Mare (2005) to estimate the counterfactual density function using a re-weighting technique.

Each household can be described with a vector (y, x, t) consisting of income y, a vector x of household characteristics, and a date t (1991 or 2007). Each observation belongs to a joint distribution function $F(y, x, t)$ of income, characteristics and date. The joint distribution of income and characteristics is the conditional distribution $F(y, x|t)$. The density of income at a given point in time, $f_t(y)$, can be written as the integral of the density of income, conditional on a set of characteristics and on a date t_y, over the distribution of individual characteristics $F(x|t_x)$ at date t_x.

$$f_t(y) = \int dF(y, x|t_{y,x} = t) = \int f(y|x, t_y = t)dF(x|t_x = t) \tag{4.3.7a}$$

$$\equiv f(y, t_y = t, t_x = t). \tag{4.3.7b}$$

The estimation of counterfactual densities combining different dates is accounted for in the last line of the notation. Under the assumption that the 2007 distribution of incomes, $F(y|x, t_y = 2007)$, does not depend on the 1991 distribution of characteristics, $F(x|t_x = 1991)$, the hypothetical counterfactual density is:

$$f(y, t_y = 2007, t_x = 1991) = \int f(y|x, t_y = 2007)dF(x|t_x = 1991) \tag{4.3.8a}$$

$$= \int f(y|x, t_y = 2007)\psi_x(x)dF(x|t_x = 2007), \tag{4.3.8b}$$

where the re-weighting function $\psi_x(x)$ is defined as

$$\psi_x(x) \equiv \frac{dF(x|t_x = 1991)}{dF(x|t_x = 2007)}. \tag{4.3.9}$$

The counterfactual density can be estimated by weighted kernel methods. The difference between the actual 2007 density and the hypothetical re-weighted density represents the effect of changes in the distribution of household characteristics. To estimate the impact of the changing household structure, we compare inequality measures for the counterfactual distribution of 2007 incomes and 1991 household structure with the observed 2007 income distribution. Re-weighting and subgroup decomposition will lead to identical results if the relationship between demographic change and inequality is linear.

4.4 Empirical Foundation

4.4.1 Data

The SOEP is a panel survey of households and individuals that has been conducted annually since 1984. A weighting procedure means respondents' data are representative for the German population (see Haisken-DeNew and Frick, 2005; Wagner et al., 2007). Issues concerning sampling and weighting methods or the imputation of information in case of item or unit non-response is well documented by the SOEP Service Group. We use waves that contain information on annual income for the longest possible period 1991–2007, in order to include East Germany after reunification. The data set contain information from 17,921 (25,366) individual observations in 6,665 (11,072) households for 1991 (2007).

4.4.2 Income Concept

We compute the change in measures of distribution (from equations (4.3.2), (4.3.4) and (4.3.6)) for equivalent pre and post fisc incomes. The progressive German tax-benefit system induces an inequality-reducing redistribution of incomes and takes into account household structures through implicit equivalence scales (ES).

Examining pre and post fisc incomes allows us to assess to what extent the German tax-benefit system compensates for changes in household structure.

SOEP data contain appropriate income variables defined as follows Grabka (2012): pre fisc income includes labor earnings, asset flows, private retirement income and private transfers; post fisc income includes pre fisc income, public transfers and statutory pensions, minus any tax payments. Both concepts of income are deflated in order to compute real incomes. Moreover, we add household imputed rental values for owner-occupied housing (Yates, 1994; Canberra Group, 2001; Smeeding and Weinberg, 2001; Frick and Grabka, 2003; Eurostat, 2007). For population weights w_i we adopt the weights from the SOEP (Grabka, 2012). In the following analysis we define the poverty line z to be 60% and the richness line ρ to be 200% of the median of equivalent pre- and post- government incomes.[5] Our main results rely on calculations using the modified OECD equivalence scale, which assigns a weight of one to the first adult household member, a weight of 0.5 to every additional adult and a weight of 0.3 to every child (OECD, 2005). In section 4.5.1 we discuss the role of the choice of equivalence scale and present results for alternative specifications.

4.4.3 Definition of Population Subgroups

The partition of the population into disjoint and exhaustive subgroups is of great importance for the following analysis.[6] According to our research question, household composition with respect to the number and age of household members is of relevance. We have already indicated that household formation is also related to labor market participation. Hence, in order to capture employment effects, our definition of population subgroups proceeds in two steps. We begin by distinguishing population subgroups according to two criteria. The first is the number of adult

[5] Alternative definitions of the poverty and richness line do not alter the qualitative findings of our analysis or the interpretation of our results.

[6] Note that compared to the population in private households, the population in institutionalized households is underrepresented in the SOEP (Haisken-DeNew and Frick, 2005, p. 182 f.). This may be selective with respect to household composition and poverty risks. Due to increasing longevity, more and more elderly can be assumed to move into retirement and nursing homes, i.e., the bias may have increased over time. However, since there is no information available for this group, we only refer to the population in private households.

household members (aged 18 or over), and the second is the presence of children (younger than 18) in the household. We further distinguish these groups according to the number of employed individuals within the household as a third criterion. Differences in the results for the two definitions are related to changing patterns in labor force participation. However, we cannot identify the causal effect, since this is already partly captured by household structure because household formation and labor force behavior can be viewed as a joint decision.

We distinguish between singles, couples and households with more than three adults, with and without children. In total we have six population subgroups according to household composition (see table 4.7.1) in the appendix. It appears that between 1991 and 2007 the population shares of three of these groups increased, while they decreased for the remaining groups. Single households made up around 16% of the population in 1991, and by 2007 this share increased to 20%. The largest group in 2007 is represented by individuals living in two-adult-households. Their share increased from 26% to over 30%. Hence, in 2007 more than half of the population lived in households with one or two adults without children. In addition, the share of individuals in single parent households increased from 2.8% to around 3.7%. Other types of households are on the retreat. One of the greatest reductions was the proportion of individuals in two-adult households with children which dropped by nearly seven percentage points to 26%. Note that those groups with growing population shares are characterized by above average and increasing levels of income inequality. Moreover, their group mean incomes display much more variation around the population's mean, i.e., the population is becoming more heterogenous both in terms of within- and between-group inequality.

The declining relative number of individuals living in households with several adults and children partly means that multiple generation-households as a form of cohabitation is clearly decreasing in Germany: The proportion of individuals in multiple generation-households decreased from 2.4% to 1.3% between 1991 and 2007. This drop contributes to increasing income inequality because of the diminishing incidence of redistribution *within households* between generations. Hence, to the degree to which this form of cohabitation is reduced, there will be more inequality.[7]

[7]Note that our income concept includes private transfer payments. Hence, we take into ac-

The definition of subgroups of the second step takes into account the employment status of household members. Hence, we further split up the beforehand defined groups based on the number of employed persons in the household. We now have 16 groups in total. In table 4.7.2 in the appendix we present the group characteristics with respect to this definition. Population subgroups defined according to household structure and employment status are internally less heterogenous and there is less variation in mean incomes. This is not surprising, since additional employed household members increase household earnings. Employed singles account for around three-quarters of the percentage point increase in the number of single households, while most of the growth of two-adult households without children is due to more couples not in employment – presumably many of retirement age.

4.5 Results

4.5.1 Decomposition

In this subsection we present the decomposition results for different measures, income concepts and regions.[8]

Pre fisc incomes. For pre fisc incomes overall inequality in reunified Germany increased by 25% between 1991 and 2007 (see table 4.5.1). Around 19.4 percentage points (pp) of this increase can be attributed to changes in household structure and employment status (summands B and C, corresponding to 77.5% of the increase),

count redistribution of income occurring *between households* but (in most cases) *within families*. Which is why our results highlight the effect of less redistribution within households.

[8]Note that the decomposition results according to equations (4.3.2), (4.3.4) and (4.3.6) are presented as percentages and percentage points. For example, ΔI_0 and the summands A to D are divided by I_0^t and multiplied by 100 each. The same holds for the decompositions of poverty and richness. The differentiation into East and West Germany is appropriate, as there are still significant income differentials between the two parts of the country. The non-convergence of income inequality is indirectly explained by much higher rates of unemployment in East Germany, which causes a high level of inequality in labor income, which is of greater importance relative to capital income in East Germany (Frick and Goebel, 2008). In addition, as is clear from figure 4.2.1, the demographic trend is more pronounced in the East.

16.0 pp to summand A, whereas summand D reduces inequality by 10 pp.[9] So the rise in inequality to be explained by A, B and C together is actually 35%, whereof A accounts for 45% and $B + C$ for 55%. In the remainder of the chapter we focus on the first definition but also report the fraction $\frac{B+C}{A+B+C}$ in table 4.5.1 for completeness. We find that the results differ quantitatively in these cases, but one cannot draw divergent conclusions.

Table 4.5.1: Inequality decomposition (1991–2007)

Income	Region	I_0^{1991}	I_0^{2007}	ΔI_0	A	B	C	D	$\frac{B+C}{\Delta I_0}$	$\frac{B+C}{A+B+C}$
Household structure and employment status										
pre fisc	Germany	0.500	0.625	25.0	16.0	11.8	7.6	-10.2	77.5	54.8
		(0.010)	(0.011)	(3.5)	(2.3)	(1.2)	(1.0)	(1.7)	(8.2)	(4.3)
	West	0.480	0.558	16.3	15.9	8.0	5.5	-12.9	83.1	45.9
		(0.012)	(0.012)	(4.0)	(2.7)	(1.2)	(1.1)	(1.8)	(16.4)	(5.4)
	East	0.514	0.872	69.6	15.7	28.9	23.9	-0.6	75.9	77.1
		(0.022)	(0.024)	(8.5)	(3.7)	(3.2)	(3.1)	(3.7)	(5.3)	(4.7)
post fisc	Germany	0.105	0.144	37.8	28.9	5.4	3.0	0.6	22.2	22.5
		(0.002)	(0.004)	(4.5)	(4.0)	(0.7)	(0.6)	(1.4)	(2.9)	(2.8)
	West	0.104	0.149	43.0	35.7	4.7	2.2	0.6	15.9	16.2
		(0.003)	(0.004)	(5.3)	(4.6)	(0.7)	(0.7)	(1.5)	(2.3)	(2.4)
	East	0.070	0.097	38.8	44.1	-0.7	7.2	-16.2	16.8	12.8
		(0.002)	(0.003)	(6.0)	(4.9)	(1.6)	(1.9)	(2.5)	(8.7)	(5.5)
Household structure only										
pre fisc	Germany	0.500	0.625	25.0	9.0	15.0	0.4	0.6	61.4	63.1
		(0.010)	(0.011)	(3.5)	(2.9)	(1.2)	(0.1)	(0.5)	(7.7)	(8.3)
	West	0.480	0.558	16.3	3.7	11.5	0.4	0.7	73.1	76.3
		(0.012)	(0.012)	(4.0)	(3.4)	(1.2)	(0.1)	(0.6)	(19.0)	(17.8)
	East	0.514	0.872	69.6	35.3	34.0	1.1	-0.8	50.5	49.9
		(0.022)	(0.024)	(8.6)	(6.4)	(3.3)	(0.3)	(1.5)	(5.6)	(5.5)
post fisc	Germany	0.105	0.144	37.8	29.4	5.4	1.2	1.7	17.4	18.3
		(0.002)	(0.004)	(4.6)	(4.4)	(0.6)	(0.3)	(1.1)	(2.1)	(2.1)
	West	0.104	0.149	43.0	34.8	4.4	1.3	2.5	13.3	14.1
		(0.003)	(0.004)	(5.4)	(5.2)	(0.6)	(0.4)	(1.3)	(1.8)	(1.9)
	East	0.070	0.097	38.8	38.1	4.4	3.7	-6.8	21.0	17.5
		(0.002)	(0.003)	(6.0)	(6.3)	(1.7)	(0.7)	(2.1)	(6.1)	(4.4)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). Results for ΔI_0 and $\frac{B+C}{\Delta I_0}$ are displayed as percentages. Results for A to D are displayed as percentage points. See footnote 8. Results are based on the modified OECD equivalence scale.

Although the contribution of summand B is somewhat larger in magnitude,

[9] Although it is straightforward to interpret the fraction $\frac{B+C}{\Delta I_0}$ as the changing population's contribution to inequality change (Jenkins, 1995; Martin, 2006), one might argue that the effects are overstated when single summands have the opposite sign of the total change. This applies to summand D in our case.

both summands B and C contribute to this result; population subgroups that are characterized by smaller household size exhibit greater within-group inequality than others over time. Thus, the increase in relative size of these groups has contributed considerably to the overall increase in inequality. Moreover, these groups have mean incomes quite different from the overall mean, and their growth contributes to increasing inequality irrespective of increasing heterogeneity within groups. At the same time, the contribution to inequality growth from summand A, which comprises changes in within-group inequality, is rather pronounced as well. This clearly indicates that population subgroups defined by household composition have become more heterogenous over time. This is especially true for the largest part of the population, i.e., those people living in one- or two-person households. In West Germany pre fisc income inequality increased by 16.3% between 1991 and 2007. The share of summands B and C is 83%. The increase in overall pre fisc inequality in East Germany since reunification in 1991 (around 70%) is much more pronounced than in the West. Shrinking household size makes up 76% of the overall change.[10]

Post fisc incomes. Our results for post fisc income inequality decomposition show that the effect of changing household structures is less pronounced than for pre fisc income inequality. Altogether, post fisc income inequality increased by 37.8%, which is larger than the increase for pre fisc income, although the level of inequality is still much lower. The proportion of summands B and C amounts to 22.2% between 1991 and 2007, which is significantly lower than for pre fisc income. Examining West Germany alone reveals that the proportion of summands B and C between 1991 and 2007 (15.9%) is lower than for Germany as a whole. In East Germany income inequality grew by 38.8%. Summands B and C account for around 16.8%.

[10]Note that in 2007 inequality in East Germany is higher for pre fisc incomes compared to the West, but it is lower for post fisc incomes. The interpretation of this pattern is related to considerably different levels of unemployment in both parts of the country. In East Germany the unemployment rate is on average nearly twice as high than in the West. Hence, the proportion of people whose pre fisc income, i.e., without transfer payments, is close to zero is much higher there, so the relevance of higher unemployment is clearly considered as a "driving force".

Welfare state effects. Our results imply that the German tax-benefit system takes into account household structure and compensates for most (but not all) increases in inequality that can be related to demographic changes. There are several policies at work. For example, we observe an increase in the number of single parents. This population group is rather poor, since they typically exhibit low employment rates, which decreased from an already low level of 34% in 1991 to below 30% in 2007 and, if employed, only work for small number of hours (see table 4.7.1). Hence, their position in the pre fisc income distribution is much worse compared to other groups. However, single parents receive important benefits, targeting children in low-income households, as the implicit equivalence scales in the tax-benefit system generously compensate for the presence of children (Fuest et al., 2010) and hence, their relative position is improving. The same holds for poor households in general, since poorer people tend to have more children than rich people. Especially among the latter group, fertility is declining the most.

Furthermore, due to the highly progressive income tax system, a large fraction of the increasing income of double-earner couples is taxed away, which leads to post fisc inequality increasing less than pre fisc inequality. In particular, the high marginal tax rates on secondary earners' income – inherent in the German system of income taxation – reduces considerably post fisc income compared to market income of married double-earner couples. This lowers the relative position of this demographic group in the income distribution. Another example where the tax-benefit system had a direct impact on household formation is concerned with the Hartz reforms: These reforms of German labor market policy in 2005 generated incentives for young unemployed adults to leave their parents' house earlier in order to receive certain social benefits (or at least a higher amount).[11]

Household structure only. In order to obtain an idea of the relative importance of changing household size, we now present results based on the narrower definition of subgroups, which ignores the employment status of the household (see lower panel of table 4.5.1). Their characteristics in terms of population share,

[11]However, these incentives were reduced by legislation in 2006. Gallie and Paugam (2000) and Klasen and Woolard (2009), among others, deal with this issue in European and developing countries respectively.

mean incomes and group-specific measures of income distribution are listed in table 4.7.1 in the appendix.

We find that the relative importance of demographic change turns out to be somewhat smaller in magnitude. For pre fisc incomes we have a fraction of 61.4% for summands B and C (West: 73%, East: 50.5%), for post fisc incomes we have 17.4% (West: 13.3%, East: 21%). Hence, without accounting for the employment status, the explanatory contribution of household structure is reduced by 16.1 (4.8) pp for pre (post) fisc incomes. These differences are due to the less importance of summand C, i.e., shifts in population shares play a minor role for increasing between-group inequality.

Summands A to D are themselves aggregations over population subgroups (see equation 4.3.2). table 4.5.2 displays the contributions of each single population subgroup to the components of inequality change for pre and post fisc incomes respectively. It becomes apparent that for both summands B and C the results presented in table 4.5.2 are mainly “driven” by certain subgroups. Not surprisingly, it is especially the growth of one- and two-adult households (groups 1 and 3) which positively contributing to overall inequality change, since these are the only ones whose proportions among the population are noticeably increasing. Another group with a smaller, but still positive, contribution are single-parent households (group 2). All these groups exhibit above-average *and* increasing levels of inequality, within as well as between subgroups (see table 4.7.1). Increasing heterogeneity within the group of single-adult households is due to the fact that nowadays this group is no longer dominated by elderly people (pensioners, widows/widowers) with low pension incomes but consists more and more of young- and middle-aged individuals at different positions in their educational or professional careers. This is confirmed by the fact that the employment rate of singles increased from below average in 1991 (43%) to slightly above average in 2007 (49%). Moreover, income inequality is comparatively high among single-adult households because they are not able to re-distribute income *within* the household, while multi-person households share resources and hence individual household members’ income shocks, e.g., due to unemployment or retirement, can be cushioned.

Table 4.5.2: Inequality decomposition (1991–2007): results per group

Income	k	Adults	Children	A_k	B_k	C_k	D_k	$\frac{B_k+C_k}{\Delta I_0}$
pre	1	1	no	-9.1	9.8	8.7	-1.0	73.8
				(2.2)	(1.4)	(1.2)	(0.4)	(11.9)
	2	1	yes	2.6	0.9	2.0	1.2	11.8
				(0.4)	(0.3)	(0.6)	(0.2)	(3.5)
	3	2	no	5.1	8.7	10.7	0.1	77.5
				(1.9)	(1.2)	(1.5)	(0.1)	(13.8)
	4	2	yes	7.0	-2.8	-13.7	0.4	-66.1
				(0.7)	(0.3)	(1.5)	(0.1)	(9.5)
	5	≥3	no	2.0	-1.5	-6.5	0.0	-31.8
				(0.4)	(0.2)	(0.9)	(0.1)	(5.5)
	6	≥3	yes	1.4	-0.2	-0.8	0.0	-3.7
				(0.2)	(0.1)	(0.7)	(0.0)	(3.4)
	Total	–	–	9.0	15.0	0.4	0.6	61.4
				(2.9)	(1.2)	(0.1)	(0.5)	(7.7)
post	1	1	no	3.5	6.5	40.3	-1.1	123.8
				(3.3)	(1.0)	(5.7)	(0.5)	(20.6)
	2	1	yes	-1.8	1.0	9.9	0.9	28.9
				(0.4)	(0.3)	(2.8)	(0.5)	(8.3)
	3	2	no	10.7	6.9	51.2	3.9	154.0
				(2.5)	(1.0)	(7.4)	(0.7)	(27.3)
	4	2	yes	10.5	-6.0	-64.9	-2.3	-188.0
				(1.4)	(0.7)	(6.9)	(0.3)	(26.4)
	5	≥3	no	5.6	-2.6	-30.8	0.3	-88.5
				(0.9)	(0.4)	(4.2)	(0.3)	(15.1)
	6	≥3	yes	0.9	-0.4	-4.5	-0.0	-12.9
				(0.4)	(0.3)	(3.3)	(0.1)	(9.5)
	Total	–	–	29.4	5.4	1.2	1.7	17.4
				(4.4)	(0.6)	(0.3)	(1.1)	(2.1)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). Results for $\frac{B_k+C_k}{\Delta I_0}$ are displayed as percentages. Results for A_k to D_k are displayed as percentage points. See footnote 8. Results are based on the modified OECD equivalence scale.

Role of the Equivalence Scale. The choice of equivalence scale is not irrelevant with respect to our research question. Inequality rankings in cross-country comparison are sensitive to different values of the equivalence-scale elasticity (Buhmann et al., 1988; Hagenaars et al., 1994; Ebert and Moyes, 2003; Bönke and Schröder, 2012). Most of the equivalence scales (ES) used in practice (e.g., Jenkins and Cowell, 1994; Burkhauser et al., 1996) can be written in the general form of

$$ES = (\theta_1 + \theta_2 \cdot N_A + \theta_3 \cdot N_C)^\gamma, \tag{4.5.1}$$

where θ_1 denotes an extra weight for the (adult) head of the household, θ_2 denotes the weight for (additional) adult household members (N_A) and θ_3 denotes the weight of children (N_C). For smaller values of the parameter γ the importance of economies of scale in household consumption increases.[12] In order to make certain that these results are not due to a specific choice of equivalence scale we calculate the fraction of summands B and C for the inequality decomposition for various specifications of the general form of the equivalence scale in equation (4.5.1). The results for both definitions of population subgroups are presented in table 4.5.3. We find that the choice of does not alter the results significantly. Not surprisingly, it turns out that the proportion of the demographic effect is somewhat larger in specifications when large economies of scale are assumed (i.e., for smaller values of γ). Moreover, we find that even for per-capita incomes, i.e., in the absence of scale economies, a sizeable fraction of inequality change (60%/77% for pre and 17%/21% for post fisc income) can be attributed to changing household and employment structure.

[12] See, e.g., Cutler and Katz (1992); Banks and Johnson (1994). Note that for $\theta_1 = \theta_2 = 0.5$, $\theta_3 = 0.3$, and $\gamma = 1$ we arrive at the modified OECD scale, for $\theta_1 = 0$, $\theta_2 = \theta_3 = 1$, and $\gamma = 0.5$ at the square-root scale, while using a scale with $\theta_1 = 0$, $\theta_2 = \theta_3 = 1$, and $\gamma = 1$ is equivalent to using per-capita incomes, i.e., assuming no economies of scale.

Table 4.5.3: Inequality decomposition (1991–2007): different equivalence scales

	$\theta_1 = \theta_2 = 0.5$						$\theta_1 = 0; \theta_2 = 1$					
	$\theta_3 = 0.3$		$\theta_3 = 0.5$		$\theta_3 = 1$		$\theta_3 = 0.3$		$\theta_3 = 0.5$		$\theta_3 = 1$	
Income	$\gamma = 0.5$	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 1$	$\gamma = 0.5$	$\gamma = 1$
	Household structure and employment status											
pre fisc	79.1	77.5	79.3	78.1	78.9	76.8	78.5	77.9	78.7	78.6	78.3	77.3
	(6.3)	(5.8)	(6.4)	(6.0)	(6.3)	(5.7)	(6.1)	(5.6)	(6.1)	(5.8)	(6.1)	(5.6)
post fisc	23.3	22.2	23.4	22.9	22.8	20.1	21.7	24.3	22.3	26.5	20.8	21.1
	(2.3)	(2.5)	(2.6)	(3.2)	(2.0)	(1.9)	(2.2)	(2.9)	(2.4)	(3.5)	(2.0)	(2.5)
	Household structure only											
pre fisc	65.1	61.4	65.4	62.1	65.8	63.0	62.9	58.1	63.1	58.6	63.6	59.7
	(8.7)	(7.7)	(8.7)	(7.8)	(8.9)	(8.4)	(8.1)	(6.8)	(8.2)	(6.9)	(8.3)	(7.2)
post fisc	21.8	17.4	21.8	17.4	21.1	13.4	18.3	15.2	18.7	16.5	19.1	17.1
	(2.5)	(2.1)	(2.5)	(2.3)	(2.7)	(2.9)	(2.1)	(2.2)	(2.1)	(2.5)	(2.3)	(3.1)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). Note that for $\theta_1 = \theta_2 = 0.5$, $\theta_3 = 0.3$, and $\gamma = 1$ we arrive at the modified OECD scale, for $\theta_1 = 0$, $\theta_2 = \theta_3 = 1$, and $\gamma = 0.5$ at the square-root scale, while using a scale with $\theta_1 = 0$, $\theta_2 = \theta_3 = 1$, and $\gamma = 1$ is equivalent to using per-capita incomes, i.e., assuming no economies of scale (see section 4.4.2).

Poverty and Richness. The results for the decomposition of poverty and richness change are presented in table 4.5.4.[13] We find that the demographic effect on poverty change sums to more than half of total change (between 50.3% and 75.1%). The richness measures for post fisc incomes increased quite considerably between 1991 and 2007 – by more than 76% for $\beta = 1$ and by two thirds for $\beta = 3$. The head count ratio for richness (HC) increased by more than 46%. Frick and Grabka (2010) provide evidence for the increasing relevance of (net) income from returns on investments, i.e., from capital income and from imputed rent for owner-occupied housing (see also section 4.4.2). This source of income is especially concentrated in top income households. Based on the same data and for the same period of time, they find a dampening effect of imputed rent on inequality, while capital income clearly contributes to rising inequality. Since both income types serve as old-age provision in addition to public pensions, it is not surprising that – in the light of an ageing society in Germany – we find evidence for more concentration at the top of the income distribution. The fraction of overall richness change that can be attributed to demographic changes amounts to minuscule values – between -1% and 2%. Although insignificant, the negative value for the richness headcount implies that changing population structure marginally dampened the growth in richness, i.e., those groups with relatively high levels of richness are becoming smaller, while "poorer" groups with low levels of richness are growing.

Household structure only. In the lower panel of table 4.5.4 we also present results of the decomposition for poverty and richness based on the distinction of population subgroups according to household structure only. Although the resulting values for the fraction of summand B are smaller in magnitude, the picture is qualitatively the same: the proportion amounts to values between 35.8% and 37.5% in case of income poverty and between 7.4% and 9% in the case of richness. That is, changing patterns in household formation contributed much more to the growth at the bottom than to the upper tail of the income distribution.

[13]Note that we restrict our analysis to post fisc incomes, which is the measure usually used as a proxy for well-being in the context of poverty (and richness) analysis.

Table 4.5.4: Poverty and richness decomposition (1991–2007)

	α	P_α^{1991}	P_α^{2007}	ΔP_α	A	B	$B/\Delta P_\alpha$
Household structure and employment status							
Poverty	HC	0.115	0.141	22.6	5.6	17.0	75.1
		(0.003)	(0.004)	(5.1)	(4.7)	(2.0)	(18.5)
	1	0.024	0.033	36.4	15.5	20.9	57.5
		(0.001)	(0.001)	(7.8)	(6.8)	(2.7)	(12.2)
	2	0.008	0.012	47.2	23.5	23.8	50.3
		(0.000)	(0.001)	(11.5)	(10.1)	(3.3)	(14.0)
	β	R_β^{1991}	R_β^{2007}	ΔR_β	A	B	$B/\Delta R_\beta$
Richness	1	0.011	0.019	76.1	74.6	1.4	1.9
		(0.001)	(0.001)	(11.5)	(12.0)	(1.9)	(2.4)
	3	0.023	0.039	65.8	65.0	0.7	1.1
		(0.001)	(0.001)	(9.7)	(10.1)	(1.8)	(2.6)
	HC	0.056	0.081	46.6	47.0	-0.4	-0.9
		(0.002)	(0.002)	(7.1)	(7.4)	(1.5)	(3.2)
Household structure only							
Poverty	HC	0.115	0.141	22.6	14.1	8.5	37.5
		(0.003)	(0.004)	(5.1)	(4.7)	(1.2)	(8.8)
	1	0.024	0.033	36.4	23.2	13.2	36.3
		(0.001)	(0.001)	(7.8)	(6.9)	(1.8)	(7.7)
	2	0.008	0.012	47.2	30.3	16.9	35.8
		(0.000)	(0.001)	(11.5)	(10.1)	(2.4)	(9.4)
	β	R_β^{1991}	R_β^{2007}	ΔR_β	A	B	$B/\Delta R_\beta$
Richness	1	0.011	0.019	76.1	70.4	5.7	7.4
		(0.001)	(0.001)	(11.6)	(11.6)	(1.2)	(1.9)
	3	0.023	0.039	65.8	60.7	5.0	7.7
		(0.001)	(0.001)	(9.7)	(9.7)	(1.2)	(2.0)
	HC	0.056	0.081	46.6	42.4	4.2	9.0
		(0.002)	(0.002)	(7.1)	(7.1)	(1.0)	(2.5)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). Results for ΔP_α and $B/\Delta P_\alpha$ are displayed as percentages. Results for A and B are displayed as percentage points. See footnote 8. Results are based on the modified OECD equivalence scale.

4.5.2 Re-weighting

A different approach to assess the effect of changing household structure on income distribution over time is to compare the actual change in distributional measures to the change that would have occurred had household structure remained unchanged between the base period of our analysis (1991) and the most recent period available (2007), everything else equal. To do so, one has to assign counterfactual population weights to the sample population of 2007 in order to arrive at a marginal distribution of household structure identical to the one in 1991.

As pointed out in subsection 4.3.2, this is done by re-defining population weights by multiplying the actual population weights with a re-weighting factor that is equal to the ratio of the population shares in the base and final period. Formally, one can write the counterfactual population weights as

$$\widetilde{w}_i^{2007} = w_i^{2007} \cdot \frac{v_{k,i}^{1991}}{v_{k,i}^{2007}} = w_i^{2007} \cdot \psi_x(x), \qquad (4.5.2)$$

where w_i^{2007} denotes the actual population weight of individual i in 2007 and $v_{k,i}$ denotes the population share of subgroup k to which individual i belongs. The re-weighting function $\psi_x(x)$ reduces to the fraction of population shares in case of not controlling for further characteristics.[14]

We apply this type of re-weighting for Germany and report calculations for different GE inequality measures (I_0, I_1, and I_2) as well as for the Gini coefficient (I_{Gini}) and the measures for poverty and richness introduced in the previous sections. We compute how large the change in measures of distribution would have been had the marginal distribution of household structure not have changed between 1991 and 2007 (Δ^{rew}) and compare it to the actual observed change (Δ^{act}).

[14] It would be possible to include additional controls in the re-weighting procedure. However, when doing so we find rather similar results (available upon request). Therefore, in order to make the re-weighting procedure and the decomposition approach directly comparable, as well as in order to compare our results to OECD (2008), we concentrate on simple re-weighting here. Note that this also corresponds to the first counterfactual in the analysis of Hyslop and Mare (2005).

One can easily show that the following holds

$$\frac{\Delta^{act} - \Delta^{rew}}{\Delta^{act}} = \frac{M^{act,07} - M^{rew,07}}{M^{act,07} - M^{act,91}}. \tag{4.5.3}$$

This term denotes the share of the changing household structure in the total change of the respective measure $M \in \{I, P, R\}$. Note that it would equal zero if the re-weighted counterfactual value in 2007 resembled the actual one, i.e., the changing household structure would not affect the change at all. In the other extreme case the term would equal 100% if the household structure were related to the total change of the measure. The results are displayed in table 4.5.5. For the re-weighting procedure one can summarize that actual growth rates of the measures of distribution – without exception – are larger than the counterfactual re-weighted growth rates for pre fisc as well as for post fisc incomes. In other words, the results of our re-weighting procedures state that inequality, poverty and richness would not have increased as much as they actually did had there not been a trend towards smaller households.

For I_0 we find results which are very close to our decomposition results. A fraction of around 80% (23.7%) of the increase in pre (post) fisc inequality is related to changes in household size. This is not surprising given the way we employ the re-weighting, i.e., only accounting for changing household structure and not adding further control variables when defining the re-weighting function. Examining other inequality measures reveals that the magnitudes of the relative importance of household structure differs, but the general pattern of rather high fractions for market income inequality and much lower values for inequality in disposable income inequality still holds. For example, around half of the increase in the Gini coefficient before taxes and transfers are related to changing population structure. Here one has to take into account that different measures highlight different parts of the income distribution differently. While the decomposable measure I_0 is more sensitive to changes in the lower tail of the distribution, the Gini coefficient is known be less sensitive to changes in the extreme tails. Furthermore, the pre fisc fraction for the GE measures I_1 and I_2 (48% and 38% respectively) are somewhat lower, but still rather large. These measures are more sensitive to the distribution's upper tail. The relative importance for post fisc inequality varies

Table 4.5.5: Re-weighting: inequality, poverty and richness (1991–2007)

	pre fisc			post fisc		
Measure	Δ^{act}	Δ^{rew}	$\frac{\Delta^{act}-\Delta^{rew}}{\Delta^{act}}$	Δ^{act}	Δ^{rew}	$\frac{\Delta^{act}-\Delta^{rew}}{\Delta^{act}}$
I_{Gini}	18.4	9.2	50.2	16.1	12.5	22.9
	(1.4)	(1.3)	(3.2)	(1.7)	(1.5)	(2.5)
I_0	25.0	5.0	80.1	37.8	28.8	23.7
	(3.6)	(2.9)	(9.4)	(4.5)	(3.9)	(2.5)
I_1	40.0	20.7	48.2	54.2	43.1	20.5
	(5.5)	(4.2)	(3.9)	(10.3)	(8.5)	(2.8)
I_2	107.1	66.7	37.7	187.2	148.7	20.6
	(37.3)	(26.5)	(4.1)	(81.3)	(65.3)	(3.1)
	post fisc incomes					
	Poverty			Richness		
P_0/R_0	22.6	10.7	52.9	46.6	40.3	13.6
	(5.1)	(4.5)	(13.1)	(7.2)	(7.2)	(4.6)
P_1/R_3	36.4	21.1	42.0	65.8	56.8	13.6
	(7.7)	(7.0)	(9.3)	(9.7)	(9.5)	(2.9)
P_2/R_1	47.2	29.4	37.7	76.1	65.9	13.4
	(11.5)	(10.2)	(10.7)	(11.5)	(11.4)	(2.9)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). Note that the results for actual (Δ^{act}) and re-weighted changes (Δ^{rew}) as well as the term $\frac{\Delta^{act}-\Delta^{rew}}{\Delta^{act}}$ are displayed as percentages, i.e., they were multiplied by 100. Results are based on the modified OECD equivalence scale.

much less – between 20.5% and 24%.

The re-weighting results for poverty and richness indices differ somewhat from the decomposition results with respect to the point estimates. However, the standard errors are quite large and hence confidence bands overlap. So these differences are not statistically significant. Moreover, they can be explained by the fact that the poverty and richness measures we employ are non-linear, since the value functions are concave. In particular, we find that between 38% and 53% of the increase in poverty measures relate to changing population structure. The fraction decreases for poverty measures which are more sensitive to extreme poverty. The corresponding result for the richness indices varies around 13–14%.

4.6 Conclusions

The aim of this chapter is to quantify the effect of continually decreasing average household size on measures of income distribution in Germany. By means of a re-weighting procedure and decompositions of changes in measures of income distribution based on SOEP data, we compute to what extent the overall changes in income distribution result from changes in population structure with respect to household composition.

Irrespective of the choice of methodology, it appears that Germany's changing population structure with respect to household composition during the period between 1991 and 2007 is associated with increasing values for indices of inequality, poverty and richness under consideration. Without the demographic trend towards smaller households, inequality, poverty and richness would have also increased. However, the levels would be far lower than they actually are. The remaining increase could be attributed to a declining bargaining power of unions, to changes in the distribution of human capital as well as to changes in occupational choices (Bourguignon et al., 2001; Hyslop and Mare, 2005; Lemieux, 2010). Investigating these factors is left to future research.

We find that the effect of demographic change on income distribution is much lower for post fisc than for pre fisc incomes. This means that the tax-benefit system in Germany provides – at least implicitly – some form of compensation for changing household structure. However, one could also argue that the German tax-benefit system itself has an effect on the demographic trend, i.e., the causal relationship could go in both directions. In this context, it is not implausible to think of household formation as an endogenous process which is partly shaped by incentives provided by macro conditions and tax-benefit systems. However, analyzing this is beyond the scope of this chapter.

4.7 Appendix

Table 4.7.1: Population subgroups: household structure (1991–2007)

k	Adults/Child.	$v_{k,1991}$	Δv_k	$\bar{y}_{k,1991}^{0,post}$	$\Delta \bar{y}_k^{0,post}$	Empl.	ΔEmpl.	Hours	ΔHours	$I_{0,post}^{k,1991}$	$\Delta I_{0,post}^{k}$	$I_{0,pre}^{k,1991}$	$\Delta I_{0,pre}^{k}$	$P_{0,post}^{k,1991}$	$\Delta P_{0,post}^{k}$	$R_{0,post}^{k,1991}$	$\Delta R_{0,post}^{k}$
1	1/no	0.158	0.042	17,332	1,384	0.43	0.06	17.0	1.6	0.152	0.020	1.301	-0.272	0.240	-0.010	0.051	0.008
		(0.004)	(0.006)	(415)	(556)	(0.02)	(0.02)	(0.7)	(0.8)	(0.011)	(0.019)	(0.050)	(0.067)	(0.013)	(0.017)	(0.007)	(0.008)
2	1/yes	0.028	0.009	12,274	-848	0.34	-0.05	11.7	-3.6	0.141	-0.056	0.345	0.427	0.431	0.061	0.026	-0.023
		(0.002)	(0.003)	(477)	(518)	(0.03)	(0.04)	(1.0)	(1.2)	(0.012)	(0.014)	(0.033)	(0.062)	(0.031)	(0.034)	(0.010)	(0.009)
3	2/no	0.258	0.053	20,900	2,542	0.53	-0.05	19.9	-2.5	0.117	0.039	0.763	0.090	0.089	-0.000	0.091	0.036
		(0.005)	(0.007)	(208)	(359)	(0.01)	(0.01)	(0.4)	(0.5)	(0.005)	(0.009)	(0.022)	(0.032)	(0.005)	(0.008)	(0.005)	(0.008)
4	2/yes	0.326	-0.068	17,317	2,665	0.46	0.00	16.9	-1.2	0.074	0.038	0.149	0.117	0.089	0.022	0.031	0.038
		(0.005)	(0.007)	(119)	(230)	(0.01)	(0.01)	(0.3)	(0.5)	(0.002)	(0.005)	(0.005)	(0.011)	(0.004)	(0.008)	(0.003)	(0.005)
5	≥3/no	0.150	-0.032	21,742	470	0.69	-0.06	25.2	-3.5	0.064	0.044	0.190	0.074	0.041	0.032	0.063	0.024
		(0.003)	(0.004)	(203)	(351)	(0.01)	(0.02)	(0.5)	(0.7)	(0.003)	(0.007)	(0.010)	(0.015)	(0.005)	(0.008)	(0.005)	(0.009)
6	≥3/yes	0.080	-0.005	17,917	28	0.53	-0.07	19.5	-4.3	0.075	0.012	0.141	0.088	0.087	0.071	0.048	-0.021
		(0.002)	(0.003)	(201)	(318)	(0.01)	(0.02)	(0.6)	(0.9)	(0.003)	(0.005)	(0.006)	(0.012)	(0.007)	(0.016)	(0.006)	(0.007)
Total	–	1.000	0.000	18,816	1,782	0.51	-0.03	19.0	-1.8	0.105	0.040	0.500	0.125	0.115	0.026	0.056	0.026
		(0.000)	(0.000)	(107)	(163)	(0.01)	(0.01)	(0.2)	(0.3)	(0.002)	(0.004)	(0.010)	(0.016)	(0.003)	(0.005)	(0.002)	(0.003)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). The population share of group k is denoted with v_k. Δ denotes the difference-operator. Group mean incomes ($\bar{y}_k$) are annual equivalent post fisc incomes (in euros, prices of 2006, modified OECD scale).

Table 4.7.2: Population subgroups: household structure and employment status (1991–2007)

k	Adults	Children	Employed	$v_{k,1991}$	Δv_k	$\bar{y}^{0,post}_{k,1991}$	$\Delta\bar{y}^{0,post}_k$	Hours	ΔHours	$I^{k,1991}_{0,post}$	$\Delta I^k_{0,post}$	$I^{k,1991}_{0,pre}$	$\Delta I^k_{0,pre}$	$P^{k,1991}_{0,post}$	$\Delta P^k_{0,post}$	$R^{k,1991}_{0,post}$	$\Delta R^k_{0,post}$
1	1	no	0	0.090	0.011	14,102	1,719	0.2	-0.0	0.125	0.029	1.216	-0.096	0.356	-0.032	0.019	0.018
				(0.003)	(0.005)	(391)	(471)	(0.1)	(0.1)	(0.012)	(0.014)	(0.074)	(0.086)	(0.020)	(0.024)	(0.005)	(0.008)
2	1	no	1	0.067	0.031	21,661	49	39.5	-1.8	0.135	0.031	0.212	0.142	0.084	0.047	0.095	-0.012
				(0.003)	(0.004)	(679)	(9)	(0.7)	(0.9)	(0.019)	(0.030)	(0.026)	(0.037)	(0.011)	(0.015)	(0.015)	(0.016)
3	1	yes	0	0.007	0.006	8,218	834	0.9	-0.7	0.132	-0.077	0.437	0.635	0.732	-0.014	0.000	0.000
				(0.001)	(0.002)	(567)	(636)	(0.6)	(0.6)	(0.025)	(0.028)	(0.052)	(0.145)	(0.052)	(0.062)	(0.000)	(0.000)
4	1	yes	1	0.021	0.004	13,726	-1,004	15.5	-3.1	0.112	-0.032	0.218	0.191	0.323	0.046	0.035	-0.030
				(0.001)	(0.002)	(518)	(544)	(1.2)	(1.5)	(0.011)	(0.014)	(0.020)	(0.046)	(0.030)	(0.037)	(0.013)	(0.013)
5	2	no	0	0.093	0.040	16,110	3,103	0.0	0.0	0.102	0.034	0.912	0.133	0.174	-0.030	0.034	0.030
				(0.003)	(0.005)	(370)	(510)	(0.0)	(0.0)	(0.011)	(0.014)	(0.047)	(0.062)	(0.012)	(0.017)	(0.007)	(0.008)
6	2	no	1	0.072	0.014	20,820	3,177	22.1	-0.3	0.104	0.072	0.228	0.191	0.069	0.011	0.079	0.042
				(0.003)	(0.003)	(418)	(1,007)	(0.7)	(1.0)	(0.008)	(0.025)	(0.020)	(0.037)	(0.008)	(0.014)	(0.012)	(0.016)
7	2	no	2	0.094	0.000	25,701	3,202	37.8	0.1	0.087	0.029	0.128	0.056	0.021	-0.001	0.157	0.065
				(0.003)	(0.004)	(418)	(527)	(0.4)	(0.6)	(0.007)	(0.009)	(0.009)	(0.014)	(0.004)	(0.007)	(0.011)	(0.017)
8	2	yes	0	0.005	0.012	12,827	187	0.3	0.5	0.063	0.065	0.813	0.119	0.372	0.137	0.000	0.021
				(0.001)	(0.001)	(601)	(857)	(0.2)	(0.5)	(0.013)	(0.020)	(0.189)	(0.215)	(0.056)	(0.066)	(0.000)	(0.008)
9	2	yes	1	0.137	-0.041	15,574	2,257	12.1	0.2	0.070	0.023	0.157	0.096	0.139	0.004	0.012	0.032
				(0.003)	(0.004)	(146)	(246)	(0.5)	(0.8)	(0.003)	(0.006)	(0.009)	(0.017)	(0.009)	(0.014)	(0.003)	(0.007)
10	2	yes	≥2	0.185	-0.039	18,724	3,475	20.9	-1.2	0.070	0.034	0.111	0.068	0.046	-0.001	0.045	0.045
				(0.003)	(0.005)	(157)	(347)	(0.4)	(0.6)	(0.003)	(0.006)	(0.005)	(0.010)	(0.003)	(0.006)	(0.005)	(0.008)
11	≥3	no	0	0.006	0.002	18,820	-3,353	0.2	0.8	0.125	0.007	1.159	-0.403	0.279	0.064	0.103	-0.072
				(0.001)	(0.001)	(1,507)	(1,718)	(0.2)	(0.5)	(0.015)	(0.023)	(0.148)	(0.159)	(0.066)	(0.079)	(0.052)	(0.053)
12	≥ 3	no	1	0.031	-0.003	19,508	359	14.1	1.5	0.079	0.055	0.264	0.088	0.090	0.044	0.031	0.019
				(0.002)	(0.003)	(508)	(909)	(1.1)	(1.6)	(0.009)	(0.023)	(0.026)	(0.045)	(0.016)	(0.023)	(0.010)	(0.015)
13	≥3	no	≥2	0.113	-0.031	22,503	1,172	29.5	-3.7	0.054	0.033	0.091	0.051	0.015	0.011	0.069	0.035
				(0.003)	(0.004)	(217)	(388)	(0.5)	(0.8)	(0.002)	(0.005)	(0.003)	(0.009)	(0.002)	(0.005)	(0.006)	(0.011)
14	≥3	yes	0	0.000	0.003	11,030	158	0.0	0.3	0.020	0.018	0.839	-0.407	0.549	0.096	0.000	0.000
				(0.000)	(0.000)	(1,165)	(386)	(0.0)	(0.3)	(0.007)	(0.017)	(0.323)	(0.322)	(0.262)	(0.275)	(0.000)	(0.000)
15	≥3	yes	1	0.015	0.004	16,383	-544	11.4	-1.3	0.110	0.007	0.271	0.072	0.184	0.173	0.067	-0.052
				(0.001)	(0.002)	(596)	(759)	(1.5)	(1.9)	(0.012)	(0.013)	(0.028)	(0.039)	(0.027)	(0.046)	(0.016)	(0.016)
16	≥3	yes	≥2	0.065	-0.012	18,302	811	21.4	-3.5	0.066	0.003	0.102	0.031	0.063	-0.006	0.044	-0.011
				(0.002)	(0.003)	(217)	(359)	(0.6)	(1.0)	(0.003)	(0.005)	(0.004)	(0.009)	(0.007)	(0.014)	(0.007)	(0.009)
Total	–	–	–	1.000	0.000	18,816	1,782	19.0	-1.8	0.105	0.040	0.500	0.125	0.115	0.026	0.056	0.026
				(0.000)	(0.000)	(107)	(163)	(0.2)	(0.3)	(0.002)	(0.004)	(0.010)	(0.016)	(0.003)	(0.005)	(0.002)	(0.003)

Note: Own calculations based on SOEP. Bootstrapped standard errors in parentheses (500 replications). The population share of group k is denoted with v_k. Δ denotes the difference-operator. Group mean incomes ($\bar{y}_k$) are annual equivalent post fisc incomes (in euros, prices of 2006, modified OECD scale).

Chapter 5

Multidimensional Affluence: Income and Wealth*

5.1 Introduction

The top of the income distribution has recently received increasing attention both in the literature on economic inequality as well as in public debate (see Atkinson and Piketty, 2007; Waldenström, 2009; Atkinson et al., 2011, for overviews). "The rich" are an important source of both economic growth and economic inequality. Moreover, they wield considerable economic and political power. Therefore, especially with regard to the design of public policies (taxation), it is important to know who the rich in society are and how many and what kind of resources they command. However, according to Frank (2007), John Kenneth Galbraith's famous statement that the rich are the most noticed and the least studied of all classes "*has never been more true than today*". When determining who belongs to the top, the literature has so far only been concerned with a single dimension (either income or wealth) and has mainly focused on the shares of top fractiles.[1] However, neither a headcount ratio nor top shares are satisfying measures for (inequality of) economic

*This chapter is based on the papers *Multidimensional Affluence: Theory and Applications to Germany and the US* and *Multidimensional Well-Being at the Top: Evidence for Germany* (both joint with Andreas Peichl, see Peichl and Pestel, 2011, 2012).

[1]See, e.g., Atkinson (2005); Dell (2005); Piketty (2005); Saez (2005); Saez and Veall (2005); Piketty and Saez (2006); Atkinson and Piketty (2007); Roine and Waldenström (2008); Roine et al. (2009); Brzezinski (2010); Roine and Waldenström (2011).

well-being at the top because they do not account for changes in the composition or in the distribution among the top. Moreover, analyzing top income and wealth shares separately does not reveal insights about their *joint* distribution. However, well-being is usually not perceived as an one-dimensional phenomenon and therefore the analysis should be extended to more dimensions (Stiglitz et al., 2009). For this reason, there has been growing interest in multidimensional poverty measurement (see, e.g., Atkinson, 2003b; Bourguignon and Chakravarty, 2003; Decancq and Ooghe, 2010; Alkire and Foster, 2011a; Decancq and Lugo, 2012).

In this chapter, we propose a class of multidimensional affluence measures which extends the analysis of top inequality to more than one dimension. This approach allows obtaining a better picture of the (joint) distribution of economic well-being at the top. First, our measures do not only take into account the number of individuals' affluent dimensions, but are also sensitive to changes in achievements within each dimension. This allows to investigate inequality among the rich and to explicitly analyze the intensity of affluence. Second, the multidimensional measures allow analyzing the joint distribution of various dimensions simultaneously. Our approach is related to the work of Alkire and Foster (2011a), who extend well-known poverty measures (Foster et al., 1984, FGT henceforth) to a multidimensional setting. We adopt an analogous approach and extend the one-dimensional affluence measures developed by Peichl et al. (2010). Central to this is a *dual cutoff method* that identifies those individuals considered to be multidimensionally affluent. In a first step, an individual is considered as dimension-specific rich when its achievement in a particular dimension of well-being exceeds the respective cutoff value. In a second step, we define which of the dimension-specific rich individuals are considered to be affluent in a multidimensional sense. This is the case if the total number of affluent dimensions is greater than or equal to a certain threshold (second cutoff). Hence, the joint distribution of dimensions under consideration is explicitly taken into account and both affluence in marginal distributions of dimensions as well as the extent of overlap in affluence between dimension is combined in one single number.

As suggested by Stiglitz et al. (2009), we consider wealth as an additional dimension besides income in order to capture the breadth of affluence (Cowell, 2011). This is important, since the rich are not a homogenous group, especially in terms of income and wealth composition (Atkinson, 2008a; Waldenström, 2009). For instance, a differentiation can be made between the high-skilled "working rich" earning large salaries and the "coupon clippers" with large wealth holdings and capital income (Kopczuk and Saez, 2004). Wealth is typically more unequally distributed than income (Jenkins and Jäntti, 2005; Davies et al., 2011) and (though positively) not perfectly correlated with it (Kennickell, 2009). In fact, marginal distributions can be shaped very differently (OECD, 2008; Jäntti et al., 2008; Roine and Waldenström, 2009). Therefore, analyzing the joint distribution reveals additional insights about the composition of the top of the distribution and allows us to quantify the contribution each dimensions to multidimensional affluence.[2]

We illustrate our approach using comparable microdata in order to analyze multidimensional affluence across countries (Germany and the US in 2007) and over time (the US from 1989 to 2007). Comparing these two countries is of special interest since they represent two distinct welfare state regimes and exhibit different trends in inequality (Fuchs-Schündeln et al., 2010; Heathcote et al., 2010). Unfortunately, administrative data comprising information on both income and wealth is not available. Hence, we must rely on survey data for our empirical illustration. We extensively discuss issues arising from this and compare our results to findings from German tax return data.

Our empirical analysis yields the following results. We find that the correlation between income and wealth is far from perfect in both countries and particularly weak in Germany. The ranking of the two countries in terms of affluence depends on the choice of multidimensional measure. When emphasizing large levels of income and/or wealth of a small group of individuals and hence inequality among the rich population, the US clearly is richer than Germany as income and wealth are much more concentrated at the very top. This type of affluence increased in the US between 1989 and 2007. These findings confirm previous results highlighting the tremendous increases at the very top (Atkinson et al., 2011). In contrast, when putting more emphasis on the homogeneity of the rich population, it turns out that

[2]In principle, it would be possible to combine both income and wealth into an extended income measure by annualizing the stock of wealth (Smeeding and Thompson, 2011). However, this implies the assumption that a stock of assets has the same characteristics as income and ignores particular functioning of wealth, e.g., as a source of power and social status or as means for consumption smoothing.

affluence is slightly larger in Germany. This type of affluence has remained almost constant in the US throughout a period of nearly two decades. Furthermore, we find that in Germany wealth predominantly contributes to intense affluence while income is more important in the US.

The chapter is organized as follows: Section 5.2 introduces the concept of measuring multidimensional affluence before we describe the data in section 5.3. Our results are presented in section 5.4. Section 5.5 concludes.

5.2 Measuring Multidimensional Affluence

5.2.1 One-dimensional Affluence

While an extensive literature on the measurement of poverty exists, little research has been carried out on richness (Medeiros, 2006). Indices of affluence have so far mostly been restricted to headcount ratios or top income shares (Eisenhauer, 2011). We argue, however, that the measurement of affluence at the top should be extended – as it has been done for poverty (see, e.g., Foster et al., 1984). A headcount ratio is only concerned with the number of people above a certain cutoff and an income change will not affect this index if nobody crosses the threshold. A top income share analyzes the amount of income for a fixed number of people without accounting for changes in the number of rich individuals, the composition of the rich subpopulation nor changes in the distribution of income among the top.

Peichl et al. (2010) propose a class of affluence measures analogously to well-known measures of poverty (Foster et al., 1984). The general idea is to take into account the number of affluent people (composition of the rich subpopulation) as well as the intensity of affluence (distribution among the rich) for individuals above a certain threshold ("affluence line"). An index of affluence is constructed as the weighted sum of the individual contributions. The weighting function is supposed to have some desirable properties, which are derived following the literature on axioms for poverty indices (especially the focus, continuity, monotonicity and subgroup decomposability axioms, see Peichl et al., 2010, for details). Thereby, the transfer axiom of poverty measurement cannot be translated one-to-one to richness measurement and has to be discussed in more detail. A poverty index satisfies the transfer axiom if the index decreases when a rank-preserving progressive transfer from a poor person to someone who is poorer takes place. This property can be translated to the richness measurement in two different ways:

- *Transfer axiom T1 (concave):* an affluence index shall increase when a rank-preserving progressive transfer between two affluent persons takes place.
- *Transfer axiom T2 (convex):* an affluence index shall decrease when a rank-preserving progressive transfer between two affluent persons takes place.

The question behind the definition of these opposite axioms is: shall an index of affluence increase if a billionaire gives an amount x to a millionaire (*T1*), or if the millionaire gives the same amount x to the billionaire (*T2*). This cannot be answered without normative judgement and depends on the research question (Peichl et al., 2010). A more equal distribution among the rich will lead to a more homogenous group, which could allow them to better coordinate in pursuing their interests. If one is interested in this case, the concave approach is more appropriate. In contrast, the convex measure reflects inequality among the rich and the concentration of resources at the very top. This view is also more consistent with the view of Atkinson (2007a) who considers richness as a source of power. In addition, there is a serious drawback to the concave approach: it is not compatible with the weak transfer axiom, i.e., how a progressive transfer from a rich individual to another person (rich or non-rich) will change the affluence index (see the discussion in Peichl et al., 2010). This implies that the choice of the richness line is much more important than in the convex case. As a consequence, the sensitivity with respect to choice of the affluence line should be carefully checked (see, e.g., the discussion in Medeiros, 2006).

Because of the two possibilities for the transfer axiom, Peichl et al. (2010) define two classes of affluence indices which either fulfil T1 or T2 as follows. Let y_i be the income of individual i, γ the affluence line (i.e., the threshold above which someone is defined to be rich) and $r = \#\{i|y_i > \gamma, i = 1, \dots, n\}$ the number of affluent persons. For *T1* the relative incomes y_i/γ have to be transformed by a function that is concave on $(1, \infty)$. Peichl et al. (2010) use $f(x) = \left(1 - \frac{1}{x^\beta}\right) \cdot \mathbf{1}_{x>1}$ where $\beta > 0$ and $\mathbf{1}_{x>1}$ denotes an indicator function taking on values of one if

$x > 1$ and zero otherwise:

$$R_{\beta}^{Cha}(\mathbf{y},\gamma) = \frac{1}{n}\sum_{i=1}^{n}\left(1 - \left(\frac{\gamma}{y_i}\right)^{\beta}\right)_{+}, \beta > 0. \tag{5.2.1}$$

The subscript "+" indicates that the expression in brackets must be greater than or equal to zero. For *T2*, Peichl et al. (2010) use $f(x) = (x-1)^{\alpha}$ for $x > 1$, with $\alpha > 1$, to obtain an affluence index that resembles the FGT index of poverty:

$$R_{\alpha}^{FGT,T2}(\mathbf{y},\gamma) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i}{\gamma} - 1\right)^{\alpha} \cdot \mathbf{1}_{y_i > \gamma} = \frac{1}{n}\sum_{i=1}^{n}\left(\left(\frac{y_i - \gamma}{\gamma}\right)_{+}\right)^{\alpha}, \alpha > 1. \tag{5.2.2}$$

In contrast to poverty, however, the normative (welfare) justification of any measure are less straightforward in the case of richness. While it is clear that poverty is a bad thing, this is less so for richness. Clearly, more affluence is bad if the threshold is set at x% of the distribution since it captures inequality – as the top income shares or the headcount ratio. However, it might be welfare enhancing if the threshold is set at a fixed absolute level as in this case more affluence of the society as a whole is captured.

5.2.2 Multidimensional Affluence

Our approach of measuring multidimensional affluence is based on a dual cutoff method: In a first step, an individual is considered as *dimension-specific affluent* when its achievement in a specific dimension of well-being exceeds the respective cutoff value. In a second step, we define which individuals (among those who are affluent with respect to at least one dimension) are considered to be affluent in a multidimensional sense with the help of a *counting methodology* (Atkinson, 2003b; Alkire and Foster, 2011a). An affluent individual is defined to be *multidimensionally affluent*, if the number of its affluence counts across all dimensions is greater than or equal to a certain threshold (second cutoff). After having identified "the rich", their individual achievements are aggregated to single-value measures of multidimensional affluence.

Dimension-specific affluence. In this first step, we need to choose which individuals are affluent in each dimension. The number of individuals in the population is denoted with n, while $d \geq 2$ denotes the number of dimensions of affluence under consideration. Define the matrix of achievements with $\mathbf{Y} = [\ y_{ij}\ ]_{n \times d}$, where y_{ij} denotes the achievement of individual $i \in \{1, \ldots, n\}$ in dimension $j \in \{1, \ldots, d\}$. For each dimension j, there is some cutoff value γ_j (i.e., the dimension-specific affluence line). Let γ denote a $1 \times d$ vector of dimension-specific cutoffs (chosen by the researcher or policy-maker). With the help of this vector, it is possible to identify, whether individual i is affluent with respect to dimension j or not. Next, define an indicator function θ_{ij}, which equals 1 if $y_{ij} > \gamma_j$ and 0 otherwise and with its help construct a $0 - 1$ matrix of dimension-specific affluence $\mathbf{\Theta^0} = [\ \theta_{ij}\ ]_{n \times d}$, where each row vector of $\mathbf{\Theta^0}$, denoted with $\theta_\mathbf{i}$, is equivalent to individual i's affluence vector. This yields a vector of affluence counts, denoted $\mathbf{c} = (c_1, \ldots, c_n)'$. Its elements $c_i = \mid \theta_i \mid$ are equal to the number of dimensions, in which an individual i is defined to be affluent.

In the case of cardinal variables in the achievement matrix $\mathbf{Y}$, it is possible to construct matrices that, in addition, do not only provide the information whether an individual i is affluent with respect to dimension j or not, but also inform about the intensity of affluence associated with the dimension under consideration. Thereby, one can distinguish the concave and the convex case (see above). If we are interested in the *convex* case, we look at the following matrix for a given cutoff γ_j:

$$\mathbf{\Theta}^\alpha = \left[\left(\frac{y_{ij} - \gamma_j}{\gamma_j} \right)_+^\alpha \right]_{n \times d} \quad \text{for } \alpha \geq 1. \tag{5.2.3}$$

In the *concave* case we have

$$\mathbf{\Theta}^\beta = \left[\left(1 - \left(\frac{\gamma_j}{y_{ij}} \right)^\beta \right)_+ \right]_{n \times d} \quad \text{for } \beta > 0. \tag{5.2.4}$$

Again, the subscript "+" indicates that the entries of matrices $\mathbf{\Theta}^\alpha$ and $\mathbf{\Theta}^\beta$ respectively must be greater than or equal to zero. The parameters α and β are sensitivity parameters for the intensity of affluence. For larger (smaller) values of α (β) more weight is put on more intense affluence. Note that $\mathbf{\Theta^0}$ is simply a special case of $\mathbf{\Theta}^\alpha$ for $\alpha = 0$ and of $\mathbf{\Theta}^\beta$ for $\beta \to \infty$ respectively. For $\alpha = 1$ the function $(y_{ij} - \gamma_j)/\gamma_j$ is just linear in y_{ij}.

In addition to the difference with respect to the normative judgement of progressive transfers between affluent individuals, the distinction between the concave and convex cases helps to understand what drives inequality at the top of the joint distribution of dimensions.

Multidimensional measures. In the second step, we have to define which individuals (among the dimension-specific rich) are affluent in a multidimensional setting. For this, we use the dual cutoff method of identification. That is, we select a cutoff value k which defines the number of dimensions in which an individual has to be rich in order to be multidimensional affluent. Formally, for an (arbitrarily chosen) number k define the identification method as

$$\phi_i^k(y_i, \gamma) = \begin{cases} 1 & \text{if } c_i \geq k, \\ 0 & \text{if } c_i < k. \end{cases} \tag{5.2.5}$$

This yields a $0-1$ vector $\phi^{\mathbf{k}}$ with entries ϕ_i^k equal to one if the number of affluent dimensions of individual i is not less than k, and is zero otherwise. In other words, individual i is considered to be *multidimensionally affluent*, if the number of dimensions in which its achievement is considered as affluent attains a certain threshold.[3] The choice of the second cutoff is usually less arbitrary than the choice of the dimension-specific affluence line γ_j. In practice, the researcher might want to choose several cutoff values and look at the different results (for instance $k \in \{1, \ldots, d\}$, i.e., all integers from 1 to the total number of dimensions under consideration). Hereby, one can think of two extreme cases. First, for $k = 1$, person i is multidimensionally affluent when she is considered as affluent in at least one single dimension (union approach). Second, for $k = d$, she is only considered as affluent, if she is affluent in all dimensions (intersection approach). In case of $1 < k < d$ we have an intermediate approach (Alkire and Foster, 2011a).

[3] An individual i can be affluent in one or more dimensions and, at the same time, not be multidimensionally affluent (when it holds that $c_i < k$), while a multidimensionally affluent person by definition is always affluent in at least k dimensions. Here, we assume equal weighting of dimensions. In principle, it is possible to allow for different weights (see appendix).

Based on this second cutoff, we can define the subset of multidimensionally affluent individuals among the whole population as $\Phi_k = \{i : \phi_i^k(y_i, \gamma) = 1\} \subseteq \{1, \dots, n\}$. The number of affluent individuals is denoted with $s^k = \mid \Phi_k \mid$.

Since, according to the focus axiom, a measure of affluence must take into account information on the affluent only, we also replace the elements of the vector of affluence counts $\mathbf{c}$ with zero, when the number of affluence counts of the according individual i does not attain the threshold k. Formally:

$$c_i^k = \begin{cases} c_i & \text{if } c_i \geq k, \\ 0 & \text{if } c_i < k. \end{cases} \tag{5.2.6}$$

This yields the vector $\mathbf{c^k} = (c_1^k, \dots, c_n^k)'$, which contains zeros for those not considered to be affluent and the number of dimensions, in which the affluent individuals are considered as affluent. That is, even in case of an individual which is affluent in several dimensions, its entry in $\mathbf{c^k}$ nevertheless might be zero if its number of affluent dimensions is smaller than the threshold k.

In order to obtain matrices that provide information on affluent individuals only, we replace the row i of $\boldsymbol{\Theta}^\alpha$ and $\boldsymbol{\Theta}^\beta$ respectively with vectors of zeros, whenever it holds that $\phi_i^k(y_i, \gamma) = 0$. Formally, define

$$\boldsymbol{\Theta}^\alpha(\mathbf{k}) = \left[\left(\frac{y_{ij} - \gamma_j}{\gamma_j} \right)^\alpha \cdot \phi_i^k(y_i, \gamma) \right]_{n \times d} \quad \text{and} \tag{5.2.7a}$$

$$\boldsymbol{\Theta}^\beta(\mathbf{k}) = \left[\left(1 - \left(\frac{\gamma_j}{y_{ij}} \right)^\beta \right) \cdot \phi_i^k(y_i, \gamma) \right]_{n \times d}. \tag{5.2.7b}$$

Now we are able to define measures of multidimensional affluence based on the definitions that were introduced in the previous two subsections. In order to derive a first multivariate measure of affluence, define the *headcount ratio* (HR) as

$$HR^k = \frac{s^k}{n}, \tag{5.2.8}$$

which is simply the proportion of affluent individuals among total population. The *average affluence share* (AAS^k) reads

$$AAS^k = \frac{\mid \mathbf{c^k} \mid}{s^k \cdot d}, \tag{5.2.9}$$

where $\mid \mathbf{c^k} \mid$ denotes the number of affluence counts among the multidimensionally affluent population. The average affluence share is hence equal to the relation of this number to the maximum number of affluence counts that would be observed when *all affluent* individuals were affluent among *all* dimensions and it holds $k/d \leq AAS^k \leq 1$. For a given number of dimensions under consideration, the value of AAS^k is close to one, when there is a very strong correlation of affluence across dimensions, i.e., those who are affluent tend to be affluent in all dimensions. The value becomes smaller if the number of dimensions decreases. It reaches its minimum value of $1/d$, when all affluent individuals are only affluent with respect to one single dimension.

Now, we can define a first measure of multidimensional affluence by simply multiplying the headcount ratio and the average affluence share. The *dimension adjusted headcount ratio* is defined as

$$R^M_{HR}(k) = HR^k \cdot AAS^k = \frac{\mid \mathbf{c^k} \mid}{n \cdot d}, \tag{5.2.10}$$

which is equal to the proportion of the total number of affluence counts to the maximum number of affluence counts that one would observe when every single individual in the population under consideration would be affluent with respect to every single dimension.[4] Contrary to the simple headcount ratio HR, the measure R^M_{HR} satisfies the property of *dimensional monotonicity*, which requires that a measure of multidimensional affluence increases (decreases) when a affluent individual ($c_i \geq k$) becomes (is no more) affluent in some dimension. That is why the AAS is incorporated in R^M_{HR}. However, the dimension adjusted headcount ratio does not satisfy the property of *monotonicity*, i.e., R^M_{HR} does not necessarily increase (decrease) when the achievement y_{ij} of a affluent individual i in dimension

[4]Hence, the nomenclature of a *headcount* ratio is somewhat misleading. However, in order to remain consistent with the literature on multidimensional poverty (Alkire and Foster, 2011a) we stick to this naming. Moreover, the measure R^M_{HR} is the multidimensional analogue to the one-dimensional headcount ratio.

j increases (decreases).Hence, it only reveals information about the width and not the depth of affluence.

The following additional measures of multidimensional affluence by contrast do satisfy the monotonicity property. Again, one can distinguish between a convex and a concave measure respectively. The *dimension adjusted multivariate affluence measures* are defined as

$$R_l^M(k) = HR^k \cdot AAS^k \cdot \frac{\mid \mathbf{\Theta^l(k)} \mid}{\mid \mathbf{c^k} \mid} = \frac{\mid \mathbf{\Theta^l(k)} \mid}{n \cdot d} \tag{5.2.11}$$

for $l \in \{\alpha, \beta\}$ and hence are equal to the sum of the elements of the matrices $\mathbf{\Theta}^\alpha(\mathbf{k})$ and $\mathbf{\Theta}^\beta(\mathbf{k})$ divided by the value $n \cdot d$ respectively. The concave measure R_β^M is normalized between zero and one, while the convex measure R_α^M is not. Although one would prefer to have normalized measures, this is not possible in the convex case without violating the monotonicity axiom. The choice of R_α^M over R_β^M emphasizes intense rather than moderate affluence.

Since we are interested in analyzing the role of dimensions (especially income and wealth) with respect to the measurement of multidimensional affluence, it seems helpful to formally disentangle the dimensions-specific contributions. Therefore, we rewrite (5.2.11) as

$$R_l^M(k) = \frac{\mid \mathbf{\Theta^l(k)} \mid}{n \cdot d} = \frac{\sum_{j=1}^d \mid \theta_\mathbf{j}^\mathbf{l}(\mathbf{k}) \mid}{n \cdot d} = \frac{1}{d} \cdot \sum_{j=1}^d \frac{\mid \theta_\mathbf{j}^\mathbf{l}(\mathbf{k}) \mid}{n} = \frac{1}{d} \cdot \sum_{j=1}^d \mathbf{\Pi_j^l(k)} \tag{5.2.12}$$

for $l \in \{\alpha, \beta\}$. Hence, $\mathbf{\Pi_j}^l(k)$ denotes the contribution of each dimension j multiplied by the total number of dimensions d. More intuitively, it is equal to the proportion of individuals that are multidimensionally affluent *and* affluent with respect to dimension j at the same time. The simple mean of all these contributions over the d dimensions yields the overall multidimensional affluence measure R_l^M. One can show that the proportional contribution of dimension j to the overall measure R_l^M, denoted with $\pi_j^l(k)$, can be written as

$$\pi_j^l(k) = \frac{\mid \theta_\mathbf{j}^\mathbf{l}(\mathbf{k}) \mid}{\mid \mathbf{\Theta^l(k)} \mid}. \tag{5.2.13}$$

Obviously, it holds that $\sum_{j=1}^{d} \pi_j^l(k) = 1$. Hence, it is possible to decompose the measures proportionally into the contributions of the single dimensions.

5.3 Empirical Application

With respect to measurement of affluence, the representativeness of individuals with (very) high income and wealth levels in the data at hand clearly is an issue. Usually, survey data are less representative at the tails of the income distribution because of small numbers of observations (Burkhauser et al., 2011, 2012). Both datasets we use address this issue.

5.3.1 Data

Administrative vs. survey data. Kopczuk and Saez (2004) discuss different reasons for discrepancies in findings between studies based on survey data and administrative tax return data. These are related to different concepts of income or wealth and to tax avoidance and evasion. The literature on top incomes typically makes use of administrative data from tax records. Piketty (2005) argues that, in contrast to other (survey) data sources, these data are homogeneous over time, comparable across country and decomposable with respect to income sources. Furthermore, administrative data do not suffer from non-response, especially regarding the top of the distribution.

Since, unfortunately, administrative data are not available to us (in case of the US) or only for a very restricted period (in case of Germany) we have to rely on survey data. We argue that both data sources are nevertheless useful for our purposes. First, both surveys provide harmonized information on income and wealth over time and allow a restriction to specific income components (see below). Second, both surveys are explicitly concerned with representativeness of top incomes and wealth holdings by specific sampling procedures. Finally, as elaborated in Alkire and Foster (2011b), our methodology requires income *and* wealth information from the same data source, which must be linked on the individual (or household) level in order to be able to assess the joint distribution. Tax return data typically do not provide both types of information simultaneously. Furthermore, they do not contain information on non-taxable income sources (e.g., owner-occupied housing or private life insurance in Germany). In addition, while survey data are subject to measurement error, tax data suffer from underreporting due to tax evasion, which is particularly severe at the top (Kopczuk and Saez, 2004; Paulus, 2011).

SOEP. The German Socio-Economic Panel Study (Wagner et al., 2007; Socio-Economic Panel, 2010) is a panel survey of households and individuals in Germany that has been conducted annually since 1984. We use the 2007 wave of the SOEP with information of 18,773 individuals (aged 17+) in 10,553 households. In order to improve its "statistical power" and the reliability of statements referring to high incomes (and hence affluence), an additional sample of high income households was included into the SOEP since wave 2002. This increased the number of observations within the top 2.5% of the income distribution considerably and hence reduced potential bias due to poor representativeness of affluent households. Since these additional observations were oversampled, population weights were adjusted accordingly to make the data representative for the German population (Frick et al., 2007). The 2002 and 2007 waves of the SOEP contain additional information on wealth that was surveyed in supplementary questionnaires (Frick et al., 2007; Frick and Grabka, 2009). The SOEP income data has been validated against administrative tax data and was found to perform reasonably well up to the top 1% of the income distribution (Bach et al., 2009). Nevertheless, we perform a robustness check using German tax microdata.

SCF. The Survey of Consumer Finances (SCF) is a triennial survey of US families with a special focus on wealth holdings. The 2007 wave of the SCF contains information on 4,422 families with a total of 11,199 members. They were sampled in two steps: First, a standard geographically based random sample and, second, a special oversampling of very wealthy families. Similar to the SOEP sampling weights make the respondents representative for the US population and missing data are imputed. The SCF provides detailed information on family income, balance sheets, use of financial services as well as pensions, labor force participation and demographic characteristics (Bucks et al., 2009).

5.3.2 Dimensions

Income. When measuring individuals' well-being, consumption is typically regarded as the best proxy for permanent income. Moreover, with regard to the rich in society, conspicuous consumption might play an important role. Unfortunately, we do not have information on consumption in our data. Therefore, we use income as our first dimension as a proxy for actual consumption. Our income measure contains market income from labor as well as private transfers and pensions from all household or family members (Bucks et al., 2009; Grabka, 2012). Since we are interested in the joint distribution of income and wealth, we do not consider income from assets, such as payments from interest, dividends or capital gains in order to avoid "double counting". Income flows from a stock of assets and the stock itself are highly correlated and the probability of being affluent in both income and wealth at the same time can be assumed to be quite high when taking capital income into account. However, a robustness check shows that the qualitative results do not change when using market income including capital income.

Wealth. As our second dimension, we choose wealth – as recommended by Stiglitz et al. (2009). Wealth serves as a source of income, utility and power as well as social status (Frick and Grabka, 2009) and helps to stabilize consumption over time (Wolff and Zacharias, 2009; Michelangeli et al., 2011). In addition, wealth and income represent distinct dimensions of satisfaction with life (D'Ambrosio et al., 2009). Moreover, wealth has been used to measure poverty (Brandolini et al., 2010; Azpitarte, 2012). While income can be defined as the "increase in a person's command over resources during a given time period" one can view wealth as "a person's total immediate command over resources" (Cowell, 2008). The requirement of *immediate* command refers to a notion of marketability of an individual's wealth stock. This can be seen as appropriate with respect to financial assets and (to a lesser extent) to housing or business property.[5] Our basic measure of individual wealth aggregates the following components: owner-occupied housing and other property (net of mortgage debt), financial assets, business assets, tangible assets (consumer durables), private pensions net of consumer credits and other

[5]This definition excludes the present value of future public pension entitlements which are non-marketable. We discuss this in detail and provide some evidence as a robustness check.

debt. Information on wealth holdings contained in both datasets differs in terms of the level of detail but both surveys target these aggregate wealth components. Moreover, a number of waves of both the SOEP and the SCF surveys serve as the original sources for the Luxembourg Wealth Study Database (LWS), an ex-post harmonized cross-national database on household assets and liabilities (Sierminska et al., 2006). We therefore adopt the LWS practice and harmonize the two data sources as much as possible.

Cutoffs. Defining the cutoffs which separate the population into affluent and non-affluent individuals with respect to the dimensions under consideration is crucial for the empirical analysis. Although there are several ways to draw a poverty line (relative vs. absolute), the underlying principle – a poor person does not meet a certain level of subsistence, while a non-poor one does – is uncontroversial. With respect to the upper tail of the distribution this is less clear. The decision how to define cutoffs is up to the researcher and the sensitivity of results should be checked for different choices of the affluence line.

One standard approach in the literature is to fix the proportion of the affluent population (e.g., the top p% of the distribution, see references in footnote 1 and Cowell, 2011). For example, in research on the "middle class" it is common to define the middle to comprise the second to fourth income quintiles (Atkinson and Brandolini, 2011). Consequently, the top (bottom) quintile represents the rich (poor) part of the society. Another way of defining a cutoff follows standard practice in poverty research and sets the cutoff at a multiple of the mean or median value of the respective distribution. For instance, Peichl et al. (2010) choose an upper threshold of 200% of the median, Barry (2002) suggests 300% of the median and Atkinson (2008a) proposes different multiples of average income as wealth cutoffs. Although one can argue in favor of both approaches we follow the first one here for two reasons: First, we want our results to be comparable to the top income literature which implicitly sets affluence lines at top quantiles. Second, a data driven choice of affluence line, i.e., a fraction of the mean or median is affected by the dispersion of the underlying distribution and hence could also be interpreted as a measure of inequality. Moreover, with regard to the differences in the skewness of the distributions it is difficult to find a common multiple for both income and wealth which is a meaningful cutoff. Therefore, we set the cutoff at the 80%-quantile of the respective distribution. Of course, this is an arbitrary choice. However, we check the sensitivity of the results with respect to the cutoff by looking at the top 10%, top 5% and top 1%. We find that the level of cutoff does not affect our results qualitatively and is hence not important for our purposes. By definition, the one-dimensional headcount ratios then equal 20% but the multidimensional headcount does not necessarily need to take on the same value, since it depends on the joint distribution of both dimensions. Since both income and wealth usually exhibit distinct profiles over the life cycle (see Paglin, 1975; Almås and Mogstad, 2012, and figure 5.6.1), we let the cutoffs vary by age of the household head and distinguish three age groups (head aged $\leq$29, 30–59 and $\geq$60) in order to take into account these life cycle patterns. The specific age groups represent the main stages of life with completion of education, prime working age and retirement age.

5.3.3 Descriptives

In order to make individuals with different household sizes comparable to each other we equivalize both income and wealth levels with the common square root scale. We express income and wealth in 2007 PPP US dollars (US$). In table 5.3.1 we present our results on mean and median income and wealth respectively as well as the age group-specific cutoffs. Wealth and income are converted to constant US dollars using the Consumer Price Index (CPI-U) available from the Bureau of Labor Statistics. Furthermore, since we are interested in affluence and hence the top of the income and wealth distribution, we disregard any adjustments to the data with respect to extreme upper values (like top-coding or trimming) in the baseline (we do this as a robustness check, though).

Table 5.3.1: Descriptives and cutoffs (2007)

	Mean	Median	Cutoff < 30	Cutoff 30–59	Cutoff 60+
United States 2007					
Income	44,982	27,252	37,021	63,245	36,358
	(434)	(358)	(1,022)	(715)	(1,269)
Wealth	355,984	70,750	35,921	280,050	590,399
	(4,741)	(1,860)	(4,878)	(7,219)	(16,899)
Germany 2007					
Income	25,415	21,670	33,784	50,290	17,732
	(336)	(455)	(1,681)	(640)	(1,281)
Wealth	134,300	43,873	26,942	173,145	259,284
	(4,289)	(2,193)	(3,090)	(4,600)	(7,228)

Note: Income and wealth in PPP US Dollars. Confidence intervals (95%) based on 500 bootstrap replications. Source: SCF/SOEP, own calculations.

Mean equivalent market income in the US equals about 45,000 US$ and hence is nearly twice the level in Germany (24,000 US$), whereas – due to the more skewed distribution – the US median value (27,000 US$) is only somewhat larger than in Germany (20,500 US$). The age-specific cutoffs for the youngest group (head aged below 30) are quite similar and differ more for the older age groups, particularly for the group of 60 years and above. For the latter, the US value exceeds twice the German value. Moreover, the age group-specific distributions reveal a typical life-cycle profile: the 80%-quantiles increase by age from the youngest to the medium group but decrease again for the oldest (also see figure 5.6.1 in the appendix). This pattern is more pronounced in Germany, where the cutoff for the group of 60 and older is only half the level of the youngest group. This is due to the fact that we rely on market incomes. Consumption resources of Germans above retirement age however heavily depend on old-age benefits from public pensions which are not included in our income definition. For the US, we find that the youngest and oldest groups exhibit nearly identical cutoff levels of around 36,000 US$.

Turning to the wealth distributions, we find that overall mean equivalent wealth in the US is about 356,000 US$ and hence is almost three times as large as in Germany (127,000 US$). Median wealth is rather low in Germany (42,000 US$) and less than one third of mean wealth. Although being significantly larger than the German median wealth level, the US median wealth of around 70,000 US$

is only about one fifth of the mean. Wealth distributions in both countries are also characterized by a specific pattern over the life cycle: The cutoffs for the age groups increase monotonically and the slope is much steeper in the US. While the youngest group differs only by about 10,000 US$, the cutoff for the oldest group is more than twice as large in the US compared to Germany.

5.4 Results

5.4.1 Shares, Correlations and One-dimensional Affluence

Income and wealth shares. In figure 5.4.1 we present our estimates of income and wealth shares of the distributions' top 10%, 5% and 1% fractiles. The upper graph shows the shares of total income and wealth belonging to top fractiles of each dimension separately. Although we apply a slightly different concept (equivalence weighting) our results are in line with previous findings of the top income literature and further studies reporting top shares (see, e.g., Atkinson et al., 2011, for an overview). For Germany, we find income shares of 6.2%–32.1% for the top 1%, 5% and 10% of the income distribution. The wealth shares vary between 21% and 55%. Compared to Germany, top income and wealth shares are significantly larger in the US. The difference between the countries varies between 13 and 20 percentage points. The top 10% of the US income distribution account for 46.5% of total income, the top 1% for 18.7%. The concentration of resources in terms of wealth is even larger. The top decile commands more than 70%. Most of this share is concentrated in the top 5% of the wealth distribution, almost half of it in the top percentile. The two other graphs take into account the joint distribution of income and wealth respectively. The middle graph shows the shares of each dimension in the top fractiles of the *other* dimension. This means, the left (right) hand side of this graph shows the income (wealth) share of the top fractiles in the wealth (income) distribution. For example, the top decile of the US wealth distribution receives about 37% of total income, while the top 10% in income command more than 50% of wealth holdings. In general, the shares are somewhat smaller compared to the shares found for the marginal distributions, especially for Germany. Finally, the lower graph presents the shares of the *joint* top fractiles.

For instance, those who are in the top percentiles of both the income and wealth distribution in Germany have 1.5% of total income and 5.5% of total wealth. Interestingly, the income shares of the joint top fractiles are only marginally above their population shares, which would imply an almost equal distribution. The joint top decile owns less than one fifth of total German wealth (18.5%). The results for the US are much larger, between 2.5 and eight times the shares in Germany: The joint top decile has one third of income and half of the wealth. These findings indicate that economic resources are much more concentrated in the US than in Germany. Generally speaking, "the rich" in Germany have either high income or wealth, while in the US they tend to have both.

Correlations. One motivation for proposing a measure of multidimensional affluence with an application to income and wealth is the fact that looking at the distribution of one dimension only is not sufficient to capture the distribution of economic well-being within a given population in general. That is why we take a closer look at the relationship between the two dimensions under consideration. In figure 5.4.2 we show results for Pearson's correlation coefficient as well as for Spearman's rank correlation coefficient. It turns out that individual positions within the marginal distributions are far from perfectly correlated. This is especially true for Germany, where we find a value of 0.28 for the total population. The correlation between income and wealth is 0.2. The rank-correlation index even takes on a slightly negative value (-0.1) and a correlation coefficient of below 0.1, when restricting the sample to individuals with at least one affluence count. For the multidimensionally affluent (i.e., affluent in both dimensions) we find a positive but rather small number of 0.2. This suggests that the rank of an individual within either the income or the wealth distribution is quite a poor predictor for the rank within the other marginal distribution. Our findings for the US however suggest a distinctly stronger relationship between positions in the income and wealth distributions respectively. The rank-correlation for the total population is 0.6, whereas we find 0.54 for the subpopulation with at least one affluent count and 0.76 for the very top with income and wealth levels both exceeding the cutoffs. Hence, the relationship between income and wealth positions is far from perfect in in Germany, but larger in the US.

Figure 5.4.1: Income and wealth shares (2007)

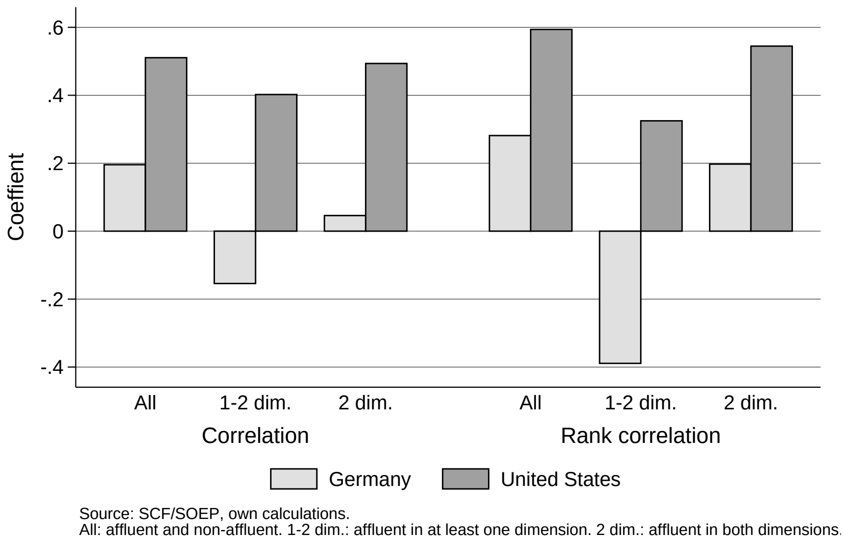


Figure 5.4.2: Income and wealth correlation (2007)

One-dimensional affluence. In table 5.4.1 we list several distributional indicators for the dimensions under consideration, focussing on one-dimensional affluence measures as well as the Gini coefficient as a standard measure of inequality. Consistent with other cross-country analysis, we find larger levels of market income inequality in the US compared to Germany (Gini: 0.56 vs. 0.42) and higher levels of wealth inequality: In the US the Gini coefficient is 0.8 and 0.65 in Germany. The one-dimensional headcount ratios for affluence by definition equal 0.2 since we set the cutoff levels to the 80%-quantiles. However, we find differences for the other affluence indicators taking into account inequality among the affluent subpopulation. The convex affluence measures (R_α) for both income and wealth are larger in US than in Germany. In particular for $\alpha = 2$, an index emphasizing extreme affluence, we find huge values of 10.5 and 7.8 for the US compared to 0.4 and 1.6. Hence, there is much more inequality among the very top of the distributions in both dimensions. Interestingly, the concave measures (R_β) turn out to be larger in Germany, which indicates that high income and wealth are more concentrated around the cutoff.

Table 5.4.1: One-dimensional Measures (2007)

	R_{HR}	$R_{\alpha=1}$	$R_{\alpha=2}$	$R_{\beta=1}$	$R_{\beta=3}$	I_{Gini}
United States 2007						
Income	0.199	0.110	10.492	0.019	0.030	0.561
	(0.000)	(0.005)	(2.074)	(0.001)	(0.001)	(0.003)
Wealth	0.200	0.156	7.794	0.021	0.030	0.798
	(0.000)	(0.006)	(0.555)	(0.000)	(0.001)	(0.002)
Germany 2007						
Income	0.200	0.101	0.397	0.032	0.053	0.416
	(0.000)	(0.010)	(0.120)	(0.002)	(0.002)	(0.005)
Wealth	0.200	0.106	1.598	0.027	0.046	0.651
	(0.000)	(0.012)	(0.541)	(0.001)	(0.001)	(0.010)

Note: Confidence intervals (95%) based on 500 bootstrap replications. Source: SCF/SOEP, own calculations.

5.4.2 Multidimensional Affluence and its Contributions

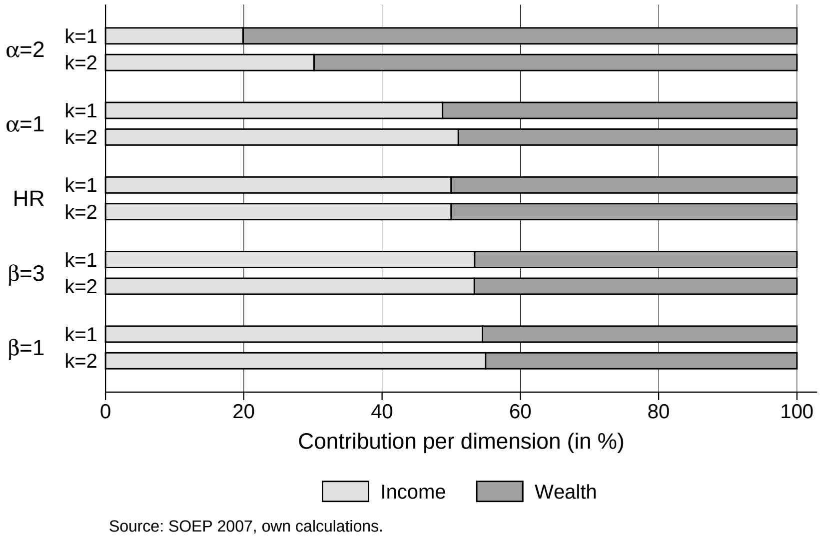
Germany vs. the US in 2007. In table 5.4.2 we present our results for different multidimensional affluence measures using different values of the second cutoff threshold k as well as different values of α and β respectively. Analogous to the one-dimensional case, the dimension adjusted headcount ratio (R^M_{HR}) is equal to 0.2 for $k = 1$ due to the choice of cutoffs. However, this is not necessarily the case for $k = 2$, where we find a larger value for the US (0.11) compared to Germany (0.08). This means that the relative number of total affluence counts is larger in the US. Turning to the convex multidimensional affluence measures (R^M_α) we find that for both levels of the second cutoff ($k = 1$ and $k = 2$) the levels are much higher in the US. Whereas the difference for $\alpha = 1$ is comparably moderate it turns out to be huge for $\alpha = 2$, which implies a strong emphasis of the very top. This implies that affluence in the US is much more concentrated at the very top of the joint distribution of income and wealth, consisting of only few households and individuals. However, looking at the concave measures (R^M_β) we find (slightly) higher levels of multidimensional affluence for Germany, in particular for $k = 1$, which results from the weaker (rank) correlation between dimensions. This indicates that affluence in Germany is more equally distributed among a larger number of households and individuals not differing too much in their income and wealth levels, whereas in the US extreme affluence results from a smaller group of affluent units where some exhibit extreme levels in both income and wealth.

Table 5.4.2: Multidimensional Measures (2007)

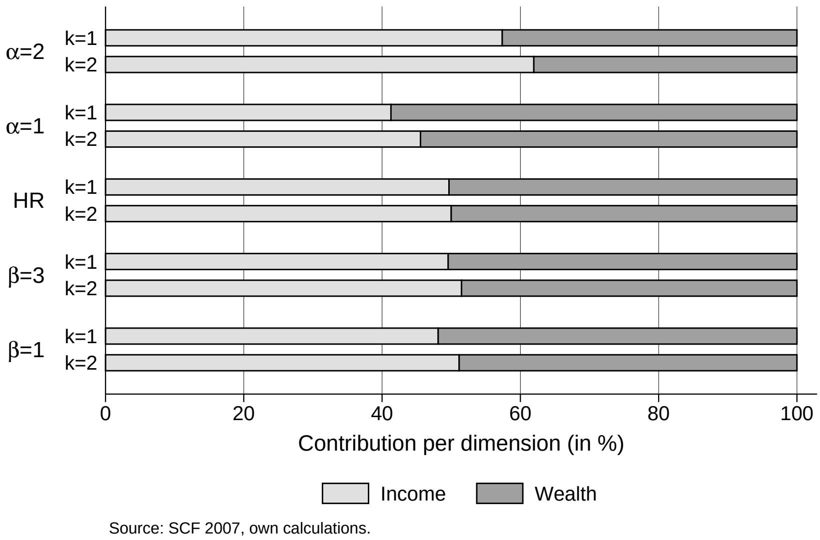
k	R^M_{HR}	$R^M_{\alpha=1}$	$R^M_{\alpha=2}$	$R^M_{\beta=1}$	$R^M_{\beta=3}$
United States 2007					
1	0.199	0.133	9.143	0.020	0.030
	(0.000)	(0.004)	(1.126)	(0.000)	(0.001)
2	0.111	0.103	8.446	0.012	0.016
	(0.002)	(0.004)	(1.113)	(0.000)	(0.000)
Germany 2007					
1	0.200	0.104	0.997	0.030	0.049
	(0.000)	(0.008)	(0.280)	(0.001)	(0.001)
2	0.081	0.051	0.457	0.013	0.020
	(0.003)	(0.006)	(0.137)	(0.001)	(0.001)

Note: Confidence intervals (95%) based on 500 bootstrap replications. Source: SCF/SOEP, own calculations.

Contributions. As we pointed out before, another advantage of our measures of multidimensional affluence is that they allow to quantify the contribution of each dimension to the overall level of affluence. Figure 5.4.3 displays the percentage contribution of income and wealth respectively. We find that in both countries the relative importance of both dimensions is quite balanced for all measures. The only exception is the convex measure for $\alpha = 2$. For this, the two countries differ substantially. The contribution of income is reduced to 20–30% in Germany depending on the second cutoff level k, whereas it amounts to around 60% in the US. This means that the composition of affluence at the very top differs a lot between the US and Germany, whereas income and wealth seem to contribute more or less evenly when extreme affluence is less emphasized.



(a) Germany



(b) United States

Figure 5.4.3: Affluence contributions per dimension (2007)

United States 1989–2007. We now turn an assessment of the development of multidimensional affluence over time in the US during the period from 1989 to 2007. We compare our results to an updated time series of top income shares in the US (Piketty and Saez, 2003, 2007b) provided by Alvaredo et al. (2011). Figure 5.6.2 in the appendix depicts shares of the top 10% to top 0.01% incomes including capital gains since this comes closest to our joint consideration of income and wealth. The share of the very top of the income distribution in the US has been increasing steadily since the mid-1990s with the exception of a short recession period at the beginning of the 2000s following the burst of the dot-com bubble. In figure 5.6.3 in the appendix we present the development of mean and median income and wealth for the total population as well as for the three subgroups according to the age of the household head. Overall, the mean values of both dimensions under consideration show stronger growth rates than the median values, indicating growing dispersion in the distribution (see figure 5.6.4 in the appendix). This is especially true for the oldest age groups, while income and wealth levels for the youngest group have remained more or less constant throughout the period under consideration. This might also be due to changes in the demographic composition with an ageing but on average wealthier society (Almås and Mogstad, 2012).

In the previous section we reported that the US and Germany clearly differ in the association between rank positions within the income and wealth distributions for 2007 data. We find that this correlation is much stronger in the US compared to Germany. Figure 5.4.4 shows the development of the rank correlation between 1989 and 2007. Throughout the whole period, it holds that the correlation has been stronger than it was in Germany in 2007 we find that there has been a considerable increase in the US since the beginning of the 1990s. For the whole population, the Spearman index grew from below 0.5 to a level of around 0.6. This growth turns out to be even stronger for the subpopulation with at least one affluence count (increase from 0.35 to 0.55) and also increased somewhat for the multidimensionally affluent population (increase from 0.65 to 0.75–0.8). Hence, the high-income individuals more often also exhibit the highest levels of wealth. This should clearly contribute to an increasing level of affluence in both dimensions.

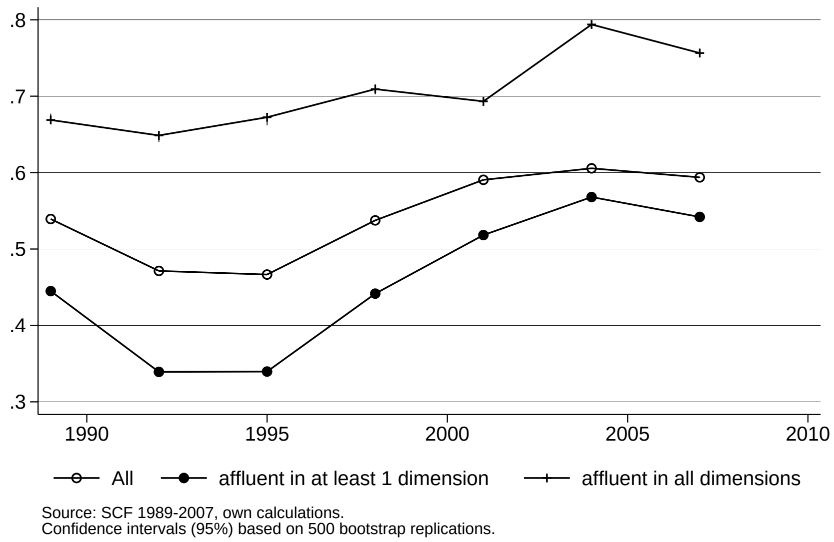
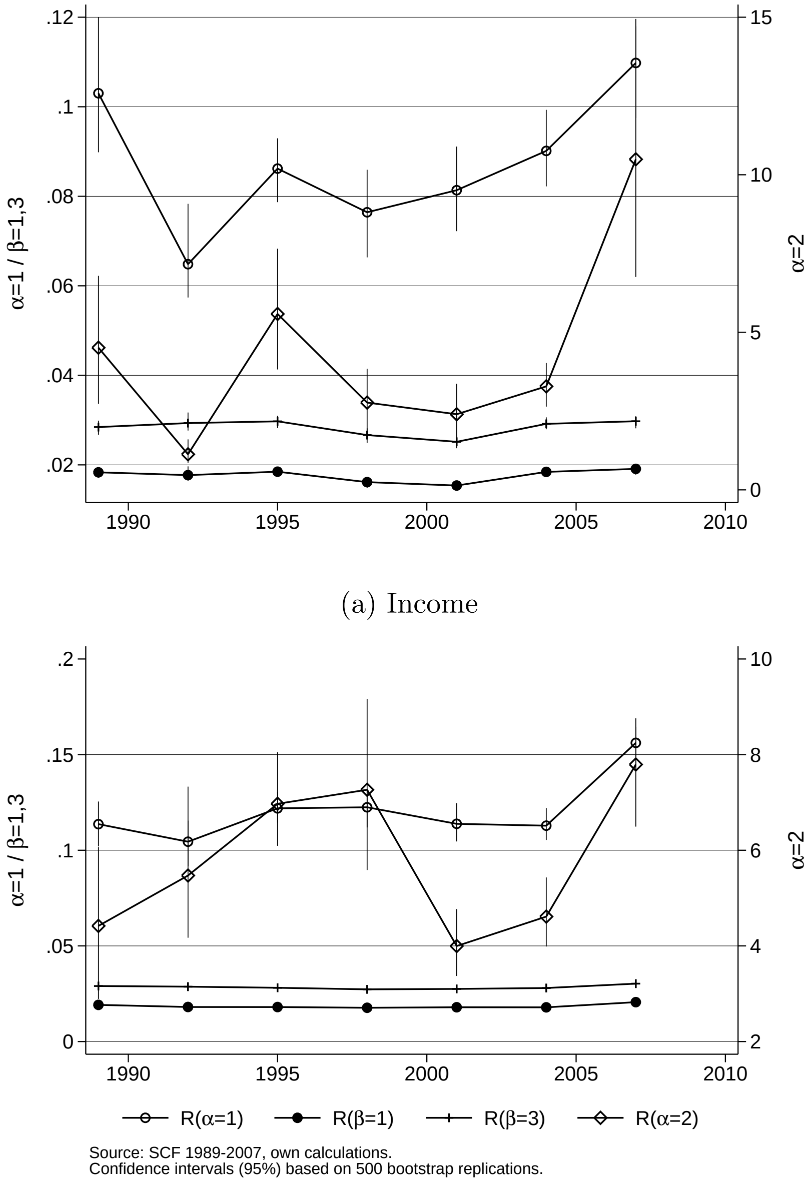


Figure 5.4.4: Rank correlation: income and wealth (US, 1989–2007)

Figures 5.4.5a and 5.4.5b depict the development of one-dimensional affluence for income and wealth respectively. For both we find that affluence measured by the concave indices (R_β) remained remarkably unchanged throughout the period 1989–2007 and shows almost no volatility at all. This is contrasted by the convex measures (R_α) putting more weight on the extreme top of the respective distributions: For income, the convex measures increased strongly since the beginning of the 2000s after having remained constant throughout the 1990s (no statistically significant changes) with the exception of a dip in 1992 due to the contraction of the US economy. Convex affluence in wealth did not significantly change throughout the first four waves (1989–1998) despite a clear increasing pattern of point estimates. The convex measures for $\alpha = 2$ dropped significantly to lower levels in 2001 and 2004 before increasing again between the 2004 and 2007 waves.



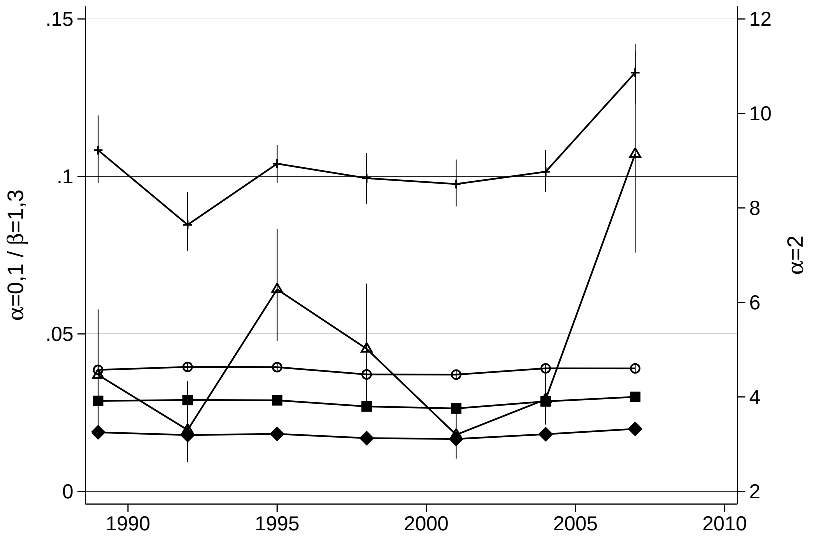
(a) Income

(b) Wealth

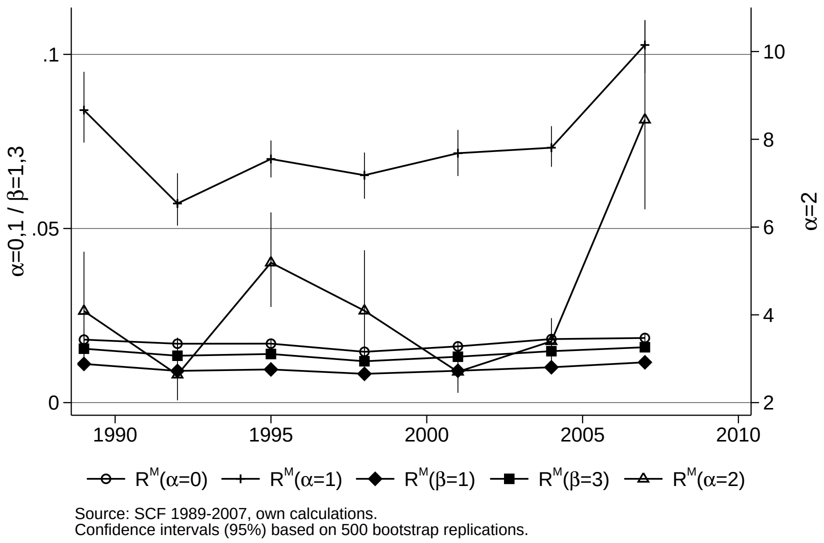
Figure 5.4.5: One-dimensional affluence (US, 1989–2007)

We present our results for multidimensional affluence in the US between 1989 and 2007 in figures 5.4.6a and 5.4.6b for the two possible levels of second stage cutoffs. The measures only differ in levels for $k = 1$ or $k = 2$ but the trend patterns over time are very similar: Relying on the concave measures yields that multidimensional affluence has remained almost constant throughout the period 1989–2007, whereas the convex measures exhibit some volatility. We find a statistically significant drop of convex measures between 1989 and 1992 for both values of α due to the contraction at that time. For $\alpha = 1$, multidimensional affluence afterwards remained constant between 1995 and 2004 and increased between 2004 and 2007. Hence, this measure remained unaffected by the recession in 2000/2001 while we find a significant drop of affluence measured with $\alpha = 2$, which implies strongly emphasizing very high achievements in both income and wealth. This means, the dot-com crisis particularly affected the very top of the distribution of economic well-being in the US, which is mainly due to its impact on wealth holdings. Although large confidence intervals (based on bootstrapping) indicate a fair amount of imprecision in estimated levels of affluence we find a very strong increase between 2004 and 2007. In fact, we observe a doubling of point estimates. Hence, in the first half of the 2000s, the top of the joint distribution of income and wealth not only recovered from its losses at the beginning of the decade but even increased their economic resources to a historically high level. However, since the available SCF data do not cover the recent crisis, it can be assumed that the Great Recession has reversed this trend sharply.[6]

[6] The 2009 SCF panel survey reinterviewed participants from the 2007 cross-sectional survey in order to capture the impact of the crisis on private finances. However, this data is not (yet) available for public use (see Bricker et al., 2011).



(a) $k = 1$



(b) $k = 2$

Figure 5.4.6: Multidimensional affluence (US, 1989–2007)

5.4.3 Extension: Weighting of Dimensions

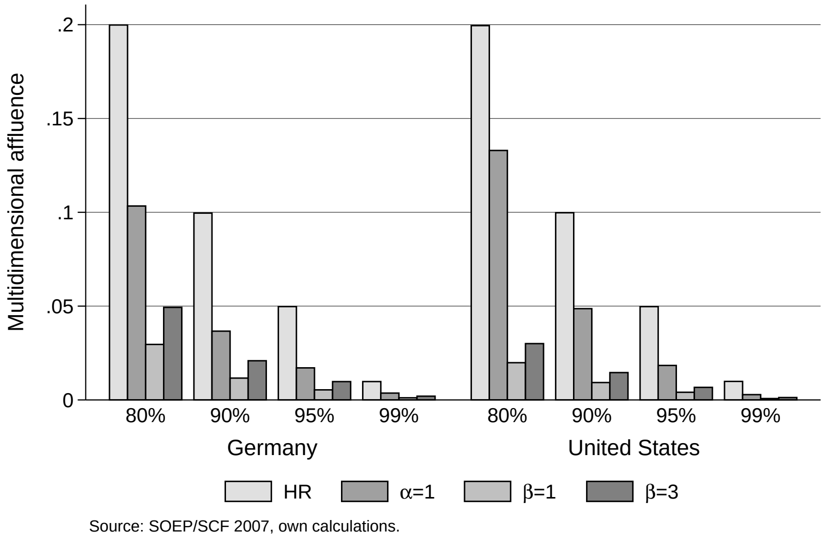
In both our theoretical consideration as well as in our empirical application of multidimensional affluence measurement we did not consider the issue of weighting dimensions and implicitly applied equal weights to both dimensions under consideration. Equal weighting is popular for its simplicity and its easy interpretation. Furthermore, it is the most appropriate choice if all dimensions are indeed equally important for economic well-being (Atkinson, 2003b; Alkire and Foster, 2011a). Decancq and Lugo (2013), however, argue that the weighting scheme determines the trade-off structure among dimensions and is crucial for choosing the dimensions since not considering several potential dimensions implicitly means assigning a weight of zero to them. Hence, any choice of weighting scheme clearly has normative implications (Decancq et al., 2009; Decancq and Ooghe, 2010). However, although equal weighting is not uncontroversial in the literature on multidimensional well-being there is also no agreement on a specific weighting scheme among various possible choices (see Decancq and Lugo, 2013, for an overview). Rather than making a specific alternative choice we present results for a range of possible combinations of different weights (see appendix).

We distinguish between Germany and the US as well as the cases of a union, an intermediate and an intersection approach to the dual cutoff method (see Alkire and Foster, 2011a, pp. 479–480). The union approach represents one extreme case where an individual is identified as multidimensionally affluent as soon as the sum of weighted counts is not below the least weight given to one of the dimensions under consideration. The other extreme approach, the intersection case, by contrast requires that the sum of weighted counts is equal to the total sum of weights. In our application using two dimensions and equal weights these cases were represented by the cutoffs $k = 1$ (union) and $k = 2$ (intersection) respectively. Allowing for different weights (and/or expanding the number of dimensions) allows intermediate cases, where an individual is affluent when its weighted counts are below the total sum of weights but are larger than the least weight.

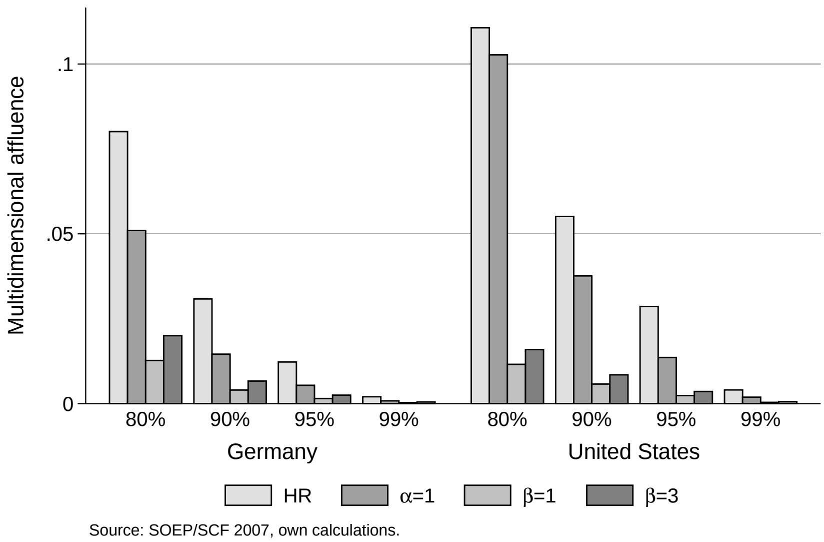
In figure 5.6.5 we plot the values of the multidimensional affluence indices against the weight of income, while figure 5.6.6 shows the contribution of this dimension for different weights (see appendix). Overall the results for the multidimensional affluence indices are not very sensitive to the weighting scheme. There is only some noise for the intermediate case. Moreover, the relationship between the relative weight of a dimension and its contribution to overall affluence is almost described by a linear function with the exception of the convex measure for $\alpha = 2$. For the German data, the contribution of income only grows slowly (the curve lies below the 45-degree line) while it increases rapidly in the US. This confirms our result that income and wealth contribute differently to multidimensional affluence when emphasizing the very top of the distributions.

5.4.4 Robustness Checks

Different cutoffs. We calculated the multidimensional affluence indices for different levels of the dimension-specific cutoffs, i.e., higher percentiles of the marginal distributions of income and wealth. As for our baseline specification, we defined the cutoffs separately by age of the household head. The results are presented in figure 5.4.7. The levels of the indices vary by the level of cutoff with smaller values for higher quantiles. However, the patterns we found for the baseline cutoff (80%-quantile of the age-specific distributions) are pretty similar. In particular, the cross-country differences remain almost unchanged, except for the concave measures. Whereas in our baseline results Germany exhibits (slightly) larger levels for this set of indices, they are almost the same for both countries or slightly larger in the US.



(a) $k = 1$



(b) $k = 2$

Figure 5.4.7: Multidimensional affluence: different cutoff levels (2007)

Administrative data for Germany. We check whether utilizing administrative data from tax records yields approximately similar results to survey data. We use German tax data (FAST[7]), which is a 10% stratified random sample from all German income tax records – about 3 million cases – available for scientific use. The FAST data provide detailed information on various aspects that are relevant for income taxation on the micro level (individuals and married couples). We use data from 2001 since this allows a comparison with the SOEP wave 2002 which comprise income and wealth information for the previous calender year.[8] Unfortunately, these data do not comprise information on wealth holdings and we have to construct and impute this information as it is not allowed to directly match the tax data with SOEP data due to German data protection regulations.

Table 5.4.3: Multidimensional Measures: administrative data (Germany, 2001)

k	R^M_{HR}	$R^M_{\alpha=1}$	$R^M_{\alpha=2}$	$R^M_{\beta=1}$	$R^M_{\beta=3}$
Germany (adminstrative data) 2001					
1	0.010	0.018	0.375	0.004	0.007
2	0.001	0.004	0.050	0.001	0.001
Germany (survey data) 2001					
1	0.010	0.007	0.041	0.003	0.005
2	0.002	0.002	0.010	0.000	0.001

Note: Source: FAST/SOEP, own calculations.

We define income as the sum of all market income subject to income taxes less income from capital (dividends) and construct a proxy for wealth holdings as the level of income from capital divided by an interest rate of around 7%, which we calculated from the SOEP (average sum of capital gains over the sum of business assets). Unfortunately, the tax data does not comprise proxies for property wealth, since especially owner-occupied housing is not subject to income taxation. Hence, capital income is an incomplete proxy for wealth since owner-occupied housing does not yield directly measurable income streams (only via

[7]FAST–*Faktisch anonymisierten Daten aus der Lohn- und Einkommensteuerstatistik*, see `http://www.forschungsdatenzentrum.de/bestand/lest/suf/2001/index.asp` (in German).

[8]The FAST data are available for 1998, 2001 and 2004; the SOEP data with wealth information for 2001 and 2006. Unfortunately, administrative tax data for the US are not available to us. Although tax record data have several advantages over survey data (esp. reliability of income information and representativeness) they do not contain direct information on wealth holdings.

imputed rents for owner-occupiers, see, e.g. Smeeding and Thompson, 2011). This poses a "serious challenge" for this capitalization of income method (Kopczuk and Saez, 2004). Hence, we also do not consider property income in the SOEP data for this comparative exercise. In addition, the (sample) populations of both data sources are not comparable. While the SOEP is designed to representatively cover the whole population, the FAST data only comprise tax payers, i.e., a specific subpopulation. In particular, pensioners are less likely to pay income taxes as in 2001 in Germany only a small share of public pension income was subject to taxation. That is why we use only one cutoff for the whole sample at the 99%-quantile since up to this level the SOEP data compare very well to the tax data (Bach et al., 2009). Table 5.4.3 presents the results, which are almost identical for the multidimensional headcount ratio as well as for the concave measures. Only for the convex indices, which put more weight on the very top, affluence measures based on tax data are unsurprisingly higher.

Outliers. As we are restricted to rather small samples for our empirical analysis, an issue arising is the precision of estimated values of multidimensional affluence indices. This is particularly true for the convex measures, which are more sensitive to extreme values at the top of the income and wealth distributions. As noted above, we apply the bootstrap method in order to derive empirical standard errors and find that the more emphasis is put on the very top the more imprecise the point estimates become. In particular, when analyzing the trend of (multidimensional) affluence over the 1989–2007 period in the US it is not always possible to detect *statistically significant* changes in affluence levels over time although point estimates show clear trends (see figures 5.4.5 and 5.4.6). Hence, there is a sort of trade-off between precision in estimation and emphasizing very intense affluence at least in the case of the convex measures. Another way to address this issue would be top-coding or even trimming the data at a specific threshold (e.g., the 99%-quantile), which is frequently applied in the literature. This is however not innocuous since it affects the absolute value of affluence measures – especially the convex ones (Van Kerm, 2007). However, we find that our qualitative results are not altered in both cases (results are available from the authors upon request).

Pension wealth. An important motive for building a wealth stock over the life cycle is precautionary saving, not only in order to smooth consumption over income shocks but in particular also as a form of old-age provision. The importance of private savings to secure a certain standard of living after retiring depends on the institutional setting (in particular the public pension system). While in Germany the most important pillar of the pension system relies on a statutory and compulsory pay-as-you-go pension scheme for dependent employees (and hence for a majority of the workforce), the system of publicly organized old-age provision in the US is less important (though not unimportant) for the individual retiree (Wolff, 2011). As a consequence, private old-age provision – in form of housing, stocks, bonds or pension funds – is of greater importance. Although the present values of future pension entitlements from a statutory pension scheme are not marketable (i.e., they cannot be sold or lend against) they nevertheless can be viewed as a special form of wealth since they represent a substitute for private old-age provision. Hence, the standard definition of net wealth described above does not take into account an important component of an individual's wealth portfolio (Frick and Heady, 2009). What follows from this line of argument is that it is desirable to include a measure of "pension wealth" when comparing countries with distinct pension systems (Frick and Heady, 2009). As an illustration, we use cell means for public pension entitlements and merge them to the SOEP data.[9] Consistent with previous findings (Rasner et al., 2011), incorporating pension wealth has a strong equalizing effect, in particular at the very top with a strong decrease in the values for $R^M_{\alpha=2}$ (see figure 5.4.8).

[9]We thank Markus M. Grabka (DIW Berlin) for providing us with the information used in Rasner et al. (2011) for different groups by age, gender, occupational status and region.

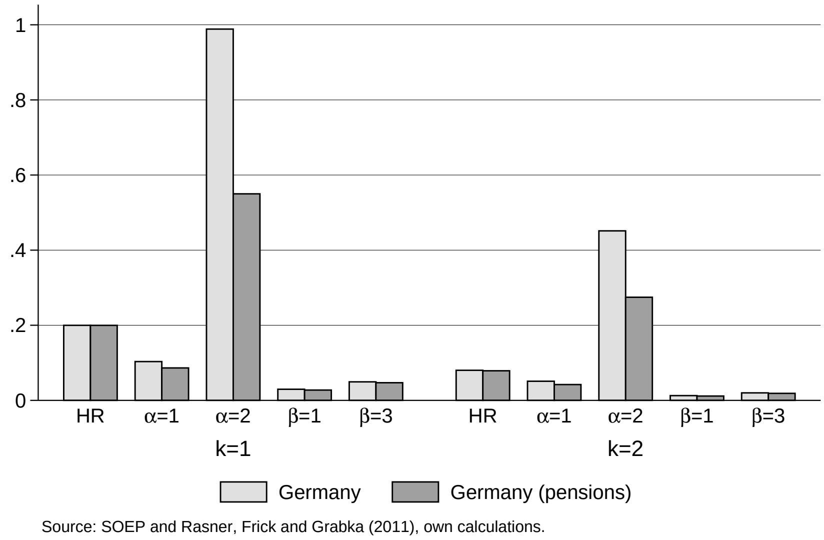


Figure 5.4.8: Multidimensional affluence: public pension wealth (Germany, 2007)

Other dimensions. We restrict our empirical illustration to income and wealth as dimensions of multidimensional affluence since these can be considered as core indicators of economic well-being. However, Stiglitz et al. (2009) have identified various key dimensions that should in principle be taken into account, when providing a more differentiated picture of a society's economic well-being. These dimensions comprise, among others, material living standards and health. Moreover, it is argued that quality of life depends on people's objective conditions and capabilities as well as on their subjective evaluations (see Sen, 1985; Anand and van Hees, 2006). In Peichl and Pestel (2012) we explicitly seize on these recommendations and apply the multidimensional approach to three dimensions reflecting different domains of life. Using SOEP data we include health as a proxy for non-material quality of life as well as self-reported satisfaction with life as dimensions besides income as traditional indicator for material well-being. We find that one third of the German population is well-off in at least one dimension but only one 1% in all three dimensions simultaneously. While the distribution of income has become more concentrated at the top, the concentration of the multidimensional well-being has decreased over time. Moreover, health as well as life satisfaction are important drivers of multidimensional richness which has important policy implications.

5.5 Conclusions

In this chapter, we propose measures for multidimensional affluence. We argue that the analysis of economic well-being, especially at the top of its distribution, should not only consider income as a single dimension, but in addition take into account further dimensions in order to provide a differentiated picture of economic well-being. We distinguish convex and concave measures of affluence, where the first put more emphasis on inequality at the very top of the joint distribution.

Using microdata from the SOEP and the SCF, we apply this framework to Germany and the United States (in 2007) and perform a cross-country analysis as well as an analysis of multidimensional affluence over time in the US (1989–2007). Conclusions derived from our results depend on the choice of multidimensional measure of affluence. It turns out, that according to the concave measures the German population is overall slightly more affluent than the US population and multidimensional affluence has remained constant during a period of nearly two decades. However, when referring to the convex measurement of multidimensional affluence, the US clearly outperforms Germany and there is volatility in affluence in the US between 1989 and 2007. In particular, based on a measure putting most emphasis on extreme affluence, we find that the very top of the joint distribution of income and wealth was responsible for most of volatility in inequality at the top. This is not only true during times of recession but also for a more recent period, when the US experienced a strong surge in multidimensional affluence.

Moreover, our approach allows to quantify the relative importance of single dimensions contributing to multidimensional affluence. We find that, in general, both income and wealth are equally important. Only when emphasizing extreme affluence there is a clear difference between the two countries: While in Germany wealth predominantly contributes to intense affluence in a multidimensional setting, income is more important in the US. Note again that our empirical application is based on survey data. Future research could employ administrative data in order to analyze several dimensions with different weights.

5.6 Appendix

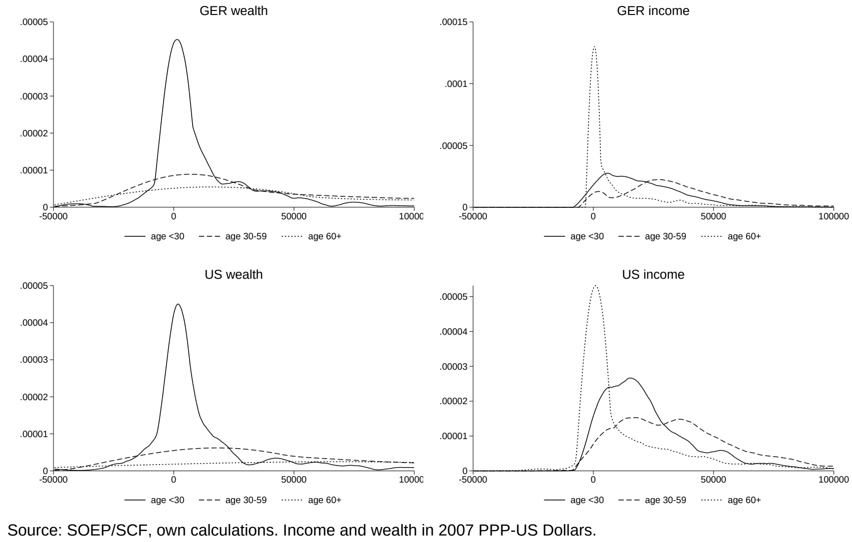


Figure 5.6.1: Income and wealth densities by age (2007)

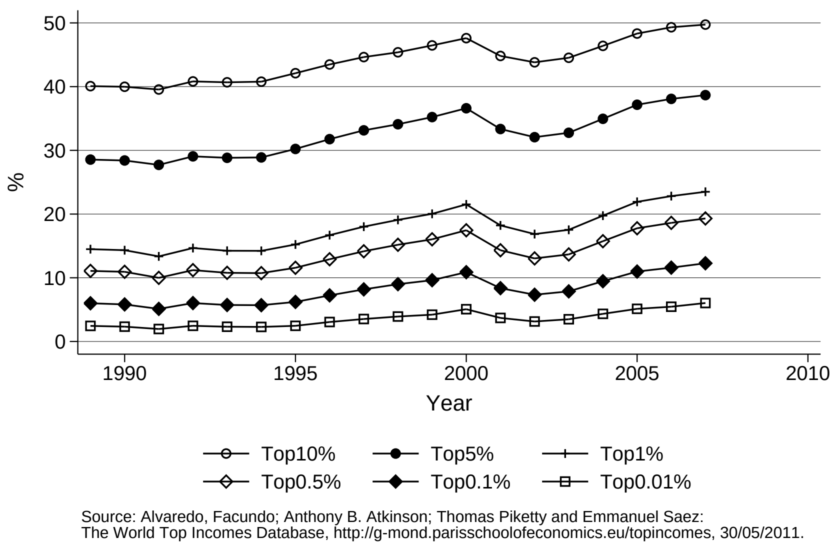
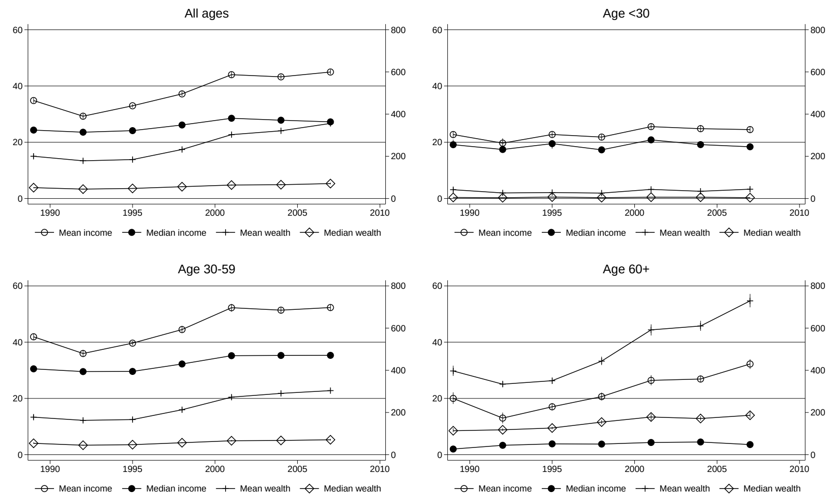
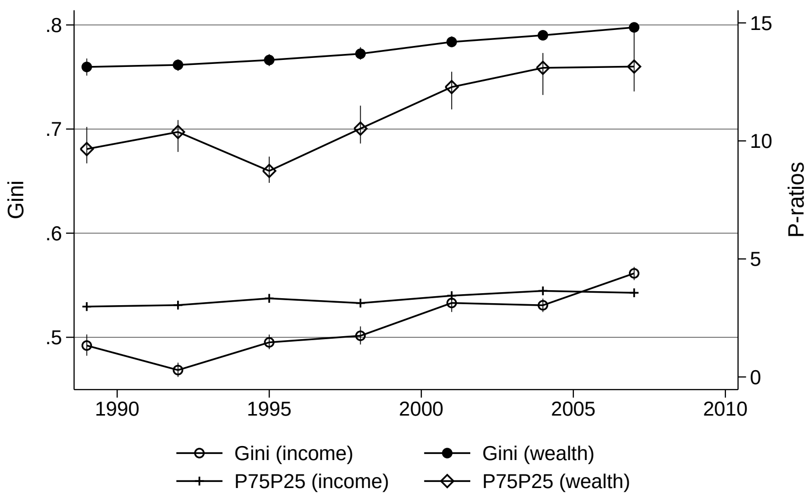


Figure 5.6.2: Top income shares incl. capital gains (US, 1989–2007)



Source: SCF 1989-2007, own calculations. Income (left) and wealth (right) in 2007 USD divided by 1,000.
Confidence intervals (95%) based on 500 bootstrap replications.

Figure 5.6.3: Income and wealth by age (US, 1989–2007)



Source: SCF 1989-2007, own calculations.
Confidence intervals (95%) based on 500 bootstrap replications.

Figure 5.6.4: Income and wealth inequality (US, 1989–2007)

Weighting of dimensions. In section 5.2.2 we described the measurement of multidimensional affluence in the case of equal weighting of dimensions. Here, we describe the more general case with different weights w_j for dimensions j, where it holds that the weights sum up to the number of dimensions under consideration ($\sum_{j=1}^{d} w_j = d$). So far we have assumed $w_j = 1 \; \forall \; j$. The identification of the dimension-specific affluent then becomes

$$\theta_{ij}^{w}(y_{ij};\gamma) = \begin{cases} w_j & \text{if } y_{ij} > \gamma_j, \\ 0 & \text{otherwise} \end{cases} \tag{5.6.1}$$

and the sum of individual i's affluent dimensions' weights $c_i^w = \sum_{j=1}^{d} \theta_{ij}^{w}$ is needed for the identification of multidimensional richness depending on the second-stage cutoff $k \in [min_j(w_j), d]$:

$$\phi_i^{k,w}(y_i,\gamma) = \begin{cases} 1 & \text{if } c_i^w \geq k, \\ 0 & \text{if } c_i^w < k. \end{cases} \tag{5.6.2}$$

Hence, the weighted matrices now read

$$\mathbf{\Theta}^{\alpha,\mathbf{w}}(\mathbf{k}) = \left[\; w_j \cdot \left(\frac{y_{ij} - \gamma_j}{\gamma_j} \right)^{\alpha} \cdot \phi_i^{k,w}(y_i,\gamma) \; \right]_{n \times d} \tag{5.6.3}$$

and

$$\mathbf{\Theta}^{\beta,\mathbf{w}}(\mathbf{k}) = \left[\; w_j \cdot \left(1 - \left(\frac{\gamma_j}{y_{ij}} \right)^{\beta} \right) \cdot \phi_i^{k,w}(y_i,\gamma) \; \right]_{n \times d} \tag{5.6.4}$$

respectively. The calculation of the multidimensional affluence measures and its contributions now works in the same as in the equal weighting case before.

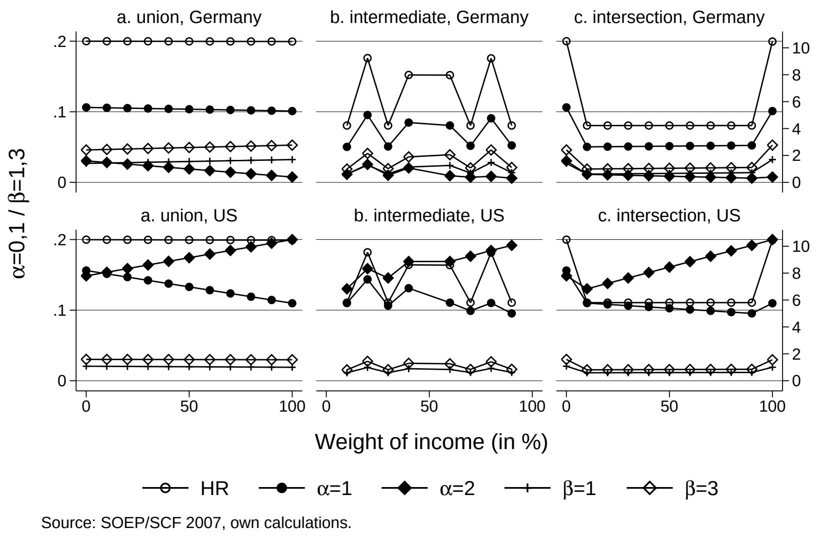


Figure 5.6.5: Multidimensional affluence: different weights (2007)

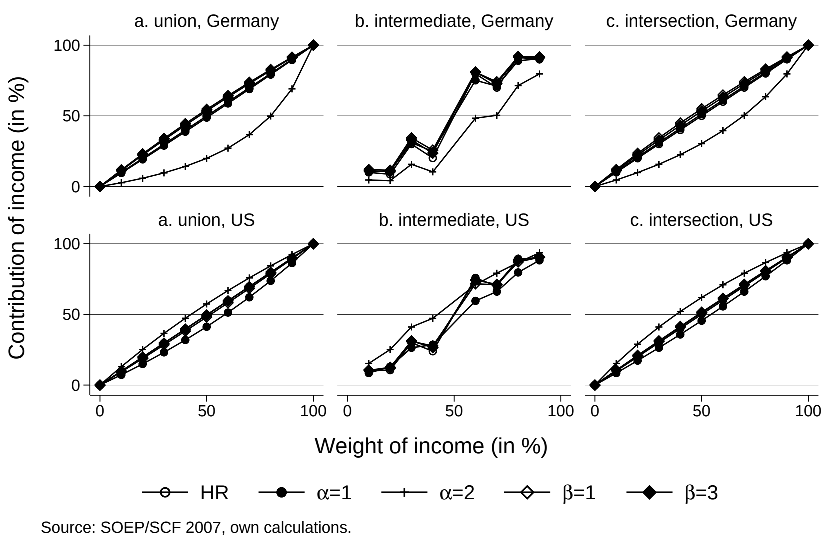


Figure 5.6.6: Affluence contributions per dimension: different weights (2007)

Chapter 6

Concluding Remarks

Growing economic inequality has recently received increasing attention. The gap between rich and poor is potentially harmful for public welfare when it exceeds a certain threshold. That is why many policy makers are concerned with increasing levels of inequality. Economists should, therefore, provide an objective basis for decision making with regard to redistributive policies. Conducting analysis of economic inequality requires a decision on the exact research subject. This is concerned with the underlying concept of economic resources as well as the extent to which the household context is involved. The studies presented in this thesis differ with respect to both dimensions. In the following, I will briefly summarize the main results and discuss implications for future research and policy making.

Chapter 2 analyzes the remuneration of members of parliament (MPs) in Germany. MPs earn significantly more than an average executive. However, politicians' earnings are not excessive compared to top level executives. Hence, answering the question whether the pay of MPs is appropriate is not straightforward and, in turn, depends on the appropriateness of the underlying control group.

With respect to equity considerations, politicians' remuneration is a good showcase for policy makers themselves. It should be recognized that the assessment of earnings differentials requires thorough scrutiny of whether high pay can be justified or not. This is especially important at the top, where excessive incomes attract lots of publicity. Individual cases, that are perceived as unfair, can potentially cement the public's attitude towards the fairness of pay in general. However, decision makers should bear in mind that above average earnings are a necessary, but not a sufficient condition for inefficient rent-seeking behavior or inequitable discrimination on labor markets. In addition, politicians' remuneration has important implications for the selection of individuals into politics and, hence, affects the quality of policy making. Future research should, therefore, deepen our understanding of the incentive systems politicians face in order to improve policy output.

Chapter 3 studies the role of marital sorting on inequality while taking into account labor supply behavior. The observed pattern of sorting in earnings has a fairly weak impact on inequality. However, after correcting for labor supply choices, sorting in productivity has a much stronger effect. This is mainly due to positive correlation in earnings potential and increases in female employment that are more concentrated in the upper part of the distribution.

From a policy maker's perspective, this result implies a trade-off between policy measures promoting female labor force participation and redistributive policies. Achieving the objective of higher female employment apparently comes at the price of higher inequality. The policy implications are ambiguous. One could argue that government intervention is not justified here, since this specific reason for increasing inequality is the result of couples' choices. However, the growing share of dual earner couples implies a declining importance of intra family redistribution, which could potentially be substituted by government redistribution. Policy advice on how to deal with this equity-efficiency trade-off can only be based on a theoretical framework of optimal taxation of couples. This should explicitly consider the role of market and non-market production of household goods and services affecting the distribution both within and across couple households as well as the selection into cohabitation and marriage.

Chapter 4 examines the role of changing household structure, especially decreasing household size, for the distribution of income. Changes in household formation are associated with income inequality, since economies of scales in household consumption are more and more lost. This effect is stronger for gross incomes than for disposable incomes. This means that the German tax and transfer system implicitly provides a compensation for changing household composition.

Chapters 3 and 4 are concerned with social changes, which have altered societies in many industrialized countries over the past decades. In many ways, the distribution of economic resources did not remain unaffected by these trends. In democracies, a society's way of life is beyond the sphere of direct political influence. At the same time, tax-benefit policies are typically viewed as mechanisms for redistributive or allocative purposes. However, there are a number of incentives inherent in these policies affecting individual and household choices (sometimes unintentionally) with respect to living arrangements. Therefore, the study of behavioral responses to policies remains at the top of future research agendas. The optimal design of tax-benefit policies needs to take into account potential indirect effects. Moreover, we should broaden our knowledge of the driving forces behind long term trends shaping the composition of societies.

Finally, chapter 5 looks at the joint distribution of income and wealth at the top. In general, both dimensions are equally important for multidimensional affluence. When emphasizing the very top, wealth predominantly contributes to intense affluence in Germany, while income is more important in the US.

The view that economic well-being is not one-dimensional is now widespread. Therefore, governments should take into account additional key dimensions when assessing society's welfare. However, when it comes to practical implementation of multidimensional evaluation (of the distribution) of well-being, there is no general consensus, neither on the choice nor on the weighting of dimensions. We use core indicators of economic well-being, since they are important determinants of economic inequality, which is the focus of this thesis. In other contexts, additional dimensions are also of great importance and it is up to the researcher to select dimensions in light of the respective research question. However, it would be beneficial for the coherence of multidimensional analyses of economic well-being if researchers agreed on a core set of dimensions and indicators.

In this dissertation, I address several building blocks in the literature on economic inequality that are not fully integrated. Formulating a comprehensive model of the distribution of economic resources is beyond the scope of this thesis. However, making progress on the development of such a theoretical framework, comprising models of earnings and income from all sources as well as models of household formation processes, is an enormous challenge for future research (Jenkins and Micklewright, 2007a). As long as such a framework does not exist, one should instead combine single pieces of the puzzle to get closer to the overall picture of economic inequality. This thesis contributes some of the pieces that were not yet fully explored.

One important part of the puzzle, which deserves further study, is the interplay between social and demographic changes on the one hand and the distribution of economic resources on the other hand. Secular trends of changing living arrangements are related to serious demographic transitions many Western societies will face in coming years. These changes will fundamentally reshape the workforce and society more generally. This is particularly true for Germany. As discussed before, economic inequality will not remain unaffected by these foreseeable changes, but our knowledge of this nexus is still limited and we do not exactly know which role policies (should) play. Hence, future research should further address this issue.

Bibliography

Aaberge, R., U. Colombino, and S. Strøm (1999). Labor Supply in Italy: An Empirical Analysis of Joint Household Decisions, with Taxes and Quantity Constraints. *Journal of Applied Econometrics 14*, 403–422.

Aaberge, R., J. K. Dagsvik, and S. Strøm (1995). Labour Supply Responses and Welfare Effects of Tax Reforms. *Scandinavian Journal of Economics 97*(4), 635–659.

Aaron, H. (1978). *Politics and the Professors*. Brookings Institutions, Washington D.C.

Abadie, A. and G. W. Imbens (2006). Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica 74*(1), 235–267.

Acemoglu, D. and D. H. Autor (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 4b, pp. 1043–1171. Elsevier, Amsterdam.

Alesina, A. and G.-M. Angeletos (2005). Fairness and Redistribution. *American Economic Review 95*(4), 960–980.

Alkire, S. and J. Foster (2011a). Counting and Multidimensional Poverty Measurement. *Journal of Public Economics 95*(7–8), 476–487.

Alkire, S. and J. Foster (2011b). Understandings and Misunderstandings of Multidimensional Poverty Measurement. *Journal of Economic Inequality 9*(2), 289–314.

Allensbacher Archiv (2008). IfD-Umfragen 10015. Institut für Demoskopie, Allensbach.

Almås, I. and M. Mogstad (2012). Older or Wealthier? The Impact of Age Adjustment on Wealth Inequality. *Scandinavian Journal of Economics 114*(1), 24–54.

Altonji, J. G. and R. M. Blanc (1999). Race and Gender in the Labor Market. In O. Oshenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3c. Elsevier, Amsterdam.

Alvaredo, F., A. B. Atkinson, T. Piketty, and E. Saez (2011). The World Top Incomes Database. `http://g-mond.parisschoolofeconomics.eu/topincomes`, 30/05/2011.

Anand, P. and M. van Hees (2006). Capabilities and Achievements: An Empirical Study. *Journal of Socio-Economics 35*, 268–284.

Antonczyk, D., B. Fitzenberger, and K. Sommerfeld (2010). Rising Wage Inequality, the Decline of Collective Bargining, and the Gender Wage Gap. *Labour Economics 17*(5), 835–847.

Arulampalam, W., A. L. Booth, and M. L. Bryan (2007). Is there a Glass Ceiling over Europe? Exploring the Gender Pay Gap across the Wage Distribution. *Industrial and Labor Relations Review 60*(2), 163–186.

Asendorpf, J. B. (2009). Living Apart Together: Alters- und Kohortenabhängigkeit einer heterogenen Lebensform. *Kölner Zeitschrift für Soziologie und Sozialpsychologie 60*(4), 749–764.

Aslaksen, I., T. Wennemo, and R. Aaberge (2005). Birds of a Feather Flock Together: The Impact of Choice of Spouse on Family Labor Income Inequality. *Labour 19*(3), 491–515.

Atkinson, A. B. (1997). Bringing Income Distribution in from the Cold. *Economic Journal 107*(44), 297–321.

Atkinson, A. B. (2003a). Income Inequality in OECD Countries: Data and Explanations. CESifo Working Paper No. 881.

Atkinson, A. B. (2003b). Multidimensional Deprivation: Contrasting Social Welfare and Counting Approaches. *Journal of Economic Inequality 1*(1), 51–65.

Atkinson, A. B. (2005). Comparing the Distribution of Top Incomes Across Countries. *Journal of the European Economic Association 3*(2–3), 393–401.

Atkinson, A. B. (2007a). Measuring Top Incomes: Methodological Issues. In A. B. Atkinson and T. Piketty (Eds.), *Top Incomes over the Twentieth Century*, pp. 18–42. Oxford University Press, Oxford.

Atkinson, A. B. (2007b). The Long Run Earnings Distribution in Five Countries: Remarkable Stability, U, V or W? *Review of Income and Wealth 53*(1), 1–24.

Atkinson, A. B. (2008a). Concentration among the Rich. In J. B. Davies (Ed.), *Personal Wealth from a Global Perspective*. Oxford University Press, Oxford.

Atkinson, A. B. (2008b). *The Changing Distribution of Earnings in OECD Countries*. Oxford University Press, Oxford.

Atkinson, A. B. and F. Bourguignon (2000). Income Distribution and Economics. In A. B. Atkinson and F. Bourguignon (Eds.), *Handbook of Income Distribution*, Volume 1, pp. 1–86. Elsevier, Amsterdam.

Atkinson, A. B. and A. Brandolini (2011). On the Identification of the "Middle Class". ECINEQ Working Paper No. 2011–217.

Atkinson, A. B. and T. Piketty (2007). *Top Incomes over the Twentieth Century*. Oxford University Press, Oxford.

Atkinson, A. B., T. Piketty, and E. Saez (2011). Top Incomes in the Long Run of History. *Journal of Economic Literature 49*(1), 3–71.

Autor, D. H., L. F. Katz, and M. S. Kearney (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics 90*(2), 300–323.

Autor, D. H., L. F. Katz, and A. B. Krueger (1998). Computing Inequality: Have Computers Changed the Labor Market? *Quarterly Journal of Economics 113*(4), 1169–1213.

Azpitarte, F. (2012). Measuring Poverty Using both Income and Wealth: A Cross-country Comparison between the U.S. and Spain. *Review of Income and Wealth 58*(1), 24–50.

Bach, S., G. Corneo, and V. Steiner (2009). From Bottom to Top: The Entire Income Distribution in Germany, 1992–2003. *Review of Income and Wealth 55*(2), 303–330.

Bach, S., G. Corneo, and V. Steiner (2011). Effective Taxation of Top Incomes in Germany. FU Berlin School of Business & Economics Discussion Paper No. 2011/18.

Banks, J. and P. Johnson (1994). Equivalence Scales and Public Policy. *Fiscal Studies 15*(1), 1–23.

Bargain, O. and T. Callan (2010). Analysing the Effects of Tax-Benefit Reforms on Income Distribution: A Decomposition Approach. *Journal of Economic Inequality 8*(1), 1 –21.

Bargain, O., M. Dolls, C. Fuest, D. Neumann, A. Peichl, N. Pestel, and S. Siegloch (2012). Fiscal Union in Europe? Efficiency, Equity and Stabilizing Effects of an EU-Wide Income Tax. IZA Discussion Paper No. 6585.

Bargain, O., M. Dolls, H. Immervoll, D. Neumann, A. Peichl, N. Pestel, and S. Siegloch (2011). Tax Policy and Income Inequality in the U.S., 1978–2009: A Decomposition Approach. IZA Discussion Paper No. 5910.

Bargain, O., K. Orsini, and A. Peichl (2012). Comparing Labor Supply Elasticities in Europe and the US: New Results. IZA Discussion Paper No. 6735.

Barry, B. (2002). Social Exclusion, Social Isolation, and the Distribution of Income. In J. Hills, J. L. Grand, and D. Piachaud (Eds.), *Understanding Social Exclusion*, pp. 13–29. Oxford University Press, Oxford.

Bartels, L. M. (2008). *Unequal Democracy. The Political Economy of the New Gilded Age*. Princeton University Press, Princeton and Oxford.

Becker, G. S. and G. J. Stigler (1974). Law Enforcement, Malfeasance, and Compensation of Enforcers. *Journal of Legal Studies 3*, 1–18.

Becker, J., A. Peichl, and J. Rincke (2009). Politicians' Outside Earnings and Electoral Competition. *Public Choice 140*(3–4), 379–394.

Belman, D. and J. S. Heywood (1989). Government Wage Differentials: A Sample Selection Approach. *Applied Economics 21*(4), 427–439.

Bender, K. A. (1998). The Central Government-Private Wage Differential. *Journal of Economic Surveys 12*(2), 177–220.

Besley, T. (2004). Joseph Schumpeter Lecture: Paying Politicians: Theory and Evidence. *Journal of the European Economic Association 2*(2–3), 193–215.

Besley, T. and A. Case (1995). Does Electoral Accountability Affect Economic Policy Choices? Evidence from Gubernatorial Term Limits. *Quarterly Journal of Economics 110*(3), 769–798.

Besley, T. and S. Coate (1997). An Economic Model of Representative Democracy. *Quarterly Journal of Economics 112*(1), 85–114.

Biewen, M. (2005). The Covariance Structure of East and West German Incomes and its Implications for the Persistence of Poverty and Inequality. *German Economic Review 6*(4), 103–132.

Biewen, M. and A. Juhasz (2012). Understanding Rising Inequality in Germany, 1999/2000–2005/06. *Review of Income and Wealth, forthcoming.*

Björklund, A. and M. Jäntti (1997). Intergenerational Income Mobility in Sweden Compared to the United States. *American Economic Review 87*(4), 1009–1018.

Blau, F. D. and L. M. Kahn (2000). Gender Differences in Pay. *Journal of Economic Perspectives 14*(4), 75–99.

Blau, F. D. and L. M. Kahn (2006). The US Gender Pay Gap in the 1990s: Slowing Convergence. *Industrial and Labor Relations Review 60*(1), 45–66.

Blau, F. D. and L. M. Kahn (2007). Changes in the Labor Supply Behavior of Married Women: 1980–2000. *Journal of Labor Economics 25*(3), 393–438.

Blinder, A. S. (1973). Wage Discrimination: Reduced Form and Structural Estimates. *Journal of Human Resources 8*(4), 436–455.

Blundell, R., A. Bozio, and G. Laroque (2011a). Extensive and Intensive Margins of Labour Supply: Working Hours in the US, UK and France. IFS Working Paper No. 01/11.

Blundell, R., A. Bozio, and G. Laroque (2011b). Labour Supply and the Extensive Margin. *American Economic Review Papers and Proceedings 101*(3), 482–486.

Blundell, R., A. Duncan, J. McCrae, and C. Meghir (2000). The Labour Market Impact of the Working Families' Tax Credit. *Fiscal Studies 21*(1), 75–104.

Bönke, T. and C. Schröder (2011). Poverty in Germany – Statistical Inference and Decomposition. *Journal of Economics and Statistics 231*(2), 178–209.

Bönke, T. and C. Schröder (2012). Country Inequality Rankings and Conversion Schemes. *Economics: The Open-Access, Open-Assessment E-Journal 6*(2012–28).

Borghans, L., A. L. Duckworth, J. J. Heckman, and B. ter Weel (2008). The Economics and Psychology of Personality Traits. *Journal of Human Resources 43*(4), 972–1059.

Bourguignon, F. and S. R. Chakravarty (2003). The Measurement of Multidimensional Poverty. *Journal of Economic Inequality 1*(1), 25–49.

Bourguignon, F., M. Fournier, and M. Gurgand (2001). Fast Development with a Stable Income Distribution: Taiwan, 1979–94. *Review of Income and Wealth 47*(2), 139–163.

Bover, O. (2010). Wealth Inequality and Household Structure: US vs. Spain. *Review of Income and Wealth 56*(2), 259–290.

Braendle, T. and A. Stutzer (2010). Public Servants in Parliament: Theory and Evidence on its Determinants in Germany. *Public Choice 145*(1–2), 223–252.

Brandolini, A., S. Magri, and T. M. Smeeding (2010). Asset-based Measurement of Poverty. *Journal of Policy Analysis and Management 29*(2), 267–284.

Bricker, J., B. K. Bucks, A. B. Kennickell, T. L. Mach, and K. B. Moore (2011). Surveying the Aftermath of the Storm: Changes in Family Finances from 2007 to 2009. Finance and Economics Discussion Series No. 2011–17.

Brzezinski, M. (2010). Income Affluence in Poland. *Social Indicators Research 99*(2), 285–299.

Bucks, B. K., A. B. Kennickell, T. L. Mach, and K. B. Moore (2009). Changes in U.S. Family Finances from 2004 to 2007: Evidence from the Survey of Consumer Finances. *Federal Reserve Bulletin*, A1–A56.

Buhmann, B., L. Rainwater, G. Schmaus, and T. M. Smeeding (1988). Equivalence Scales, Well-Being, Inequality and Poverty: Sensitivity Estimates Across Ten Countries Using the Luxembourg Income Study (LIS) Database. *Review of Income and Wealth 34*(2), 115–142.

Bundesministergesetz (2008). Gesetz über die Rechtsverhältnisse der Mitglieder der Bundesregierung. Bundesgesetzblatt I, S. 2018.

Bundestag (2009). Entwurf eines Siebenundzwanzigsten Gesetzes zur Änderung des Abgeordnetengesetzes. Deutscher Bundestag, Drucksache 16/6924, Heeneman, Berlin.

Bundestag (2010). Verhaltensregeln für Mitglieder des Deutschen Bundestages. Deutscher Bundestag, Geschäftsordnung des Deutschen Bundestages und Geschäftsordnung des Vermittlungsausschusses.

Bundestag (2011a). Fundstellenverzeichnis der Rechenschaftsberichte. Deutscher Bundestag, `http://www.bundestag.de/bundestag/parteienfinanzierung/rechenschaftsberichte/index.html`.

Bundestag (2011b). Hinweise zur Veröffentlichung der Angaben gemäß Verhaltensregeln im Amtlichen Handbuch und auf den Internetseiten des Deutschen Bundestages. Deutscher Bundestag, `http://www.bundestag.de/bundestag/abgeordnete17/nebentaetigkeit/hinweise17.html`.

Bundeswahlleiter (2011). Ergebnisse der Wahlen zum Deutschen Bundestag. `http://www.bundeswahlleiter.de/de/bundestagswahlen/`.

Burkhauser, R. V., S. Feng, S. Jenkins, and J. Larrimore (2011). Trends in United States Income Inequality Using the March Current Population Survey: The Importance of Controlling for Censoring. *Journal of Economic Inequality 9*(3), 393–415.

Burkhauser, R. V., S. Feng, S. Jenkins, and J. Larrimore (2012). Recent Trends in Top Income Shares in the USA: Reconciling Estimates from March CPS and IRS Tax Return Data. *Review of Economics and Statistics 94*(2), 371–388.

Burkhauser, R. V., T. M. Smeeding, and J. Merz (1996). Relative Inequality and Poverty in Germany and the United States Using Alternative Equivalence Scales. *Review of Income and Wealth 42*(4), 381–400.

Burtless, G. (1999). Effects of Growing Wage Disparities and Changing Family Composition on the U.S. Income Distribution. *European Economic Review 43*(4–6), 853–865.

Burtless, G. (2009). Demographic Transformation and Economic Inequality. In W. Salverda, B. Nolan, and T. M. Smeeding (Eds.), *The Oxford Handbook of Economic Inequality*, pp. 435–454. Oxford University Press, Oxford.

Cadigan, J. (2005). The Citizen Candidate Model: An Experimental Analysis. *Public Choice 123*(1–2), 197–216.

Caliendo, M. and S. Kopeinig (2008). Some Practical Guidance for the Implementation of Propensity Score Matching. *Journal of Economic Surveys 22*(1), 31–72.

Canberra Group (2001). Final Report and Recommendations. Expert Group on Household Income Statistics, Ottawa.

Cancian, M. and D. Reed (1998). Assessing the Effects of Wives' Earnings on Family Income Inequality. *Review of Economics and Statistics 80*(1), 73–79.

Cancian, M. and D. Reed (1999). The Impact of Wives' Earnings on Income Inequality: Issues and Estimates. *Demography 36*(2), 173–184.

Caprara, G. V., C. Barbaranelli, C. Consiglio, L. Picconi, and P. G. Zimbardo (2003). Personalities of Politicians and Voters: Unique and Synergistic Relationships. *Journal of Personality and Social Psychology 84*(4), 849–856.

Card, D. and J. E. DiNardo (2002). Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. *Journal of Labor Economics 20*(4), 733–783.

Card, D. and T. Lemieux (2001). Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis. *Quarterly Journal of Economics 116*(2), 705–746.

Caselli, F. and M. Morelli (2004). Bad Politicians. *Journal of Public Economics 88*(3–4), 759–782.

Clark, Andrew, E., P. Frijters, and M. A. Shields (2008). Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles. *Journal of Economic Literature 46*(1), 95–144.

Cobb-Clark, D. and S. Schurer (2012). The Stability of Big-Five Personality Traits. *Economics Letters 115*(1), 11–15.

Corneo, G. (2005). The Rise and likely Fall of the German Income Tax, 1958–2005. *CESifo Economic Studies 51*, 159–186.

Cowell, F. A. (2008). *Measuring Inequality.* Oxford University Press, Oxford.

Cowell, F. A. (2011). Inequality among the Wealthy. CASE Papers No. 150.

Creedy, J. and G. Kalb (2006). *Labour Supply and Microsimulation. The Evaluation of Tax Policy Reforms.* Edward Elgar, Cheltenham/Northampton.

Cutler, D. M. and L. F. Katz (1992). Rising Inequality? Changes in the Distribution of Income and Consumption in the 1980s. *American Economic Review 82*(2), 546–551.

Daly, M. C. and R. G. Valletta (2006). Inequality and Poverty in United States: The Effects of Rising Dispersion of Men's Earnings and Changing Family Behaviour. *Economica 73*(289), 75–98.

D'Ambrosio, C., J. R. Frick, and M. Jäntti (2009). Satisfaction with Life and Economic Well-Being: Evidence from Germany. *Schmollers Jahrbuch – Journal of Applied Social Sciences 129*(2), 283–295.

Davies, J. B., S. Sandström, A. B. Shorrocks, and E. N. Wolff (2011). The Level and Distribution of Global Household Wealth. *Economic Journal 121*(551), 223–254.

De Paola, M. and V. Scoppa (2011). Political Competition and Politician Quality: Evidence from Italian Municipalities. *Public Choice 148*(3), 547–559.

Decancq, K., A. Decoster, and E. Schokkaert (2009). The Evolution of World Inequality in Well-Being. *World Development 37*(1), 11–25.

Decancq, K. and M. A. Lugo (2012). Inequality of Well-Being: A Multidimensional Approach. *Economica 79*(316), 721–746.

Decancq, K. and M. A. Lugo (2013). Weights in Multidimensional Well-Being: An Overview. *Econometric Reviews 32*(1).

Decancq, K. and E. Ooghe (2010). Has the World Moved Forward? A Robust Multidimensional Evaluation. *Economics Letters 107*(2), 266–269.

Decancq, K., A. Peichl, and P. Van Kerm (2012). Unequal by Marriage? A Copula-based Decomposition of Household Inequality in the US, mimeo.

Dell, F. (2005). Top Incomes in Germany and Switzerland over the Twentieth Century. *Journal of the European Economic Association 3*(2–3), 412–421.

Dell, F. (2007). Top Incomes in Germany Throughout the Twentieth Century: 1891–1998. In A. B. Atkinson and T. Piketty (Eds.), *Top Incomes over the Twentieth Century*, pp. 365–425. Oxford University Press, Oxford.

Devereux, P. J. (2004). Changes in Relative Wages and Family Labor Supply. *Journal of Human Resources 39*(3), 696–722.

Diermeier, D., M. Keane, and A. Merlo (2005). A Political Economy Model of Congressional Careers. *American Economic Review 95*(1), 347–373.

DiNardo, J. E., N. M. Fortin, and T. Lemieux (1996). Labor Market Institutions and the Distribution of Wages, 1973–1992: A Semiparametric Approach. *Econometrica 64*(5), 1001–1044.

Djankov, S., R. La Porta, F. L. de Silanes, and A. Shleifer (2010). Disclosure by Politicians. *American Economic Journal: Applied Economics 2*(2), 179–209.

Dustmann, C., J. Ludsteck, and U. Schönberg (2009). Revisiting the German Wage Structure. *Quarterly Journal of Economics 124*(2), 843–881.

Ebert, U. and P. Moyes (2003). Equivalence Scales Reconsidered. *Econometrica 71*(1), 319–343.

Eggers, A. C. and J. Hainmueller (2009). MPs for Sale? Estimating Returns to Office in Postwar British Politics. *American Political Science Review 103*(4), 513–533.

Ehrenberg, R. G. and J. L. Schwarz (1987). Public Sector Labor Markets. In O. Oshenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 2. Elsevier, Amsterdam.

Eisenhauer, J. G. (2011). The Rich, the Poor, and the Middle Class: Thresholds and Intensity Indices. *Research in Economics 65*(4), 294–304.

European Social Survey (2007). *Exploring Public Attitudes, Informing Public Policy: Selected Findings from the First Three Rounds.*

Eurostat (2007). *Comparative EU Statistics on Income and Living Conditions: Issues and Challenges. Proceedings of the EU-SILC Conference, Helsinki, 6.–8. November 2006.* Office for Official Publications of the European Communities, Luxembourg.

Ferraz, C. and F. Finan (2008). Exposing Corrupt Politicians: The Effects of Brazil's Publicly Released Audits on Electoral Outcomes. *Quarterly Journal of Economics 123*(2), 703–745.

Ferraz, C. and F. Finan (2009). Motivating Politicians: The Impact of Monetary Incentives on Quality and Performance. NBER Working Paper No. 14906.

Fortin, N. M. and T. Lemieux (1997). Institutional Changes and Rising Wage Inequality: Is There a Linkage? *Journal of Economic Perspectives 11*(2), 75–96.

Foster, J., J. Greer, and E. Thorbecke (1984). A Class of Decomposable Poverty Measures. *Econometrica 52*(3), 761–766.

Frank, R. L. (2007). *Richistan: A Journey Through the American Wealth Boom and the Lives of the New Rich.* Random House, New York.

Frässdorf, A., J. Schwarze, and M. M. Grabka (2011). The Impact of Household Capital Income on Income Inequality – A Factor Decomposition Analysis for Great Britain, Germany and the USA. *Journal of Economic Inequality 9*(1), 35–56.

Frenette, M., D. A. Green, and K. Milligan (2007). The Tale of the Tails: Canadian Income Inequality in the 1980s and 1990s. *Canadian Journal of Economics 40*(3), 734–764.

Frick, J. R. and J. Goebel (2008). Regional Income Stratification in Unified Germany Using a Gini Decomposition Approach. *Regional Studies 42*(4), 555–577.

Frick, J. R., J. Goebel, M. M. Grabka, O. Groh-Samberg, and G. G. Wagner (2007). Zur Erfassung von Einkommen und Vermögen in Haushaltssurveys: Hocheinkommensstichprobe und Vermögensbilanz im SOEP. SOEPpaper on Multidisciplinary Panel Data Research No. 19.

Frick, J. R. and M. M. Grabka (2003). Imputed Rent and Income Inequality: A Decomposition Analysis for Great Britain, West Germany and the U.S. *Review of Income and Wealth 49*(4), 513–537.

Frick, J. R. and M. M. Grabka (2009). Wealth Inequality on the Rise in Germany. *DIW Weekly Report 5*(10), 62–73.

Frick, J. R. and M. M. Grabka (2010). Accounting for Imputed and Capital Income Flows in Inequality Analysis. In D. Besharov and K. Couch (Eds.), *Measuring Poverty, Income Inequality, and Social Exclusion.* Oxford University Press, Oxford.

Frick, J. R., M. M. Grabka, and R. Hauser (2010). *Die Verteilung der Vermögen in Deutschland – Empirische Analysen für Personen und Haushalte.* edition sigma, Berlin.

Frick, J. R., M. M. Grabka, and J. Marcus (2007). Editing and Multiple Imputation of Item-Non-Response in the 2002 Wealth Module of the German Socio-Economic Panel (SOEP). SOEPpaper on Multidisciplinary Panel Data Research No. 18.

Frick, J. R. and B. Heady (2009). Living Standards in Retirement: Accepted International Comparisons are Misleading. *Schmollers Jahrbuch – Journal of Applied Social Sciences 129*(2), 309–319.

Fuchs-Schündeln, N., D. Krüger, and M. Sommer (2010). Inequality Trends for Germany in the Last Two Decades: A Tale of Two Countries. *Review of Economic Dynamics 13*(1), 103–132.

Fuest, C., J. Niehues, and A. Peichl (2010). The Redistributive Effects of Tax Benefit Systems in the Enlarged EU. *Public Finance Review 38*(4), 473–500.

Gagliarducci, S. and T. Nannicini (2012). Do Better Paid Politicians Perform Better? Disentangling Incentives from Selection. *Journal of the European Economic Association, forthcoming.*

Gagliarducci, S., T. Nannicini, and P. Naticchioni (2010). Moonlighting Politicians. *Journal of Public Economics 94*(9–10), 688–699.

Gallie, D. and S. Paugam (2000). The Social Regulation of Unemployment. In D. Gallie and S. Paugam (Eds.), *Welfare Regimes and the Experience of Unemployment in Europe*, pp. 351–374. Oxford University Press, Oxford.

Gangl, M. (2004). RBOUNDS: Stata Module to Perform Rosenbaum Sensitivity Analysis for Average Treatment Effects on the Treated. Statistical Software Components, Boston College Department of Economics.

Gerber, A. S., G. A. Huber, D. Doherty, and C. M. Dowling (2011). The Big Five Personality Traits in the Political Arena. *Annual Review of Political Science 14*, 265–287.

Gersbach, H. (2009). Competition of Politicians for Wages and Office. *Social Choice and Welfare 33*(1), 51–71.

Gilens, M. (2005). Inequality and Democratic Responsiveness. *Public Opinion Quarterly 69*(5), 778–796.

Gilens, M. (2012). *Affluence & Influence. Economic Inequality and Political Power in America.* Princeton University Press, Princeton and Oxford.

Goldfarb, R. S. and T. C. Leonard (2005). Inequality of What among Whom?: Rival Conceptions of Distribution in the 20th Century. *Research in The History of Economic Thought and Methodology 23a*, 75–118.

Goldin, C. and L. F. Katz (2008). *The Race between Education and Technology.* Harvard University Press, Cambridge.

Gorodnichenko, Y. and K. S. Peter (2007). Public Sector Pay and Corruption: Measuring Bribery from Micro Data. *Journal of Public Economics 91*(5–6), 963–991.

Gottschalk, P. and S. Danziger (2005). Inequality of Wage Rates, Earnings and Family Income in the United States, 1975-2002. *Review of Income and Wealth 51*(2), 231–254.

Gottschalk, P. and T. M. Smeeding (1997). Cross-National Comparisons of Earnings and Income Inequality. *Journal of Economic Literature 35*(2), 633–687.

Grabka, M. M. (2012). Codebook for the PEQUIV File 1984–2010. CNEF Variables with Extended Income Information for the SOEP. Data Documentation 57, DIW Berlin.

Grabka, M. M., J. Schwarze, and G. G. Wagner (1999). How Unification and Immigration Affected the German Income Distribution. *European Economic Review 43*(4–6), 867–878.

Gregory, R. G. and J. Borland (1999). Recent Developments in Public Labor Markets. In O. Oshenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3c. Elsevier, Amsterdam.

Hagenaars, A. J. M., K. de Vos, and M. A. Zaidi (1994). *Poverty Statistics in the Late 1980s: Research Based on Micro-Data.* Office for Official Publications of the European Communities, Luxembourg.

Haisken-DeNew, J. P. and J. R. Frick (2005). Desktop Companion to the German Socio-Economic Panel (SOEP). Version 8.0, DIW Berlin.

Hartog, J. and H. Oosterbeek (1993). Public and Private Sector Wages in the Netherlands. *European Economic Review 37*(1), 97–114.

Hauser, R. (2003). The Development of the Distribution of Income and Wealth in Germany – An Overview. In R. Hauser and I. Becker (Eds.), *Reporting on Income Distribution and Poverty. Perspectives from a German and European Point of View.* Springer, Berlin and Heidelberg.

Hay, C. (2007). *Why We Hate Politics*. Polity Press, Cambridge.

Heathcote, J., F. Perri, and G. Violante (2010). Unequal We Stand: An Empirical Analysis of Economic Inequality in the United States, 1967–2006. *Review of Economic Dynamics 13*(1), 15–51.

Heckman, J. (1976). The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models. *Annals of Economic and Social Measurement 5*, 475–492.

Heckman, J. (1979). Sample Selection Bias as a Specification Error. *Econometrica 47*(1), 153–161.

Heim, B. T. (2007). The Incredible Shrinking Elasticities. *Journal of Human Resources 42*(4), 881–918.

Hundley, G. (1991). Public- and Private-Sector Occupational Pay Structures. *Industrial Relations 30*(3), 417–434.

Hyslop, D. R. and D. C. Mare (2005). Understanding New Zealand's Changing Income Distribution, 1983–1998: A Semi-Parametric Analysis. *Economica 72*(3), 469–495.

Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review. *Review of Economics and Statistics 86*(1), 4–29.

Imbens, G. W. and J. M. Wooldridge (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature 47*(1), 5–86.

Jäntti, M., E. Sierminska, and T. M. Smeeding (2008). The Joint Distribution of Household Income and Wealth: Evidence from the Luxembourg Wealth Study. OECD Social, Employment and Migration Working Paper No. 65, Paris.

Jenkins, S. P. (1995). Accounting for Inequality Trends: Decomposition Analysis for the UK, 1971–86. *Economica 62*(245), 29–63.

Jenkins, S. P. and F. A. Cowell (1994). Parametric Equivalence Scales and Scale Relativities. *Economic Journal 104*(425), 891–900.

Jenkins, S. P. and M. Jäntti (2005). Methods for Summarizing and Comparing Wealth Distributions. ISER Working Paper No. 2005–05.

Jenkins, S. P. and J. Micklewright (2007a). *Inequality and Poverty Re-examined.* Oxford University Press, Oxford.

Jenkins, S. P. and J. Micklewright (2007b). New Directions in the Analysis of Inequality and Poverty. ISER Working Paper No. 2007-11.

Jenkins, S. P. and P. Van Kerm (2005). Accounting for Income Distribution Trends: A Density Function Decomposition Approach. *Journal of Economic Inequality 3*(1), 43–61.

Juhn, C. and K. M. Murphy (1997). Wage Inequality and Family Labor Supply. *Journal of Labor Economics 15*(1), 72–97.

Juhn, C., K. M. Murphy, and B. Pierce (1993). Wage Inequality and the Rise in Returns to Skill. *Journal of Political Economy 101*, 410–441.

Karoly, L. A. and G. Burtless (1995). Demographic Change, Rising Earnings Inequality, and the Distribution of Personal Well-Being, 1959–1989. *Demography 32*(3), 379–405.

Katz, L. F. and D. H. Autor (1999). Changes in the Wage Structure and Earnings Inequality. In O. Ashenfelter and D. Card (Eds.), *Handbook of Labor Economics*, Volume 3a. Elsevier, Amsterdam.

Kennickell, A. B. (2009). Ponds and Streams: Wealth and Income in the U.S., 1989 to 2007. Finance and Economics Discussion Series No. 2009–13.

Klasen, S. and I. Woolard (2009). Surviving Unemployment Without State Support: Unemployment and Household Formation in South Africa. *Journal of African Economies 18*(1), 1–51.

Kopczuk, W. and E. Saez (2004). Top Wealth Shares in the United States, 1916–2000: Evidence from Estate Tax Returns. *National Tax Journal 57*(2), 445–487.

Kotakorpi, K. and P. Poutvaara (2011). Pay for Politicians and Candidate Selection: An Empirical Analysis. *Journal of Public Economics 95*(7–8), 877–885.

Kunze, A. (2005). The Evolution of the Gender Wage Gap. *Labour Economics 12*(1), 73–97.

Lemieux, T. (2006). Increasing Residual Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill? *American Economic Review 96*(3), 461–498.

Lemieux, T. (2010). What Do We Really Know About Changes in Wage Inequality? In K. G. Abraham, J. R. Spletzer, and M. Harper (Eds.), *Labor in the New Economy*, pp. 17–59. NBER Books, Cambridge.

Leuven, E. and B. Sianesi (2010). PSMATCH2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. Statistical Software Components, Boston College Department of Economics.

Luttmer, E. F. P. (2005). Neighbors As Negatives: Relative Earnings And Well-Being. *Quarterly Journal of Economics 120*(3), 963–1002.

Mare, R. D. and C. R. Schwartz (2005). Trends in Educational Assortative Marriage from 1940 to 2003. *Demography 42*(4), 621–646.

Martin, M. A. (2006). Family Structure and Income Inequality in Families with Children, 1976 to 2000. *Demography 43*(3), 421–445.

Mattozzi, A. and A. M. Merlo (2008). Political Careers or Career Politicians? *Journal of Public Economics 92*(3–4), 597–608.

McCarty, N. and J. Pontusson (2009). The Political Economy of Inequality and Redistribution. In W. Salverda, B. Nolan, and T. M. Smeeding (Eds.), *The Oxford Handbook of Economic Inequality*, pp. 665–692. Oxford University Press, Oxford.

McFadden, D. (1974). Conditional Logit Analysis of Qualitative Choice Behavior. In P. Zarembka (Ed.), *Frontiers in Econometrics*, pp. 105–142. Academic Press, New York.

Medeiros, M. (2006). The Rich and the Poor: The Construction of an Affluence Line from the Poverty Line. *Social Indicators Research 78*(1), 1–18.

Melly, B. (2005). Private Sector Wage Differentials in Germany: Evidence from Quantile Regression. *Empirical Economics 30*(2), 505–520.

Messner, M. and M. K. Polborn (2004). Paying Politicians. *Journal of Public Economics 88*(12), 2423–2445.

Meyer, B. and J. Sullivan (2010). Consumption and Income Inequality in the U.S. since the 1960s. Working paper, University of Notre Dame.

Meyer, B. and J. Sullivan (2011). Consumption and Income Poverty over the Business Cycle. *Research in Labor Economics 32*, 51–82.

Michelangeli, A., E. Peluso, and A. Trannoy (2011). Detecting a Change in Wealth Concentration without the Knowledge of the Wealth Distribution. *Journal of Economic Inequality 9*(3), 373–391.

Mincer, J. A. (1974). *Schooling, Experience, and Earnings.* NBER Press, Cambridge.

Minsheu, J. (1599). The Dictionarie in Spanish and English, London.

Mookherjee, D. and A. F. Shorrocks (1982). A Decomposition Analysis of the Trend in UK Income Inequality. *Economic Journal 92*(368), 886–902.

Murray, C. (2012). *Coming Apart. The State of White America, 1960–2010.* Crown Forum, New York.

Musgrave, R. A. (1959). *The Theory of Public Finance – A Study in Public Economy.* McGraw-Hill, New York.

Nyhus, E. K. and E. Pons (2005). The Effects of Personality on Earnings. *Journal of Economic Psychology 26*(3), 363–384.

Oaxaca, R. (1973). Male-Female Wage Differentials in Urban Labor Markets. *International Economic Review 14*(3), 693–709.

OECD (2005). What Are Equivalence Scales? Organisation for Economic Co-Operation and Development, Paris.

OECD (2008). Growing Unequal? Income Distribution and Poverty in OECD Countries. Organisation for Economic Co-Operation and Development, Paris.

OECD (2011). Divided we stand. Why Inequality keeps rising. Organisation for Economic Co-Operation and Development, Paris.

Osborne, M. J. and A. Slivinski (1996). A Model of Political Competition with Citizen-Candidates. *Quarterly Journal of Economics 111*(1), 65–96.

Paglin, M. (1975). The Measurement and Trend of Inequality: A Basic Revision. *American Economic Review 65*, 598–609.

Paulus, A. (2011). Tax Evasion and Measurement Error: A Comparison of Survey Income with Tax Records. mimeo.

Pederson, P. J., J. B. Schmidt-Sørensen, N. Smith, and N. Westergård-Nielsen (1990). Wage Differentials Between the Public and Private Sectors. *Journal of Public Economics 41*(1), 125–145.

Peichl, A. (2012). The World is Flat: Existing Tax Benefit Systems Approximate a Linear One, mimeo.

Peichl, A. and P. Doerrenberg (2012). The Impact of Redistributive Policies on Inequality in OECD Countries. IZA Discussion Paper No. 6505.

Peichl, A. and N. Pestel (2011). Multidimensional Affluence: Theory and Applications to Germany and the US. IZA Discussion Paper No. 5926.

Peichl, A. and N. Pestel (2012). Multidimensional Well-Being at the Top: Evidence for Germany. *Fiscal Studies, forthcoming.*

Peichl, A., N. Pestel, and H. Schneider (2012). Does Size Matter? The Impact of Changes in Household Structure on Income Distribution in Germany. *Review of Income and Wealth 58*(1), 118–141.

Peichl, A., N. Pestel, and S. Siegloch (2012). The Politicians' Wage Gap: Insights from German Members of Parliament. *Public Choice, forthcoming.*

Peichl, A., T. Schaefer, and C. Scheicher (2010). Measuring Richness and Poverty: A Micro Data Application to Europe and Germany. *Review of Income and Wealth 56*(3), 597–619.

Peichl, A., H. Schneider, and S. Siegloch (2010). Documentation IZAΨMOD: The IZA Policy SImulation MODel. IZA Discussion Paper No. 4865.

Piketty, T. (2005). Top Income Shares in the Long Run: An Overview. *Journal of the European Economic Association 3*(2–3), 382–392.

Piketty, T. and E. Saez (2003). Income Inequality in the United States, 1913–1998. *Quarterly Journal of Economics 118*(1), 1–39.

Piketty, T. and E. Saez (2006). The Evolution of Top Incomes: A Historical and International Perspective. *American Economic Review Papers and Proceedings 96*(2), 200–205.

Piketty, T. and E. Saez (2007a). How Progressive is the U.S. Federal Tax System? A Historical and International Perspective. *Journal of Economic Perspectives 21*(1), 3–24.

Piketty, T. and E. Saez (2007b). Income and Wage Inequality in the United States 1913–2002. In A. Atkinson and T. Piketty (Eds.), *Top Incomes over the Twentieth Century*, pp. 141–225. Oxford University Press, Oxford.

Poterba, J. (2007). Income Inequality and Income Taxation. *Journal of Policy Modeling 29*, 623–633.

Poutvaara, P. and T. Takalo (2007). Candidate Quality. *International Tax and Public Finance 14*(1), 7–27.

Querubin, P. and J. M. Snyder (2009). The Returns to US Congressional Seats in the Mid-19th Century. In E. Aragones, C. Bevia, H. Llavador, and N. Schofield (Eds.), *The Political Economy of Democracy*. BBVA, Bilbao.

Rasner, A., J. R. Frick, and M. M. Grabka (2011). Extending the Empirical Basis for Wealth Inequality Research Using Statistical Matching of Administrative and Survey Data. SOEPpapers on Multidisciplinary Panel Data Research No. 359.

Reed, D. and M. Cancian (2009). Rising Family Income Inequality: The Importance of Sorting, mimeo.

Roemer, J. E. (1998). *Equality of Opportunity*. Harvard University Press, Cambridge.

Roine, J., J. Vlachos, and D. Waldenström (2009). The Long-Run Determinants of Inequality: What Can We Learn from Top Income Data? *Journal of Public Economics 93*(7–8), 974–988.

Roine, J. and D. Waldenström (2008). The Evolution of Top Incomes in an Egalitarian Society: Sweden, 1903–2004. *Journal of Public Economics 92*(1–2), 366–387.

Roine, J. and D. Waldenström (2009). Wealth Concentration over the Path of Development: Sweden, 1873–2006. *Scandinavian Journal of Economics 111*(1), 151–187.

Roine, J. and D. Waldenström (2011). Common Trends and Shocks to Top Incomes – A Structural Breaks Approach. *Review of Economics and Statistics 93*(3), 832–846.

Rosenbaum, P. R. (2002). *Observational Studies*. Springer, New York.

Rosenbaum, P. R. and D. B. Rubin (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika 70*(1), 41–55.

Rosenbaum, P. R. and D. B. Rubin (1985). Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. *American Statistician 39*(1), 33–38.

Saez, E. (2005). Top Incomes in the United States and Canada over the Twentieth Century. *Journal of the European Economic Association 3*(2–3), 402–411.

Saez, E. and M. Veall (2005). The Evolution of High Incomes in Northern America: Lessons from Canadian Evidence. *American Economic Review 95*(3), 831–849.

Salverda, W., B. Nolan, and T. M. Smeeding (2009). Introduction. In W. Salverda, B. Nolan, and T. M. Smeeding (Eds.), *The Oxford Handbook of Economic Inequality*, pp. 3–22. Oxford University Press, Oxford.

Schwartz, C. R. (2010). Earnings Inequality and the Changing Association between Spouses' Earnings. *American Journal of Sociology 115*(5), 1524–1557.

Schwarze, J. (1996). How Income Inequality Changed in Germany Following Reunification: An Empirical Analysis Using Decomposable Inequality Measures. *Review of Income and Wealth 42*(1), 1–11.

Sen, A. K. (1985). *Commodities and Capabilities*. North Holland, Amsterdam.

Senik, C. (2005). Income Distribution and Well-being: What can we learn from Subjective Data? *Journal of Economic Surveys 19*(1), 43–63.

Shorrocks, A. F. (1980). The Class of Additively Decomposable Inequality Measures. *Econometrica 48*(3), 613–625.

Shorrocks, A. F. (1984). Inequality Decomposition by Population Subgroups. *Econometrica 52*(6), 1369–1385.

Shorrocks, A. F. (1999). Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value. Unpublished Paper, University of Essex, Colchester, UK.

Sierminska, E., A. Brandolini, and T. M. Smeeding (2006). Comparing Wealth Distribution Across Rich Countries: First Results from the Luxembourg Wealth Study. LWS Working Paper No. 1.

Slemrod, J. (1992). Taxation and Inequality: A Time-Exposure Perspective. In J. Poterba (Ed.), *Tax Policy and the Economy*, Volume 6, pp. 105–127. MIT Press, Cambridge.

Smeeding, T. M. and J. P. Thompson (2011). Recent Trends in Income Inequality: Labor, Wealth and More Complete Measures of Income. *Research in Labor Economics 32*, 1–50.

Smeeding, T. M. and D. H. Weinberg (2001). Toward a Uniform Definition of Household Income. *Review of Income and Wealth 47*(1), 1–24.

Socio-Economic Panel (2010). Data for Years 1984–2009, Version 26. SOEP.

Socio-Economic Panel (2011). Data for Years 1984–2010, Version 27. SOEP.

Solt, F. (2008). Economic Inequality and Democratic Political Engagement. *American Journal of Political Science 52*(1), 48–60.

Statistisches Bundesamt (2008a). Bevölkerung und Erwerbstätigkeit: Zusammenfassende Übersichten Eheschliessungen, Geborene und Gestorbene. Wiesbaden.

Statistisches Bundesamt (2008b). Mikrozensus 2008. Fachserie 1, Reihe 3, Bevölkerung und Erwerbstätigkeit, Haushalte und Familien, Wiesbaden.

Statistisches Bundesamt (2009). Mikrozensus: Haushaltszahlen ab 2005. Wiesbaden.

Stiglitz, J. E. (2012). *The Price of Inequality: How Today's Divided Society Endangers Our Future*. W. W. Norton & Company, New York/London.

Stiglitz, J. E., A. Sen, and J.-P. Fitoussi (2009). Report by the Commission on the Measurement of Economic Performance and Social Progress. Paris.

Van Kerm, P. (2007). Extreme Incomes and the Estimation of Poverty and Inequality Indicators from EU-SILC. In *Comparative EU Statistics on Income and Living Conditions: Issues and Challenges*, pp. 83–94. Eurostat.

Van Soest, A. (1995). Structural Models of Family Labor Supply. *Journal of Human Resources 30*(1), 63–88.

Wagner, G. G., J. R. Frick, and J. Schupp (2007). The German Socio-economic Panel Study (SOEP): Scope, Evolution and Enhancements. *Schmollers Jahrbuch – Journal of Applied Social Sciences 127*(1), 139–169.

Waldenström, D. (2009). Lifting All Boats? The Evolution of Income and Wealth Inequality over the Path of Development. In *Lund Studies in Economic History*, Volume 51. Media-Tryck, Lund University.

Welch, F. (1999). In Defense of Inequality. *American Economic Review Papers and Proceedings 89*(2), 1–17.

Wolff, E. N. (2011). Pensions in the 2000s: the Lost Decade? NBER Working Paper No. 16991.

Wolff, E. N. and A. Zacharias (2009). Household Wealth and the Measurement of Economic Well-Being in the United States. *Journal of Economic Inequality 7*(2), 83–115.

Yates, J. (1994). Imputed Rent and Income Distribution. *Review of Income and Wealth 40*(1), 43–66.

Curriculum Vitae

Nico Pestel

Personal Details

- **Born:** 28 July 1983 in Goch (Germany)
- **Citizenship:** German
- **Marital Status:** Married
- **Languages:** German and Dutch (native), English (fluent), French (basic)

Education

- **Since 10/2009:**
  Doctoral Student in Economics, University of Cologne
  Supervisor: Prof. Dr. Clemens Fuest
- **10/2004–09/2009:**
  Diplom-Volkswirt (Grade: 1.5), University of Cologne

Position

- **Since 10/2009:**
  Resident Research Affiliate, Institute for the Study of Labor (IZA) in Bonn
- **01/2012–02/2012:**
  Visiting Scholar, Catholic University of Leuven (Belgium)