

Explaining Inequality in Economic Outcomes: An Empirical and Experimental Approach

Inaugural-Dissertation

zur Erlangung des akademischen Grades eines Doktors
der Wirtschafts- und Sozialwissenschaften
der Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

vorgelegt von

Diplom-Volkswirtin Lena Mareike Detlefsen

aus Flensburg

Kiel, 2018

Gedruckt mit Genehmigung der
Wirtschafts- und Sozialwissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel

Dekan: Prof. Dr. Till Requate

Erstbegutachtung: Prof. Dr. Dr. Ulrich Schmidt

Zweitbegutachtung: Prof. Dennis Snower Ph.D.

Drittbegutachtung: Prof. Dr. Stefan Trautmann

Tag der Abgabe der Arbeit: 14.06.2018

Tag der mündlichen Prüfung: 15.10.2018

ACKNOWLEDGEMENTS

I owe my gratitude to all people who made this dissertation possible. First and foremost, I want to thank Ulrich Schmidt. Thank you Ulli for giving me the possibility to work on this thesis, for leaving me free to do my very divers research, for your support and encouragement throughout all these years, but also thank you for always remembering me to never forget to enjoy my life. Thank you for the great years at the Chair of Public Economics, Social Policy and Health Economics!

Special thanks also to Prof. Dennis Snower, who kindly accepted to be the second referee reporting on my doctoral thesis.

I also want to thank Carsten Schröder, without whom I would never have started this dissertation. Thank you for your support and helpful feedback throughout all these years.

Particularly I want to thank my colleagues from the 4th floor. Thank you that you made the years working on my dissertation and working at the Chair to a great time. All the lunch breaks, coffee breaks and discussion breaks with you helped me to get through my dissertation time. Especially, I want to thank Katharina. Without our lively and inspiring discussions on research and life, without your support and our joint projects I would never have finished this dissertation with so much passion and so much joy. Thank your Katharina!

Most of all, I thank my family, my parents, my sister and Jan and Oskar. Thank you, that you supported me throughout all these years, never questioned my work and always remembered me that there is so much more in life than the academic world and research. Especially Jan, thank you for your support, encouragement and patience throughout my dissertation!

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Introduction

Economic inequality is a crucial issue for modern societies and everyone is affected by it. Be that due to the fact that differences in social status lead to social problems, like lack of social cohesion and lower trust levels within a society or due to the fact that health and mortality are linked to the socio-economic status, with the rich ones being better off (e.g. Gustavsson and Jordahl, 2008; Wilkinson and Pickett, 2011). These consequences make economic inequality a highly relevant topic for researchers and policymakers. In the last years economic inequality has obtained increased attention (e.g. Piketty, 2014; Atkinson, 2015) as research documents increased economic inequality, such as earnings and wealth, for a wide range of industrialized countries, e.g. U.S. (Kopczuk et al., 2010), Great Britain (Belfield et al., 2017), France (Garbinti et al., 2016) and Germany (Dustmann et al., 2009). At the same time studies show that economic inequality is persistent over more than one generation (Braun and Stuhler, 2018).

This leads to an important distinction which has to be made when talking about inequality. Economic inequality can be subdivided into inequality in outcomes and inequality in opportunities (Roemer, 1998). The first compares ex-post differences for example in individual earnings or wealth within a society or between societies which are seen as a result of individual effort. The second is interested in ex-ante differences in circumstances for which individuals cannot be held responsible. This can be for instance the family background (Roemer, 1998), in particular the socio-economic background, which impacts lifetime earnings (Björklund et al., 2006) and economic preferences, such as risk tolerance, social preferences and competitiveness (Dohmen et al., 2012; Kosse and Pfeiffer, 2012; Bauer et al., 2014; Deckers et al., 2015; Almas et al., 2016). Policy makers aim to reduce inequality in outcomes for examples by redistributing income and introducing general minimum wages (Great Britain 1999, Germany 2015) and to ensure equal opportunities for example by investing in education, and taking affirmative action like the introduction of gender quotas for greater equality of women and men in leadership positions (Norway 2005, Germany 2015).

My thesis contributes to the discussion about inequality using two different approaches, an empirical and an experimental approach. In the first part (paper one and two) I use an empirical approach to explain inequality in economic outcomes, here earnings. For the analysis, I use two data sets for Germany provided by the Research Data Center of the

German Federal Employment Agency at the Institute for Employment Research. In the first paper, I focus on a theoretical problem of inequality measurement: the earnings accounting period. The focus of the second paper is on earnings inequality caused by structural change in the labor market and sample selection effects. In the second part of my thesis (paper three and four) I use an experimental approach to contribute to the literature on inequality in opportunities. I use economic experiments on risk preferences to examine the impact of gender quotas on risk preferences of groups compared to individuals (third paper) and economic preferences on risk and time preferences and trust to know what part of observed outcome inequality may be attributed to the family background and in particular to the sibling composition (fourth paper).

Part I of the thesis

The first part of the thesis contributes to the literature explaining inequality in outcomes using an empirical approach. Empirical analysis of earnings inequality highly depends on the availability of detailed datasets. New administrative data sources for instance in Germany stimulated earnings inequality research in recent years (e.g., Fitzenberger and Kurz, 2003; Dustmann et al., 2009; Card et al., 2013). For the two papers included in this part, I use data sets provided by the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research, first the Regional file (IABS R-04) and second the Integrated Labour Market Biographies (SIAB 7514). Reasons for the increase in measured earnings inequality can be of methodological character or emerge through labor market changes.

One methodological reason for changes in measured earnings inequality can be the accounting period in which earnings are measured. Under mild assumptions, Shorrocks (1978) has proved that measured inequality must decrease when the period over which income is measured, the accounting period, increases. The first paper “Earnings inequality - Does the accounting period matter?” investigates whether the accounting period of earnings matters for the measurement of inequality and seeks to shed light on the quantitative size of this effect. The results indicate that the choice of the accounting period not only seriously affects the level of inequality, but that the size of the effect varies over time.

Labor market changes which explain part of the variation are among others the decline of unionization, the increase of female labor force participation, and demographic aging and structural change (e.g. Dustmann et al., 2009; Chevan and Stokes, 2000). The second paper “Earnings inequality and sectoral Change: A decomposition exercise for Germany” contributes to the discussion on earnings inequality by focusing on structural change. My co-author and I apply in that paper an inequality decomposition framework to study how sectoral change has altered the German earnings distribution since unification. The decomposition is implemented for the employed population, as in many previous analyses, and for the employable population. While the first is standard in this literature, the latter reveals a more precise picture of the population as the sample also includes in addition to the standard sample the unemployed, assigned to the sector of previous employment, and marginally employed workers. We find that for both populations earnings inequality has increased over time and that the increase is driven both by widening inequalities within and between sectors. In quantitative terms, this increase is larger for the employable compared to the employed population. The choice of the population not only matters for the size of the changes in the earnings distribution, it can also alter its sign. We find diverging trends after 2010, with further increases in earnings inequality for the employed fraction of the population and decreases in earnings inequality for the employable population.

Part 2 of the thesis

The second part of the thesis contributes to the literature on inequality in opportunities using an experimental approach. For the two papers included in this part me and my coauthors designed and conducted experiments. For the third paper, we conducted experiments with students from the University of Kiel and for the fourth paper with pupils from secondary schools in Schleswig-Holstein.

To reduce inequality in opportunities policymakers introduced women quotas for boards in many European countries. This change in the group composition can impact many important economic decisions and as most of these decisions involve risk the third paper of my thesis "Can gender quotas prevent excessive risk-taking? The effect of gender composition on group decisions under risk" analyses how the level of risk-taking within a group is influenced by its gender composition. In particular, my co-authors and I look at the shift of risk-taking between group and individual decisions and analyze to which extent this shift depends on the gender composition in the group. We derive a gender-specific polarization hypothesis which states

that compared to individual preferences, male-dominated groups will shift towards higher risk-taking than female dominated ones. Our experimental tests reveal a systematic impact of gender composition on group shifts which supports our hypothesis and points into the direction that a higher share of females may prevent excessive risk-taking. This currently unpublished manuscript is joint work with Katharina Lima de Miranda and Ulrich Schmidt.

Economic preferences, like risk and time preferences, might help explain the heterogeneity in economic outcomes like earnings (Castillo et al., 2011; Sutter et al., 2013; Golsteyn et al., 2014; Khwaja, 2006; Chabris et al., 2008). Studies, for example, found that impatient individuals have on average lower lifetime incomes (Golsteyn et al., 2014). The family background plays thereby an important role. Not only studies show that a large share (20 % to 63%) of the variation in economic preferences can be explained by genetic variation (Cesearine et al., 2009; Zyphur et al., 2009), also the family as an environment can impact economic preferences (Dohmen et al., 2012; Kosse and Pfeiffer, 2012; Bauer et al., 2014; Deckers et al., 2015; Almas et al., 2016). The fourth paper “Are Economic Preferences Shaped by the Family Context? The impact of birth order and siblings’ sex composition on economic preferences?” focuses on the formation of economic preferences in childhood and adolescence as they have been shown to have long-term consequences for social and economic outcomes later in life. Hence, it is important to understand what shapes economic preferences. Running experiments with 525 teenagers, we examine the effects of both birth order and siblings' sex composition on economic preferences. We find that both aspects matter. Second born children are typically less patient, less risk averse, and more trusting. However, siblings' sex composition interacts with these findings, such that the common finding that second-born children are more risk-taking is only confirmed in case of same-sex siblings, while for mixed-sex siblings gender effects dominate birth order. For trust, gender differences are larger for mixed-sex siblings than in the single-sex case. Patience is the only case where siblings’ sex composition does not matter.

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Overview of Papers and Co-authorship

This thesis includes the following papers:

Detlefsen, L. M. (2012). Earnings Inequality - Does the Accounting Period Matter?.
Schmollers Jahrbuch, 132(2), 297-321.

Detlefsen, L. M. and Schröder, C. (2018). Earnings Inequality and Sectoral Change: A
Decomposition Exercise for Germany. mimeo.

Lima de Miranda, K., Detlefsen, L., and Schmidt, U. (2018). Can Gender Quotas Prevent
Excessive Risk Taking? The Effect of Gender Composition on Group Decisions under Risk.
mimeo.

Detlefsen, L., Friedl, A., Lima de Miranda, K., Schmidt, U. and Sutter, M. (2018). Are
Economic Preferences Shaped by the Family Context? The Impact of Birth Order and
Siblings' Sex Composition on Economic Preferences. mimeo

Each co-author contributed significantly to the concept, design and content of the articles.

Part I

Paper 1: Earnings Inequality - Does the Accounting Period Matter?

By LENA MAREIKE DETLEFSEN

Lena Mareike Detlefsen (2012). Earnings Inequality – Does the Accounting Period Matter? Schmolters Jahrbuch: Vol. 132, No. 2, pp. 297-321. <https://doi.org/10.3790/schm.132.2.297>

Under mild assumptions, Shorrocks (1978) has proved that measured inequality must decrease when the period over which income is measured, the accounting period, increases. The present work seeks to shed light on the quantitative size of this effect using a huge representative German database for the period 1975-2004. Our results indicate that the choice of the accounting period not only seriously affects the level of inequality. We can also show that the size of the effect varies over time

JEL classification: D31, D63, O15

Key words: Inequality, accounting period, earnings

* Detlefsen, Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Lena.Detlefsen@ifw-kiel.de).

Paper 2: Earnings Inequality and Sectoral Change: A Decomposition Exercise for Germany

BY LENA MAREIKE DETLEFSEN, AND CARSTEN SCHRÖDER*

We apply an inequality decomposition framework to study how sectoral change has altered the German earnings distribution since unification. The decomposition is implemented for the employed population, as in many previous analyses, and for the employable population. The latter also includes the unemployed, assigned to the sector of previous employment. Administrative earnings records from the German social security authorities serve as the empirical basis. We find that, for both populations, earnings inequality has increased over time, and that the increase is driven both by widening inequalities within and between sectors. In quantitative terms, this increase is larger for the employable compared to the employed population. The choice of the population not only matters for the size of the changes in the earnings distribution, it can also alter its sign. We find diverging trends after 2010, with further increases in earnings inequality for the employed fraction of the population and decreases in earnings inequality for the employable population.

JEL classifications: D31, J00, J31, J40

Key words: Inequality, earnings, structural change, sample selection

* Detlefsen: Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Lena.Detlefsen@ifw-kiel.de). Schröder: Free University Berlin and DIW Berlin/SOEP, 10108 Berlin, Germany (cschroeder@diw.de).

Introduction

Increasing earnings and wage inequality is a phenomenon which is well documented for many countries, like the US, UK and Germany (e.g. Bluestone and Harrison, 1988; Maxwell, 1989; Kremer and Maskin, 1996; Katz and Autor, 1999; Antonczyk and Kohn, 2011; Dustman et al., 2009; Card et al., 2013). Literature provides several explanations for the rise in inequality including the decline of unionization, the increase of female labor force participation, and demographic aging (e.g. Dustmann et al., 2009; Chevan and Stokes, 2000). Another intensely investigated link is the one between structural change and inequality (e.g., Danzinger, 1976; Nelson and Lorence, 1988; Kassab, 1992; Valletta, 1997; Chevan and Stokes, 2000; Jenkins, 1995; Fitzenberger and Kurz, 2003; and Card et al., 2013). General findings are, that shifts from manufacturing employment to service employment are responsible for part of the increase in wage and earnings inequality (Chevan and Stokes, 2000; Autor and Dorn, 2013) For Germany Card et al. (2013) report substantial increases in inequality in average wages across industries over the last decades. This is supplemented by the findings of Dustmann et al. (2014) who find significant wage trend differences between tradable manufacturing and partly in tradable service sectors in Germany.

Previous studies on sectoral change and (gross) earnings inequality typically focus on full-time employed men. As a result, the effect of layoffs and part-time work on the overall earnings distribution and the sectoral-specific distributions is ignored as well as gender-specific trends. The sample selection can, however, be crucial. The contribution of working hours to earnings inequality can be substantial (Checchi et al., 2016). Additionally, research has shown that developments in work tasks differ between men and women (Black and Spitz-Oener, 2010) and that population subgroups have different impacts on the increase in inequality (Stein, 2017).

This study, therefore, adds to the discussion about increasing earnings inequality by decomposing overall inequality into between and within sector inequality, examining the inter-temporal trends of its sub-aggregates, assessing the sample selection effect and testing for statistical significance.

Our analysis relies on earnings records from the German Institute for Employment Research: the Integrated Labour Market Biographies (SIAB). The data is the weakly anonymous sample of the integrated Labor market biographies (version 1975-2014) (see

Antoni et al., 2016).¹ Most important for our purposes, the SIAB data includes earnings, days worked, sector, and employment status. Except for civil servants and self-employed, SIAB covers nearly all employees in Germany. Our analysis covers the post-unification period 1992 to 2014 and distinguishes twelve sectors coming from manufacturing, services, as well as public enterprises and institutions. To assess the layoff effect, we examine two populations. The first population, like in previous works, is the employed population (from now on: employed sample). The second population, in addition, covers registered unemployed and marginally employed individuals (in short, extended sample). An unemployed person is assigned to the sector of her/his last employment. Marginal employment (also called “mini-jobs”) means an employment relationship with a rather low level of earnings and usually short duration.² For both populations, we perform inequality decomposition by sectors using inequality indices from the entropy class. These indices can be written as the sum of two components: a within- and a between-sector component (see Jenkins, 1995). The first component is a weighted average of the sector-specific inequalities. The second component reveals differences in sector-specific average earnings. Comparing the estimates for the two populations sheds light on how sector-specific rates of unemployment (layoffs) and marginal employment shape the distribution. The jackknife is used for statistical inference.

Our empirical analysis reveals the following insights. First, for both populations, the employable and employed, earnings inequality has increased over time. While the increase is moderate for the employed sample, inequality rises substantially for the employable sample, e.g. the mean log deviation increases from 0.205 to 0.254 for the employed population, while it increases from 0.267 to 0.533 for the employable. In other words, ignoring layoffs (and marginal employment) leads to a sizable underestimation of inequalities and its rise over time. Second, trends differ with regard to the population. We find diverging trends after 2010, with further increases in earnings inequality for the employed fraction of the population and decreases in earnings inequality for the employable population. Third, decomposing the inequality reveals that most of the increase in inequality and the general trends can be explained by the within-sector inequality, particularly for women and the employable population. Fourth, the main sectors driving the increases in inequality are the service and

¹ The data was accessed via guest stay at the Research Data Center of the Federal Agency for Labor in the Institute for Labor Market and professional research (FDZ) and then by means of controlled data processing at the FDZ.

² In Germany, particularly social security and income tax rules apply to marginal employment.

public sectors, due to increasing employment shares, high within sector inequalities, and low relative earnings,

The paper is structured as follows. Section II discusses the literature regarding structural change and earnings inequality, Section III embeds the subsequent micro-economic inequality decomposition in a general policy and macroeconomic context. Section IV describes our data set and the variables of interest. Section V introduces the decomposition framework, which we use to obtain our results in Section VI. In Section VII we test our results for sensitivity, which is followed by a discussion of our results in Section VIII and a conclusion in Section IX.

II. The literature on sectoral change and earnings distributions: a methodological review

Empirical research on sectoral change and earnings distributions have a long tradition of pioneering works dating back to the late 1980s (i.e., Bluestone and Harrison, 1988; and Maxwell, 1989). The rising interest in inequality, equity and social justice, improvements in data infrastructure, and the rapid transformation of societies in a globalizing world have stimulated research in recent years (e.g., Valletta (1997) and Chevan and Stokes (2000) for the US, Jenkins (1995) for the UK and Fitzenberger and Kurz (2003), Dustmann et al. (2009) and Card et al. (2013) for Germany). The following review focuses on methodological aspects in order to explain how our analysis complements previous works.

The first important methodological aspect concerns the definition of the working sample. Most studies of earnings distributions and sectoral change focus on full-time male employees (e.g. Katz and Autor, 1999; Autor and Dorn (2013), Fitzenberger and Kurz, 2003; Fitzenberger and Kohn, 2006; Dustmann et al., 2009; Antonczyk et al., 2010; and Antonczyk and Kohn, 2011). Few studies, e.g. Card and DiNardo (2002), Black and Spitz-Oener (2010), Card et al. (2013), include women or part-time workers. Ex-ante, the size, and magnitude of the effects of the sample restrictions on earnings distributions are not always clear and are hardly addressed in previous works. For example, enlarging the homogeneous sample of full-time male employees by marginal employees or unemployed males most likely will increase measured earnings inequality, but the effect magnitude is unclear. How the inclusion of female persons changes inequality, is ex-ante unclear. The effect depends on the degrees of

inequality within the male and female earnings distribution and the gender-gap in average earnings.

The second aspect concerns the type of microdata being used: survey or administrative data. The main advantage of survey data is the detailed information on individual and household socio-demographics like income (by sources), household composition, education, employment status, etc. However, it is self-reported data, meaning that it is sometimes hard to assess its validity. Further, sample size can be an issue, particularly for analyses on small subpopulations. These limitations explain the interest of the profession in large-scale administrative data sources, usually collected by the social-security or tax authorities. While for administrative data validity is usually not an issue, it usually provides only a limited set of background variables. Further, the data reflect the institutional and legal framework and changes therein, demanding detailed institutional knowledge by the researcher, careful computation, and interpretation of results. As an example, our database does not cover self-employed persons and civil servants who are exempted from mandatory unemployment insurance. As another example, because of an assessment ceiling, the data is censored from above. Sometimes, the type of data being used simply is determined by availability. Most works for the US relies on survey data (CPS) (e.g. Valletta, 1997; Katz and Autor, 1999; Card and DiNardo, 2002). For Germany, studies use both survey data (e.g., Fitzenberger and Kurz, 2003), i.e. the Socio-economic Panel (SOEP), and administrative data (e.g. Steiner and Wagner, 1998; Fitzenberger and Kohn, 2006; Dustmann et al., 2009; Antonczyk and Kohn, 2011, and Card et al., 2013).

The third aspect concerns the analytical framework for studying the relationships between sectoral change and inequality. Ideally, the framework should allow a systematic and complete assessment of the relationships. Here we are using inequality indices from the entropy class, because these indices are decomposable, and thus permit a detailed analysis of the relationships between sectoral change and inequality. Decomposability means that an index can be written as a sum of two components. The first component is the within component. It is a weighted sum of earnings inequalities within sectors. The second component is the between component, capturing the differences in average earnings across sectors. To our knowledge, a decomposition exercise by sectors is rare to find, even in the international context. One exception is Jenkins (1995) for the UK. Other studies usually refer to inequality indices as the non-decomposable Gini index (Chevan and Stokes, 2000) or

simpler statistics like the 90/10 ratio (e.g. Card and DiNardo, 2002), while others rely on regression analyses (Lemieux, 2006, and Antonczyk et al., 2010).

The fourth aspect concerns statistical significance. Most previous studies starting with Bluestone and Harrison (1988) up to Card and DiNardo (2002) do not provide standard errors for inequality indices, making it difficult to assess the significance of detected patterns. Only recent research, e.g., Fitzenberger and Kurz (2003), Fitzenberger and Kohn (2006) and Antonczyk et al. (2010), Antonczyk and Kohn (2011), provide standard errors of inequality estimates. Standard errors are usually derived by an implementation of resampling methods like the bootstrap or jackknife. Here we apply the jackknife as, compared to bootstrapping, its computational burden is much smaller for large datasets such as ours (see Karoly and Schröder, 2015).

In sum, the present study seeks to complement the previous literature in the following ways. We investigate if and how the sample definition, i.e. the inclusion of the unemployed, alters the relationship between sectoral change and inequality using a large-scale administrative data set for Germany. We build our analysis on an inequality-decomposition framework which allows a comprehensive and complete assessment of the aforementioned relationship, and, by means of a Jackknife procedure, we test for statistical significance of our findings.

III. Macroeconomic environment and major policy changes between 1992 and 2014

This section seeks to embed the subsequent micro-economic inequality decomposition in a general policy and macroeconomic context. During the investigation period 1992-2014, several substantial social and labor-market reforms have been implemented (see Card et al., 2013, for details). To fight high unemployment rates in the first half of the 1990s, in 1996 the Labor Law Act for promotion of employment was introduced, which, amongst others, extended the maximal duration of fixed-term contracts from one to two years. In the same year, the first sector-specific minimum wage was introduced in the construction sector (start date 1.1.1997). Several further sector-specific minimum wages were introduced after 2009 in the construction sector (2009, 2011, 2012), household-related services (2009), public services (2010, 2012), infrastructure (2011), economic services (2011, 2012) and manufacture of food products, beverages and tobacco (2014) (for an overview see Schröder, 2014). Since 1999, marginal-employment jobs (“Minijobs”) have been integrated into the Social security system.

Another set of reforms took place during the 2000s, the so-called Hartz reforms (2003-5). These reforms meant a substantial liberalization of the German labor market: eliminating the employee share of social security taxes for marginal employment, leading to an increase of marginal employment, and lowering the unemployment benefits. In the Great Recession year, 2009 more than 2% of the German workforce was on short-time work (see, e.g., Cahuc and Carcillo, 2011).



FIGURE 1 GDP: 1992 TO 2014

Note: Database: Federal Statistical Office; solid line = GDP; Basis year (100) = 2010

Important information for understanding inequality and sectoral changes is the macroeconomic environment. Figure 1 provides the time series of the GDP, Figure 2 the unemployment and marginal employment rates and Figure 3 sector-specific gross value added (GVA), the value of goods and services produced in particular sectors of the economy. Eight sectors are distinguished: (1) finance and insurance services, (2) information and communication, (3) production, (4) construction, (5) public services, (6) general services, (7) business services and (8) trade, infrastructure and hospitality. All indicators are expressed relative to the normalized 2010 value (= 100) and the GDP and the GVAs are given in real values. Reform periods and the Great Recession are indicated by vertical lines.



FIGURE 2 UNEMPLOYMENT RATE AND MARGINAL EMPLOYMENT RATE: 1992 TO 2014

Note: Database: Federal Statistical Office; solid line = unemployment rate, short-dashed line = marginal employment rate; Basis year (100) = 2010

Figure 1 indicates a quite robust upwards trend of GDP. The total increase over the observation period amounts to 32.5 percent. There is a mild dip in 2003 and a marked one in 2009 as a result of the Great Recession. Figure 2 shows that the unemployment rate increases from 1992 to 1997. It then follows a recovery of the labor market, lowering the unemployment rate towards 2001, before the rate rises again with a peak value in 2005. The adjacent recovery period lowers the unemployment rate again towards 2014 with only a small peak in 2009, the year of the financial crises. After the 1999 incorporation of marginal employment into social security, such occupational relationships became prevalent in the data. Since 2005 it has stabilized and is slightly decreasing towards 2014. The inter-temporal changes in the incidence of unemployment and marginal employment should affect the inequality time series for the employed and employable population in different ways. For example, a rise in unemployment means that the newly unemployed persons drop out of the employed sample. The direction of the effect is ex-ante unclear, as it hinges on the correlation between layoffs and earnings. For the employable population, higher unemployment will usually rise inequality because the earnings of the newly unemployed people drop to zero, and most inequality indices put a higher weight on the earnings levels at the bottom of the distribution. Only in the case of a highly positive correlation between layoffs and earnings, an inverse effect eventually arises.

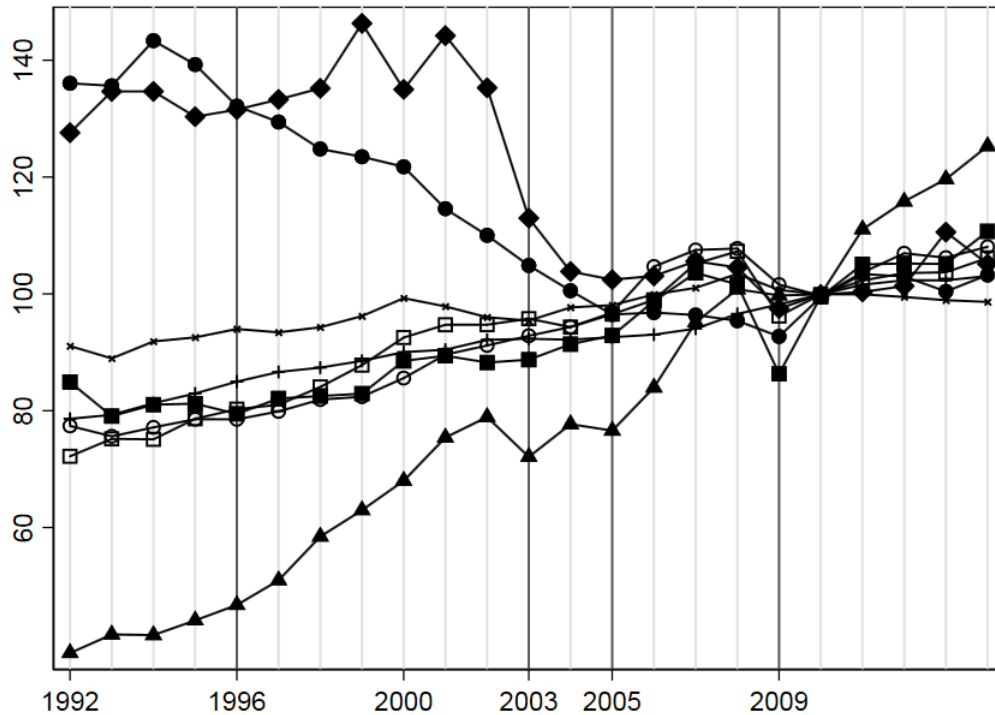


FIGURE 3 GVA's: 1992 TO 2014

Note: Database: Federal Statistical Office; ◆ = finance and insurance services, ▲ = information and communication, ■ = production, ● = construction, + = public services, x = general services, □ = business services, ○ = trade, infrastructure and hospitality industry; Basis year (100) = 2010

The eight sectors' GVA time series in Figure 3 evolve rather differently. Most prominent are the changes for the construction sector (●), the finance and insurance services (◆) and information and communication (▲). The construction sectors GVA shows a marked decline from 1994 to 2009: relative to the 2010 level, it decreases by about 30 percent. Afterwards, the GVA stabilizes. The finance and insurance services decrease substantially between 2001 and 2009, by ca. 32%, but also start stabilizing afterwards. The information and communication sectors GVA, on the other hand, more than doubled between 1992 and 2004, with only small dampening periods between 2003 and 2005 and between 2008 and 2010. The GVA's of the five other sectors increase rather steadily over the observation period - except in the recession years 2003 to 2005 and 2009. The changes in sectoral GVAs have ambiguous implications for the earnings distribution. Suppose a faster GVA growth rate implies higher earnings in the sector but does not affect earnings inequality in the sector. Further suppose the sector-specific earnings are distributed more (less) equally than in other sectors, and average earnings in the sector are below average earnings over all sectors. As a result, the within-sector inequality component will increase (decrease) while the between component will decrease (increase).

IV. Data

A. Basic data description and preparation

Our database is the Integrated Labour Market Biographies (SIAB) assembled by the Institute for Employment Research. SIAB is a representative 2% sample of the population of the Integrated Employment Biographies (IEB) and is regarded as the most comprehensive administrative micro database on employment biographies for Germany (see Antoni et al., 2016). IEB covers individuals in the following statuses: employed subject to social security, marginally employed, benefit recipients in accordance with German Social Code Book II or III, job seekers registered with the Federal Employment Agency (Bundesagentur für Arbeit), registered participants in an employment or training measure. Altogether, SIAB covers the employment histories of 1,639,325 individuals. Their employment biographies are documented in a total of 45,793,010 data rows.³ The SIAB is provided as employment spell data, recorded on a daily basis. For each spell, we make use of the following information: employment status, sector code, gross daily wage. The data provide multiple records for individuals with changing employment status within a year. For our analysis, the SIAB spell data must be converted to annual data. Technical details on the conversion and the construction of each variable are provided in Appendix B.

Crucial for our analysis is the variable earnings. In the data, earnings are censored from above at the assessment ceiling.⁴ We use the censored earnings variable for our main analysis. To test for sensitivity of our results we, however, account for the censoring by implementing a Pareto imputation as in Piketty and Saez (2003) and Kopczuk et al. (2010).⁵ To consider inflation, we convert nominal earnings into real earnings by using the price indices from Deutsche Bundesbank (basis year is 2010)⁶. Further details on the earnings variable can be found in the Appendix B.1.1.

Another important variable is employment status. We distinguish the following statuses:

³ For further information see Antoni et al. (2016).

⁴ Special payments such as Christmas bonuses are averaged over the whole employment period.

⁵ The assumption behind the Pareto imputation is that high earnings beyond a particular income threshold (y_{low}) follow the Pareto law (linear relationship between log earnings and (1-CDF)). Based on the noncensored observations above y_{low} , the so-called Pareto coefficient is estimated. Using the coefficient, we replace each censored earnings value with a random draw from the upper tail of the appropriate conditional earnings distribution (see Appendix B.1.2).

⁶ Further we convert 0 earnings into 0.01 euros to work with log earnings.

1. Employee subject to social security
2. Marginal employee
3. Non-regular employee
4. Unemployed
5. Apprentice and trainee
6. Person in partial retirement

Of course, the employment status can change within a given year. Then we make the following convention to define the employment status: The status “employed subject to social security” is assigned if an individual is employed subject to social security at least once in a year. Otherwise, the status is determined by the activity with the longest sub-annual duration period. We have discarded people “far from the labor market.” With “far from the labor market” we mean individuals, who receive subsistence allowances or are retired, are unable to work or are underage, or individuals whose employment status is not defined (see Appendix A Table B.1 for details).

Concerning the sector codes, SIAB provides a 3-digit sector classification according to the classification scheme 1973 (see Eberle et al., 2011). Based on the classification scheme, we distinguish twelve sectors:

Manufactural sectors	}	(1)	manufacture of basics, goods and consumer products
		(2)	manufacture of structural metal products
		(3)	custom steel forming, manufacture of crafts, hardware and engineering
		(4)	manufacture of food products, beverages and tobacco
		(5)	construction
		(6)	trade (wholesale and retail sector)
		(7)	infrastructure (transportation, communication, energy, recreation industry)
Service sectors	}	(8)	household-related services
		(9)	FIRE (finance, insurance, real estate) + professional services
		(10)	economic services
Public sectors	}	(11)	public services: educational institutions, asylums and hospitals
		(12)	public institutions: organizations, administrative institutions

If an employee changes the sector within a year, we assign her/him to the sector with the longer sub-annual employment period (see Appendix B.1.1 for details). Further details on the assignment to sectors appear in Table B.2 in Appendix B.

B. Observation period and sample selection

Our observation period begins after the German unification in 1992.⁷ Further, to keep only transitory unemployed individuals, we have dropped all individuals not directly attached to the labor market: people receiving subsistence allowance, unable to work, underage, without status or retirees. This sample is broader compared to previous studies and thus we refer to it as the extended sample.

From the extended sample, we construct a subsample consistent with the definition in previous analysis: West German men employed subject to social security, from now on referred to as standard sample (S-sample)). Further, we have constructed sub-samples distinguished by gender, employment status (employed subject to social security vs. all workers (including the unemployed)), and region of residence (residents from the new (east) and old federal states (west)). Table 1 gives an overview of all samples and Table gives the sample-specific numbers of observations and sector-specific population shares in 1992 and 2014.

TABLE 1 OVERVIEW SAMPLES

Sample	Short	Men	Women	East	West	Employed	Un. + Marg. Employed
Standard sample	S-Sample	x			x	x	
Extended standard sample	EX-S-Sample	x			x	x	x
Employed male sample	EM-M-Sample	x		x	x	x	
Extended male sample	EX-M-Sample	x		x	x	x	x
Employed female sample	EM-F-Sample		x	x	x	x	
Extended female sample	EX-F-Sample		x	x	x	x	x
Employed sample	EM-Sample	x	x	x	x	x	
Extended sample	EX-Sample	x	x	x	x	x	x

⁷ Starting earlier would require us to further distinguish between residents of FRG and GDR.

TABLE 2 SAMPLE-SPECIFIC NUMBERS OF OBSERVATIONS AND POPULATION SHARES BY SECTORS

Sample	Year	Total	Population share by sectors											
			1	2	3	4	5	6	7	8	9	10	11	12
S-sample	1992	263601	0.165	0.141	0.103	0.030	0.115	0.114	0.088	0.032	0.069	0.030	0.044	0.069
	2014	258459	0.106	0.120	0.088	0.021	0.078	0.119	0.092	0.039	0.114	0.099	0.067	0.058
EX-S-sample	1992	291606	0.164	0.144	0.102	0.029	0.118	0.114	0.086	0.033	0.068	0.029	0.044	0.068
	2014	320106	0.098	0.112	0.081	0.020	0.077	0.125	0.089	0.051	0.113	0.098	0.078	0.059
EM-M-sample	1992	333341	0.149	0.128	0.095	0.029	0.132	0.108	0.099	0.032	0.065	0.031	0.048	0.084
	2014	314587	0.102	0.113	0.083	0.021	0.084	0.116	0.095	0.041	0.110	0.105	0.070	0.060
EX-M-sample	1992	366090	0.149	0.131	0.095	0.028	0.135	0.109	0.097	0.033	0.064	0.031	0.048	0.081
	2014	388644	0.094	0.105	0.077	0.020	0.082	0.121	0.091	0.053	0.110	0.104	0.081	0.062
EM-F-Sample	1992	251131	0.092	0.033	0.060	0.033	0.020	0.173	0.049	0.068	0.095	0.031	0.192	0.154
	2014	272213	0.042	0.025	0.035	0.023	0.014	0.156	0.038	0.068	0.121	0.080	0.270	0.127
EX-F-Sample	1992	275929	0.092	0.033	0.060	0.034	0.020	0.173	0.048	0.071	0.096	0.030	0.195	0.148
	2014	368661	0.039	0.023	0.031	0.025	0.015	0.164	0.035	0.097	0.116	0.086	0.253	0.115
EM-sample	1992	584472	0.124	0.087	0.080	0.030	0.084	0.136	0.078	0.047	0.078	0.031	0.110	0.114
	2014	586800	0.074	0.072	0.061	0.022	0.051	0.135	0.069	0.054	0.115	0.093	0.163	0.091
EX-sample	1992	642019	0.125	0.089	0.080	0.031	0.085	0.136	0.076	0.049	0.078	0.031	0.111	0.110
	2014	757305	0.067	0.065	0.054	0.022	0.049	0.142	0.064	0.075	0.113	0.095	0.165	0.087

Notes: Database is SIAB; Own calculations.

Concerning sector-specific employment shares given in Table 2, we find a sizable rise in economic services and decrease in manufactural sectors and construction: of all employed, in 1992 about 3 percent belonged to the economic services, and about 10 percent in 2014. The respective numbers for manufactural sectors and construction are about 41 and 25.7 percent. The pattern of the construction sectors fits the decreasing trend of the sector's GVA, while the pattern of the service sectors fits the increases in their GVA's inter-temporal trends in Figure 3.

TABLE 3 SECTOR-SPECIFIC SHARES OF WOMEN

Sample	Year	Sector-specific share of women											
		1	2	3	4	5	6	7	8	9	10	11	12
EM-sample	1992	0.318	0.162	0.325	0.464	0.103	0.545	0.273	0.614	0.525	0.43	0.749	0.580
	2014	0.262	0.162	0.266	0.491	0.122	0.539	0.258	0.588	0.487	0.397	0.769	0.648
EX-sample	1992	0.318	0.16	0.325	0.470	0.1	0.546	0.271	0.622	0.532	0.427	0.753	0.578
	2014	0.282	0.172	0.279	0.54	0.147	0.563	0.269	0.634	0.501	0.440	0.748	0.638

Notes: Database is SIAB; Own calculations.

Table gives an overview of the sector-specific shares of women in the employed and employable sample. Most noticeable are the differences concerning the manufactural sectors (1-4) and construction (5) and the service and public sectors (8-12), with males overrepresented in the former and females in the latter sectors. In general, the share of women is higher in the employable sample compared to the employed.

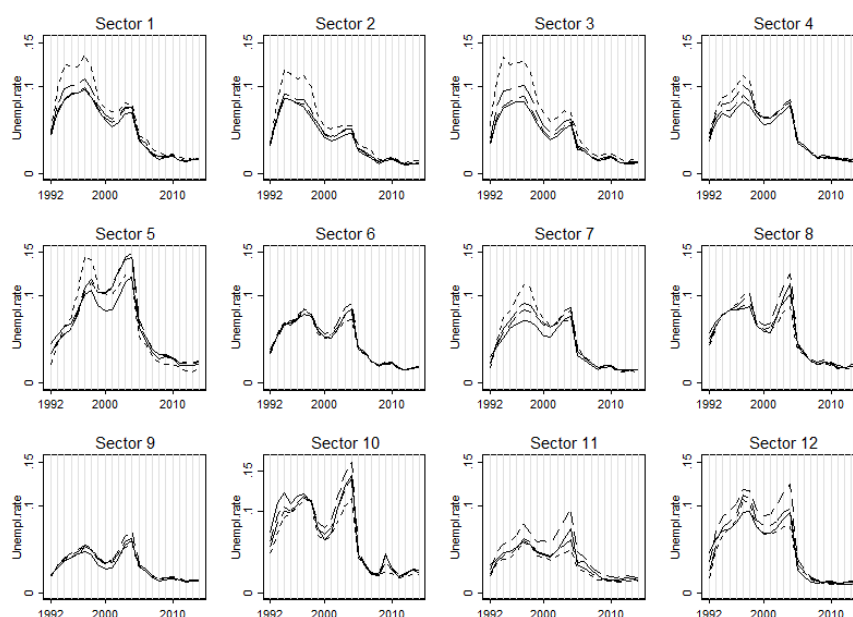


FIGURE 4 SAMPLE-SPECIFIC UNEMPLOYMENT RATES BY SECTORS

Note: Database is SIAB; Own calculations. Solid line = EX-S-Sample, dash= EX-M-Sample, short dash= EX-F-Sample, long dash= EX-Sample.

Most important for our analysis are rates of unemployment and marginal employment. Figure 4 and Figure 5 show time-series of sample- and sector-specific unemployment rates (Figure 4) and marginal employment rates (Figure 5). Consistent with the macro series sector-specific unemployment rates increase towards the end of the 90s, decrease thereafter until 2000, increase again towards 2004, and then decrease. However, we find substantive differences between the sectors and samples. Highest unemployment rates concern the construction sector (5) and the economic services (10) with rates up to 15 percent. Apart from that, the sector-specific unemployment rates move around 5 percent to 10 percent. The EX-S-Sample has overall the lowest unemployment rates. Sample differences occur between the EX-M- and EX-F-Sample. The EX-F-Sample has higher unemployment rates in the manufacturing sectors (1-4), especially during the 1990's. The EX-M-Sample, on the other hand, has higher unemployment rates in most of the service sectors (9-12).

The general picture of the trend of marginal employment discussed in Section 3 is apparent in most of the sectors: stable shares except for an increase between 2002 and 2005. This picture is especially apparent in the household related services (8). In general, there are again substantive differences between the sectors and samples. The marginal employment rate is highest in the household related services (8) and the economic services (10) and over all

sectors, except for the public sectors, the share of marginal employment is markedly higher in the EX-F-Sample compared the male samples.

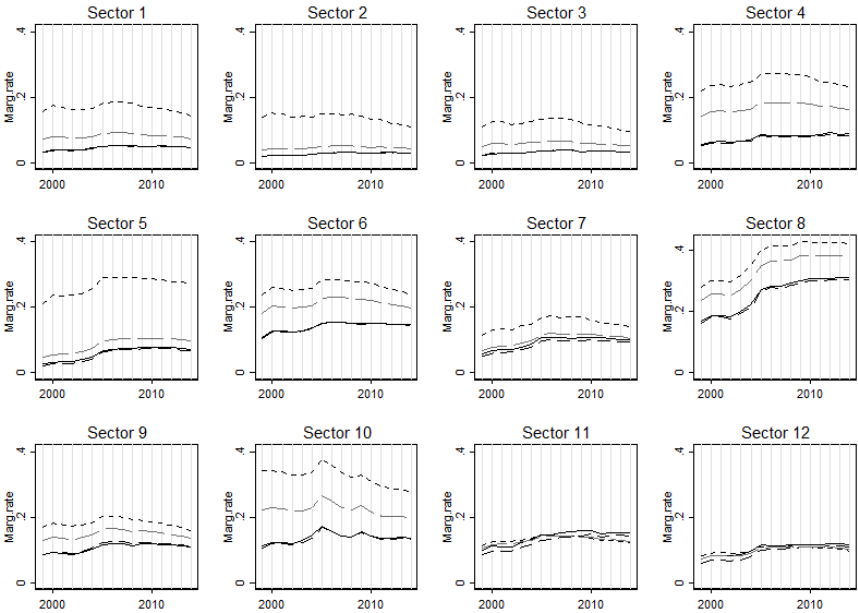


FIGURE 5 SAMPLE SPECIFIC MARGINAL EMPLOYMENT RATES BY SECTORS

Note: Database is SIAB; Own calculations. Solid line = EX-S-Sample, dash= EX-M-Sample, short dash= EX-F-Sample, long dash= EX-Sample.

Taken together the results for the unemployment rate and the marginal employment rate we find clear differences between sectors and samples. Therefore, we expect to see effects on our inequality analysis on all samples through the inclusion of unemployment and marginally employed individuals.

V. Inequality decomposition and inference

We measure and decompose inequality with indices from the entropy class. We use three different indices: the mean log deviation (in the following $I(0)$), which is sensitive to changes in the earnings differences at the lower tail of the distribution, the Theil index ($I(1)$) which is sensitive to changes in the middle of the distribution and the half coefficient of variation squared ($I(2)$) which is sensitive to changes that affect the upper tail of the earnings distribution (see Cowell (2011)). All three indices allow inequality decomposition by sectors in a within-sector (W) and a between-sector component (B):

$$I(c) = W(c) + B(c) \quad (1)$$

More precisely, following Jenkins (1995), $I(0)$, $I(1)$ and $I(2)$ can be written in the following forms:

$$I(0) = \sum_{k=1}^m (v_k * I(0, k)) + \sum_{k=1}^m \left(v_k * \ln \left(\frac{1}{s_k} \right) \right)$$

$$\text{with } I(0, k) = \frac{1}{N_k} * \sum_{i=1}^{N_k} \left(\ln \left(\frac{\bar{y}_k}{y_i} \right) \right) \quad (2)$$

$$I(1) = \sum_{k=1}^m (s_k * v_k * I(1, k)) + \sum_{k=1}^m \left(s_k * v_k * \ln \left(\frac{\bar{y}_k}{\bar{y}} \right) \right)$$

$$\text{with } I(1, k) = \frac{1}{N_k} * \sum_{i=1}^{N_k} \left(\frac{y_i}{\bar{y}_k} * \ln \left(\frac{y_i}{\bar{y}_k} \right) \right) \quad (3)$$

$$I(2) = \sum_{k=1}^m (v_k * s_k^2 * I(2, k)) + \sum_{k=1}^m \left(\frac{1}{2} * v_k * (s_k^2 - 1) \right)$$

$$\text{with } I(2, k) = \frac{1}{2N_k} * \sum_{i=1}^{N_k} \left(\left(\frac{y_i}{\bar{y}_k} \right)^2 - 1 \right) \quad (4)$$

where y_i denotes the individual earnings, \bar{y}_k the mean earnings in sector k , N_k the number of individuals in sector k , k the given sector, m the number of sectors, $s_k = \frac{\bar{y}_k}{\bar{y}}$ is sector mean earning in k relative to the population average earning, $v_k = \frac{N_k}{N}$ is the population share in k .

To perform statistical inference, we apply the jackknife (see Tukey (1958), Efron (1982), Efron and Gong (1983) and Wolter (1985)). To get jackknife statistics for the standard error of inequality indices, one uses subsets of the original database, leaves out one observation at a time from the sample and calculates the inequality index each time. The standard errors are then calculated, following Wolter (1985), by:

$$SE_{\theta} = \left(\frac{(N-1)}{N} * \sum_{i=1}^N (I(c, -i) - I(c))^2 \right)^{0.5} \quad (5)$$

with $I(c)$ being the inequality index for the whole sample and $I(c; -i)$ being the inequality index with individual i left out. Computing the jackknife standard error estimate relies on the N values of $I(c; -i)$, one jackknife statistic per subset. For large samples, the computational burden to compute all jackknife indices seems to be large, but Karoly and Schröder (2015) and Karoly (1989) show an efficient algorithm to derive the jackknife statistics and the jackknife between and within statistics, respectively. The decomposition of all three indices as well as associated jackknife components can be found in Appendix B.2.

Inequality changes can be further decomposed using the approximation by Mookherjee and Shorrocks (1982). Their method allows us to decompose the change in inequality into changes resulting from increasing inequality within sectors (A), changes resulting from changes in population shares of sectors (B+C) and changes resulting from changes in relative earnings of sectors (D).

$$\begin{aligned} \Delta I_0 &= I_0(t+1) - I_0(t) \\ &\approx \underbrace{\sum_{k=1}^m \bar{v}_k \Delta I(0, k)}_A + \underbrace{\sum_{k=1}^m \overline{I(0, k)} \Delta v_k}_B \\ &\quad - \underbrace{\sum_{k=1}^m (\bar{s}_k - \overline{\ln(s_k)}) \Delta v_k}_C + \underbrace{\sum_{k=1}^m (\overline{v_k s_k} - \bar{v}_k) \Delta \ln(y_k)}_D \end{aligned} \quad (6)$$

Where Δ is the difference operator and a bar over the variables stands for the mean of the base and current period, e.g. $\bar{v}_k = \frac{(v_k(t) + v_k(t+1))}{2}$.

VI. Results

A. Inequality trends

We start our analysis by comparing in Figure 6 the inequality trends of the $I(0)$ index for the employed West German male sample (S-Sample) with the trends of the three other employed samples: the employed male sample (i.e., West and East German; EM-M-Sample), the employed female sample (EM-F-Sample) and the employed sample (i.e. men and women; EM-Sample), and four employable samples (i.e. employed, marginal employed and unemployed): the employable West German male sample (EX-S-Sample), the employable male samples (EX-M-Sample), the employable female sample (EX-F-Sample) and the employable sample (EX-F-Sample). In this and all subsequent graphs results for the employed sample are indicated by black lines and by grey lines for the employable sample. Surrounding whiskers indicate 95 percent Jackknife confidence intervals.

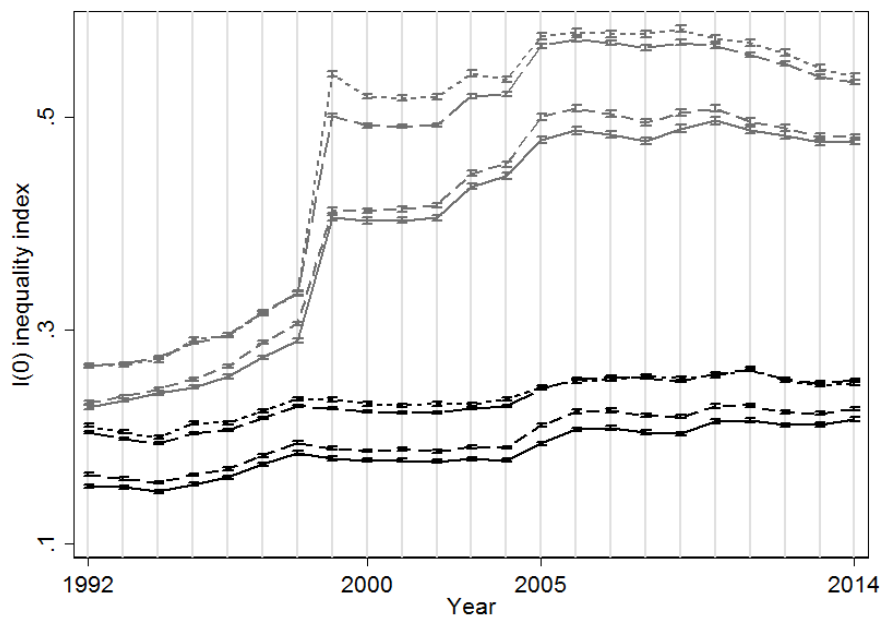


FIGURE 6 $I(0)$ INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE SAMPLES

Note: Database is SIAB; Own calculations. Black lines = Employed Samples, Grey lines= Employable Samples; Solid line = West German Men, dash= German Men, short dash= German Women, long dash= German Men and Women, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

For the S-sample, the mean-log deviation ($I(0)$) indicates a moderate rise of inequality over the observation period. From 1992 to 2014 the point estimate of the mean-log deviation increases from about 0.154 to 0.216, an increase of about 41 percent. The increase is smaller for the three other employed samples. The lowest increase shows the EX-F-Sample with an increase of only 19 percent. However, the three samples all show a significantly higher level

of inequality, e.g. 0.250 in the EX-F-Sample compared to 0.216 in the S-Sample. When the samples are extended the general increase (e.g. EX-S-Sample: 110 percent) and the level of inequality is markedly higher: 0.478 (EX-S-Sample) vs. 0.216 (S-Sample) in 2014. Having a closer look at the inter-temporal trends reveals that this difference is particularly due to the inclusion of marginally employed since 1999. Insurance became mandatory for marginal employees in 1999 implying a substantial influx of individuals with low earnings into the employable sample. This influx explains the kink in the time series for the employable samples. Until 1998 inequality increases steadily in the employed and employable samples, with 1999 inter-temporal trends start to differ. While inequality in the employed samples temporarily decreases and is then stable until 2004 to increase again in the subsequent time, inequality increases markedly in 1999 and between 2002 and 2005 in the employable samples, then stabilizes, but starts to decrease after 2010. In general, the time trends of overall earnings inequality in the employable samples fit the trends of the unemployment rate. Trends in the employed sample as afore-mentioned differ and cannot, in general, be linked to the unemployment trends. For though unemployment rates decrease after 2005, earnings inequality further increases in the employed samples. This leads to increasing inequality differences between the employed and employable samples in the middle of 2000 and decreasing differences in the last years.

To check whether the increase in inequality and the sample differences are driven by within sector or between sector inequality, we compare in Figure 7 the results for the within-sector component and in Figure 8 the between sector inequality across samples. The *within sector component* closely tracks the mean log deviation of each sample. However, the increase of within-sector inequality is lower than the increase of overall inequality in all samples, e.g. for the S-Sample we find an increase of about 27 percent compared to 41 percent in overall inequality. The decrease of inequality after 2010 in the employable samples is thereby also more evident. Nevertheless, within sector inequality explains about 95 percent of total inequality in 1992 and about 86 percent in 2014 in the S-Sample. This share is even higher in the female sample and in all employable samples, yet decreasing.

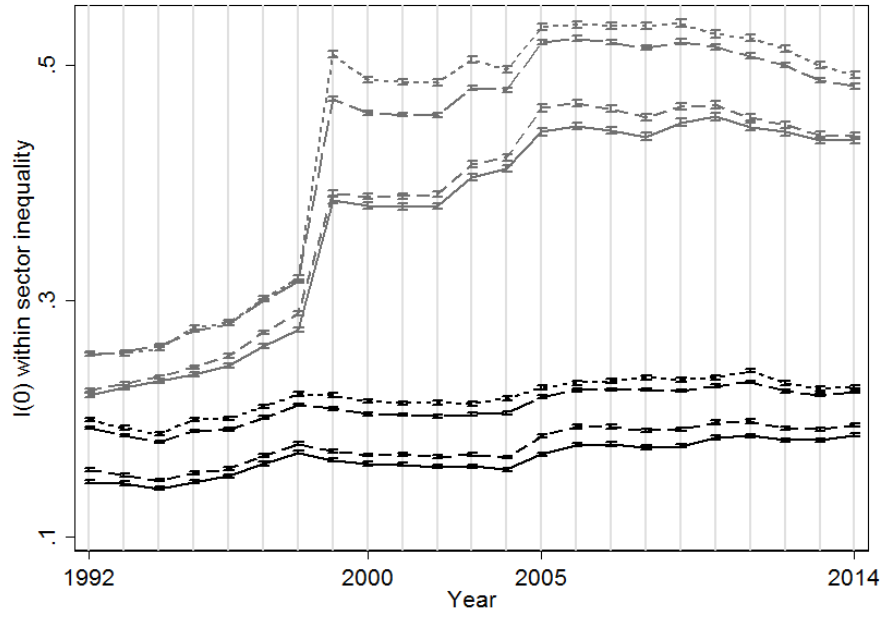


FIGURE 7 WITHIN SECTOR INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE SAMPLES

Note: Database is SIAB; Own calculations. Black lines = Employed Samples, Grey lines= Employable Samples; Solid line = West German Men, dash= German Men, short dash= German Women, long dash= German Men and Women, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

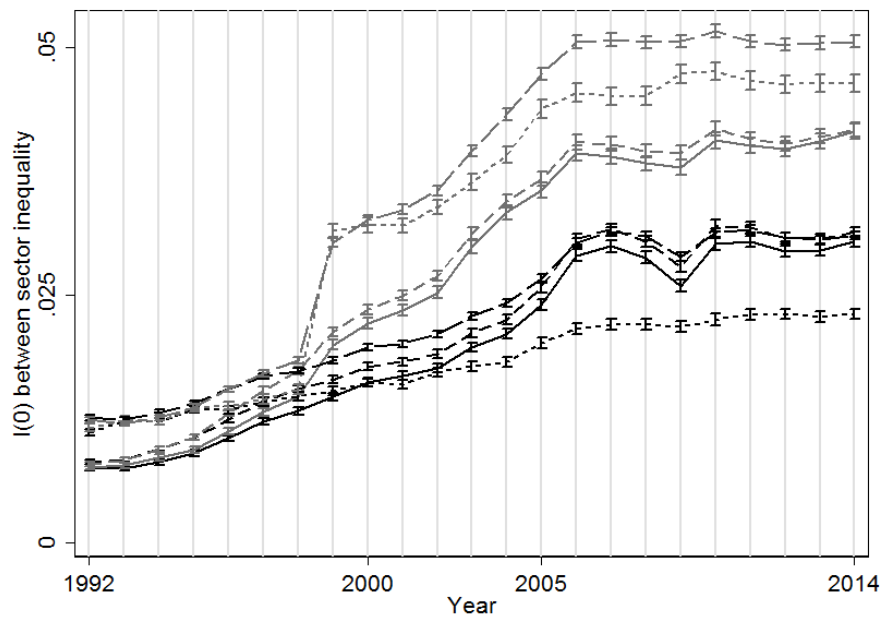


FIGURE 8 BETWEEN SECTOR INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE SAMPLES

Note: Database is SIAB; Own calculations. Black lines = Employed Samples, Grey lines= Employable Samples; Solid line = West German Men, dash= German Men, short dash= German Women, long dash= German Men and Women, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

Between sector inequality extremely increased in all samples. The increase is thereby higher in the employable samples compared to the employed samples. This difference is most pronounced in the female samples. The increase of between sector inequality is comparably low and steady for the EM-F-Sample with 108 percent between 1992 and 2014 (S-Sample: 308 percent) while it is 301 percent for the EX-F-Sample. In general, the trend of the between sector inequality component of the employable samples closely follows the between component of the employed samples until 1999. After including marginally employed workers in the sample in 1999 both curves diverge as between sector inequality increases substantially in the extended samples. In 2009 between sector inequality in the employed male sample decreases significantly, while no effect is visible in the female samples.

Summarized we see that inequality trends differ between men and women and between the employed and employable sample. Albeit the dominant driver of the inequality increase for both samples comes from within sector inequalities. Between sector inequalities only contribute to the general trends in the employed samples and dampen the effect of decreasing inequality in the employable samples. To analyze the reasons for between and within sector inequality trends in more detail we proceed with an investigation of its sub-aggregates: sector-specific population shares, sector-specific inequality and sector mean earnings relative to overall mean earnings (s_k).

B. Decomposing between and within inequality into its sub-aggregates

TABLE 4 DECOMPOSITION OF INEQUALITY INTO ITS SUB-AGGREGATES

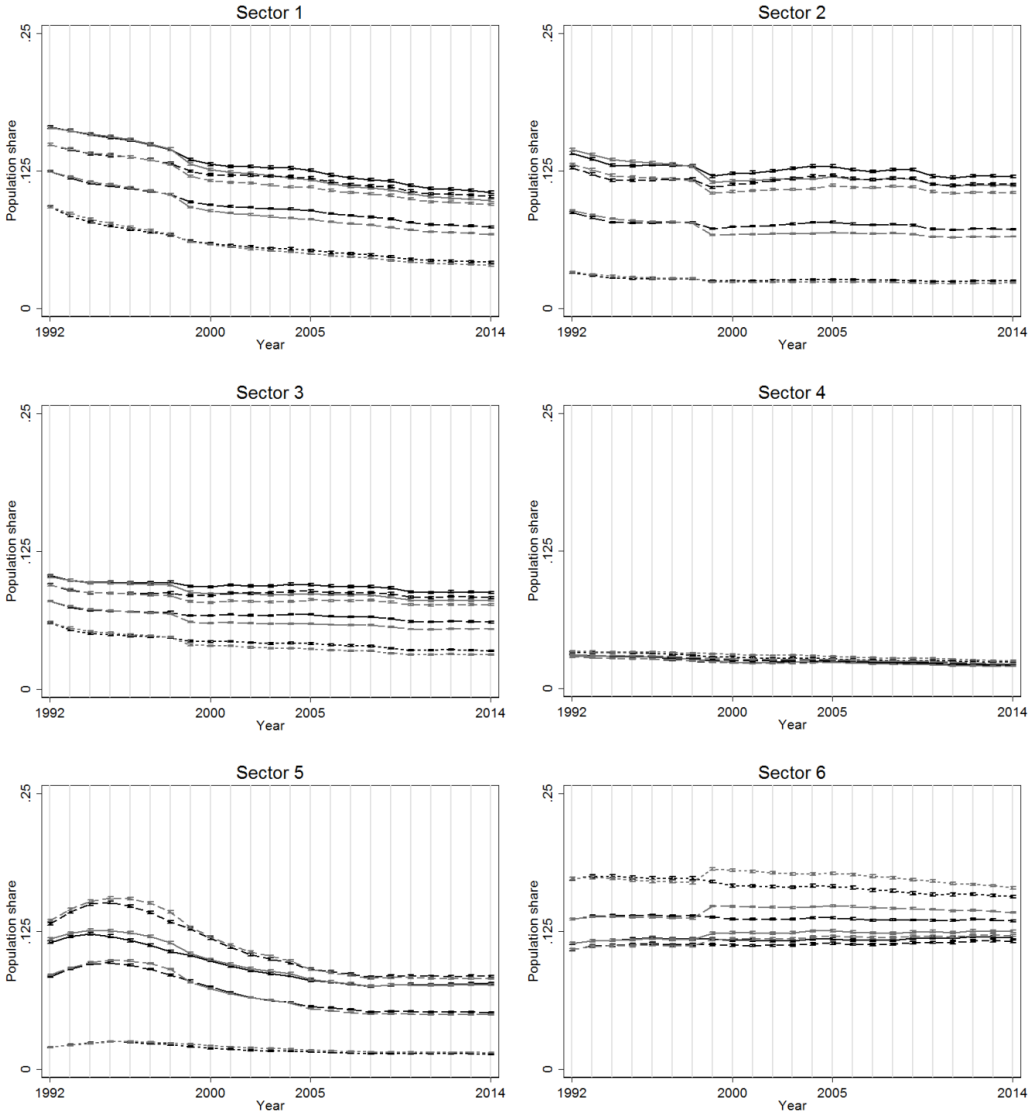
Data	Year	Contribution to ΔI due to changes in						
		I_0	$\%I_0$	ΔI_0	Within sector inequality (A) $\sum v_k \Delta I_0^k$	Population shares (B+C) $\sum I_0^k \Delta v_k$	$\sum ((s_k - \log(s_k)) \Delta v_k)$	Mean sector earnings (D) $\sum (v_k s_k - v_k) \Delta \log(\mu_k)$
S-Sample	1992	0.154			0.021			0.031
	2014	0.216	41	0.063	(0.334)	(0.019- 0.008)=0,011	(0.175)	(0.489)
EX-S-Sample	1992	0.288			0.184			0.042
	2014	0.478	110	0.250	(0.735)	(0.032-0.008)=0.024	(0.096)	(0.169)
EM-M-Sample	1992	0.165			0.020			0.031
	2014	0.226	37	0.061	(0.335)	(0.017-0.008)=0.011	(0.18)	(0.511)
EX-M-Sample	1992	0.232			0.185			0.043
	2014	0.482	108	0.250	(0.742)	(0.031-0.009)=0,022	(0.088)	(0.171)
EM-F-Sample	1992	0.210			0.020			0.014
	2014	0.250	19	0.040	(0.510)	(0.007-0.002)=0.005	(0.125)	(0.361)
EX-F-Sample	1992	0.267			0.219			0.040
	2014	0.538	102	0.271	(0.809)	(0.017-0.005)=0.012	(0.044)	(0.146)
EM-Sample	1992	0.205			0.015			0.023
	2014	0.254	24	0.049	(0.305)	(0.016-0.005)=0.011	(0.225)	(0.477)
EX-Sample	1992	0.267			0.199			0.045
	2014	0.533	100	0.266	(0.749)	(0.028-0.007)=0.021	(0.079)	(0.169)

Note: Database is SIAB; Own calculations. In brackets, the share of e.g. $\frac{A}{\Delta I_0}$ is given.

General – In a first step we decompose the general increase in inequality in each sample over the time interval from 1992 to 2014 into changes resulting from increasing inequality within sectors (A), changes resulting from changes in population shares of sectors (B+C) and changes resulting from changes in relative earnings of sectors (D). The results are given in Table. Taking the S-Sample as an example we see that the increase in inequality by 0.063 (41 percent) can be divided into 0.021 being contributed by changes of inequality within sectors, 0.011 by changes in population shares and 0.031 by changes in mean sector earnings. So the changes in relative earnings of sectors are the main driver of increasing earnings inequality for West German employed men. Comparing the results with the results of the other employed samples, we find that for women the changes in inequality within sectors are the main force behind the increase in earnings inequality, e.g. to the change in inequality by 0.040 inequality changes within sectors contributes 0.020, and to a lesser extent changes in relative mean earnings of sectors (0.014). The same pattern is observable when we extend the samples to the employable part. Inequality within sectors contributes more than 70 percent to the increase in earnings inequality in all employable samples, and the contributions of the

changes in population shares and especially the changes in relative earnings of sectors decrease substantially.

The decomposition results give us a first hint that earnings inequality increased not only due to increasing within and between sector inequality, but more precisely due to increases in inequality within sectors and changes in relative earnings of sectors, and to a much smaller extent due to changes in sector-specific populations shares. Inequality within sectors is thereby much more important for women and for the employable part of the population. In a next step, we will not only focus on the decomposition of change in earnings inequality, but we will look at the inter-temporal trends of sector-specific inequalities, population shares, and the sector mean earnings relative to overall mean earnings (s_k) and investigate whether specific sectors drive the increase in earnings inequality.



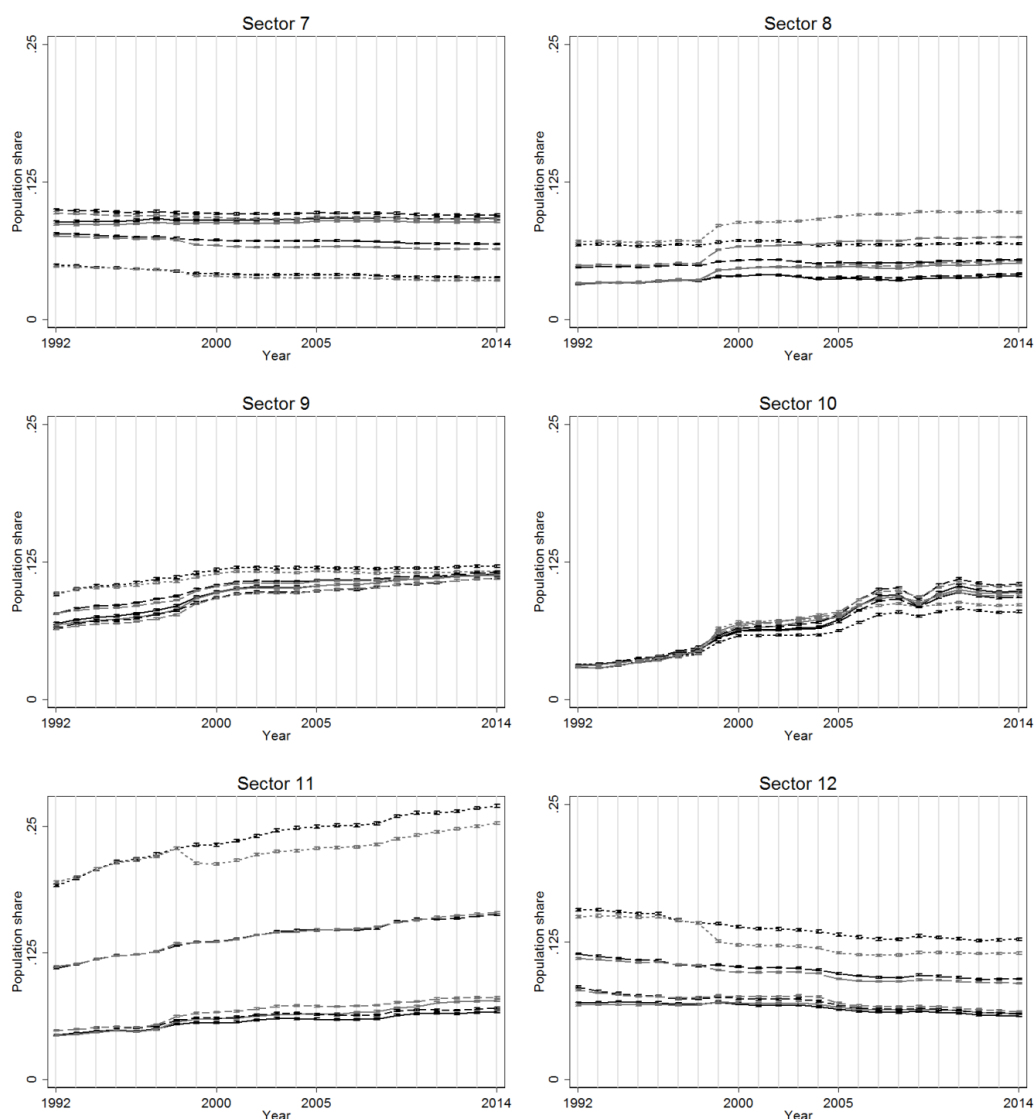
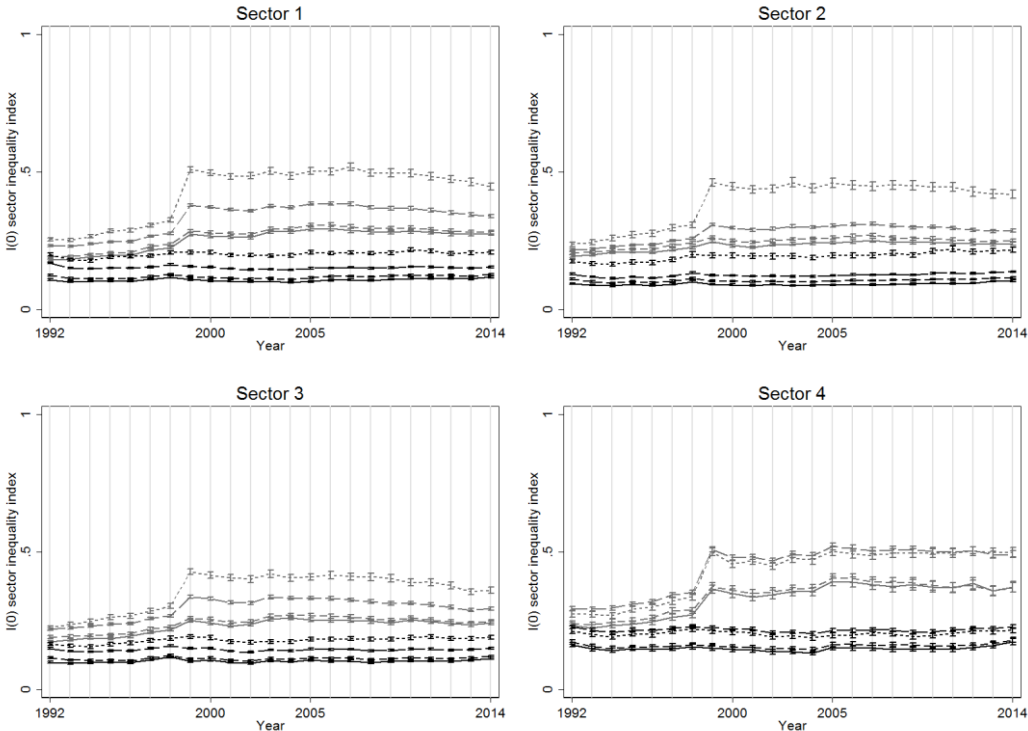


FIGURE 9 SECTOR SPECIFIC POPULATION SHARES FOR THE EMPLOYED AND EMPLOYABLE SAMPLES

Note: Database is SIAB; Own calculations. Black lines = Employed Samples, Grey lines= Employable Samples; Solid line = West German Men, dash= German Men, short dash= German Women, long dash= German Men and Women, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

Population share – The first sub-aggregate, which we will compare are the sector-specific population shares, shown in Figure 9, as they are important for the within sector and between sector component. The Figure reveals several important findings. First, some sectors gain while others lose importance, in terms of employment shares. To the sectors who gain importance belong the service sectors (8-10) and public services (11), which increase their population shares by up to 96% (EX-S-sample). In the S-sample the share, for example, increased from 17.5 percent in 1992 to 32 percent in 2014. To the group who lose importance belong the manufactural sectors (1-4), construction (5) and public institutions (12). Their

shares decrease by more than 20 percent in all samples, e.g. in the S-Sample from 62.3 percent in 1992 to 47 percent in 2014. For trade (6) and infrastructure (7), it depends on the sample. They gain importance in the male samples (increase between 5 and 10 percent) and lose importance in the female samples (decrease between 5 and 10 percent). Second, there are further gender-specific differences. In the male samples the manufacturing sectors (1-4) and construction (5) play a more dominant role. They comprise in 1992 55.5 percent of employees in the S-sample compared to only 23.8 percent in the EM-F-sample. In the female samples trade (6), household-related services (8) and the public sectors (11+12) are more important, e.g. in 1992 they comprise 26 percent of the employment in the S-sample and 58.6 percent in the EM-F-sample. The largest increase in employment shares is visible in the economic services (10), e.g. in the S-Sample the share increases by 234 percent from 3 percent to ca. 10 percent. The third important result is that sector-specific population shares are very similar for the employable and the employed sample. Significant differences are only visible after 1998, with lower shares in the manufacturing (1-4) and public sectors (11+12) and higher shares in trade (6) and household related services (8). The trends of the shares are stable for most sectors, except for drops/rises in 1999. Only the construction sector (5) and economic services (10) show a different pattern. The construction sector first increases its shares at the beginning of the 90s, which is then followed by a clear decrease in population shares. The economic services (10) increase their share especially after 1998, yet the shares show a marked kink in 2009 in all samples.



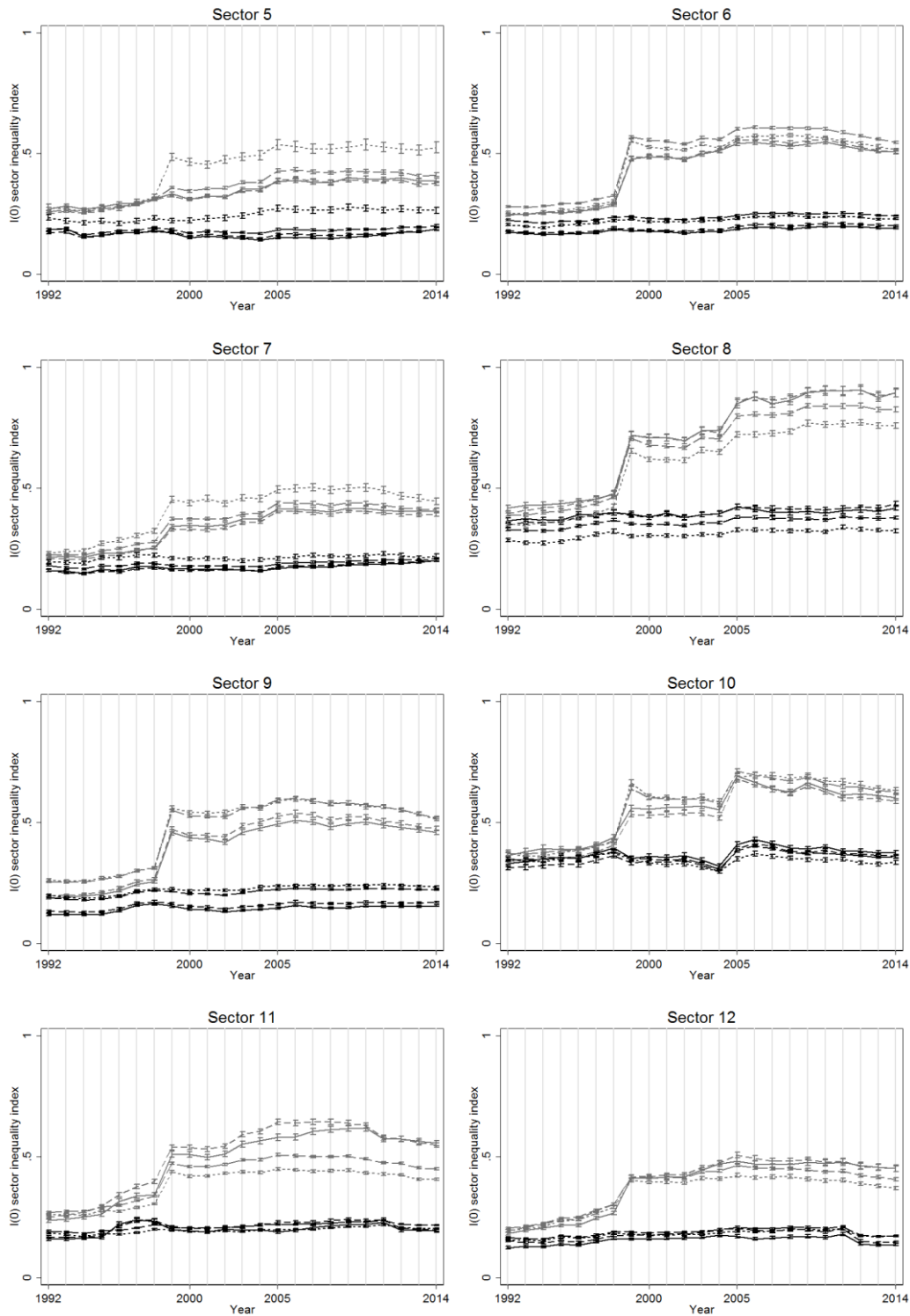
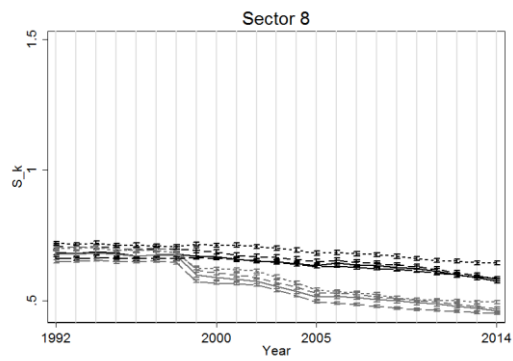
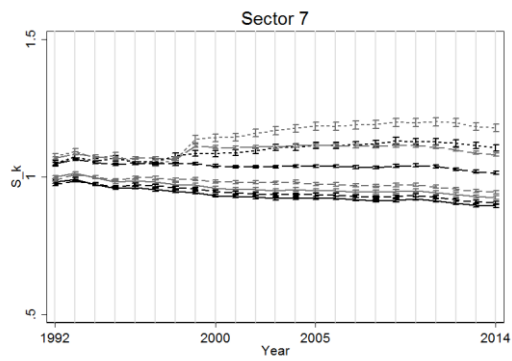
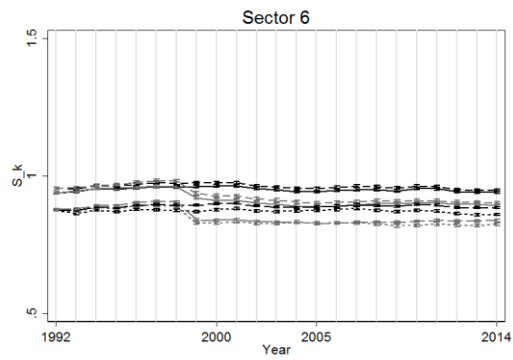
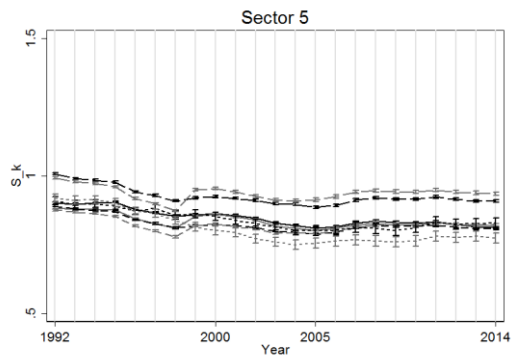
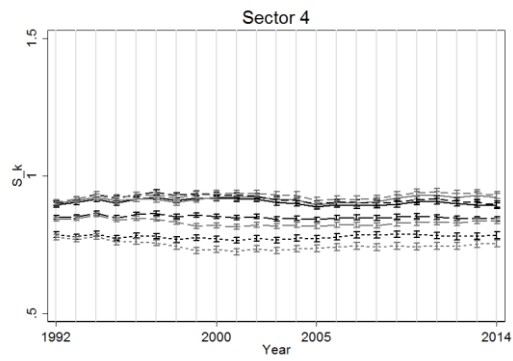
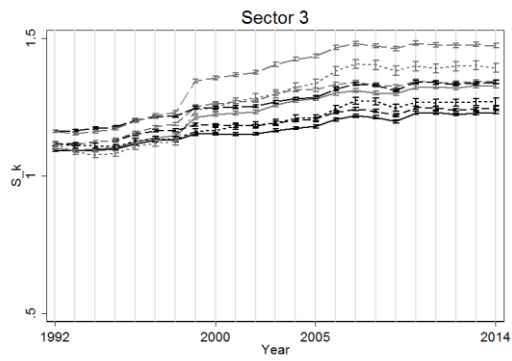
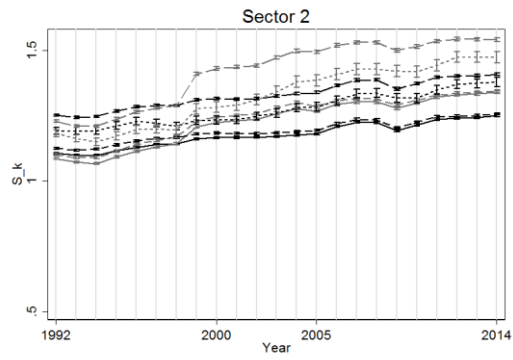
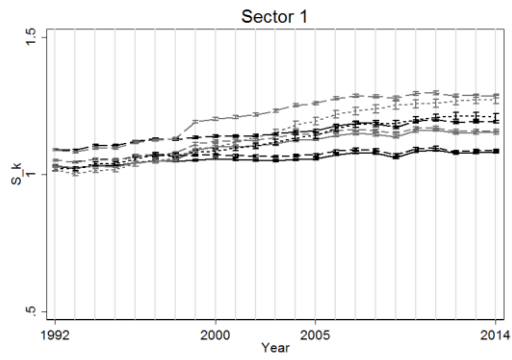


FIGURE 10 SECTOR SPECIFIC $I(0)$ INDICES FOR THE EMPLOYED AND EMPLOYABLE SAMPLES

Note: Database is SIAB; Own calculations. Black lines = Employed Samples, Grey lines= Employable Samples; Solid line = West German Men, dash= German Men, short dash= German Women, long dash= German Men and Women, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

Sector-specific mean-log deviations – The second sub-aggregate of the within component are the sector-specific mean-log deviations, which are illustrated in Figure 10. The first important result which we find here is, that in the employed samples two sectors attract attention: household related (8) and economic (10) services show notable higher values of sector-specific inequality (S-sample: household-related services (8) = 0.365, economic services (10) = 0.330 compared to manufacture of structural metal products (2) = 0.093 in 1992). This picture is moderated in the employable samples, which leads us to the second conclusion: Sector-specific inequality is significantly higher in all sectors in the employable samples, but especially in trade (6, S-Sample: 0.190; EX-S-Sample: 0.506 in 2014), infrastructure (7, S-Sample: 0.200; EX-S-Sample: 0.406 in 2014) and the service sectors (8-10, e.g. economic services: S-Sample: 0.375; EX-S-Sample: 0.602 in 2014). But not only is the level of inequality higher, also the increase in inequality. The extension can even lead to changing trends from decreasing (-4.69 percent) to increasing inequality (+69.58 percent) within the economic services (10) for the female sample. Third, there are gender-specific differences present in the comparison of sector-specific inequality. Inequality is much higher for women, employed and employable, in the manufactural sectors (1-4), whereas inequality is higher for men in household-related (8) and public services (11). Having a closer look at the inequality trends within the sectors, we find that inequality trends differ between the employed and employable samples. Starting with the employed samples, we find no general trend in the samples. Inequality is quite stable in the manufactural sectors (1-4), while we find more variation in the service and public sectors (8-12). One example are the economic services (10), which show a kink in 2004 with a marked increase in inequality afterwards and the public sectors (11 +12) which show clear decreases in inequality after 2011. However, there are also substantial differences between men and women. One example of gender-specific trends can be found in the construction sector (5). Inequality in the S-Sample decreases between 1998 and 2005, while inequality increases for women at the same time. Trends in the employable samples are more similar. Most obvious are the increases in inequality in 1999, especially in the female sample (EX-F-Sample) and trade (6), infrastructure (7), and all service and public sectors (8-12). In general, inequality is increasing in the employable samples throughout the 1990's, but at the beginning of the 2000s inequality stabilizes, only to increase again especially between 2003 and 2005. Afterwards, inequality decreases again in most sectors. One exception are the economic services (10), who albeit the general decrease show a significant increase in 2010 in the employable male samples.



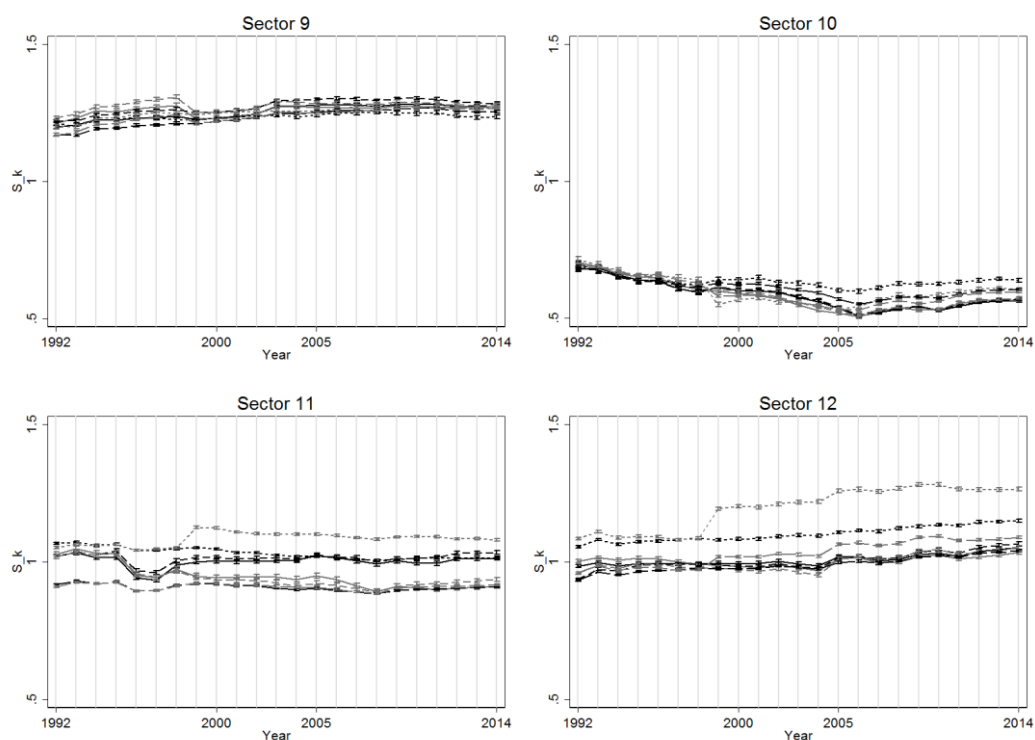


FIGURE 11 SECTOR MEAN EARNINGS RELATIVE TO OVERALL MEAN EARNINGS (s_k) FOR THE EMPLOYED AND EMPLOYABLE SAMPLES

Note: Database is SIAB; Own calculations. Black lines = Employed Samples, Grey lines= Employable Samples; Solid line = West German Men, dash= German Men, short dash= German Women, long dash= German Men and Women, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

Sector-specific average earnings relative to economy-wide average earnings (s_k)

- The second sub-aggregate for the between component are the sector-specific average earnings relative to economy-wide average earnings (s_k) illustrated in Figure 11. Values above (below) 1 indicate that average earnings in the specific sector are higher (lower) than economy-wide average earnings. The first finding, which Figure 11 reveals, is the marked difference between household-related services (8) and economic services (10), with very low ratios, sector-specific average earnings relative to economy-wide average earnings, down to 0.5 and the manufacturing sectors (1-3) and FIRE (9) with ratios far above 1 up to 1.5. These differences increase further over the time interval as the manufacturing sectors (1-3) increase their ratios (S-Sample: between 5 to 13 percent) while the ratio of economic services (10) decreases further (S-Sample: -17.2 percent). This pattern is observable in all employed and employable samples. For FIRE (9) and household related services (8), it is sample specific. For women, the first improves its position while the latter deteriorates. For men, this is only true in the employed sample, in the employable sample the relation reverses. The ratios of all other sectors lie around 1. The second important finding is that we find gender-specific differences in most sectors: The ratio of women is higher in the manufacturing sectors (1-3),

infrastructure (7) and the public sectors (11+12), while the ratio in the male samples is significantly higher in manufacture of food products, beverages and tobacco (4), trade (6) and household related services (8), while in the latter and in manufacture of basics, goods and consumer products (1), the differences emerge after 1999. When we extend the samples the manufactural sectors (1-3) and infrastructure (7) improve their position, while manufacture of food products, beverages and tobacco (4), trade (6) and household related services (8) deteriorate. Interesting are the public services (11), where extending the sample to the employable part leads to complete different reactions in the male and female samples. The ratio increases for women when extending the sample, and decreases for men. When we look closer at the inter-temporal trends, we find that large differences between the employed and employable samples occur in 1999 and afterwards, especially for the female samples.

VII. Sensitivity analysis

Two important normative decisions are underlying our decomposition analysis. The first decision concerns the inequality aversion parameter c . By setting c equal to 0, we have studied a particular case of the entropy class, the mean log deviation. In the present Section, we explore the sensitivity of our results to variations of the parameter. Particularly, we study two cases, $c = 1$ and $c = 2$, resulting in the Theil index $I(1)$ and half the coefficient of variation squared $I(2)$. The second decision concerns the censored earnings. We compare our previous results from the original censored distribution with the Pareto-imputed distribution. Our main analysis is the most conservative scenario as it yields a lower bound of earnings inequality. Therefore we expect inequality to be higher in the earnings imputed samples. For this sensitivity analysis, we use our standard sample (S-sample) and our extended standard sample (EX-S-sample).

A. Other indices

We start by looking at the results of the $I(1)$ and $I(2)$ results. The Theil index ($I(1)$) refers primarily to the middle of the earnings distribution in contrast to the mean log deviation ($I(0)$), which refers to the lower tail and the $I(2)$ index, half the coefficient of variation squared, which is most sensitive to earnings inequality at the upper tail. Figure A.1 in the Appendix illustrates the overall $I(1)$ index and Figure A.2 the overall $I(2)$ index. Figure A.3 and Figure A.4 illustrate their within and Figure A.5 and Figure A.6 their between components for the S- and the EX-S-sample. Both indices, the $I(1)$ and $I(2)$, increased as well between 1992 to 2014 in both samples, e.g. the $I(1)$ index in the S-Sample by 46.62 percent

and in the EX-S-Sample by 84.76 percent. The increases of both indices in the employed sample are thereby larger compared to the I(0) index, whereas the increases in the EX-S-Sample are smaller compared to the I(0) index. The same holds true for the within component (I(1) index: S-Sample: 28.11 percent; EX-Sample: 67.03 percent). The increases of the between component are slightly smaller in both samples compared to the I(0) index (I(1) index: S-Sample: 293 percent; EX-S-Sample: 421 percent). However, the between component plays a more important role in case of these two indices and its share increases between 1992 to 2014, e.g. for the between sector I(1) index in the S-Sample from 7 percent to 19 percent. The intertemporal trends are similar to the trend of the I(0) index, yet we do not find a decrease in overall earnings inequality after 2010 in the EX-S-sample and a less pronounced increase in earnings inequality in 1999.

Figure A.7 and Figure A.8 illustrate the sector-specific I(1) and I(2) indices. The results are similar to the ones we find for the I(0) index: inequality increases within all sectors and the increases are higher in the extended sample. However, extending the sample has a smaller impact for the I(1) and I(2) indices compared to the I(0) index and increases in inequality within sectors in the S-Sample are already higher. When we look at the inter-temporal trends we find smaller increases in inequality in 1999 in the extended sample, otherwise, trends are quite similar. Only the decreases after 2010 in the extended sample are less marked.

Summarized we can say that the results of the I(1) and I(2) index support our main results of the I(0) index, namely the overall inequality increase. However, for the employed part of the population earnings inequality increases more when looking at the upper or middle tail of the earnings distribution (I(2) or I(1)) whereas extending the sample has as assumed a higher impact for the lower tail of the earnings distribution (I(0)).

B. Pareto imputation

The next step is to check if our results are robust to earnings imputation to correct for the earnings assessment ceiling for example as done by e.g. Card et al. (2013). By imputing earnings we attribute earnings which lie above the social security assessment ceiling in each sector in order to mimic the actual earnings distribution. Figure A.9 compares the overall I(0) index results for the case with and without earnings imputation. Figure A.10 compares the within components and Figure A.11 the between components. Figure A.12 compared the

sector-specific $I(0)$ inequality results. In all Figures the solid line illustrates the results without earnings imputation and the dashed line the results with earnings imputation.

When comparing the results we find that inequality is higher in case of earnings imputation. However, trends do not change. Our main results can be therefore seen as a lower bound of earnings inequality, but as the $I(0)$ index focuses on the lower tail of the earnings distribution omitting earnings imputation has no large impact on sample differences.

VIII. Discussion

Our results regarding the steady increase of earnings inequality in the employed samples fit the findings of increasing wage inequality for Germany of Dustmann et al. (2009) and Card et al. (2013). Yet, when we extend our samples to the employable part of the population, trends differ. Not only is the measured inequality higher, we find that inequality trends differ. While earnings inequality for the employed part increases especially after 2004, the rise in inequality in the employable samples is closely chronologically connected to the Hartz reforms in the middle of the 2000s, with high increases in inequality between 2002 and 2005. However, afterwards earnings inequality decreases for the employable part of the population. This stands in contrast to the aforementioned studies. Yet we validate thereby findings of Stein (2017) who reports that the increase in inequality in Germany is mainly due to full-time employed males. Our results also show in this direction, that earnings inequality only increases when considering the employed fraction without marginal employed and unemployed individuals.

The subsequent decomposition results reveal that particularly within sector inequality is responsible for the increase in earnings inequality and in case of the employable samples for the decrease in inequality in the last decade. Thereby the decrease in population shares of the manufacturing sectors and the construction sector and the increase in inequality within the service sectors lead to the increase in within sector inequality. This supports the literature claiming that shifts from manufacturing employment to service employment are responsible for parts of the increase in wage and earnings inequality (Chevan and Stokes, 2000; Autor and Dorn, 2013). Our study adds that especially household-related services show a markedly higher level and increase of inequality. This fits the study by Dustmann et al. (2014) who find significant wage trend differences between tradable manufacturing and partly in tradable service sectors in Germany.

We can show that also between sector inequality increases steadily over the time interval and only decreases in the recession year independent of the sample under investigation. This is due to the fact that first sector-specific average earnings get more dispersed, supporting results by Card et al. (2013), who report substantial increases in inequality in average wages across industries over the last decades. Second, we find high increases in population shares of two sectors with very low relative earnings, household-related services and economic services boosting between sector inequalities.

Our robustness checks reveal that the general results are not driven by the fact that earnings are censored in our data set. This result supports the finding of Dustmann et al. (2009) who compared different imputation methods with the censored data using IAB data sets. The choice of inequality measures however has an impact for the employed part of the population as earnings inequality increases more when looking at the upper or middle tail of the earnings distribution (I(2) or I(1)). This fits to findings of Card et al. (2013), who document higher levels of wage dispersion for the upper tail compared to the lower tail of the wage distribution. Extending the sample on the other hand has a higher impact for the population with low earnings (I(0)) as unemployed and marginally employed workers belong to this group and cause higher dispersion of earnings at the lower tail of the earnings distribution.

IX. Conclusion

Rising earnings inequality has been documented for many industrialized countries and recent literature shows that wage inequality started to grow in the last decades also in Germany (e.g. Dustmann et al., 2009). At the same time the unemployment rate fluctuates with high rates during the 2000s and the rate of marginally employed workers increased substantially. Our data shows however that these trends differ across sectors with high unemployment rates across all manufacturing and construction sectors and high rates of marginal employment in service sectors. This leads to the purpose of our study. We want to add to the discussion about earnings inequality by decomposing overall inequality into between and within sector inequality, examining the inter-temporal trends of its sub-aggregates and particularly assessing the sample selection effect. We start our study by decomposing the Mean Log Deviation by sectors and compare in a next step the estimates for two populations: (1) the employed fraction of the population and (2) the employable population which covers in addition marginally employed and registered unemployed

individuals. Furthermore, we consider different samples: West German men, German men, German women and a full German sample.

We find that earnings inequality increases for all employed and employable samples between 1992 and 2014 with substantially higher levels and increases of earnings inequality in the employable samples. However, most important is, trends differ with regard to the population. We find diverging trends after 2010, with further increases in earnings inequality for the employed fraction of the population and decreases in earnings inequality for the employable population. Decomposing the inequality reveals that most of the increase in inequality and the general trends can be explained by the within-sector inequality. This is particularly the case for the female and the employable samples. Our subsequent decomposition reveals that the change in population shares is thereby far less important than the change in inequalities within sectors. Only for employed men, changes in relative earnings of sectors also contribute substantially to the increase in inequality. The main sectors driving the increases in inequality are the service and public sectors. First, we find shifts in employment from the manufacturing sectors and the construction sectors to the services sectors and public services. Second, within sectors inequalities are higher for the service and public sectors. Third, relative earnings are lower than average in the service sectors. Extending the samples enhances these trends and differences. Especially household related and economic services contribute to the increase in inequality.

Our results are important as earnings and wage inequality is widely discussed in the public and among scientist. So far the main result was that wage and earnings inequality increased over the last years. Our results show that this is only the case for the whole time horizon between 1992 and 2014 if we focus on the employed part of the population. Including marginal and unemployed workers, changes as afore-discussed the picture. Hence, the discussion so far was only concentrated on the employed fraction of the population and leaves a large fraction of the population unconsidered. The sectors driving the earnings inequality are sectors, where women are overrepresented, and which show high rates of marginal employment, especially household related and economic services. So concentrating on full-time employed male workers, as done in many studies so far, leads to a substantial underestimation of inequality.

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A. Additional Graphics

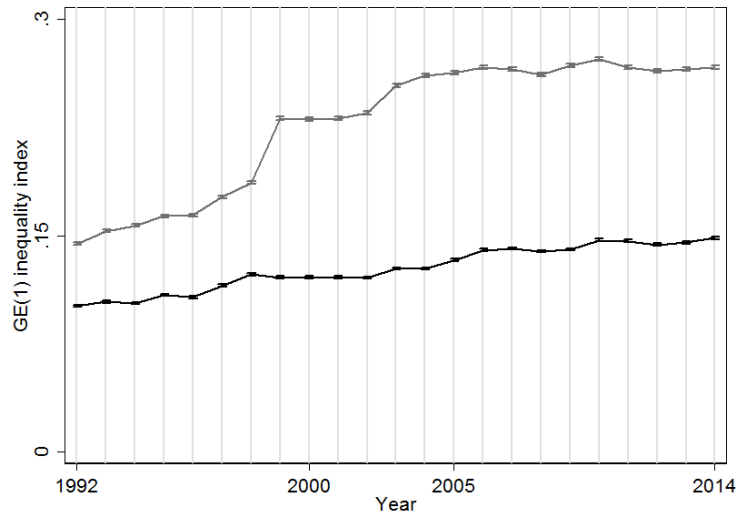


FIGURE A.1 I(1) INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

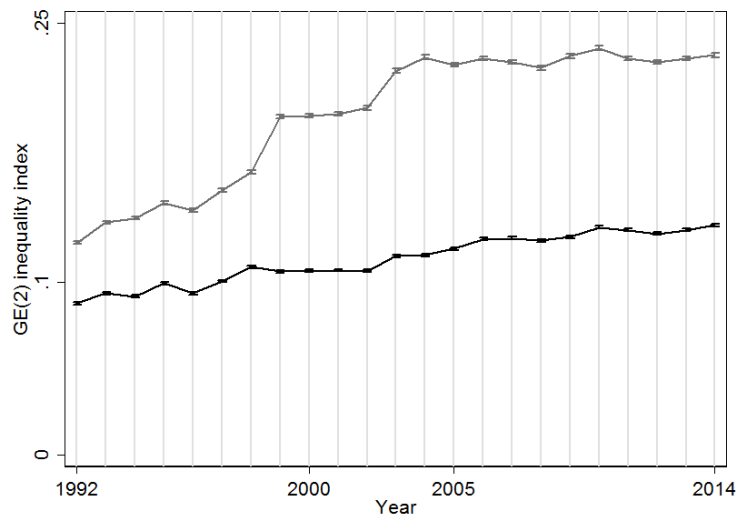


FIGURE A.2 I(2) INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

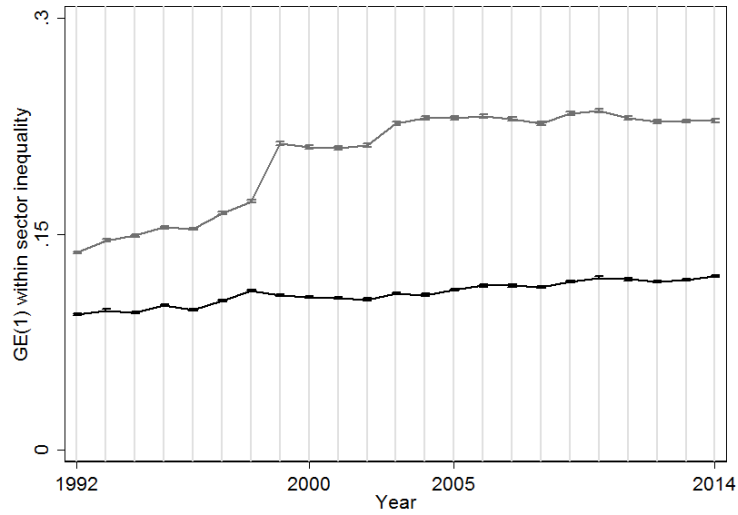


FIGURE A.3 I(1) WITHIN SECTOR INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

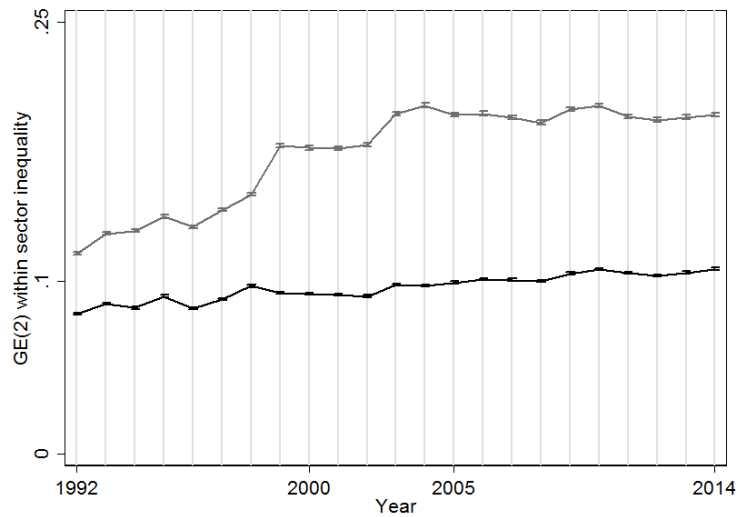


FIGURE A.4 I(2) WITHIN SECTOR INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

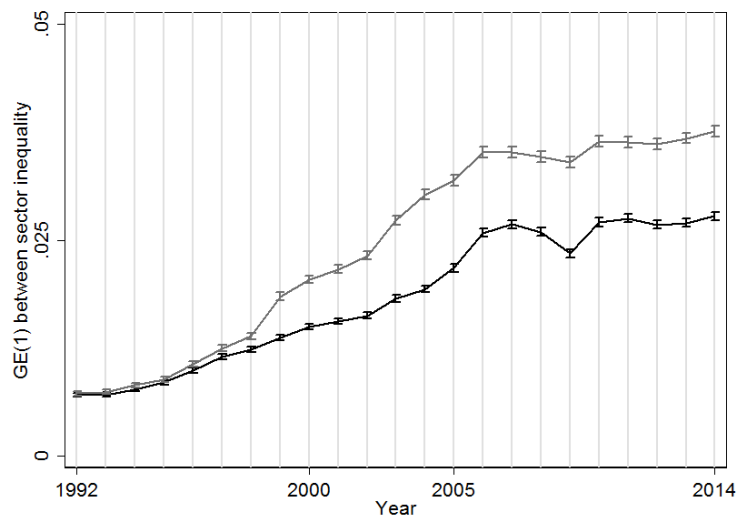


FIGURE A.5 I(1) BETWEEN SECTOR INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

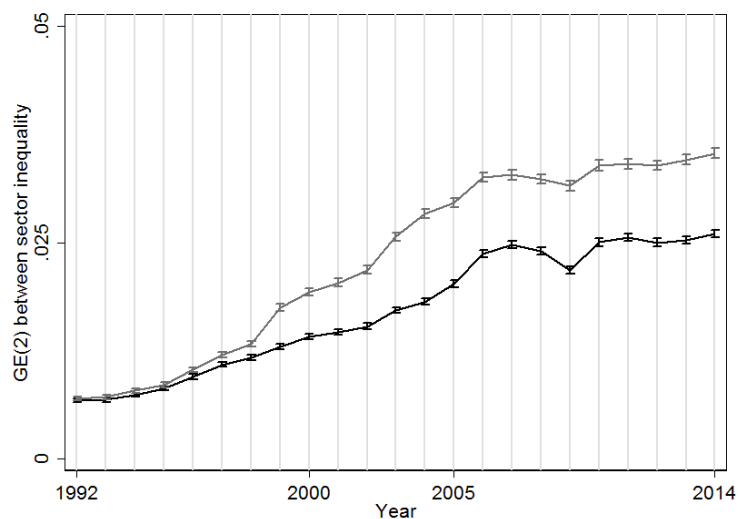
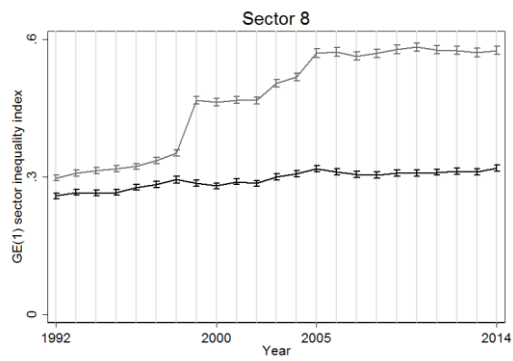
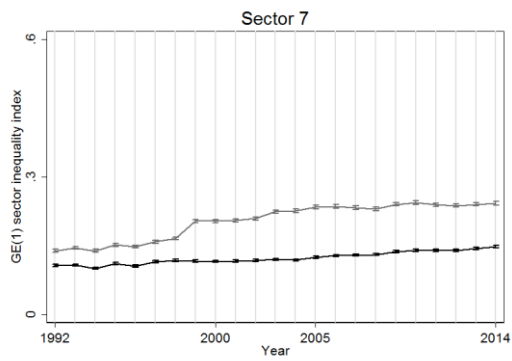
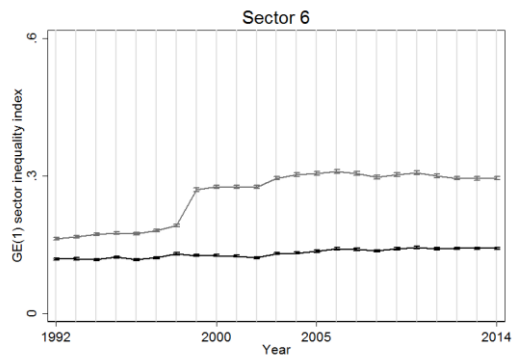
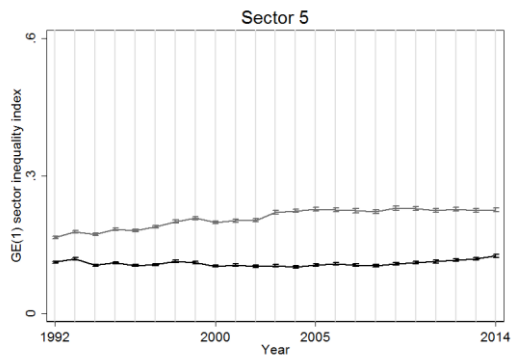
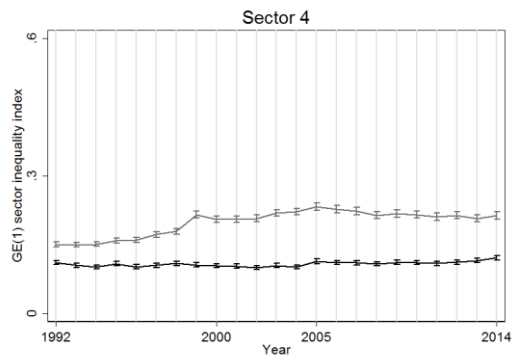
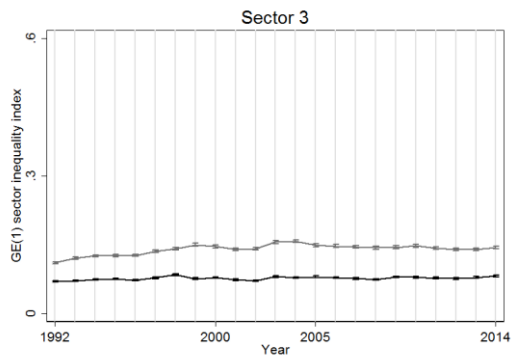
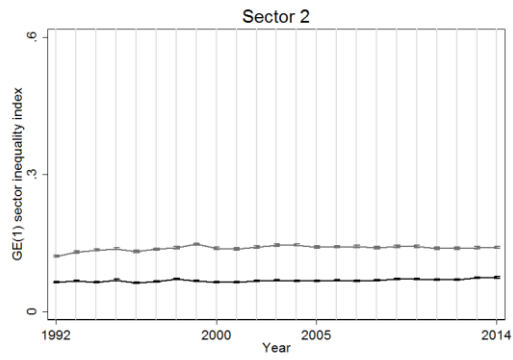
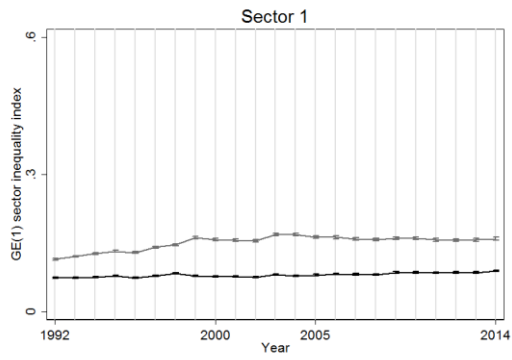


FIGURE A.6 I(2) BETWEEN SECTOR INEQUALITY RESULTS FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.



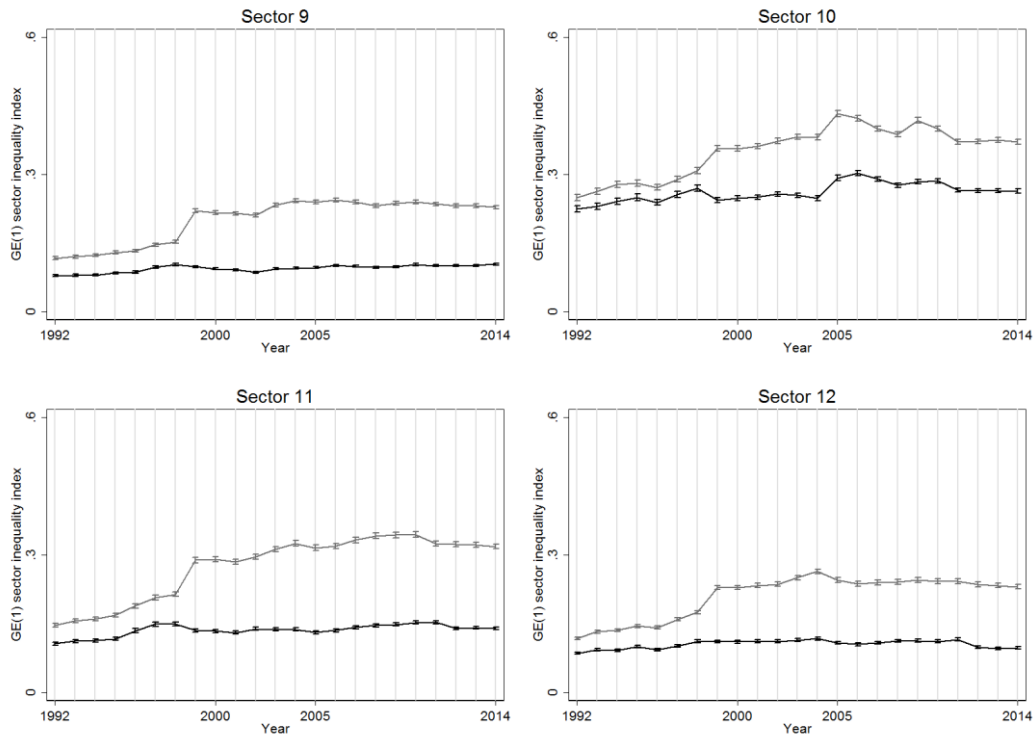
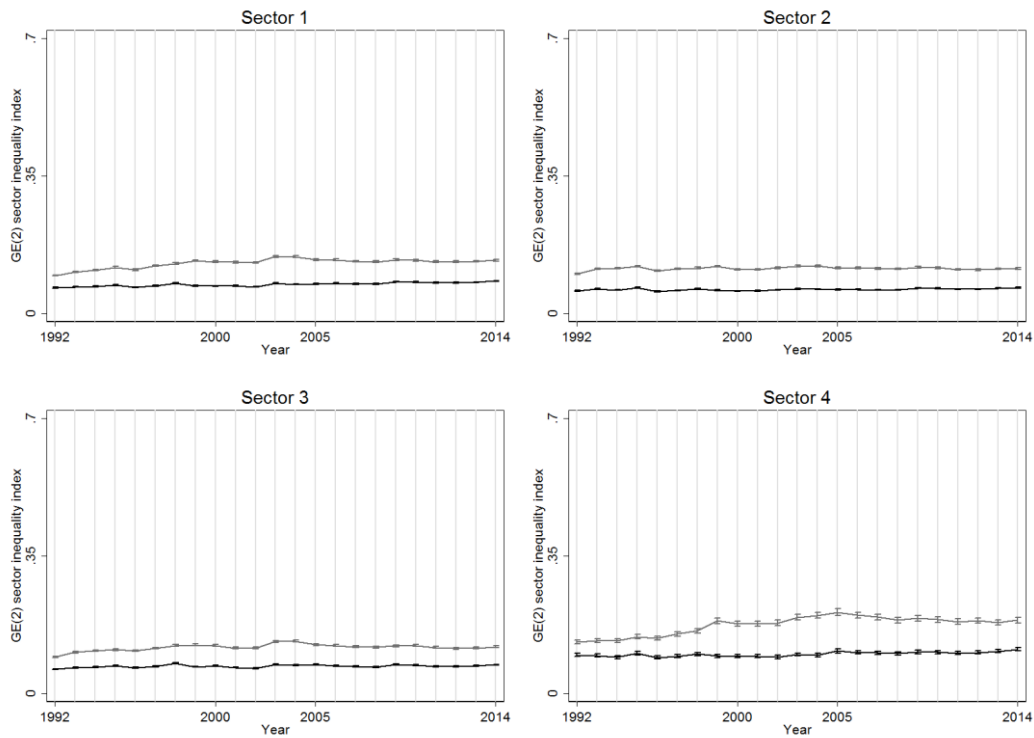


FIGURE A.7 SECTOR SPECIFIC I(1) INDICES FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.



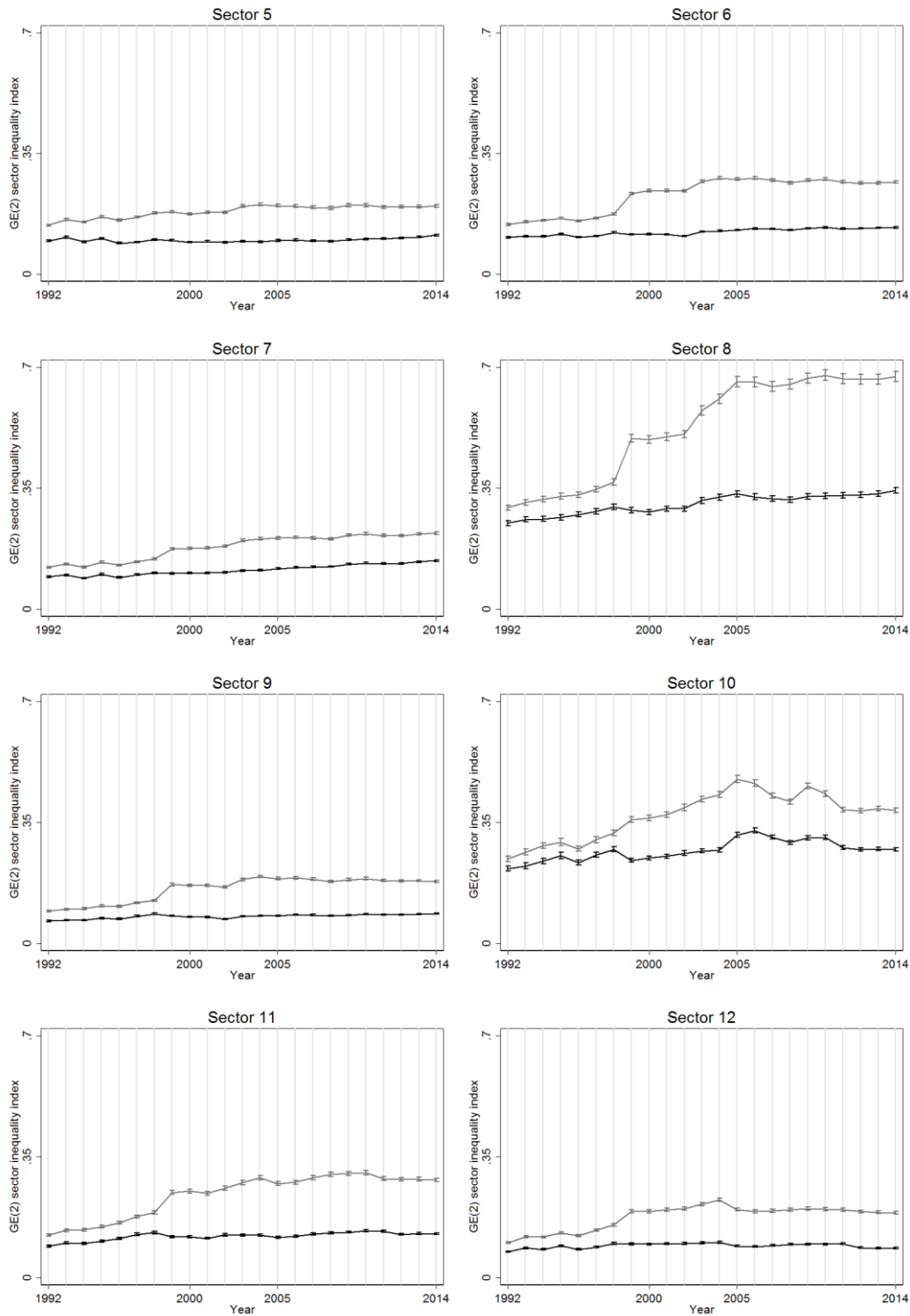


FIGURE A.8 SECTOR SPECIFIC I(2) INDICES FOR THE EMPLOYED AND EMPLOYABLE WEST GERMAN MALE SAMPLES

Note: Database is SIAB; Own calculations. Black solid lines = S-Sample, Grey solid lines= EX-S Sample, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

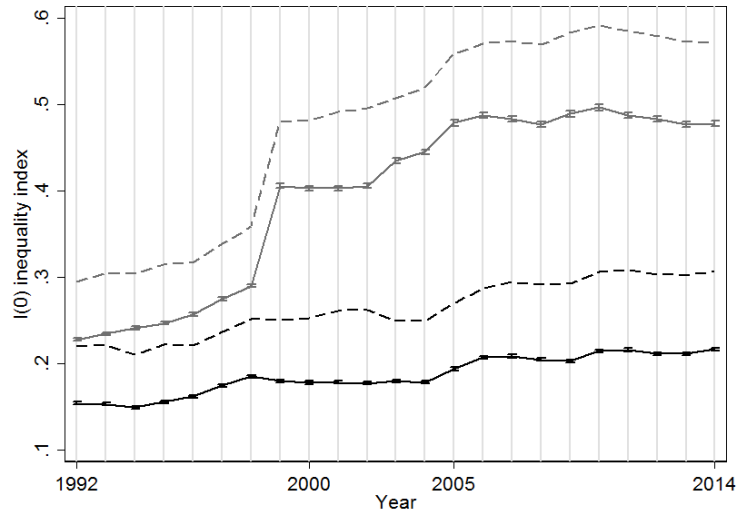


FIGURE A.9 I(0) INEQUALITY RESULTS FOR THE WEST GERMAN MALE SAMPLE: PARETO IMPUTATION VS. NO PARETO IMPUTATION

Black lines = Employed West German Male Samples, Grey lines= Employable West German Male Samples; Solid line = No Pareto imputation, dash= Pareto imputation, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

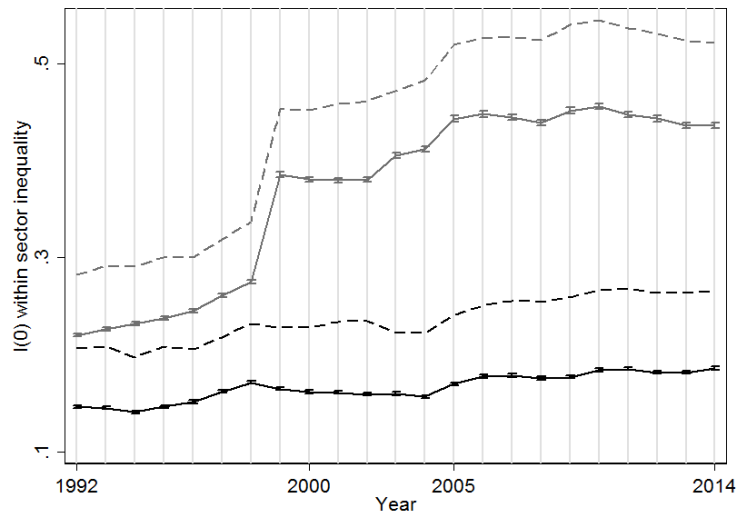


FIGURE A.10 WITHIN I(0) INEQUALITY RESULTS FOR THE WEST GERMAN MALE SAMPLE: PARETO IMPUTATION VS. NO PARETO IMPUTATION

Black lines = Employed West German Male Samples, Grey lines= Employable West German Male Samples; Solid line = No Pareto imputation, dash= Pareto imputation, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

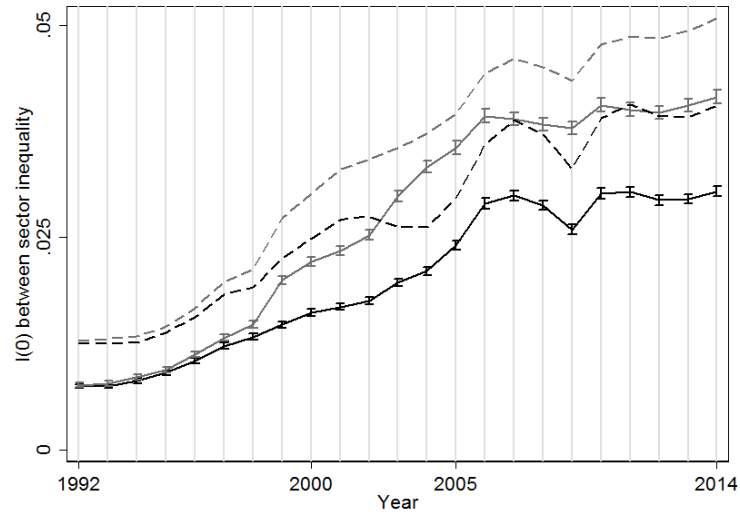
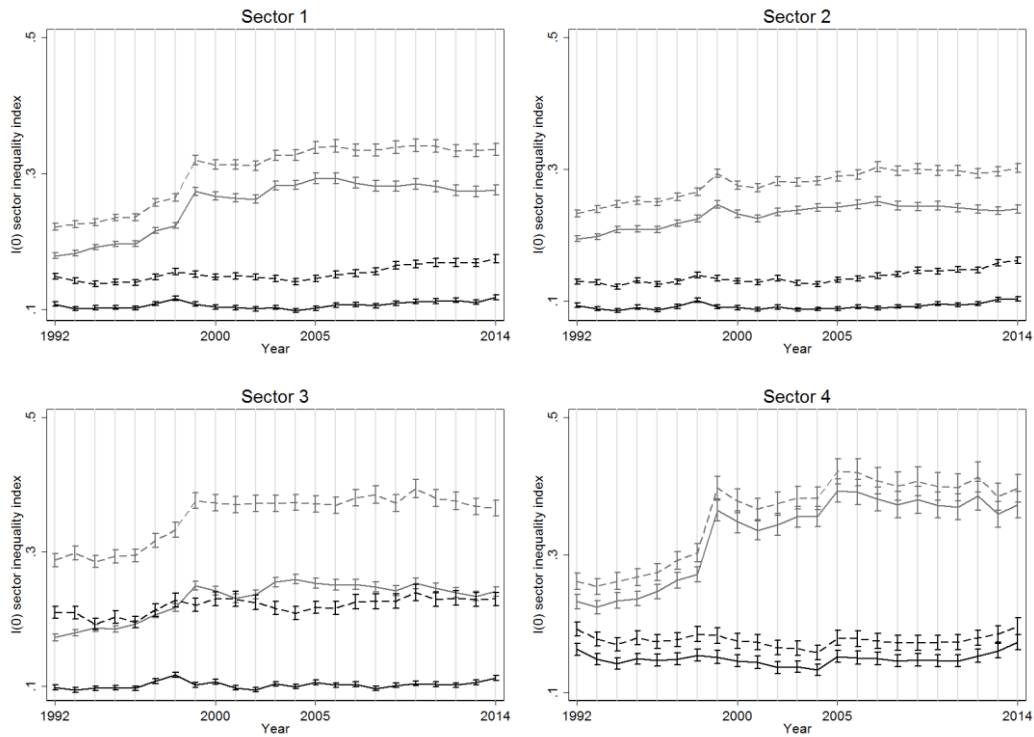


FIGURE A.11 BETWEEN $I(0)$ INEQUALITY RESULTS FOR THE WEST GERMAN MALE SAMPLE: PARETO IMPUTATION VS. NO PARETO IMPUTATION

Black lines = Employed West German Male Samples, Grey lines= Employable West German Male Samples; Solid line = No pareto imputation, dash= pareto imputation, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.



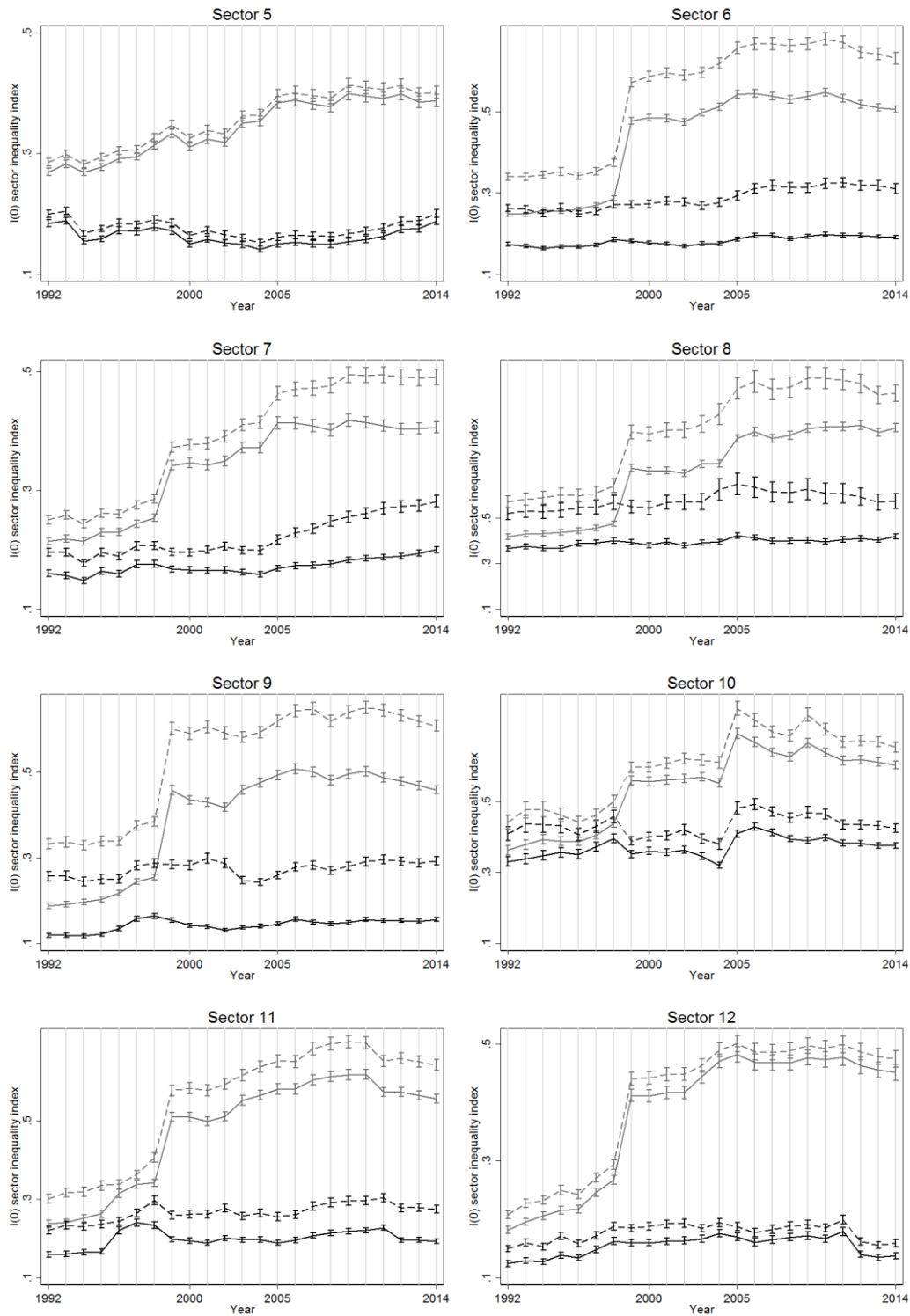


FIGURE A.12 I(0) INEQUALITY RESULTS FOR THE WEST GERMAN MALE SAMPLE: PARETO IMPUTATION VS. NO PARETO IMPUTATION

Black lines = Employed West German Male Samples, Grey lines= Employable West German Male Samples; Solid line = No Pareto Imputation, dash= Pareto Imputation, whiskers = 95% confidence intervals. Confidence intervals are small, and thus hardly visible.

B. Data Appendix

B.1. Data and data preparation

The SIAB dataset contains static variables such as sex, age education and also dynamic variables such as daily earnings, social security status, type of employment, sector classification and working region on daily basis. The employee's gross daily wage is calculated from the fixed-period wages reported by the employer and the duration of the (non-split) original notification period in calendar days (see Berge et al., 2013). As the dynamic variables are given on daily basis, it is possible to have two or more information per year per person and to get the annual information we have to transform the data set. In the following we explain our steps to get from daily wages etc. to annual wages etc..

We are concentrating in our analysis on the following variables: personal identification number (persnr), firm identification number (betnr), starting date of a working episode (begepi), end date of a working episode (endepi), sex (frau), birth year (gebjahr), nation (nationgr), daily gross wages (tentgelt), occupation (beruf), occupational status (stib), social security status (erwstat), region of residence (wobula), job location (aobula).

First we drop all individuals with no information given for daily earnings, starting/end period, social security status (tentgelt endepi begepi spell = . or if erwstat = .z; .n). In a next step, we aggregate the 28 employment status into 7 employment status given in Table B.1 and the sector classifications into 12 main sectors as given in Table B.2.

TABLE B 1 CLASSIFICATION OF EMPLOYMENT STATUS

Social security status	Social security status in SIAB	Description
1	1, 2, 5, 13, 14, 15, 31, 35, 41, 45, 51, 55	Unemployment
3	3, 10, 11, 17, 18, 32, 34, 54, 119, 120, 149	Furthest away from the labor market
101	101, 140, 143, 203, 33, 43, 53	Employment subject to social security contributions
102	141, 102, 105, 106	Apprentices, trainees
103	103, 142	Partial retirement
109	201, 209, 109	Marginal employment
118	118, 205	Non-regular employment

TABLE B 2 CLASSIFICATION OF SECTORS

Sector	Number in classification 1973	Description
1	90-209, 41-89, 220, 221, 380-530	Manufacture of basic, goods and consumer products
2	230, 231, 240, 260-300,	Manufacture of structural metal products
3	210, 211, 301-379	Custom steel forming, manufacture of crafts and hardware and engineering
4	540-581	Manufacture of food products, beverages and tobacco
5	590-616, 250	Construction
6	620-625	Wholesale and retail sector
7	630-683, 722, 842, 843, 40	Infrastructure (Communication, energy, recreation industry, transportation)
8	700, 703, 720, 730, 731, 760-771, 844, 845, 860, 900	Household related services
9	690, 691, 790, 791, 800, 810, 820	FIRE (Finance, insurance, real estate)+ professional services (accountants, lawyers, architects, management consultants)
10	721, 774, 801, 821, 822, 830, 850, 851, 861-865	Economic services
11	701, 702, 710, 711, 712, 740-758, 772, 773, 780-785, 954, 996	Educational institutions, asylums and hospitals
12	870-890, 910-950, 953	Organizations and administrative institutions

B1.1. Restructuring of the database - In the SIAB dataset the variables are given on daily basis in a spell data set, but as our analysis relies on annual information on wages, employment status, and sector affiliation, we need to restructure the data set to construct annual variables. The spell lengths in the SIAB data set can differ and spells not necessarily terminate at the end of a calendar year, but lengthen over several years, the transformation/restructuring process, therefore, consists of some steps which we explain by using an example containing three individuals which are illustrated in Table B.3, Table B.4, and Table B.5.

TABLE B.3 SNAPSHOT BEFORE RESTRUCTURING

Pers-Nr	Start	End	Daily earnings	Status	Year	Sector	Region
1	01.01.1992	22.06.1992	13	101	1992	7	5
1	23.06.1992	27.01.1995	25.7	1	1992	.	.
1	02.06.1995	31.12.1995	51.3	101	1995	3	9
1	01.01.1996	31.12.1996	25	101	1996	3	9
1	01.01.1997	31.12.1997	50.8	101	1997	3	9
2	01.01.1989	26.01.1989	24.8	101	1989	5	5
2	29.06.1989	03.05.1992	14	1	1989	.	.
2	16.05.1992	05.03.1993	28.9	1	1992	.	.
3	01.01.1994	31.12.1994	127.8	101	1994	1	5
3	01.01.1995	31.12.1995	76	101	1995	1	5
3	01.01.1996	16.01.1998	16.3	1	1996	.	.
3	14.08.1998	12.11.1998	44.1	1	1998	.	.
3	13.11.1998	26.11.1998	37.2	1	1998	.	.
3	27.11.1998	21.12.1998	28.4	1	1998	.	.

Note: Data is a fictive example of the SIAB database.

In Table B.3 the variables are given as in the SIAB database. We have the personal identification number (Pers-Nr), starting date of a working episode (Start), end date of a working episode (End), daily gross wages (Daily earnings), social security status (Status), sector classification of 1973 (Sector) and job location (Region).

As we can see in Table B.3, there are cases in which spells may lengthen over several years (grey shaded lines) or there is more than one spell given per year, for example there are four spells given for the year 1998 for individual three. Therefore, to get the annual information we first have to split spells which lengthen over several years and in a second step sum all information up to get annual information.

TABLE B.4 SNAPSHOT AFTER THE FIRST PHASE OF RESTRUCTURING

Pers. Nr	Start	End	Daily earnings	Status	Year	Sector	Region	Spell days	Earnings	Annual days	Annual earnings
1	01.01.1992	22.06.1992	12.97	101	1992	7	5	172	2231.09	365	7195.05
1	23.06.1992	31.12.1992	25.72	1	1992	7	5	193	4963.96	0	0
1	01.01.1993	31.12.1993	25.72	1	1993	7	5	365	9387.8	365	9387.8
1	01.01.1994	31.12.1994	25.72	1	1994	7	5	365	9387.8	365	9387.8
1	01.01.1995	27.01.1995	25.72	1	1995	7	5	27	694.44	318	14573.03
1	16.03.1995	01.06.1995	37.73	2	1995	7	5	77	2905.21	0	0
1	02.06.1995	31.12.1995	51.28	101	1995	3	9	214	10973.38	0	0
1	01.01.1996	31.12.1996	24.98	101	1996	3	9	365	9118.33	365	9118.33
1	01.01.1997	31.12.1997	50.83	101	1997	3	9	365	18553.91	365	18553.91
2	01.01.1989	26.01.1989	24.79	101	1989	5	5	26	644.47	212	3260.60
2	29.06.1989	31.12.1989	13.99	2	1989	5	5	187	2616.13	0	0
2	01.01.1990	31.12.1990	13.99	2	1990	5	5	365	5106.35	365	5106.35
2	01.01.1991	31.12.1991	13.99	2	1991	5	5	365	5106.35	365	5106.35
2	01.01.1992	03.05.1992	13.99	2	1992	5	5	123	1720.77	353	8365.47
2	16.05.1992	31.12.1992	28.89	1	1992	5	5	230	6644.7	0	0
2	01.01.1993	05.03.1993	28.89	1	1993	5	5	64	1848.96	64	1848.96
3	01.01.1994	31.12.1994	127.75	101	1994	1	5	365	46629.26	365	46629.26
3	01.01.1995	31.12.1995	75.99	101	1995	1	5	365	27735.69	365	27735.69
3	01.01.1996	31.12.1996	16.31	1	1996	1	5	365	5953.15	365	5953.15
3	01.01.1997	31.12.1997	16.31	1	1997	1	5	365	5953.15	365	5953.15
3	01.01.1998	16.01.1998	16.31	1	1998	1	5	16	260.96	146	5493.46
3	14.08.1998	12.11.1998	44.13	1	1998	1	5	90	3971.7	0	0
3	13.11.1998	26.11.1998	37.24	1	1998	1	5	14	521.36	0	0

Note: Data is a fictive example of the SIAB database.

In Table B.4 the database is extended by the new variables “spell days” (working days in each spell), “Earnings” (earnings in each spell = spell days * Daily earnings), “annual days” (annual working days) and “annual earnings” (annual earnings= sum over all “Earnings” in each year).

In a first step, we need to indicate cases where spells overlap (all grey shaded lines in Table B.3), so all cases where the given period is longer than a year. These cases which lengthen over several years get divided into spells of max. one year (see shaded grey lines in Table B.4). We then calculate the spell days in each spell (variable “spell days”).

To get the annual earnings we multiply each spell days by the earnings given in each spell (“Daily earnings”), so we get each spell earnings (variable “Earnings” in Table B.4). In the last step we sum the earnings up over each year and we get the annual earnings (variable “Annual earnings” in Table B.4).

To get the other annual variables, for the status, the region and the sector classification, we first assume the status “employed subject to social security” to be dominant over all other statuses in one year, e.g. individual one in the year 1992 status 101 = employed subject to social security is chosen although the status 1 has more spell days (193 > 172). All other statuses are assumed to count equal, so the status with most spell days is chosen,⁸ e.g. for individual two in the year 1992 the status 1 is chosen as the status 1 has more spell days than the status 2 (230 > 123.) The same steps take place for the region, the sector etc.. The region, sector etc. with most spell days in the year is then the annual region, sector etc..

For the variables region and sector classification, there is only information given, if the individual is employed subject to social security otherwise there is no information given. However, as we want to analyze the effects of industrial restructuring over the years, we also want to include people who got unemployed, marginally employed in each sector. Therefore we write these variables forward. So if the individual was employed in sector x for example and gets unemployed the person still gets the sector x as sector, when she starts working again she gets the new sector for example y written, e.g. for individual one in the years after 1992 we write the sector classification “Sector = 7” forward, so also in the years 1992, 1993 and 1994 the sector classification Sector is equal to seven until a new information for the sector classification occurs in 1995.

⁸ If two spells (except “employed subject to social security”) have the exact same duration, its chosen by hazard (by random number) which status and associate region etc. is chosen, therefore we add per hazard a random number to each spell days.

TABLE B. 5 SNAPSHOT AT THE END OF RESTRUCTURING

Pers.- Nr.	Year	Annual y	Annual days	Status	Sector	Region
1	1992	7195.05	365	1	7	5
1	1993	9387.8	365	1	7	5
1	1994	9387.8	365	1	7	5
1	1995	14573.03	318	101	3	9
1	1996	9118.33	365	101	3	9
1	1997	18553.91	365	101	3	9
2	1989	3260.60	212	1	5	5
2	1990	5106.35	365	1	5	5
2	1991	5106.35	365	1	5	5
2	1992	8365.47	353	1	5	5
2	1993	1848.96	64	1	5	5
3	1994	46629.26	365	101	1	5
3	1995	27735.69	365	101	1	5
3	1996	5953.15	365	1	1	5
3	1997	5953.15	365	1	1	5
3	1998	5493.46	146	1	1	5

Note: Data is a fictive example of the SIAB database.

To get the resulting database illustrates in Table B.5 which is used for our analysis, only the annual variables remain, so only the personal identification number, the year, annual earnings, annual working days, the annual status, annual sector classifications and the annual region are left.

B.1.2 Pareto Imputation -The earnings variable in the SIAB dataset right-censored, we therefore follow Bönke (2009) by using a Pareto-based approach to estimate the earnings which lay on or over the social security contribution assessment ceiling (SSCAC). Bönke (2009) follows in his paper concepts used by Piketty and Saez (2003), Kopczuk et al. (2010). The assumption behind the approach is, that earnings starting from a point under the SSCAC (y_{low}) follow a Pareto distribution and by estimating the Pareto coefficient for these earnings it is possible to estimate the earnings distribution of the earnings laying on or over the SSCAC. We assume following Bönke (2009) that the highest 15% below the SSCAC follow a Pareto distribution⁹.

⁹ We assume the SSCAC to be 98% of the original SSCAC, to include all top-coded earnings.

Assuming that individual earnings $w_i > y_{low}$ are Pareto distributed the probability to observe earnings greater or equal to $w_i > SSCAC$ is given by

$$1 - F(w_i) = \left(\frac{w_i}{y_{low}}\right)^{-\alpha} \quad (B.1)$$

with $F(w_i)$ being the cumulative density distribution. Assuming n to be the number of individuals with $w_i > y_{low}$ and $i = 1; \dots; n$. The individuals i are ranked in ascending order according to their earnings. From equation (B.1) each individual's rank r_i in the earnings distribution is determined as

$$r_i = n * F(w_i) = n * \left(1 - \left(\frac{w_i}{y_{low}}\right)^{-\alpha}\right) \quad (B.2)$$

In top-coded data, individual earnings are available up to a SSCAC ceiling. If an individual earns more, reported earnings are $w_i = SSCAC$. Assume that m out of n earners to receive earnings above the contribution ceiling $SSCAC > y_{low}$. Since for m earners neither r_i nor w_i is observable, we estimate the parameters of the Pareto-distribution by exploiting earnings data from the interval $[y_{low}, SSCAC]$. Rearranging equation (B.2) yields

$$\ln\left(1 - \frac{r_i}{n}\right) = -\alpha * \ln\left(\frac{w_i}{y_{low}}\right) \quad (B.3)$$

Estimating the following equation:

$$\ln(P) = \alpha * \ln\left(\frac{y_i}{y_{low}}\right) \quad (B.4)$$

with $P = 1 - F(y_i)$ with $F(.)$ being the cumulative density distribution, y_i the earnings. With equation (9) we can estimate the Pareto coefficient $\hat{\alpha}$ with ordinary least square estimation (OLS) without a constant for the interval $[y_{low}; SSCAC)$ for every sector in every year. With the estimated Pareto-coefficient, unobserved earnings above the contribution ceiling SSCAC can be estimated by rearranging (B.2):

$$\widehat{w}_i = y_{low} * \left(1 - \frac{\widehat{r}_i}{n}\right)^{\frac{1}{\widehat{\alpha}}} \quad (B.5)$$

where \widehat{w}_i denotes the estimated earnings and \widehat{r}_i the assumed rank.

B.2 Statistical inference- Jackknife - In the following $y = (y_1, y_2 \dots)$ is the vector of earnings for N individuals, k indexes the group membership of individual i , $W(c)$ and $B(c)$ with $c = 0, 1, 2$ are the between and within group components without leaving one out and $W(c; -i)$ and $B(c; -i)$ with $c = 0, 1, 2$ the within and between group components without individual i . \bar{y} is the mean earnings, $\overline{y_{(i)}}$ the mean earning without i , \bar{y}_k the mean earning of group k , $\overline{y_{k,(i)}}$ the mean earning of group k without i , y_i is the earning of individual i , N is the total number of individual and N_k the number of individuals in group k .

The decomposition of the $I(0)$ index into within and between inequality is given in the equations (B.6) and (B.7):

$$W(0) = \sum_{k=1}^m \left(\frac{1}{N} * \sum_{i=1}^{N_k} \left(\ln \left(\frac{y_k}{y_i} \right) \right) \right) \quad (\text{B.6})$$

$$B(0) = \sum_{k=1}^m \left(\frac{N_k}{N} * \ln \left(\frac{\bar{y}}{\bar{y}_k} \right) \right) \quad (\text{B.7})$$

and the associated jackknife components in the equations (B.8) and (B.9):

$$\begin{aligned} & W(0, -i) \\ &= \frac{N}{(N-1)} * W(0) - \frac{1}{(N-1)} \\ & * \ln(y_i) - \frac{N_k}{(N-1)} * \ln(\bar{y}_k) + \frac{(N_k-1)}{(N-1)} * \ln(\overline{y_{k,(i)}}) \end{aligned} \quad (\text{B.8})$$

$$\begin{aligned} & B(0, -i) \\ &= \frac{N}{(N-1)} * B(0) - \frac{N}{(N-1)} \\ & * \ln(\bar{y}) + \ln(\overline{y_{(i)}}) + \frac{N_k}{N-1} * \ln(\bar{y}_k) - \frac{(N_k-1)}{(N-1)} \ln(\overline{y_{k,(i)}}) \end{aligned} \quad (\text{B.9})$$

The decomposition of the I(1) index into within and between inequality is given in the equations (B.10) and (B.11):

$$W(1) = \sum_{k=1}^m \left(\frac{\bar{y}_k}{\bar{y}} * \frac{1}{N} * \sum_{i=1}^{N_k} \left(\frac{y_i}{\bar{y}_k} * \ln \left(\frac{y_i}{\bar{y}_k} \right) \right) \right) \quad (\text{B.10})$$

$$B(1) = \sum_{k=1}^m \left(\frac{\bar{y}_k}{\bar{y}} * \frac{N_k}{N} * \ln \left(\frac{\bar{y}_k}{\bar{y}} \right) \right) \quad (\text{B.11})$$

and the associated jackknife components in the equations (B.12) and (B.13):

$$\begin{aligned} & W(1, -i) \\ &= \frac{N}{(N-1)} * \frac{\bar{y}}{\bar{y}_{(i)}} * W_1 - \frac{y_i}{(N-1) * \bar{y}_{(i)}} \\ & * \ln(y_i) + \frac{N_k * \bar{y}_k}{(N-1) * \bar{y}_{(i)}} * \ln(\bar{y}_k) - \frac{(N_k-1) * \bar{y}_{k,(i)}}{(N-1) * \bar{y}_{(i)}} * \ln \bar{y}_{k,(i)} \end{aligned} \quad (\text{B.12})$$

$$\begin{aligned} & B(1, -i) \\ &= \frac{N}{(N-1)} * \frac{\bar{y}}{\bar{y}_{(i)}} * B_1 + \frac{y_i}{(N-1) * \bar{y}_{(i)}} * \ln(\bar{y}) \\ & - \ln \left(\frac{\bar{y}_{(i)}}{\bar{y}} \right) - \frac{N_k * \bar{y}_k}{(N-1) * \bar{y}_{(i)}} * \ln(\bar{y}_k) + \frac{(N_k-1) * \bar{y}_{k,(i)}}{(N-1) * \bar{y}_{(i)}} * \ln(\bar{y}_{k,(i)}) \end{aligned} \quad (\text{B.13})$$

The decomposition of the I(2) index into within and between inequality is given in the equations (B.14) and (B.15):

$$W(2) = \sum_{k=1}^m \left(\frac{\bar{y}_k^2}{\bar{y}} * \frac{1}{2N} * \sum_{i=1}^{N_k} \left(\left(\frac{y_i}{\bar{y}_k} \right)^2 - 1 \right) \right) \quad (\text{B.14})$$

$$B(2) = \sum_{k=1}^m \frac{1}{2} * \frac{N_k}{N} * \left(\left(\frac{\bar{y}_k}{\bar{y}} \right)^2 - 1 \right) \quad (\text{B.15})$$

and the associated jackknife components in the equations (B.16) and (B.17):

$$\begin{aligned}
 & W(2, -i) \\
 = & \frac{N}{(N-1)} * \frac{\bar{y}}{\bar{y}_{(i)}} * W(2) - \frac{1}{2 * (N-1)} * \frac{y_i^2}{\bar{y}_{(i)}} + \frac{N_k}{2 * (N-1)} * \frac{\bar{y}_k}{\bar{y}_{(i)}} \\
 & - \frac{(N_k - 1)}{2 * (N-1)} * \frac{\bar{y}_{k,(i)}}{\bar{y}_{(i)}}
 \end{aligned} \tag{B.16}$$

$$\begin{aligned}
 & B(2, -i) \\
 = & \frac{N}{(N-1)} * \frac{(\bar{y})^2}{(\bar{y}_{(i)})^2} * B(2) - \frac{N_k}{2 * (N-1)} * \frac{(\bar{y}_k)^2}{(\bar{y}_{(i)})^2} + \frac{(N_k - 1)}{2 * (N-1)} \\
 & * \frac{(\bar{y}_{k,(i)})^2}{(\bar{y}_{(i)})^2}
 \end{aligned} \tag{B.17}$$

Part II

Paper 3: Can Gender Quotas Prevent Excessive Risk Taking? The Effect of Gender Composition on Group Decisions under Risk

KATHARINA LIMA DE MIRANDA, LENA DETLEFSEN, AND ULRICH SCHMIDT*

This study contributes to the public debate on gender quotas and the literature on gender and risk taking by analyzing how the level of risk taking within a group is influenced by its gender composition. In particular we look at the shift of risk taking between group and individual decisions and analyze to which extent this shift depends on the gender composition. We derive a gender-specific polarization hypothesis which states that, compared to individual preferences, male dominated groups will shift towards higher risk taking than female dominated ones. Our experimental tests reveal a systematic impact of gender composition on group shifts which supports our hypothesis and points into the direction that a higher share of females may prevent excessive risk taking.

JEL classifications: C91, D81, J16

Key words: risky shift, group decisions, gender, monetary incentives

* Lima de Miranda: Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Katharina.Miranda@ifw-kiel.de). Detlefsen: Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Lena.Detlefsen@ifw-kiel.de). Schmidt: University of Kiel, University of Johannesburg and Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Ulrich.Schmidt@ifw-kiel.de)

I. Introduction

Many important economic and politically relevant decisions are made by groups, for example in boards of directors or supervisory boards, but also in parliaments or other political bodies. The overwhelming majority of these decision-making bodies are dominated by men, a fact that has been critically debated in public for years. In order to strengthen the equal participation of women and men in leadership positions, gender quotas have been introduced in many European countries. While gender quotas are justified by promoting gender equality, in particular promote women's representation in decision making bodies, it remains an open question how a rising share of women in these positions will impact decision making. The present paper will focus on risky decision making and in particular on excessive risk taking, as evidenced by the 2008 financial crisis. A relation between gender and excessive risk taking has been suggested also by Christine Lagarde, head of the IMF, in May 2010: "*if Lehman Brothers had been "Lehman Sisters," today's economic crisis clearly would look quite different*"¹⁰. This study contributes to the public debate on gender quotas and the literature on gender and risk taking by analyzing how the level of risk taking within a group is influenced by its gender composition

The difference between individual and group decisions has been an intensively debated issue in social psychology since the seminal work of Stoner (1961). A stylized fact is the "risky shift" which means that groups in most cases take higher risks than individuals (Kogan and Wallach, 1967). Such a risky shift can well be regarded as excessive risk taking. The evidence on risky shifts is originally based on studies employing choice dilemma questionnaires. In recent years, several studies analyzed group decisions under risk with monetary incentivized experiments. Here the evidence is rather mixed. While some studies replicate a risky shift (Sutter, 2009; Nieboer, 2015), others find that groups predominantly take less risk than individuals (Masclot et al., 2009; Baker et al. 2008; Shupp and Williams, 2008; Pahlke et al., 2012) or observe no systematic differences at all (Harrison et al., 2013).

It is an open question whether the mixed results could result from differences in the gender composition of groups. Evidence documents that women are consistently more risk averse than men in financial risk taking and many other domains (Byrnes et al., 1999; Croson and Gneezy, 2009). Hence there are good reasons to expect that gender composition has a strong impact on risky group decisions (Hannagan and Larimer, 2010). Surprisingly, to the best of our knowledge no previous

¹⁰ May 11, 2010, in The International Herald Tribune - The Opinion Pages: "Women, Power and the Challenge of the Financial Crisis" by Christine Lagarde at that time France's minister for the economy, industry and employment.

study systematically analyzed whether the incidence of risky and cautious shifts is affected by the gender composition of groups. In order to analyze this relationship, we utilize the “risk as value” hypothesis of Brown (1965) to construct a gender-specific polarization hypothesis which states that, relative to individual preferences, male dominated groups shift towards higher risk taking than female dominated ones. We test this proposition with a simple lottery choice experiment under monetary incentives. Our results show a clear and significant pattern which supports this hypothesis. While we observe risky shifts for male dominated groups, female dominated groups take less risk than individual group members.

Among alternative hypotheses to explain the risky shift phenomenon, the risk as value hypothesis has received most support (Vidmar, 1970; Bauer and Turner, 1974). It proposes that (moderate) risk taking is a socially approved trait. When some subjects learn during the group decision process that they are more risk averse than others they question whether their intended choices are in line with the cultural norm. Therefore, the risky shift is caused by the more risk averse subjects revising their proposed choices to higher riskiness. In our view, risk tolerance is a cultural norm particularly for men and to a much lower degree for women (Trimpop, 1994). Therefore, we hypothesize that mainly men increase their risk tolerance if they have to reveal their preferences in a group context. Strong support for our view is provided by the experiment of Daly and Wilson (2001). They compare risky decisions made in private with those made in public where subjects have to announce their individual choice in front of a group of peers. It turned out that men took significantly more risk in the public than in the private condition whereas there was no effect for women. The experiment of Daly and Wilson was on individual risk taking. Transferring this result to group decisions suggests that a risky shift is due to male members who want to appear more risk tolerant in the group context compared to their individual decision. Therefore, the risky shift should be enhanced by the share of males in the group.

We formalize our gender-specific polarization hypothesis more precisely in Section III. Before, we will describe our experimental design in Section II. Presentation of results in Section IV is followed by a discussion in Section V.

II. Experimental Design

A. Participants and Procedure

The experiment was carried out in July 2015 at the student canteen of the University of Kiel, Germany. During three days 255 people participated in our study. The gender ratio was balanced (50.6% females) and average age was 23.95 (SD 4.61). Recruiters invited customers of the canteen to take part in an economic experiment. Potential participants were told that they will receive a €2 participation fee and could gain additional money by playing a lottery. Groups of three people were formed, discreetly varying the group's gender composition and requiring that group members were not familiar to each other. All other group characteristics were randomly allocated¹¹. Overall, there were 22 purely female groups (further mentioned as FFF), 21 groups with two women and one man (FFM), 21 groups with one woman and two men (FMM) and 21 purely male groups (MMM), an overview is given in Table 1.

TABLE 1 GENDER COMPOSITION OF GROUPS

Gender composition	Nb of groups	Nb of participants
FFF	22	66 women
FFM	21	42 women; 21 men
FMM	21	21 women; 42 men
MMM	21	63 men ¹²
Overall	85	255

As the groups were formed, it was explained to the participants that they had to take a risky decision as a group first, then had to fill out a questionnaire on their own and in the end had to reunite in their initial group to receive their payment. After the groups were formed a card showing six alternative lotteries was handed to them (see Figure 1). Participants were told that the group had to choose exactly one of these lotteries by consensus. There were no time constraints for discussion and reaching consensus (no group took longer than 5 minutes to reach a consensus). When participants within a group agreed on a lottery, they stated their choice to the experimenter and were handed the questionnaires, which had to be filled out in private. The questionnaire included an individual risk preference task (which equaled the group task with all amounts divided by three), basic demographic questions (gender, age, highest educational degree, amount of siblings),

¹¹ Randomization was successful and only small significant differences between groups were found, see Table A 1 and Table A 2 in the Appendix.

¹² One group member did not submit the individual decision and questionnaire.

happiness (self-reported happiness on a five point Lickert scale), and questions on the Big Five personality traits. After filling out the questionnaires participants reunited in their groups. To determine the payoff a coin was flipped twice. The first coin flip indicated whether the group or the individual lottery choice would be relevant for payment. The second coin flip determined the outcome – high or low payoff - according to either the group or individual choice.

B. Methods

Risk preferences. - To elicit risk preferences, a well-established task developed by Eckel and Grossman (2002) was used. The groups had to choose by consensus exactly one out of six lotteries depicted in Figure 1. The lotteries were represented with coins that had two colored sides indicating the size of a gain (in Euro) – orange (high gain) and pink (low gain). For all six lotteries, chances to win the high or low gain were equal (50% probability). The lotteries increased in risk and expected value starting from lottery 1 with a sure gain of €12 (or €4 for each group member) to lottery 5 with an expected value of €15 (€8 or €2 for each group member). Lottery 6 had the same expected value as lottery 5 but higher risk (€9 or €1 for each group member) and allows detecting risk loving attitudes. The number of the chosen lottery by the group will be referred to as group choice (GC) in the sequel. In general, the higher GC the lower is the degree of risk aversion of the given group. To control for individual risk preferences the questionnaire included the same lottery task, but with individual gains (i.e. group amount divided by 3). Responses to this task will be termed individual choice (IC). Again, a higher number of IC indicates a lower degree of risk aversion. The group shift is given by $GC - IC$ where $GC - IC > (< 0)$ indicates a risky (cautious) shift.

A critical feature of experimental designs to analyze group polarization is the order of elicitation of individual and group choices. Most of the previous studies elicited individual preferences first. We deliberately reversed this order but are aware that both procedures have their pros and cons. In general, if a subject has to make more than one evaluation, the former evaluations will serve as anchor which can bias the later ones (Ariely et al., 2003). This seems to favor the procedure of eliciting individual preferences first. Recent evidence shows, however, that also individual decisions are heavily influenced by the social context, in particular by the gender composition. Castillo et al. (2015) for instance let subjects make individual risk taking decisions while sitting in a room with other people. Although the decisions are fully private and not revealed to other subjects, the gender composition in the room has a systematic impact on individual preferences. Consequently, also in the case of group decisions the gender composition of the group will influence individual risk preferences. This effect is, however, at least reduced if subjects anchor on

their individual decision they made before in private, i.e. without any influence of the social context. In our view, the social context is an important determinant of group decisions which motivated us to have the group decision first. We test whether the group composition has a systematic impact on the individual preferences elicited in the second step and found no significant effects (see Section 4). Also Harrison et al. (2013) show that the order between group and individual decisions has no influence on individual risk preferences.

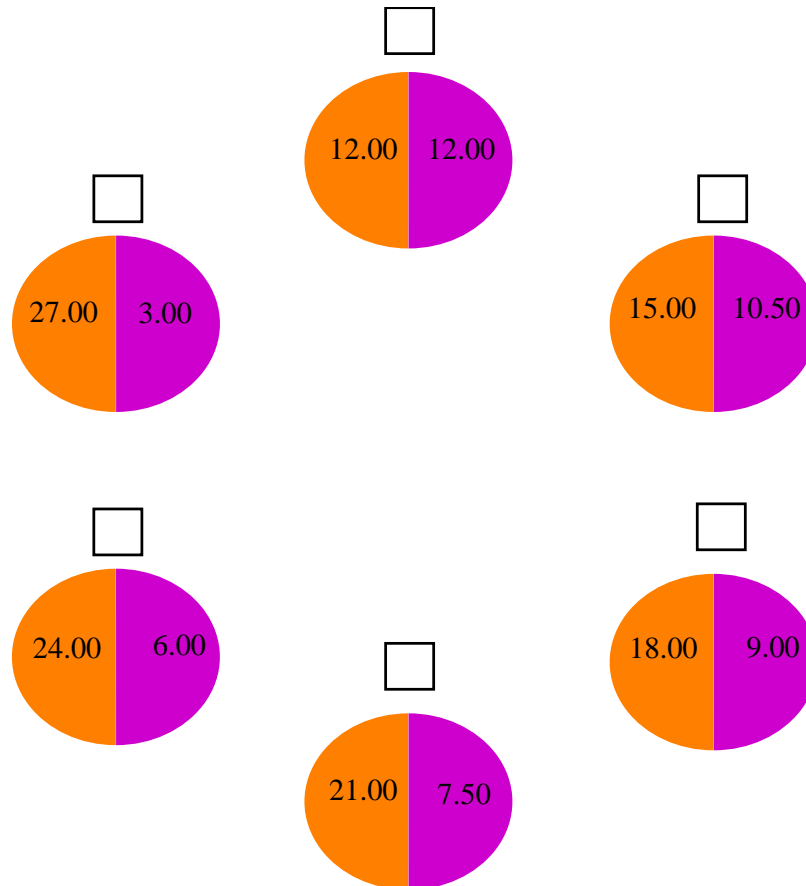


FIGURE 1: LOTTERIES FOR GROUP DECISION-MAKING

Personality traits. - To control for specific characteristics of participants, which might influence the consensus building process for the group decision, we included questions on the Big Five personality traits. These are aimed to reveal five dimensions of personality: extraversion, agreeableness, conscientiousness, neuroticism and openness to experience. They were measured by self-reports of the NEO Five-Factor Inventory using 60 items, i.e. 12 items per domain (Costa and McCrae, 2004 translated in German by von Borckenau and Ostendorf, 2008). These factors may appear influential while making a risky decision within the group or individually. For instance, it may happen that more extravert people tend to be very convincing during the group discussion (Zhang and Casari, 2012), whereas people who are very agreeable tend to let other people decide and easily agree with others' choices independently of their own preferences (Barry and Friedman, 1998; Müller and Schwieren, 2012). We could also expect that more conscious people will reveal

more risk-aversion compared to those who have a lower level of conscientiousness (Zhang and Casari, 2012; Mayfield, Perdue, Wooten, 2008). Therefore, we found it useful to include the personality test to our questionnaire in order to control for each of those five characteristics in the empirical analysis.

III. Hypotheses

There exists abundant evidence that women are more risk averse than men in financial risk taking (Croson and Gneezy, 2009, Charness and Gneezy, 2012) although the effects are sometimes small and task-specific (Filippin and Crosetto, 2016). For the task employed in the present paper gender differences were consistently observed such that we expect to see them also in our data.

Hypothesis 1: IC is higher for men than for women

One can expect that women's higher degree of risk aversion will also be reflected in the group choice, i.e. risk taking of groups is increasing with the number of male members. Some initial, though partly conflicting, evidence in the context of investment games has been reported by Nieboer (2015) and Bogan et al. (2013). Although we did not give any instructions to subjects how they should come to the group decision a reasonable benchmark in the decision process is given by the outcome under majority voting. From the political economy literature it is well-known that the median voter determines the outcome of majority voting (Black, 1948). Assuming that women are more risk averse than men, the median voter is more likely to be female in female dominated groups (FFF & FFM) and male in male dominated groups (FMM & MMM). From Hypothesis 1, we, therefore, get the next hypothesis.

Hypothesis 2: GC is higher in male than in female dominated groups.

The main focus of the present paper is to compare individual and group choices. The risk as value hypothesis would predict a general risky shift which has not been observed in studies based on similar designs as ours. We assume in line with the experimental results of Daly and Wilson (2001) that particularly men change their individual preferences towards higher risk taking in group contexts. This is consistent with the risk as value hypothesis where risk taking is a cultural value mainly for men. It implies that the tendency to risky shifts increases when the median voter is a man. This gender-specific polarization hypothesis is formalized as follows.

Hypothesis 3: GC – IC is higher in male than in female dominated groups.

IV. Results

A. *Individual Choice*

The average individual choice was 3.56 (SD=1.74) and in line with Hypothesis 1 we find that men take more risk (Mean 4.06, SD=1.66) than women (mean=3.07, SD 1.68). In Table 2 the results of ordered Probit regressions with individual choice as dependent variable are depicted. The gender difference is highly statistically significant (at the 1% level). Risk taking also seems to increase with age in our sample. Personality characteristics play a role in the sense that more conscious participants take less risk on average. In order to see whether the group composition had an influence on the individual choice we added a dummy variable for single-sex groups, turning one when the group is composed of only men or only women (Models 2-4) and the group composition, namely the number of male participants (Model 5). Both coefficients (single-sex and number of males) are insignificant and we therefore conclude that there is no group composition effect on the individual choice. This is consistent with the results of Harrison et al. (2013) and allows us to compare group and individual choices in the next subsection.

TABLE 2 ORDERED PROBIT REGRESSIONS WITH INDIVIDUAL CHOICE AS DEPENDENT VARIABLE

	Model 1	Model 2	Model 3 Women only	Model 4 Men only	Model 5 Group types
Female	-0.611*** (0.15)	-0.604*** (0.15)			-0.523*** (0.20)
Age (in years)	0.068** (0.03)	0.064** (0.03)	0.075* (0.04)	0.042 (0.04)	0.063** (0.03)
Singlesex		-0.227 (0.17)	-0.331 (0.23)	-0.142 (0.23)	
Male=0 (FFF)					Reference group
Male=1 (FFM)					0.290 (0.24)
Male=2 (FMM)					0.308 (0.29)
Male=3 (MMM)					0.151 (0.31)
Neuroticism	-0.003 (0.01)	-0.004 (0.01)	-0.013 (0.01)	0.002 (0.01)	-0.004 (0.01)
Extraversion	0.015 (0.01)	0.015 (0.01)	0.013 (0.01)	0.016 (0.01)	0.015 (0.01)
Openness	-0.002 (0.01)	-0.002 (0.01)	0.000 (0.01)	-0.002 (0.01)	-0.002 (0.01)
Agreeableness	-0.001 (0.01)	-0.002 (0.01)	-0.012 (0.01)	0.006 (0.01)	-0.002 (0.01)
Consciousness	-0.021*** (0.01)	-0.022*** (0.01)	-0.026** (0.01)	-0.020* (0.01)	-0.022*** (0.01)
Constant	1.628 (1.10)	1.261 (1.18)	0.884 (1.61)	1.677 (1.65)	1.540 (1.11)
No. of Obs.	240	240	127	113	240
Pseudo R2	0.045	0.048	0.042	0.018	0.049
Prob > chi2/F	0.000	0.000	0.015	0.422	0.000

Notes: Standard errors are clustered at the group level and are given in parenthesis,

Significance level: * p<0.10, ** p<0.05, *** p<0.010.

B. Group Choice

In a first step we simply compare the means of the group decisions between group types. Figure 2 shows that risk-taking of groups increases with the number of male group members¹³. A pairwise comparison of the means with a two-sample Wilcoxon rank-sum test shows that there is a significant difference between purely male (MMM) and purely female groups (FFF) and also between male dominated (FMM) and female dominated (FFM) groups. The differences between purely female (male) and female (male) dominated groups is however not statistically significant. This pattern is fully in line with Hypothesis 2: If men are consistently more risk tolerant than women, the median voter theorem implies a strong difference between FFM and FMM but no differences between FFF and FFM or FMM and MMM.

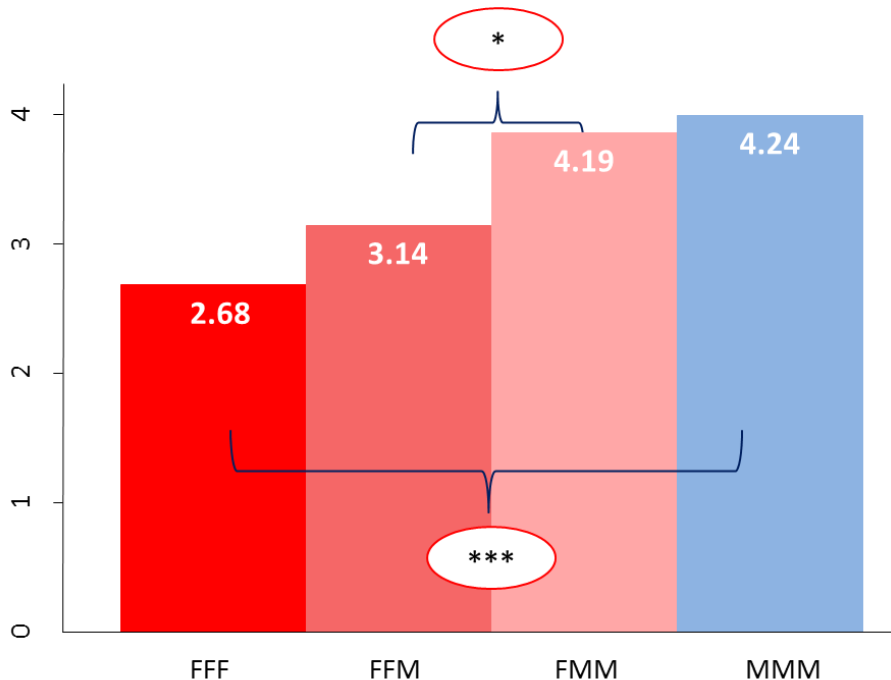


FIGURE 2 AVERAGE GROUP CHOICE BY GROUP TYPES

Notes: Pair-wise comparison of the group means with a two-sample Wilcoxon rank-sum test, Significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

We therefore continue with our analysis by looking at female dominated (FFF and FFM) and male dominated groups (FMM and MMM). Figure 3 depicts the average group choice by female and male dominated groups and shows that male dominated groups take significantly more risk. The average difference between the groups is more than one step in our lottery choice task (male dominated 4.21 (SD=1.68) and female dominated 2.91 (SD=1.64)).

¹³ A regression analysis with the group choice as dependent variable and number of male group members as independent variable (see Appendix, Table A 3) we find that the coefficient is highly significant which confirms that risk taking of the group increases with the number of men in the group. This finding supports previous results by Bogan et al. (2013) and particularly by Nieboer (2015).

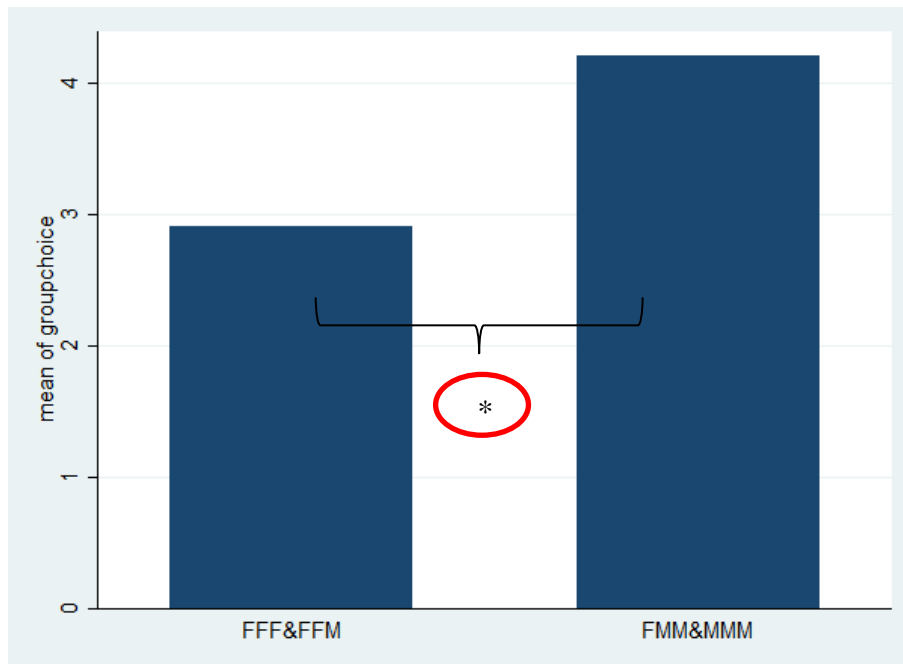


FIGURE 3 AVERAGE GROUP CHOICE BY FEMALE/MALE DOMINATED GROUPS

Notes: Two-sample Wilcoxon rank-sum test ($z = -3.494$, $\text{Prob}>|z| = 0.0005$)

To provide further insight into the group choice we conducted ordered probit regressions with the group choice as dependent variable and male dominated as independent variable (Table 3, Model 1). The coefficient is highly significant and confirms that risk taking of the group is higher in male dominated groups. This effect remains significant when controlling for the average of the group member's individual choices (Model 2). The positive coefficient for the average individual choice shows, as expected, that the groups' risk taking increases with the individual choices of the group members. The fact that the adjusted R2 increases substantially from Model 1 to Model 2 further shows that the average individual choice explains a rather large proportion of variation in the group choice. All other control variables added (group averages of highest degree, age, happiness, number of siblings – Model 3) do not alter the results and turn out to be statistically insignificant.

TABLE 3 ORDERED PROBIT REGRESSIONS WITH GROUP CHOICE AS DEPENDENT VARIABLE AND MALE DOMINATED AS INDEPENDENT VARIABLE PLUS CONTROLS.

	Model 1	Model 2	Model 3
Male dominated groups (FMM & MMM)	0.852*** (0.24)	0.588** (0.25)	0.537** (0.25)
IC (group mean)		0.560*** (0.11)	0.616*** (0.12)
Age (group mean)			-0.071 (0.05)
Degree (group mean)			-0.087 (0.27)
Happiness (group mean)			-0.199 (0.18)
Siblings (group mean)			-0.139 (0.19)
Constant	1.246*** (0.21)	3.283*** (0.47)	0.697 (1.30)
No. of Obs.	85	85	85
Psd. R2	0.045	0.133	0.150
Prob > chi2/F	0.000	0.000	0.000

Notes: Regressions at the group level, Standard errors in parenthesis, Significance level: * p<0.10, ** p<0.05, *** p<0.010

C. Risky Shift and Polarization

The fact that there is an additional effect of male dominated groups while controlling for the group mean of IC (see Table 3)¹⁴ points into the direction that there is gender specific polarization in our data. It shows that male dominated groups shift their preferences towards higher risk taking in the group context beyond the effect that male dominated groups have higher group choices due to their on average higher individual preferences. We will, therefore, proceed by analyzing the difference between group and individual choice in more detail. Table 4 depicts group and individual choice for all group compositions. The first row of the table shows that GC and IC are identical over all groups. This means that there is no general risky or cautious shift in our data. Rows 2 and 3 show that, in line with Hypothesis 3, the difference between group and individual choice (GC – IC) is substantially higher in male than in female dominated groups. A Wilcoxon test confirms that this pattern is significant at the 5%-level ($z = -2.05$). It is important to note that while the difference (GC-IC) is negative in female dominated groups, implying that the group choice is on average even more risk averse than the individual choice, it is positive for male dominated groups, implying that

¹⁴ Adding the median of the group member's individual choices as a control instead of the group mean leads to similar results, see Appendix Table A 4.

group members in male dominated groups are willing to take even more risk in the group than they would be willing individually. Rows 4 to 7 show that this pattern is consistent over all group compositions separately, i.e. negative difference for FFF and FFM and positive difference for FMM and MMM.

In Table 2 it was shown that IC is not significantly influenced by the gender composition of the group a subject was assigned to. In order to reconfirm that the pattern we observe is not caused by biased measurement of IC we report in the fourth column of Table 4 hypothetical values of IC. These were constructed as follows: We took average values of IC for men and women over all groups. These averages obviously cannot be biased by group membership. Hypothetical IC for each group can now be calculated by taking the weighted sum of the average of females (3.07) and males (4.06) according to the respective group composition. It turns out that the pattern we observed with IC is rather similar to those which would be obtained by Hypothetical IC. In all cases there is a cautious shift for female dominated groups and a risky shift for male dominated ones.

The regression analysis in Table 5 supports the descriptive findings from Table 4. In Model 1 we analyze the shift from individual to the group decision at the group level and take the difference between GC and mean IC as the dependent variable. The results show that switching from female to male dominated groups significantly increases the difference between group choice and individual choice, thereby confirming Hypothesis 3. Consequently, a risky shift is more likely in male dominated groups.

TABLE 4 COMPARING GROUP AND INDIVIDUAL CHOICE

	Group type	GC	IC	GC – IC	Hypothetical IC	GC – Hypo. IC	N
1	All	3.55 (1.78)	3.56 (1.74)	0	3.55	0	254
2	Female dom. (FFF & FFM)	2.91 (1.64)	3.18 (1.65)	- 0.27	3.23	-0.32	129
3	Male dom. (FMM & MMM)	4.21 (1.68)	3.95 (1.76)	0.26	3.89	0.32	125
4	FFF	2.68 (1.52)	2.82 (1.58)	- 0.14	3.07	-0.39	66
5	FFM	3.14 (1.77)	3.56 (1.64)	- 0.42	3.40	-0.26	63
6	FMM	4.19 (1.91)	4.02 (1.85)	0.17	3.73	0.46	63
7	MMM	4.24 (1.45)	3.89 (1.67)	0.35	4.06	0.18	62

Notes: Standard deviations in parenthesis.

Model 1 further analyzes whether the group shift is influenced by the mean individual choice of the group. In case of general polarization one would expect a cautious shift for groups with a low mean IC and a risky shift for groups with a high mean IC. Consequently, the coefficient for mean IC should be significantly positive. Since this is not the case we can conclude that there is no general pattern of polarization in our data.

TABLE 5 OLS REGRESSIONS WITH GROUP SHIFT AS DEPENDENT VARIABLE

	Model 1 GC – mean(IC)	Model 2 GC – IC
Male dominated groups (FMM & MMM)	0.740** (0.32)	1.314*** (0.41)
IC (Group mean)	-0.255* (0.13)	-0.254 (0.16)
Female		0.738** (0.30)
Age		-0.068 (0.06)
Degree		-0.044 (0.16)
Siblings		-0.119 (0.08)
Happiness		-0.166 (0.13)
Consciousness		0.020* (0.01)
Constant	0.540 (0.47)	1.468 (1.35)
No. of Obs.	85	240
Adj. R2	0.056	0.089
Prob > chi2/F	0.035	0.005

Notes: Model 1 - Regression at the group level, Model 2 – Regression at the individual level and clustered at the group level, Standard errors are given in parenthesis, Significance level: * p<0.10, ** p<0.05, *** p<0.010

We further investigate the determinants of the observed difference between group and individual decision at the individual level (Model 2). Here we take the difference between the group and the individual choice as the dependent variable. Also this regression confirms a significant increase in GC-IC when switching from female to male dominated groups, indicating a gender-specific polarization. We further find that two other variables influence the difference between group and individual choice significantly, female and consciousness. From Table 2 we know that females and more conscious subjects have lower values of IC which obviously leads to higher values of GC-IC and explains the sign of the coefficient.

To gain further insight, Figure 4 shows the average distance between the lowest (highest) individual choice in the group and the group choice. One can see that for female dominated groups the distance from the highest IC to GC is larger than from the lowest IC, implying that in female dominated groups individuals tend to correct their individual preferences towards less risk taking in the group. This shows that in female dominated groups the lowest IC dominates the group decision. In contrast, the opposite is true for male dominated groups, here the distance between the lowest IC and GC is larger than the distance between the highest IC and GC. This is in line with the risk as value hypothesis which states that the risky shift is caused by the more risk averse subjects revising their proposed choices to higher riskiness. Our claim that this is particularly pronounced for men is supported by the fact that GC-lowest IC is significantly higher in male dominated groups than in female dominated groups.

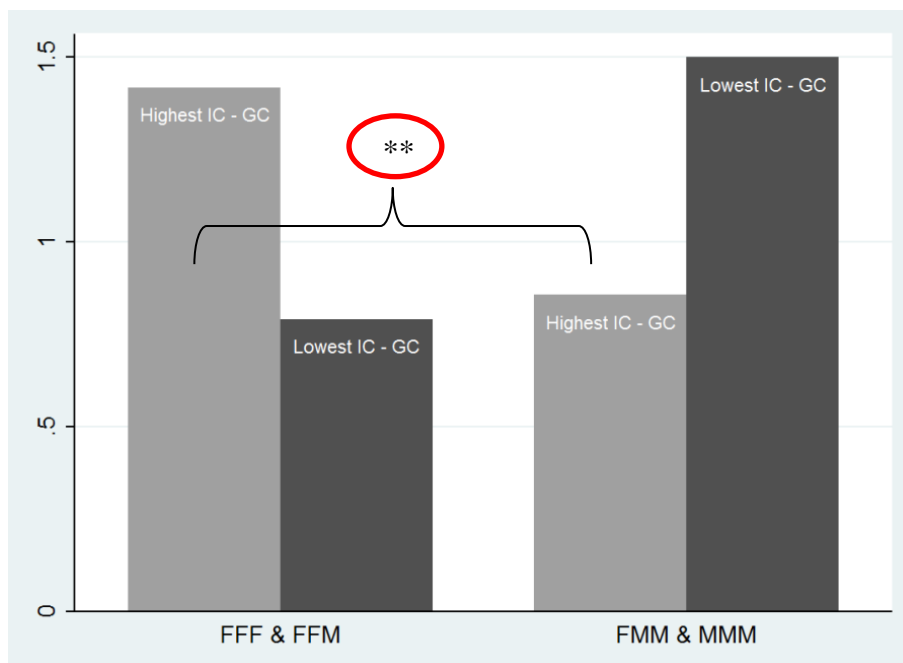


FIGURE 4 AVERAGE DISTANCE BETWEEN HIGHEST (LOWEST) IC IN THE GROUP AND GC

Notes: Two-sample Wilcoxon rank-sum test ($z = -2.010$, $\text{Prob}>|z| = 0.044$).

V. Discussion

Our study has shown that the gender composition of groups has a systematic impact on their choice behavior between risky options and the pattern of group polarization. The fact that women are more risk averse than men for our elicitation method is reflected also in group choices as a lower fraction of female group members leads to increased risk taking. Overall, we do not observe any pattern of group polarization as individuals and groups make on average equally risky choices. However, when we take account of the group composition a clear pattern emerges: while male dominated groups shift to higher riskiness the opposite is true for female dominated ones. This

pattern supports our gender-specific polarization hypothesis. As risk taking is a cultural norm particularly for men, we were expecting the group shift to be more risky for male dominated groups. This systematic impact of gender composition on group shifts points into the direction that gender quotas can well be expected to prevent excessive risk taking. In our simple design with groups of three subjects a majority of females were necessary to prevent risky shifts but in larger groups a lower share may be sufficient. An open question is also the behavior of gender-balanced groups which were not taken into account by our study.

While our evidence is rather clear-cut it may, nevertheless, be sensitive with respect to the elicitation method. Filippin and Crosetto (2016) showed that gender differences in risk taking are particularly pronounced for elicitation methods which involve, as ours, a safe option. In the absence of such an option gender differences are minor which should also reduce the effects of group composition. Also the direction of group shifts seems to depend on the elicitation method. While we do not observe a general shift in our data other studies which also employ monetary incentives did. Pairwise choice, elicitation of willingness-to-pay, and the Holt-Laury method generated a cautious shift in previous studies (Masclot et al., 2009; Baker et al. 2008; Shupp and Williams, 2008; Pahlke et al., 2012). In contrast, for the investment game of Gneezy and Potters (1997) risky shifts were observed (Sutter, 2009; Nieboer, 2015). It is an open question for future research which impact gender composition will have under these alternative elicitation methods.

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Appendix

TABLE A 1: RANDOMIZATION FEMALES

Variable	Group type			T-Test (two-sided)		
	FFF	FFM	FMM	FFF vs. FFM	FFF vs. FMM	FMM vs. FFM
Individual choice	2.82 (SD 1.58)	3.36 (SD 1.67)	3.29 (SD 1.98)	0.09*	0.27	0.88
Age	23.36 (SD 3.2)	25.6 (SD 8.36)	24.57 (SD 2.64)	0.05*	0.12	0.59
Degree	1.44 (SD .98)	1.6 (SD 1.11)	1.91 (SD 1.09)	0.45	0.07*	0.3
Happiness	3.96 (SD 1.04)	3.48 (SD 1.25)	3.71 (SD 1.35)	0.03**	0.4	0.49
Happiness today	3.61 (SD 1.14)	3.38 (SD 1.32)	3.62 (SD 1.36)	0.35	0.97	0.51
No. Siblings	1.46 (SD 1.23)	1.74 (SD 1.53)	1.52 (SD 1.12)	0.29	0.82	0.57
Neuroticism (NStd)	48.26 (SD 9.12)	48.8 (SD 9.57)	50.29 (SD 8.71)	0.77	0.37	0.56
Extraversion (Estd)	49.02 (SD 9.26)	50.7 (SD 10.26)	49.95 (SD 7.02)	0.39	0.67	0.77
Openness (Ostd)	46.02 (SD 11.86)	48.45 (SD 11.31)	46.67 (SD 7.95)	0.3	0.82	0.52
Agreeableness (VStd)	52.36 (SD 9.71)	55.18 (SD 11.27)	54.67 (SD 8.21)	0.18	0.33	0.86
Consciousness (GStd)	51.5 (SD 8.72)	52.18 (SD 11.69)	55.67 (SD 9.13)	0.74	0.06*	0.24

Notes: Significance level: * p<0.10, ** p<0.05, *** p<0.010.

TABLE A 2: RANDOMIZATION MALES

Variable	Group type			T-Test(two-sided)		
	MMM	FMM	FFM	MMM vs. FMM	MMM vs. FFM	FMM vs. FFM
Individual choice	3.89 (SD 1.67)	4.38 (SD 1.7)	3.95 (SD 1.57)	0.15	0.88	0.34
Age	23.19 (SD 3.58)	24.07 (SD 3.6)	23.91 (SD 3.38)	0.22	0.43	0.86
Degree	1.37 (SD 0.95)	1.45 (SD 0.97)	1.1 (SD 0.63)	0.67	0.22	0.13
Happiness	3.84 (SD 1.04)	3.83 (SD 1.17)	3.95 (SD 1.20)	0.98	0.68	0.71
Happiness today	3.69 (SD 0.99)	3.64 (SD 1.21)	3.62 (SD 0.97)	0.82	0.77	0.94
No. Siblings	1.42 (SD 1.18)	1.31 (SD 1.05)	1.43 (SD 1.29)	0.63	0.98	0.7
Neuroticism (NStd)	48.26 (SD 9.38)	47.33 (SD 10.89)	48.05 (SD 7.09)	0.65	0.93	0.79
Extraversion (Estd)	51.84 (SD 8.28)	51.83 (SD 9.75)	50.48 (SD 10.92)	0.998	0.55	0.62
Openness (Ostd)	48.87 (SD 8.35)	48.52 (SD 10.50)	48.67 (SD 11.35)	0.85	0.93	0.96
Agreeableness (VStd)	50.23 (SD 10.40)	51.36 (SD 10.34)	52.57 (SD 11.04)	0.59	0.38	0.67
Consciousness (GStd)	51.35 (SD 9.75)	52.16 (SD 10.99)	48.28 (SD 9.99)	0.71	0.25	0.21

Notes: Significance level: * p<0.10, ** p<0.05, *** p<0.010.

TABLE A 3: ORDERED PROBIT REGRESSIONS WITH GROUP CHOICE AS DEPENDENT VARIABLE AND NUMBER OF MALE GROUP MEMBERS AS INDEPENDENT VARIABLE PLUS CONTROLS

	Model 1	Model 2	Model 3
Nb. of male group Members	0.370*** (0.10)	0.237** (0.11)	0.215* (0.11)
IC (group mean)		0.558*** (0.11)	0.616*** (0.12)
Degree (group mean)			-0.047 (0.27)
Age (group mean)			-0.077 (0.05)
Happiness (group mean)			-0.180 (0.18)
Siblings (group mean)			-0.147 (0.19)
Constant	1.374*** (0.23)	3.331*** (0.47)	0.719 (1.30)
No. of Obs.	85	85	85
Pseudo R2	0.043	0.130	0.147
Prob > chi2/F	0.000	0.000	0.000

Notes: Regressions at the group level, Standard errors in parenthesis, Significance level: * p<0.10, ** p<0.05, *** p<0.010

TABLE A 4: ORDERED PROBIT REGRESSIONS WITH GROUP CHOICE AS DEPENDENT VARIABLE AND GENDER DOMINATION AS INDEPENDENT VARIABLE PLUS CONTROLS (IC GROUP MEDIAN).

	Model 1	Model 2	Model 3
Male dominated groups (FMM & MMM)	0.852*** (0.24)	0.583** (0.25)	0.552** (0.25)
IC (group median)		0.461*** (0.09)	0.489*** (0.10)
Degree (group mean)			-0.047 (0.05)
Age (group mean)			-0.152 (0.27)
Happiness (group mean)			-0.163 (0.18)
Siblings (group mean)			-0.141 (0.18)
Constant	1.246*** (0.21)	2.932*** (0.41)	0.848 (1.31)
No. of Obs.	85	85	85
Pseudo R2	0.045	0.135	0.147
Prob > chi2/F	0.000	0.000	0.000

Notes: Regressions at the group level, Standard errors in parenthesis, Significance level: * p<0.10, ** p<0.05, *** p<0.010

TABLE A 5: OLS REGRESSIONS WITH GROUP SHIFT AS DEPENDENT VARIABLE

	Model 1 GC – mean(IC)	Model 2 GC - IC
Male dominated groups (FMM & MMM)	0.659** (0.33)	1.256*** (0.42)
IC (Group median)	-0.121 (0.11)	-0.140 (0.14)
Gender		0.756** (0.30)
Age		-0.075 (0.06)
Degree		-0.043 (0.16)
Siblings		-0.127 (0.08)
Happiness		-0.162 (0.13)
Consciousness		0.022* (0.01)
Constant	0.103 (0.40)	1.152 (1.35)
No. of Obs.	85	240
Adj. R2	0.027	0.076
Prob > chi2/F	0.121	0.007

Notes: Model 1 - Regression at the group level, Model 2 – Regression at the individual level and clustered at the group level, Standard errors are given in parenthesis, Significance level: * p<0.10, ** p<0.05, *** p<0.010.

Paper 4: Are Economic Preferences Shaped by the Family Context? The Impact of Birth Order and Siblings' Sex Composition on Economic Preferences

LENA DETLEFSEN, ANDREAS FRIEDL, KATHARINA LIMA DE MIRANDA, ULRICH SCHMIDT AND MATTHIAS SUTTER *

Abstract

The formation of economic preferences in childhood and adolescence has long-term consequences for social and economic outcomes later in life. Hence, it is important to understand what shapes economic preferences. Running experiments with 525 teenagers, we examine the effects of both birth order and siblings' sex composition on economic preferences. We find that both aspects matter. Second born children are typically less patient, less risk averse, and more trusting. However, siblings' sex composition interacts with these findings, such that the common finding that second born children are more risk taking is only confirmed in case of same-sex siblings, while with mixed-sex siblings gender dominates birth order. For trust, gender differences are larger with mixed-sex siblings than in the single-sex case. Only for patience siblings' sex composition does not matter.

JEL classifications: C93, D10, D90, J12

Key words: Birth order, preferences, stereotypes

* Detlefsen, Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Lena.Detlefsen@ifw-kiel.de). Friedl: Friedrich-Alexander University Erlangen-Nürnberg, Lange Gasse 20, DE-90403 Nürnberg, (andreas.friedl@fau.de). Lima de Miranda: Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Katharina.Miranda@ifw-kiel.de). Schmidt: University of Kiel, University of Johannesburg and Kiel Institute for the World Economy, Kiellinie 66, DE-24105 Kiel, Germany (Ulrich.Schmidt@ifw-kiel.de). Sutter: Max Planck Institute for Research on Collective Goods Bonn, and University of Cologne, Germany (matthias.sutter@coll.mpg.de)

I. Introduction

Economic preferences shape the outcomes of one's life to a large extent. For instance, time preferences are related to school performance and thus educational achievements, meaning that they affect labor market performance and lifetime income (Heckman et al., 2006; Castillo et al., 2011; Moffitt et al., 2011; Golsteyn et al., 2014; Alan and Ertac, 2017). Risk preferences have an influence on financial behavior (Meier and Sprenger, 2010, 2013), and social preferences, like trust and reciprocity, are important for cooperation within a society and can even help markets work efficiently (Fehr et al., 1993; Knack and Keefer, 1997; Zak and Knack, 2001; Kerschbamer et al., 2017).

Only in more recent years, economists have become very much interested in the formation of economic preferences. Promoting a better understanding of the development of economic preferences promises to provide insights into the sources of heterogeneity in economic preferences among subjects, and therefore also reveals potential anchor points for policy interventions to mold economic preferences. While genetic studies show that some variation in economic preferences can be explained by genetic variation (Cesarini et al., 2009; Zyphur et al., 2009), large parts of differences in economic preferences still require additional explanations that are related to different environments in which subjects grow up and make economic choices. Besides looking at the influence of schools and peer groups, the influence of families has naturally captured lots of attention in this literature about the formation of economic preferences. For instance, several important studies have addressed the influence of the socio-economic status of parents on children's economic preferences, typically finding that higher socio-economic status of parents goes along with more patient children who are also more risk tolerant, more often prosocial and more competitive (Dohmen et al., 2012; Kosse and Pfeiffer, 2012; Bauer et al., 2014; Deckers et al., 2015; Almas et al., 2016). Besides parents, it is straightforward to see that siblings also have an influence on each other. This is due to the fact that siblings compete for parental attention – inducing them to adapt their behavior to reach this goal, which may lead to differentiate one's behavior from siblings' behavior to capture more attention (Sulloway, 1996; Hertwig et al., 2002). However, siblings can also learn from each other by imitating other siblings, often the older ones who have higher status (Rust et al., 2000).

In fact, there is an influential literature showing that birth order affects *outcomes*. For example, later born children have lower IQ (Bjerkedal et al., 2007; Black et al., 2011), lower education (Black et al., 2005; Booth and Kee, 2008; Härkönen, 2014), higher mortality risks (Barclay and

Kolk, 2015; Modin, 2002), they earn less (Behrman and Taubman, 1986; Björklund and Jäntti, 2012) and are more likely to smoke (Black et al., 2016). The development of cognitive skills is substantially influenced by older siblings (Dai and Heckman, 2013). Interestingly, there is much less evidence on how birth order affects *economic preferences*, with the latter then having an impact on economic outcomes. Moreover, the related literature – discussed below in more detail – typically focuses on birth order effects and puts less emphasis on siblings’ sex composition (referring to whether siblings have the same sex or are of different sex).

Given that birth order and sibling’s sex composition are important for parental behavior and sibling’s interaction and potential imitation or differentiation (Whiteman et al., 2007), we are going to study how birth order and siblings’ sex composition affects three key domains of economic preferences, namely time, risk and trust preferences. The aim of this study is to disentangle the birth order and the siblings’ sex composition effect on economic preferences, and check whether these effects also interact with a subject’s sex.

We present an experimental study with 525 adolescents, all attending 10th grade and on average 15 years of age. We focus in our study on adolescents and do this for several reasons. First, this age is of immense practical importance and of scientific interest, as it is right at the border between having to accept the decision of one’s parents and making one’s own (significantly influential) life decisions for the first time. Second, adolescence is a phase in life which sets the cornerstone for lifetime outcomes such as educational choices, or the creation of habits which are known to be hard to change once acquired (smoking, drinking or unhealthy diet).¹⁵ Third, adolescents are still integrated into their family context and, therefore, family composition should not be diluted by developments in life after leaving the parents’ house. Fourth, work on siblings’ role in gender development suggests that the differentiation of siblings (in relation to other siblings) sets in during adolescence as youths focus on developing their unique identities (Grotevant, 1978; McHale et al., 2001).

The experiment with 10th graders was run during regular school hours, thus minimizing drop-outs and self-selection issues. The experimental elicitation of time, risk, and trust preferences was incentivized, and questionnaire data allows us to relate experimental choices to the family context, in particular to both birth order and siblings’ sex composition. The set of economic preferences

¹⁵ For example smoking during adolescence, even infrequently, is a highly significant predictor of later regular smoking, up to the point that those who did not smoke during adolescence will most likely never start smoking (Chassin et al., 1990).

investigated, and the opportunity to speak to both the importance of birth order and siblings' sex composition and to identify the relative effect of both factors sets our paper apart from previous studies. Overall, the research in economics regarding birth order, siblings' sex composition and economic preferences is still scarce. Some important studies focus on risk preferences – one of the three types of economic preferences we are looking at – and the influence of the family context. Dohmen et al. (2012) show that first born children are more similar to their parents in terms of risk preferences than later born ones and Alan et al. (2017) report that the correlation between mother's and daughter's risk preferences is very strong and significant, while it is much weaker and insignificant for mothers and boys. Consistent with this view, later born children have been found to be less risk averse than first borns using field behavior data (Yiannakis, 1976; Sulloway and Zweigenhaft, 2010). Using a large Swedish survey sample of adults, Lampi and Nordblom (2011) relate both time and risk preferences to birth order, finding that later born children are less patient than first born children. Three features distinguish their work from ours. Their survey did not involve incentives, they had adult participants, and they did not investigate trust. The only studies we know that focus on birth order effects and use incentivized experiments are the studies by Courtiol et al. (2009) and Okudaira et al. (2015). Courtiol et al. (2009) found in a sample of French students that first born children are less trustful than later born children in a standard investment game by Berg et al. (1995). They used an incentivized experiment, but in comparison to our paper they did not relate their findings to siblings' sex composition, nor did they study risk or time preferences. Furthermore, while we studied adolescents for the reasons explained above, Courtiol et al. (2009) let adult university students participate in their study. Okudaira et al. (2015) examined competitive behavior and reported no birth order effects. Yet, they found that the siblings' sex composition matters; men with older sisters were less competitive than men with older brothers in their Japanese high school sample. So, they considered both birth order and siblings' sex composition, as we do, but we consider a much broader set of economic preferences by focusing on risk, time, and trust preferences.

We find that birth order is one important factor for all three preferences and, moreover, that for trust and risk preferences, the siblings' sex composition has a significant impact as well. First born children are in general more patient and trust less than second born children. However, while patience is independent of the siblings' sex composition, trust increases for boys in mixed sex families. Additionally, second born children are only more risk taking in single sex families. In mixed sex families children vary in their risk preferences with regard to the gender. Boys are more risk taking than girls, but there is no birth order effect. Most of these results are in line with our hypotheses that we are going to present in the following section II. Afterwards, we introduce in

section III the experimental design of our study. Section IV presents our results in detail. Section V discusses the results and relates them in particular to our hypotheses, and section VI concludes the paper.

II. Hypotheses

The birth order position and siblings' sex composition are important for children and may affect economic preferences for two reasons. First, parental investment differs among siblings. First born children usually have access to more family resources than later born ones (Sulloway, 1996). For example it has been shown both theoretically and empirically that first born children spend more quality time with their parents than second born children, even when parents try to divide their time equally between their offspring (Hertwig et al., 2002; Price, 2008). They also benefit from an early absence of sibling rivals for a share of parental investment (Jacobs and Moss, 1976).¹⁶ Not only birth order has an impact on parental treatment, also the siblings' sex composition is important. In general it has been found, that parents favor the child of their own sex such that mothers spend least time with their children if she has only boys (Crouter et al., 1995; McHale et al., 2000). This differentiated parental treatment is especially apparent in mixed-sex dyads, where mothers and fathers tend to spend relatively more time with the child of their own sex and their treatment tends to differ more between boys and girls. Gender specific treatment can lead to an enforcement of gender socialization and gender stereotypical behavior of children, which is more pronounced in mixed-sex dyads. It has been shown for example that boys who spend more time with their fathers comply more with gender stereotypes (Lawson et al., 2015) and that girls with brothers do on average more housework (Crouter et al., 1999; McHale et al., 1999, 2000)

Second, in addition to differentiated parental investment, the presence of siblings as such plays an important role in child development. Children react to siblings and do this in two different ways (e.g. Whiteman et al., 2007). First, children compete as afore-mentioned over parental attention. To reduce direct competition and to get a share of parental time children try to find their own niche to make it difficult for parents to compare them. This attempt to differentiate oneself from other siblings is known as de-identification (Sulloway, 1996). The de-identification process can depend on the birth order (Sulloway, 1996) and is in general more pronounced if siblings have different sex (Feinberg et al., 2003). The second mechanism is social learning. Children learn from their siblings and copy the behavior, making for example girls with brothers more masculine and boys with

¹⁶ It has been shown that first born children grow faster (Meredith, 1950; Wingerd, 1970) such that there exists a strong and significant negative correlation between birth order and height (Hatton and Martin, 2010; Lundborg et al., 2014).

sisters more feminine (Rust et al., 2000). This process can be especially important for younger siblings due to the tendency of imitating higher status models (Rust et al., 2000) and for same sex dyads due to higher intimacy (e.g. Buhrmester, 1992; Hetherington, 1991; Tucker, Barber, and Eccles, 1997). Social learning can lead to the fact that children who have an older sibling of the other sex have less stereotyped gender role concepts (Stoneman et al., 1986; Rust et al., 2000).

From the above considerations we can derive the following hypotheses for our three domains of economic preferences.

A. Time preferences

First born children tend to spend more quality time with their parents (Price, 2008) and to conform more with parental values (Sulloway, 1995, 1996) than their younger siblings. In the case of time preferences this would lead to first born children being more patient than their younger siblings given that adults have been found to be in general more patient than adolescents (Lahav et al, 2010). The reaction of the second born child would be to be less patient if they follow the aspect of de-identification or to be also patient if they follow social learning.

Hypothesis 1: a) Second born children are less patient than first born children if de-identification is present. b) There are no time preference differences between first born children and second born children if social learning is present.

Time preferences show in general no clear pattern with regard to the gender of the child.¹⁷ Therefore, parental behavior should not be different in this matter, nor should social learning and de-identification differ between single sex and mixed sex siblings.

Hypothesis 2: The siblings' sex composition has no influence time preferences.

B. Risk Preferences

In line with Sulloway (1995;1996), Dohmen et al. (2012) found that first born children are more similar to their parents in terms of risk preferences than later born ones and that the willingness to take risks decrease with age. The size of the differences between first and second born depends on the siblings' de-identification and social learning.

¹⁷ Dohmen et al. (2010) and Deckers et al. (2015) found that boys are more patient than girls, while studies by Bettinger and Slonim (2007) and Castillo et al. (2011) found that girls are more patient than boys.

Hypothesis 3: a) Second born children are less risk averse than first born children if de-identification is present. b) There are no risk preference differences between first born children and second born children if social learning is present.

However, as risk preferences have been found to differ between boys and girls (Croson and Gneezy, 2009, Cárdenas et al., 2012; Deckers et al., 2015) and parents have been found to differ in their treatment of girls and boys especially in the encouragement of sex-typed activities (Lytton and Romney, 1991) we presume that the results for de-identification or social learning in families with single sex or mixed sex siblings will be different. First, studies found that the de-identification process is more pronounced with mixed sex siblings compared to single sex siblings (Feinberg et al., 2013), so children might rather try to differ from their siblings by acting in line with the gender stereotype than by differing with respect to birth order. In the case of mixed sex siblings this would imply that girls will tend to become more risk averse and boys more risk seeking, regardless of their birth order position. Second, studies show that children copy their siblings (e.g., Brim, 1958; Koch, 1956; Sutton-Smith and Rosenberg, 1970). Therefore, gender differences should be smaller with mixed sex siblings.

Hypothesis 4: The siblings' sex composition has an influence on risk preferences, such that birth order has a stronger impact in case of same sex siblings.

C. Trust

Different from time and risk preferences, social learning is an important mechanism for trust behavior. Children learn from their siblings, especially younger siblings from their older siblings (Rust et al., 2000). Older brothers and sisters are more likely to reciprocate than younger children and thus younger siblings experience more instances of positive reciprocity than do older siblings (Hardin, 2001). This is in line with the finding that trust increases from early childhood to early adulthood (Sutter and Kocher, 2007) and that children trust older children in general more than children of their own age (Harbaugh et al., 2003).

Hypothesis 5: Second born children trust more than first born children.

The social learning process might differ with regard to the gender composition of siblings. While men trust in general more, women reciprocate more (Buchan et al., 2008). So if boys have sisters

they learn that they can trust (their sisters), while girls with brothers learn the opposite. This could lead to differences in the trust level between mixed and single sex siblings.

Hypothesis 6: Gender differences in the trust levels are more pronounced in mixed sex siblings. Boys trust more if they have sisters. Girls trust less if they have brothers.

III. Experimental Design

Our study was carried out in 27 classes from eight secondary schools in the German state of Schleswig-Holstein, including 525 students who were all attending 10th grade in school (with an average age of 15.95 years). The schools included three different types of secondary schools that vary in level and length of schooling.¹⁸ Having different school types offered us the possibility to get students with different socio-economic and intellectual backgrounds. The study was approved by the Ministry of School and Professional Education and the principals and teachers of the participating schools gave permission to conduct the experiments during regular school hours. Parents were informed about the experiment and also gave their permission. Participation of students was, of course, also voluntary, but none opted out.

The experiment was computerized, using the mobile Kiel Econ Lab and z-tree (Fischbacher, 2007). Experimental sessions were conducted with up to 25 participants per session in dedicated class rooms and lasted about 45 minutes. Since the experiments were run during regular school hours we minimized dropouts and self-selection. All students faced the same set of explanations, decision tasks, questionnaires and payoffs. While inside a classroom all students faced the same sequence of decision tasks, it was randomized on the class level in order to account for possible order effects. The experiments were incentivized and each subject was paid according to her or his choices. At the end of the experimental session, one decision was randomly selected for payment. It was explained that the choices were anonymous and that payments would be handed out in sealed envelopes, which one experimenter would prepare and another experimenter would distribute to the

¹⁸ The school types are Gymnasium (3 schools), Gemeinschaftsschule (3), and Regionalschule (2). Since 2014, the education act of Schleswig-Holstein (Schleswig-Holsteinisches Schulgesetz) intends a two-tier secondary education system with community schools (Gemeinschaftsschule) and high schools (Gymnasium), which start after 4 years of elementary school. We also have two regional schools (Regionalschule) in our sample, a school type to be discontinued after 2019. The main differences between the different school types are the following. In a community school all educational qualifications of secondary education can be acquired in a common educational background. This is the first general education qualification ("Erster allgemeinbildender Schulabschluss") after the 9th grade, the "Mittlere Reife" after the 10th grade, which both qualify for vocational training, and in addition the "Abitur" after the 13th grade, qualifying for university admission. High schools prepare students for higher education. In the majority of high schools, students can achieve their "Abitur" after the 12th grade. Regional schools terminate after the 10th school year, thus they can not qualify for university admission (information from this paragraph is based on the state's website (Landesportal Schleswig-Holstein; 2017)).

participants in a double blind procedure. Payments ranged from €0 to €10, with an average of €4.32. Students were directly paid in cash¹⁹, except if future payments became necessary in the time preference task, in which case a sealed envelope was handed to the teacher who was instructed to hand it to the according subject on the determined date in the future. The teachers had no information regarding the task and could therefore draw no conclusion about the behavior of the children.

A. Time Preferences

Time preferences were elicited through a choice list of 20 binary choices (similar to the lists used in Bettinger and Slonim, 2007, or Sutter et al., 2013, who also worked with children and who reported good understanding of children). In the list presented in Table 1, subjects were asked to choose between a payment today and a payment in three weeks. The early payment remained fixed at €4.00 and the delayed payment increased monotonically in €0.10 steps from €4.00 to €5.90. To calculate the future equivalent, we take the switching point between the last immediate payment and the first delayed payment. The choice lists were designed in a way that it was not possible to switch more than once from the left to the right hand side in each list, a procedure that has been used in other experiments as well (e.g., Dohmen et al., 2010). In the example in Table 1 the future equivalent would be 4.25€. Higher levels of the future equivalent indicate a higher level of impatience.

TABLE 1 EXAMPLE: CHOICE LIST FOR TIME PREFERENCES

1)	€4.00 today	<input checked="" type="checkbox"/>	or	€4.00 in 3 weeks	<input type="checkbox"/>
2)	€4.00 today	<input checked="" type="checkbox"/>	or	€4.10 in 3 weeks	<input type="checkbox"/>
3)	€4.00 today	<input checked="" type="checkbox"/>	or	€4.20 in 3 weeks	<input type="checkbox"/>
4)	€4.00 today	<input type="checkbox"/>	or	€4.30 in 3 weeks	<input checked="" type="checkbox"/>
5)	€4.00 today	<input type="checkbox"/>	or	€4.40 in 3 weeks	<input checked="" type="checkbox"/>
...	
20)	€4.00 today	<input type="checkbox"/>	or	€5.90 in 3 weeks	<input checked="" type="checkbox"/>

¹⁹ We were able to pay all children in cash, except for one school. In this school the children could earn coupons for the cafeteria, which was perceived as equivalent to cash because students could spend their coupons on whatever they liked in the canteen, for example lunch or sweets.

B. Risk preferences

We elicited risk preferences by using the design of Eckel and Grossman (2002). This design has been shown to be easy to understand for a broad range of socioeconomic groups with diverse mathematical skills (Dave et al., 2010), making it suitable also for our study with children. The students had to choose one out of the six lotteries displayed in Figure 1. In each lottery, the chances to win a high or low prize were equal to 50%. The lotteries increased in risk and expected value, starting from the top of Figure 1 with a sure gain of €4 to the two last lotteries (moving in clockwise order) with an expected value of €5. Overall, risk aversion decreased from the first to the last lottery. Note that the two last lotteries had the same expected value, but the lottery with prizes €9 or €1 had higher risk than the penultimate one with prizes of €8 or €2.

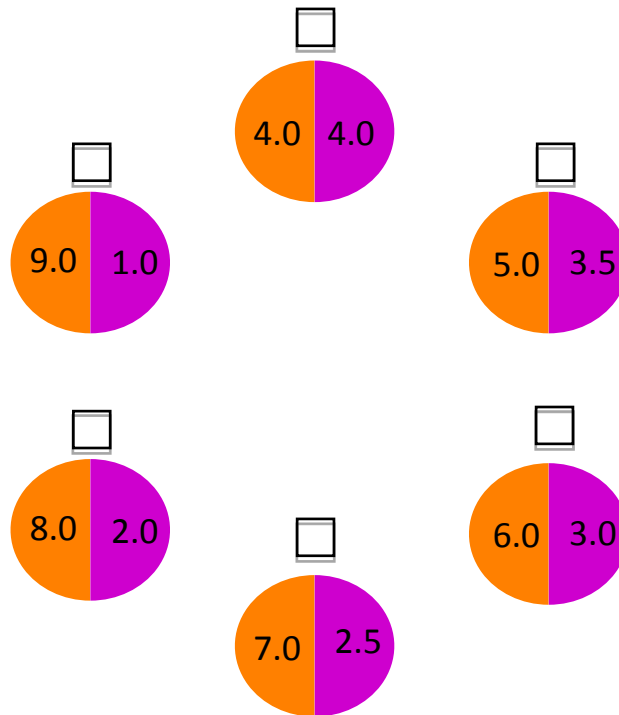


FIGURE 1: RISK PREFERENCE TASK

Notes: The lottery at the top will be coded as Lottery 1, and in clockwise order the following lotteries are coded as lotteries 2-6. Higher lottery numbers imply more risk taking.

C. Trust

Trust was elicited with the investment game by Berg, Dickhaut, and McCabe (1995). Both players in this game were endowed with €2 in the beginning. The sender could then transfer an amount between €0 and €2 to the receiver. The transfer was tripled and the receiver could return any amount between zero and the tripled transfer to the sender. While participants played in both roles, we are going to focus on the sender's decision to measure trust.

D. Further Variables of Interest

In addition to the tasks on time, risk and trust preferences, the subjects had to solve ten raven matrices as an indicator for cognitive reflection. At the end of the experiment a questionnaire with demographic questions as well as questions regarding individual field behavior was administered (see the Appendix for all items). Demographic questions included age, gender, height, weight, number of siblings, age of siblings and siblings' sex, as well as information about their parents. Furthermore, the socioeconomic background was measured with the family affluence scale (FAS) (Currie et al., 1997), which has been especially developed for children and builds on self-reported information on a subject's household (own room, holidays, number of books, cars and computers). Higher levels thereby indicate a higher socio-economic background (Boyce et al., 2006).

IV. Results

Table 2 presents an overview of the descriptive statistics and the experimental choices. In our complete sample of 525 students, 50.3 percent are male. The average age is 15.95 years and 40 percent of students attend to a Gymnasium, which is close to the German average (of 46 percent). On average, the students have 1.57 siblings (1.16 biological siblings). 12.57 percent of them are only children, 47.81 percent have one sibling and 23.81 percent have two siblings. Of those who have siblings, 34.5 percent are first born, 31.6 percent are second born, 13.7 percent are third born, and 6.3 percent are fourth or later born children.

In the following analysis, we have to exclude those students who are single children. Moreover, we focus our analysis on first born and second born children, since birth order effects are assumed to be largest between the oldest children in families (Schacter et al., 1976, 1978). In order to keep a sufficiently large sample size, we do not only restrict our sample to families with two children only, but also include families with three children (while analyzing only the first and second born). This yields a set of 312 adolescents, whose summary data are shown on the right-hand side of Table 2. Regarding the economic preferences there are no significant differences between the samples. The only differences between the samples is the age of the mothers as our children have in general a younger mother, as we only concentrate on first and second born children. Of those 312 adolescents, almost exactly 50% are first born and 50% are second born, and 67.6% of them grew up in families with a single sex siblings-composition. When examining the effect of the sex-composition of siblings in the paper, we will consider only the sex of the first born and second born child and classify the composition as either single sex or mixed sex. Since we also include families with three children, our approach presented in the paper ignores the sex of the third child. In

Appendix B we show that the main results presented in the paper are robust to a more conservative splitting of the sample with respect to siblings' sex composition where we define single sex as only those cases where all siblings have the same sex also in families with three children. Given this robustness, we proceed here with our approach of looking at the sexes of the first born and second born only.

TABLE 2 DESCRIPTIVE STATISTICS

Variable	Complete Sample					Sub-Sample (Families with 2 or 3 children)					Diff. (Prob > z)
	Obs.	Mean	SD	Min	Max	Obs.	Mean	SD	Min	Max	
Male	525	0.503	0.501	0	1	312	0.522	0.500	0	1	0.5840
Age	525	15.945	0.644	15	18	312	15.939	0.651	15	18	0.8586
Gymnasium	525	0.4	0.490	0	1	312	0.43	0.496	0	1	0.4021
FAS	525	11.337	2.293	4	16	312	11.43	2.264	4	16	0.5002
Raven test	525	7.088	1.09	0	10	312	7.09	1.164	0	10	0.8660
Pocket money	524	37.821	36.794	0	587	311	36.949	40.876	0	587	0.4207
Mother's age at birth	524	46.315	4.718	32	64	312	45.715	4.34	32	57	0.0900
No. Siblings Spacing in years (1 st /2 nd)	525	1.511	1.094	0	5	312	1.199	0.4	1	2	0.0004
First born	525	0.345	0.476	0	1	312	0.5		0	1	0.0000
Second born	525	0.333	0.472	0	1	312	0.5		0	1	0.0000
Single sex	525	0.571	0.495	0	1	312	0.676	0.469	0	1	0.0026
<i>Experimental choices</i>											
Future equivalent	525	4.904	0.624	4	5.9	312	4.885	0.613	4	5.9	0.6921
Risk	525	2.596	1.689	1	6	312	2.705	1.721	1	6	0.3800
Trust	525	1.313	0.595	0	2	312	1.298	0.597	0	2	0.7637

Notes: We test differences between the samples by using the Wilcoxon ranksum test.

A. Time preferences

Table 3 shows the average choices in the time preferences experiment. The numbers in the table indicate the future equivalent, i.e., the amount of money that participants need to get in three weeks in order to give up an immediate payment of €4.00. On average, this future equivalent is €4.89€ (in the complete sample of 525 students: 4.90€). It differs only slightly, and insignificantly, across gender with €4.87 for the boys and €4.91 for girls (Wilcoxon ranksum test: $z = -0.245$, Prob > |z| = 0.8063).

TABLE 3 DESCRIPTIVE STATISTICS: TIME PREFERENCES (FUTURE EQUIVALENT, IN €)

	All	Boys		Girls	
		Single sex	Mixed sex	Single sex	Mixed sex
1 st born	4.812	4.733	4.82	4.869	4.886
2 nd born	4.957	4.932	5.083	4.944	4.91
All (mixed/single)		4.833	4.951	4.907	4.898
All	4.885		4.885		4.905

The average future equivalent for first born children is 4.812€ and for second born children 4.957€. This difference is significant at the 5%- level ($z = -2.025$, $\text{Prob} > |z| = 0.0428$). Table 4 presents a Tobit regression that includes several background variables. In Model 1 it confirms that there is no gender difference in patience. Model 2 shows, however, a strong birth order effect, such that second-born children are significantly more impatient than first-born children, which is consistent with our Hypothesis 1 a).

As we do not have a gender effect in our data, the question remains if we nevertheless find differences between mixed and single sex siblings. Dropping gender and birth order in Model 3 shows that mixed sex in itself has no significant impact. This is also true when retaining the variables “Male” and “2nd born” in Model 4. Yet, motivated by Hypothesis 2, in Model 5 we control more carefully for interaction effects of mixed sex composition with birth order or gender. As we see, both interaction terms (2nd born * Mixed sex and Men * Mixed sex) are not significant and do not alter our birth order effect sizes. Therefore, this model shows that there is no difference between mixed and single sex siblings’ compositions, which means that we cannot reject our Hypothesis 2 (of finding no effect of the siblings’ sex composition).

TABLE 4 RESULTS: TIME PREFERENCES

	(1)	(2)	(3)	(4)	(5)
Male	-0.045 (0.07)			-0.035 (0.07)	-0.092 (0.09)
2 nd born		0.218*** (0.07)		0.213*** (0.07)	0.211** (0.10)
Mixed sex			0.070 (0.09)	0.050 (0.09)	-0.046 (0.18)
Interaction					0.011 (0.20)
2nd born*Mixed sex					0.188 (0.17)
Interaction					0.188 (0.17)
Men * Mixed sex					0.188 (0.17)
Risk (std.)	-0.008 (0.06)	-0.023 (0.06)	-0.016 (0.05)	-0.021 (0.06)	-0.026 (0.06)
Raven (std.)	0.025 (0.05)	0.029 (0.05)	0.028 (0.05)	0.030 (0.05)	0.035 (0.05)
Pocket money (std.)	0.070* (0.04)	0.071* (0.04)	0.068 (0.04)	0.070* (0.04)	0.064 (0.04)
FAS (std.)	-0.173*** (0.05)	-0.165*** (0.05)	-0.174*** (0.05)	-0.165*** (0.05)	-0.168*** (0.05)
Mother's age (std.)	0.064 (0.05)	0.013 (0.05)	0.064 (0.05)	0.013 (0.05)	0.007 (0.05)
No. of Siblings	0.201* (0.10)	0.188* (0.10)	0.194* (0.10)	0.194* (0.10)	0.191* (0.10)
Spacing	0.009 (0.03)	0.008 (0.03)	0.008 (0.03)	0.007 (0.03)	0.008 (0.03)
constant	4.669*** (0.15)	4.551*** (0.15)	4.637*** (0.15)	4.554*** (0.14)	4.584*** (0.13)
Sigma constant	0.663*** (0.03)	0.657*** (0.03)	0.663*** (0.04)	0.656*** (0.03)	0.654*** (0.03)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.037	0.047	0.037	0.048	0.049
Prob > chi2/F	0.002	0.000	0.003	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.133
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.504

Notes: Dependent variable is the future equivalent in Euros. Control variables are spacing (between first and second born, in years), number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS) and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Besides our main interest in birth order and siblings' sex composition effects, we note from Table 4 two further independent variables that are significant for time preferences. Children from a higher socioeconomic background (with a higher score in the family affluence scale FAS) are more patient (consistent with recent findings by Deckers et al., 2015) and children from families with 3 children are less patient than children from families with 2 children.

A. Risk preferences

Table 5 presents the descriptive statistics for our risk preferences experiment. We show the average of the lottery number chosen from Figure 1, where Lottery 1 yielded a sure payment of €4, while Lottery 6 had a 50:50 chance for €9 or €1. Higher lottery numbers indicate a larger willingness to take risks, therefore. Overall, we find an average of 2.71 (in the complete sample of 525 students: 2.60). There is a strong gender difference between boys (M=3.10) and girls (M=2.27; Wilcoxon ranksum test: $z = -4.282$, $\text{Prob} > |z| = 0.0000$).

TABLE 5 DESCRIPTIVE STATISTICS: RISK PREFERENCES (AVERAGE LOTTERY NUMBER)

	All	Boys		Girls	
		Single sex	Mixed sex	Single sex	Mixed sex
1 st born	2.577	2.578	3.842	2.083	2.56
2 nd born	2.833	3.189	3.667	2.5	1.967
All (mixed/single)		2.884	3.755	2.292	2.264
All	2.709		3.104		2.269

Notes: The numbers indicate the average lottery number chosen from Figure 1. Higher numbers imply more risk taking.

The average lottery number for first born children is 2.58, compared to 2.83 for second born. This difference is not significant ($z = -1.367$, $\text{Prob} > |z| = 0.1717$). The Tobit regression analysis²⁰ in Table 6 confirms the significant differences between boys and girls in our sample (Model 1), and indicates no birth order effect (Model 2). Therefore we have to reject our Hypothesis 3a) that de-identification might trigger a birth order effect. Rather, Model 2 in Table 6 looks as if social learning might make first and second born children indistinguishable in their risk preferences. Yet, in Hypothesis 4 we were arguing that the siblings' sex composition should matter for risk preferences. Model 3 in Table 6 offers a first piece of evidence that this is (weakly significantly) the case. But most importantly we consider again Model 5 that includes the interaction terms between siblings' sex composition and gender, respectively birth order. We find that second born children are significantly less risk averse than first born children in single sex compositions, while in mixed sex compositions the birth order effect is negative (-0.676), but not significant. This suggests that in single-sex compositions the process of de-identification yields a significant birth order effect. We also note from Model 5 that in mixed sex compositions the gender effect is larger than in single sex compositions (2.585 compared to 1.014). Hence, we confirm Hypothesis 4 that birth order effects depend on the sibling's sex composition. Furthermore, our results suggest that the underlying mechanism is not social learning, but that de-identification differs with the sibling's sex

²⁰ Our results are robust to using alternatively an ordered probit regression (since the lottery number as the dependent variable is an ordinal variable. In Appendix B we show that ordered probit yields qualitatively identical results. This invariance to the regression technique also applies to the discussion of trust preferences later in this section.

composition: in single sex compositions, de-identification seems to work by birth order, whereas in mixed sex compositions gender lets siblings differentiate from each other, independent of birth order.

Four further variables in Table 6 are also important for risk preferences. Children who answer more raven matrices correctly, who receive more pocket money and who come from a better socioeconomic background (FAS) are in general more willing to take risks. The spacing between first and second born (in years) has a decreasing impact on risk taking.

TABLE 6 RESULTS: RISK PREFERENCES

	(1)	(2)	(3)	(4)	(5)
Male	1.444*** (0.42)			1.490*** (0.42)	1.014** (0.47)
2 nd born		0.583 (0.39)		0.494 (0.39)	1.030** (0.41)
Mixed sex			0.626* (0.34)	0.712* (0.37)	0.847 (0.58)
Interaction 2nd born*Mixed sex					-1.706** (0.68)
Interaction Men * Mixed sex					1.571** (0.61)
Raven (std.)	0.428** (0.18)	0.414** (0.18)	0.428** (0.18)	0.443** (0.18)	0.447** (0.18)
Pocket money (std.)	0.452* (0.26)	0.487* (0.27)	0.502* (0.29)	0.421* (0.25)	0.316 (0.23)
FAS (std.)	0.333** (0.16)	0.390** (0.16)	0.360** (0.15)	0.336** (0.15)	0.327** (0.15)
Mother's age (std.)	-0.037 (0.20)	-0.230 (0.20)	-0.099 (0.20)	-0.158 (0.20)	-0.197 (0.22)
No. of Siblings	-0.156 (0.44)	0.059 (0.43)	0.067 (0.42)	-0.159 (0.43)	-0.129 (0.41)
Spacing	-0.159** (0.08)	-0.178** (0.08)	-0.193** (0.08)	-0.177** (0.08)	-0.194*** (0.07)
constant	2.137*** (0.47)	2.383*** (0.57)	2.529*** (0.51)	1.690*** (0.49)	1.723*** (0.53)
Sigma constant	2.760*** (0.19)	2.839*** (0.17)	2.839*** (0.17)	2.726*** (0.19)	2.678*** (0.18)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.036	0.022	0.023	0.042	0.051
Prob > chi2/F	0.000	0.000	0.000	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.252
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.000

Notes: Dependent variable is the risk level. Control variables are spacing, number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

A. Trust

The data about trust are given in Table 7. The average amount sent is €1.30€ (in the complete sample of 525 students: €1.31). It differs largely between boys (€1.38) and girls (€1.21; Wilcoxon ranksum test: $z = -2.774$, $\text{Prob} > |z| = 0.0055$). Comparing first born children (€1.22) and second born children (€1.38) also reveals a significant difference ($z = -2.474$, $\text{Prob} > |z| = 0.0134$). The Tobit regression analysis in Table supports both findings: Boys send more than girls (Model 1) and second born children send more than first born children (Model 2). This confirms Hypothesis 5.

TABLE 7 DESCRIPTIVE STATISTICS: TRUST (AMOUNT SENT AS SENDER, IN EUROS)

	All	Boys		Girls	
		Single sex	Mixed sex	Single sex	Mixed sex
1 st born	1.215	1.227	1.421	1.188	1.08
2 nd born	1.381	1.434	1.593	1.261	1.283
All (mixed/single)		1.331	1.507	1.225	1.182
All	1.298		1.377	1.211	1.377

Next, we look again how the siblings' sex composition interacts with gender and with birth order. From Model 5 of Table 8 we note second born children are more trusting (i.e., send more money in the trust game) in both types of sex composition and that there is no significant difference in this birth order effect between single sex and mixed sex compositions. The gender effect seems to originate from the mixed sex compositions, as only the joint effect of "Male" plus "Men * Mixed sex" is significantly different from zero. This confirms Hypothesis 6, such that boys trust more if they have sisters, and girls trust less if they have brothers. In single sex compositions there is no gender difference in trust, however.

TABLE 8 RESULTS: TRUST

	(1)	(2)	(3)	(4)	(5)
Male	0.240** (0.11)			0.263** (0.12)	0.157 (0.12)
2 nd born		0.226** (0.11)		0.220** (0.11)	0.221** (0.10)
Mixed sex			0.133 (0.11)	0.151 (0.11)	-0.011 (0.16)
Interaction 2nd born*Mixed sex					0.007 (0.18)
Interaction Men * Mixed sex					0.360* (0.19)
Risk (std.)	0.091* (0.05)	0.108* (0.06)	0.113* (0.06)	0.072 (0.05)	0.062 (0.05)
Raven (std.)	0.084* (0.05)	0.081* (0.04)	0.080* (0.05)	0.091* (0.05)	0.100** (0.05)
Pocket money (std.)	-0.005 (0.04)	0.001 (0.04)	-0.004 (0.04)	-0.007 (0.04)	-0.019 (0.04)
FAS (std.)	0.014 (0.06)	0.029 (0.06)	0.019 (0.06)	0.024 (0.06)	0.020 (0.06)
Mother's age (std.)	0.101* (0.06)	0.041 (0.07)	0.092 (0.06)	0.048 (0.07)	0.037 (0.07)
No. of Siblings	0.100 (0.16)	0.129 (0.15)	0.138 (0.16)	0.090 (0.15)	0.090 (0.15)
Spacing	-0.047* (0.03)	-0.051* (0.03)	-0.053* (0.03)	-0.053* (0.03)	-0.052* (0.03)
constant	1.387*** (0.20)	1.366*** (0.20)	1.437*** (0.21)	1.242*** (0.20)	1.290*** (0.20)
Sigma constant	0.884*** (0.06)	0.885*** (0.06)	0.890*** (0.06)	0.876*** (0.06)	0.873*** (0.06)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.028	0.027	0.024	0.036	0.039
Prob > chi2/F	0.000	0.000	0.004	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.223
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.009

Notes: Dependent variable is the amount send (trust).. Control variables are spacing, number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS), risk preferences and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Two background variables are significant over all model specifications shown in Table 8: the number of correctly answered raven matrices and spacing between first and second born child. Children who answer more matrices correctly are more trusting (which is reminiscent of findings for adults in Dohmen et al., 2010), and trust is reduced if the spacing (in years) between first and second born increases.

V. Discussion

Our general results for time, risk and trust preferences match the typical patterns observed in other studies. On average, our students are risk averse and impatient – like, e.g., in studies with children and teenagers of Bettinger and Slonim (2007), Castillo et al. (2011) or Sutter et al. (2013) – and send more than half of their endowment in the trust game – like the adolescents in the study of Sutter and Kocher (2007). Our findings on gender also resemble earlier results. We find boys to be more risk taking than girls, which is a common finding in the literature (see, e.g., Croson and Gneezy, 2009; Cárdenas et al. 2012; Deckers et al., 2015). In the trust game, boys are more trusting than girls, a result that is in line with data in Sutter and Kocher (2007). With respect to time preference, we do not observe gender differences in our sample. In this preference domain, results vary a lot, however. For instance, Dohmen et al. (2010) and Deckers et al. (2015) report boys to be more patient than girls, while Bettinger and Slonim (2007) and Castillo et al. (2011) present the opposite result. So it seems that there is not yet any consensus on whether gender differences in time preferences exist, and if so, in which direction. However, gender *per se* has not been the main issue of our project.

Rather, the main focus of this paper is to examine the impact of birth order position and of siblings' sex composition on economic preferences. Previous studies have mainly focused on birth order only (Dohmen et al., 2012; Yiannakis, 1976; Sulloway and Zweigenhaft, 2010; Lampi and Nordblom, 2011; Courtiol et al., 2009) and disregarded the siblings' sex composition. According to evidence from developmental psychology – as discussed in section II – both birth order and siblings' sex composition can have a major influence on the development of preferences and the impact might be different for each. We therefore add to the existing literature by jointly analyzing the influence of birth order and siblings' sex composition as well as extending the analysis to adolescents and we improve internal validity by using incentivized experiments.

Regarding *time preferences*, we find that second born children are less patient than first born children (see Table 5). This is in line with Hypothesis 1 a) and gives support for the de-identification theory, where siblings tend to develop different behaviors in order to be distinguishable for the parents and so get more attention and resources from them. Our finding mirrors one particular result by Lampi and Nordblom (2011) who found in their survey study with adults that middle born children – in their study typically the second born children – are the least patient ones. In line with Hypothesis 2 the birth order effects do not depend on the siblings' sex composition and remain significant when controlling for the latter.

Regarding *risk preferences*, we find no significant birth order effect between first and second born children. Therefore, we have to reject Hypothesis 3 a), which postulated that first born children are more risk averse. This seems to stand in contrast to other studies that have reported a birth order effect on risk taking (Sulloway and Zweigenhaft, 2010; Lampi and Nordblom, 2011). Yet, when we add the siblings' sex composition to our analysis, we see that the effect of birth order is considerably more differentiated than postulated in previous studies (see Hypothesis 4). Our results show that birth order effects are only visible in when siblings have the same sex. In such a single sex environment, we confirm that second born children are less risk averse than first born children. In families with both girls and boys, children seem to distinguish themselves from their siblings rather via their gender than via their birth order position. Here we find that differentiation works through gender, and not through birth order. Boys with sisters are more risk taking than girls with brothers, regardless of their birth order. Our study therefore substantiates the finding that children are more likely to follow gender-specific stereotypes in mixed sex environments than in single sex ones (Lawson et al., 2015). Both effects, birth order for single sex environment and gender for mixed sex environment are compatible with the theory of de-identification among siblings.

Regarding *trust preferences*, we find that second born children send more money in the trust game than first born children. This is in line with Hypothesis 5 and confirms the findings by Courtiol et al. (2009) who studied students around the age of 20. We additionally show that the results are also significant when risk preferences are included as control variable and when the siblings' sex composition is taken into account. As discussed above, we find gender differences in trust, with boys trusting more than girls. When we add the siblings' sex composition to our analysis, we find that gender differences in trust levels are larger (and significant) in mixed sex environments than in single sex environments. Boys and girls with same sex siblings send the same amount on average while boys with sisters send more than girls with brothers. This means that the development of trust depends on the environment, in our case the birth order position and the siblings' gender. This finding is in line with Hypothesis 6 and lends support to social learning theory in the domain of trust, with the underlying mechanism that boys with sisters learn that they can trust (their sisters), while girls with brothers learn the opposite.

VI. Conclusion

In our paper we focused on two aspects within the family context which can help to explain differences in preferences between children: birth order and siblings' sex composition. We ran incentivized experiments with several hundreds of tenth graders (average age of 15.95 years) during regular school hours, thus minimizing any concerns about self-selection or drop-outs. To the best of our knowledge, our study is the first looking at birth order *and* siblings' sex composition together in large set of economic preferences (of risk, time and trust preferences) and investigating humans in a particularly interesting period of development, i.e., in adolescence.

We find that both aspects, birth order and siblings' sex composition, matter. However, it depends on the preference which aspect is of particular interest. Starting with time preferences, we find strong birth order effects, such that second born children are less patient than first born children. This effect is independent of the gender of the siblings, so it does not matter whether siblings have the same sex or not. For risk and trust preferences, however, the siblings' sex composition does make a difference, and for these two types of economic preferences it would be misleading to only look at birth order. Regarding risk preferences, children identify with the gender stereotype in mixed sex environments where boys are much more willing to take risks than girls, irrespective of birth order. In a single sex environment, this is not the case, and there birth order generates de-identification of (same sex) siblings. Concerning trust preferences, we find that second born children send more money in the trust game than first born children in both types of siblings' sex composition, but that the gender differences are larger in mixed sex than in single sex environments.

Our results are important in three different ways. First, we show that time preferences vary with regard to birth order, with first born children being more patient. Since studies show that time preferences are a good predictor for important life-time outcomes (Khwaja et al., 2006; Chabris et al., 2008; Castillo et al., 2011; Sutter et al., 2013; Golsteyn et al., 2014), these differences may be one explanation why birth order effects have been found in field behavior related to education (Black et al., 2005; Booth and Kee, 2008; Härkönen, 2014), earnings (Behrman and Taubman, 1986; Björklund and Jäntti, 2012), or health (Black et al., 2016). Second we contribute to the discussion about de-identification within a family. In case of time preferences where no gender differences are visible, de-identification by birth order is important. We show however, that in the case of risk preferences where we find strong gender differences, de-identification by birth order is only visible in single sex environments. When siblings have different sexes, de-identification by

gender seems to be more important. So far, de-identification by birth order has been discussed exclusively for risk preferences and sex composition has not been taken into account (e.g., Sulloway and Zweigenhaft, 2010). Our results highlight that in case of the availability of gender specific stereotypes (e.g., Siegrist et al., 2002; Eckel and Grossman, 2002, 2008) siblings' sex composition might have a larger impact than the birth order position. This result is important as Lampi and Nordblom (2011) have shown that risk preferences can explain part of the earnings differences between siblings and our results also speak to a recent study by Cools and Patacchini (2017) who report that women with brothers earn less than women with sisters. Third, we show that in case of trust social learning seems to play a role. Sutter and Kocher (2007) have shown that trust increases for children with age and is relatively stable during adulthood. Our results show that the family context works as one important environment to form trust behavior of children and it highlights that it matters with whom children interact in their families for how much they trust in others. Overall, therefore, the family context with respect to birth order and the sex composition of children has an important influence on the development of economic preferences and can help explain the large heterogeneity in these preferences across subjects. Given that risk, time and trust preferences are so important for lifetime outcomes, we consider it as an important contribution to advance our understanding of how family matters for the formation of these preferences.

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Appendix (for online use)

A. Experiments

In the following we will conduct five experiments. In each experiment you have to make an economic decision. At the end of the five experiments the computer will determine by chance which one out of the five experiments will be relevant for your payment. If you have made multiple decisions in the respective experiment, the computer will choose one of the decisions. This means that you will receive the payment of one of the decisions in one of the experiments. Since you don't know which decision will be relevant later on, you should treat each decision as if it was the relevant one. As you will see, the sums paid are notable. Please consider your decision with care. There is no right or wrong, we are interested in your personal opinion. Please do not talk to your fellow students throughout the entire experiment. Should you have a question at any point, please don't hesitate to raise your finger. One of the conductors of the experiment will come to you and answer your question.

Decision sheet Z

As in the example below, in this situation you have to decide between column A or B.

Example:

	Column A		Column B		
1)	4,00€ today	<input type="checkbox"/>	or	4,90€ in 3 weeks	<input type="checkbox"/>

Payment „today“ means that you will receive the money today at the end of the experiment.

Payment “in 3 weeks” means that you will receive the money in exactly 3 weeks.

Payment “in 6 weeks” means that you will receive the money in exactly 6 weeks.

There are 2 pages with 20 rows each. You start with the first row and work your way down answering row by row. For each row you choose between 4 Euros (column A) and a different amount 3 weeks later (column B). Please consider the date of payment. The amount in column A remains the same for each row. The amount in column B rises constantly with each row. Once you have chosen column B once, you should not switch back to column A.

Situation 1

For each row, please choose between 4 Euros today and the rising amount in 3 weeks. Once you have chosen column B for the first time, you should not switch to column A anymore.

	Column A		or	Column B	
1)	4€ today	<input type="checkbox"/>		4,00€ in 3 weeks	<input type="checkbox"/>
2)	4€ today	<input type="checkbox"/>		4,10€ in 3 weeks	<input type="checkbox"/>
3)	4€ today	<input type="checkbox"/>		4,20€ in 3 weeks	<input type="checkbox"/>
4)	4€ today	<input type="checkbox"/>		4,30€ in 3 weeks	<input type="checkbox"/>
5)	4€ today	<input type="checkbox"/>		4,40€ in 3 weeks	<input type="checkbox"/>
6)	4€ today	<input type="checkbox"/>		4,50€ in 3 weeks	<input type="checkbox"/>
7)	4€ today	<input type="checkbox"/>		4,60€ in 3 weeks	<input type="checkbox"/>
8)	4€ today	<input type="checkbox"/>		4,70€ in 3 weeks	<input type="checkbox"/>
9)	4€ today	<input type="checkbox"/>		4,80€ in 3 weeks	<input type="checkbox"/>
10)	4€ today	<input type="checkbox"/>		4,90€ in 3 weeks	<input type="checkbox"/>
11)	4€ today	<input type="checkbox"/>		5,00€ in 3 weeks	<input type="checkbox"/>
12)	4€ today	<input type="checkbox"/>		5,10€ in 3 weeks	<input type="checkbox"/>
13)	4€ today	<input type="checkbox"/>		5,20€ in 3 weeks	<input type="checkbox"/>
14)	4€ today	<input type="checkbox"/>		5,30€ in 3 weeks	<input type="checkbox"/>
15)	4€ today	<input type="checkbox"/>		5,40€ in 3 weeks	<input type="checkbox"/>
16)	4€ today	<input type="checkbox"/>		5,50€ in 3 weeks	<input type="checkbox"/>
17)	4€ today	<input type="checkbox"/>		5,60€ in 3 weeks	<input type="checkbox"/>
18)	4€ today	<input type="checkbox"/>		5,70€ in 3 weeks	<input type="checkbox"/>
19)	4€ today	<input type="checkbox"/>		5,80€ in 3 weeks	<input type="checkbox"/>
20)	4€ today	<input type="checkbox"/>		5,90€ in 3 weeks	<input type="checkbox"/>

Situation 2

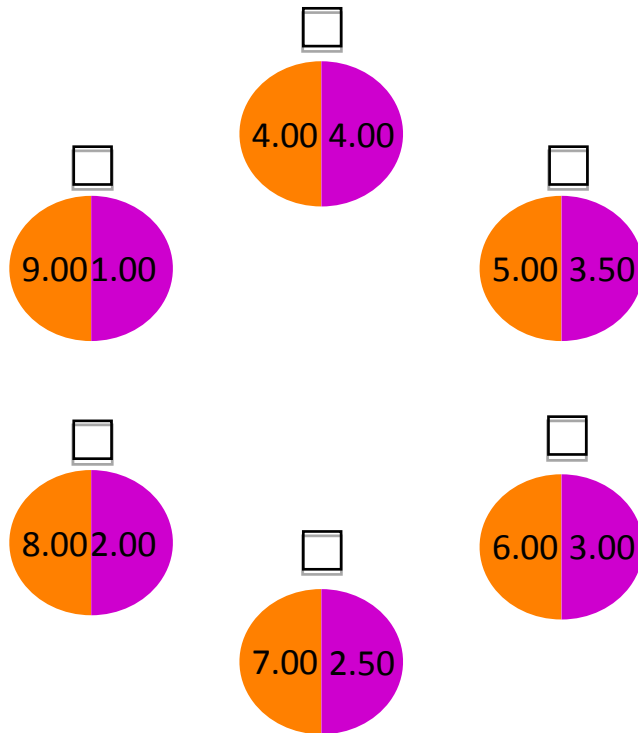
For each row, please choose between 4 Euros in 3 weeks and the rising amount in 6 weeks. Once you have chosen column B for the first time, you should not switch to column A anymore.

	Column A		Column B		
21)	4€ in 3 weeks	<input type="checkbox"/>	or	4,00€ in 6 weeks	<input type="checkbox"/>
22)	4€ in 3 weeks	<input type="checkbox"/>	or	4,10€ in 6 weeks	<input type="checkbox"/>
23)	4€ in 3 weeks	<input type="checkbox"/>	or	4,20€ in 6 weeks	<input type="checkbox"/>
24)	4€ in 3 weeks	<input type="checkbox"/>	or	4,30€ in 6 weeks	<input type="checkbox"/>
25)	4€ in 3 weeks	<input type="checkbox"/>	or	4,40€ in 6 weeks	<input type="checkbox"/>
26)	4€ in 3 weeks	<input type="checkbox"/>	or	4,50€ in 6 weeks	<input type="checkbox"/>
27)	4€ in 3 weeks	<input type="checkbox"/>	or	4,60€ in 6 weeks	<input type="checkbox"/>
28)	4€ in 3 weeks	<input type="checkbox"/>	or	4,70€ in 6 weeks	<input type="checkbox"/>
29)	4€ in 3 weeks	<input type="checkbox"/>	or	4,80€ in 6 weeks	<input type="checkbox"/>
30)	4€ in 3 weeks	<input type="checkbox"/>	or	4,90€ in 6 weeks	<input type="checkbox"/>
31)	4€ in 3 weeks	<input type="checkbox"/>	or	5,00€ in 6 weeks	<input type="checkbox"/>
32)	4€ in 3 weeks	<input type="checkbox"/>	or	5,10€ in 6 weeks	<input type="checkbox"/>
33)	4€ in 3 weeks	<input type="checkbox"/>	or	5,20€ in 6 weeks	<input type="checkbox"/>
34)	4€ in 3 weeks	<input type="checkbox"/>	or	5,30€ in 6 weeks	<input type="checkbox"/>
35)	4€ in 3 weeks	<input type="checkbox"/>	or	5,40€ in 6 weeks	<input type="checkbox"/>
36)	4€ in 3 weeks	<input type="checkbox"/>	or	5,50€ in 6 weeks	<input type="checkbox"/>
37)	4€ in 3 weeks	<input type="checkbox"/>	or	5,60€ in 6 weeks	<input type="checkbox"/>
38)	4€ in 3 weeks	<input type="checkbox"/>	or	5,70€ in 6 weeks	<input type="checkbox"/>
39)	4€ in 3 weeks	<input type="checkbox"/>	or	5,80€ in 6 weeks	<input type="checkbox"/>
40)	4€ in 3 weeks	<input type="checkbox"/>	or	5,90€ in 6 weeks	<input type="checkbox"/>

Decision sheet R

In this situation, you have to choose one out of six coins. Each coin has two sides – orange and pink – showing amounts in Euro. For the coin you choose – no matter which one it is – you have a 50% chance to be paid out the orange side and a 50% chance to be paid out the pink side. Depending on which side faces up, you will receive the amount indicated on the coin (in Euro).

Please choose the coin that appeals best to you.



Decision sheet S

In this situation one person is in charge of the decision on amounts of money paid him- or herself and to another person. The other person has to accept the decision and has no influence on it.

For this task the computer will assign to you another person from this class. The computer will determine at random whether you decide for you and the other person or whether the other person decides for him- or herself and for you.

For each row, decide between column A and column B, now.

	Column A		Column B
1)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 3€ for you and 2€ for the other person <input type="checkbox"/>
2)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 4€ for you and 3€ for the other person <input type="checkbox"/>
3)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 5€ for you and 3€ for the other person <input type="checkbox"/>
4)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 5€ for you and 4€ for the other person <input type="checkbox"/>
5)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 3€ for you and 5€ for the other person <input type="checkbox"/>
6)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 4€ for you and 5€ for the other person <input type="checkbox"/>
7)	4€ for you and 4€ for the other person	<input type="checkbox"/>	or 5€ for you and 6€ for the other person <input type="checkbox"/>

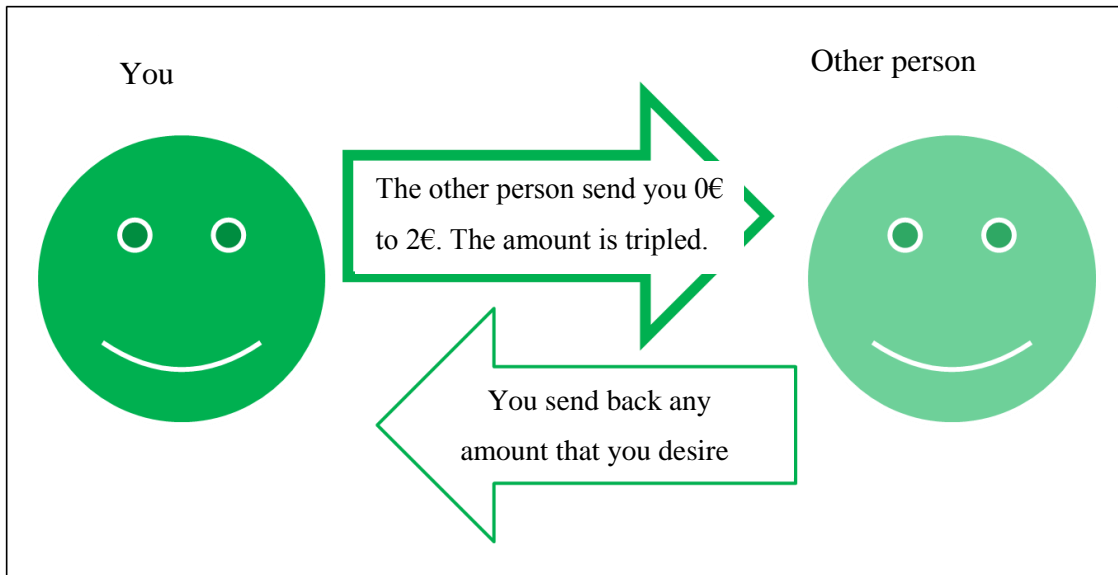
Decision sheet T

In this situation you do not only make a decision for yourself but also for another person from this class. For that purpose, the computer will assign you to a person from this class. You will be shown two situations in which you have to make a decision. The computer will determine your role and the role of your partner at the end of the experiment at random.

Situation 1

Initially, you and the other person receive 2.00 € each. You now have the opportunity to send to your partner between 0€ and 2.00€.

The money sent will be tripled by the organizer. The other person thus receives 3 times as much as you sent. The other person then sends back to you any amount he or she desires. This amount can be between 0€ and 8.00€ ($2.00€ \cdot 3 + 2.00€ = 8.00€$) and will not be tripled.



Your payment amounts to=

2€ – transfer to the other person + transfer from the other person to you

The other person's payment amounts to=

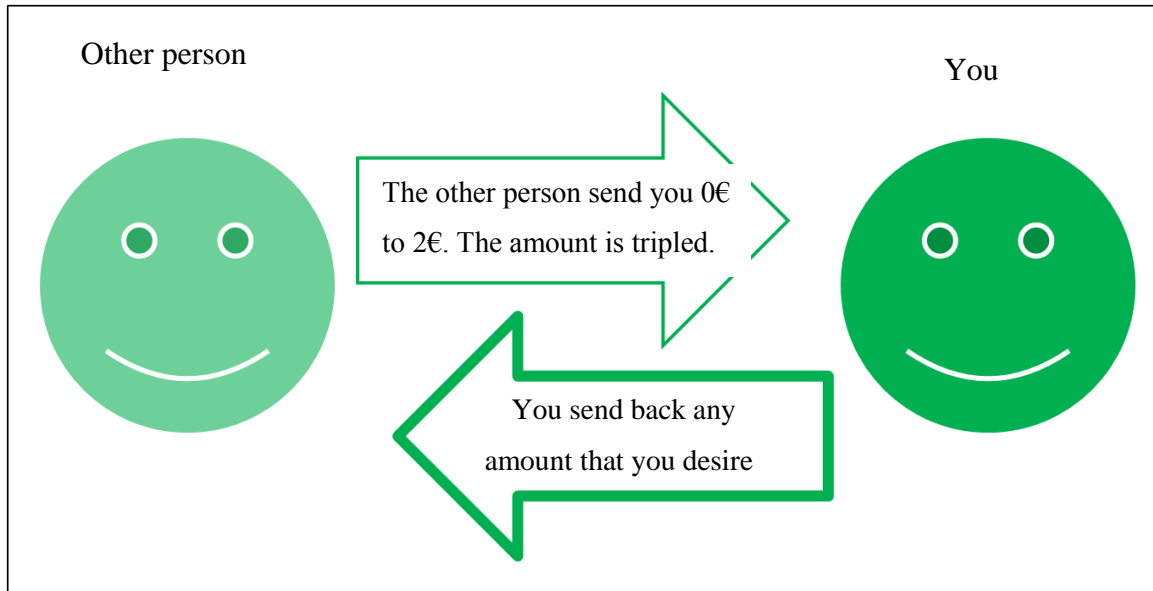
2€ + transfer from you – transfer to you

How much money do you wish to send to the other person? _____

Situation 2

Initially, you and the other person receive 2.00€ each. The other person now has the opportunity to send to you between 0€ and 2.00€. The money sent is tripled by the organizer. You thus receive 3 times as much as the other person sent to you.

You send back any amount that you desire. This amount can be between 0€ and 8.00€ ($2.00€ \times 3 + 2.00€ = 8.00€$) and will not be tripled.



Your payment amounts to=

$2€ + \text{transfer from the other person to you} - \text{transfer to the other person from you}$

The other person's payment amounts to=

$2€ - \text{transfer to you} + \text{transfer from you}$

Please choose how much you wish to send back.

The other person sends you 0€.

How much money do you wish to send back? _____

The other person sends you 0.50€. Hence, you receive 1.50€ (after tripling).

How much money do you wish to send back? _____

The other person sends you 1.00€. Hence, you receive 3.00€ (after tripling).

How much money do you wish to send back? _____

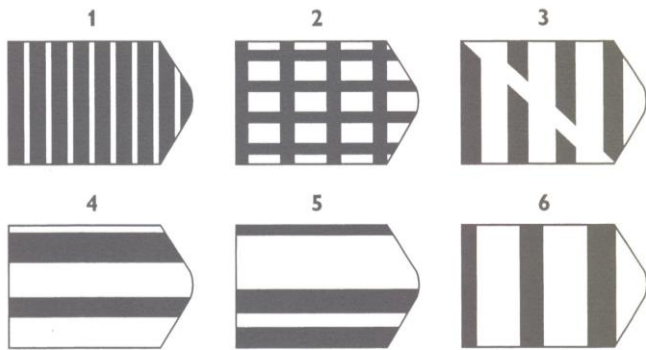
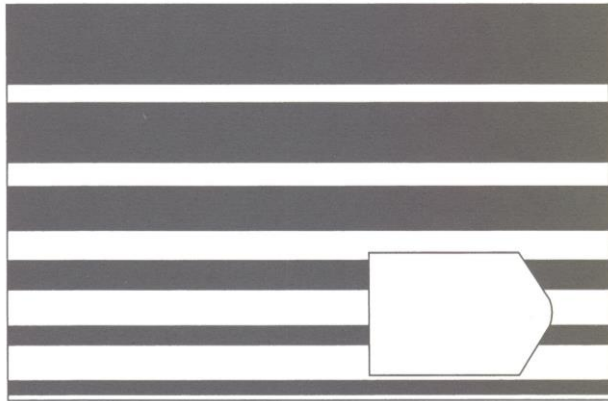
The other person sends you 1.50€. Hence, you receive 4.50€ (after tripling).

How much money do you wish to send back? _____

The other person sends you 2.00€. Hence, you receive 6.00€ (after tripling).

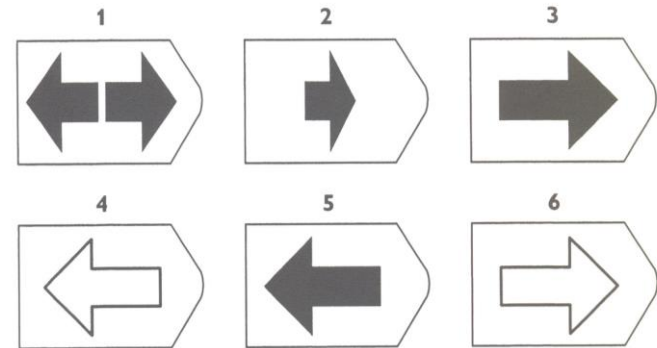
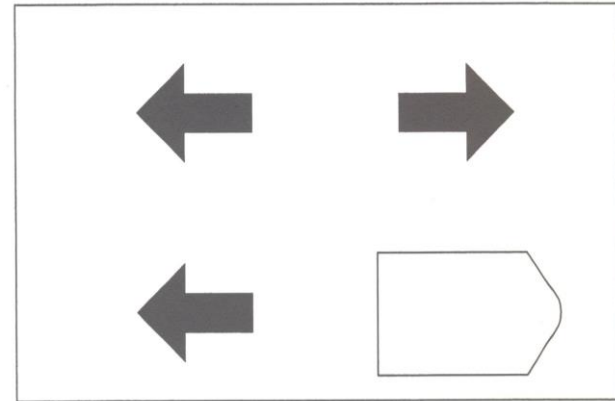
How much money do you wish to send back? _____

2 of 10



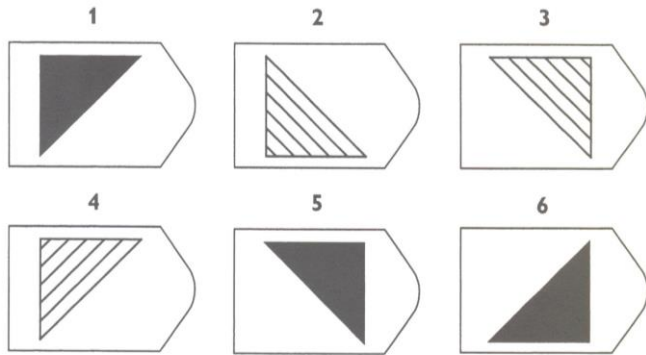
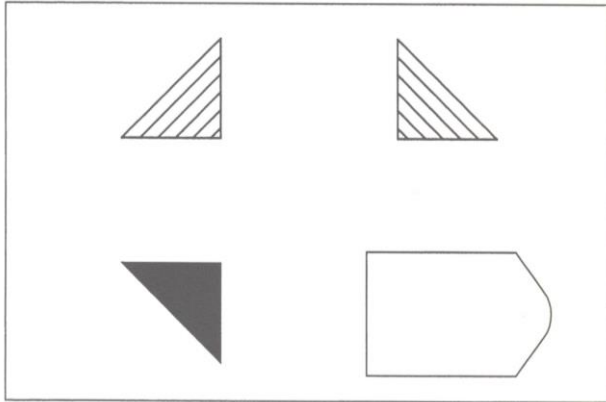
Which option completes the picture? ____

3 of 10



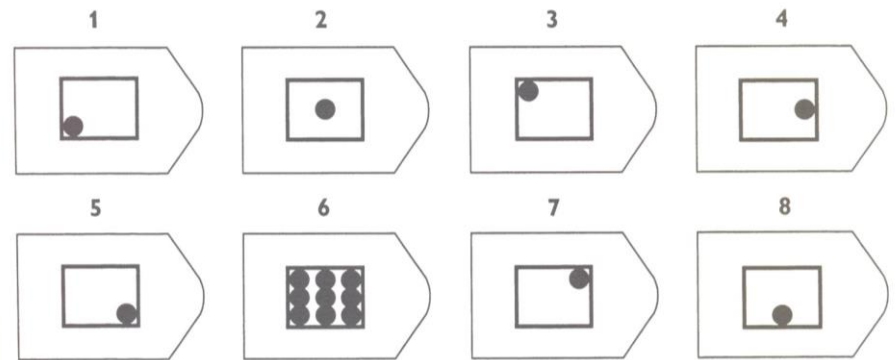
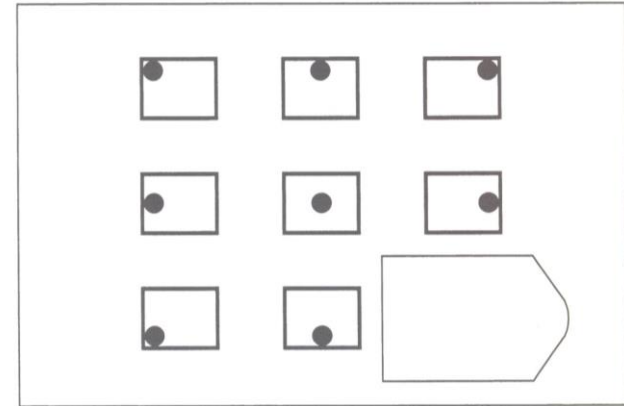
Which option completes the picture? ____

4 of 10



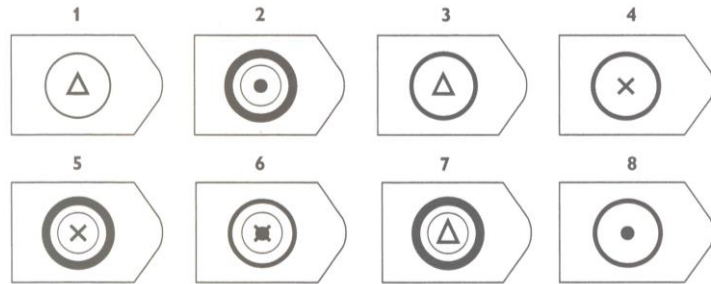
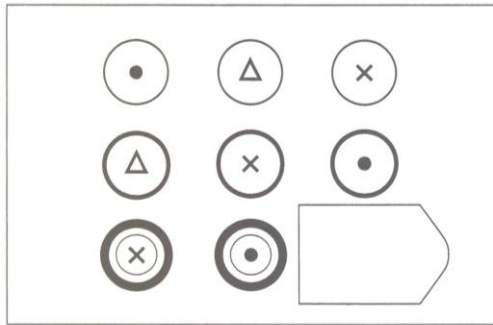
Which option completes the picture? ____

5 of 10



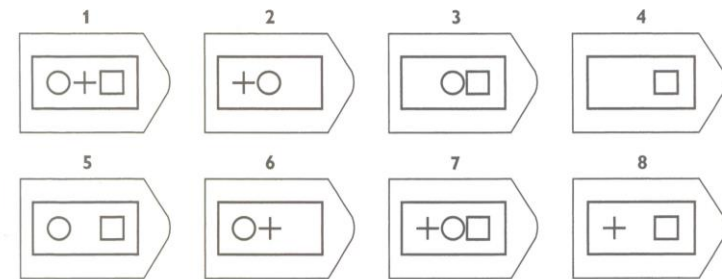
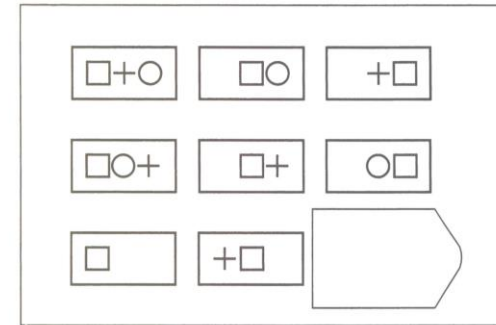
Which option completes the picture? ____

6 of 10



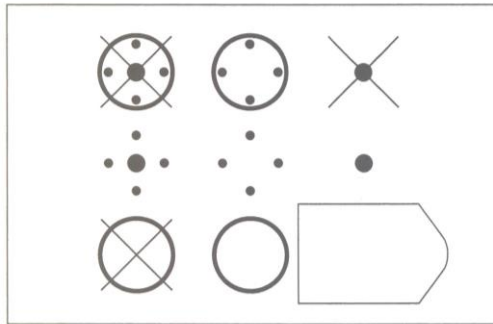
Which option completes the picture? ____

7 of 10



Which option completes the picture? ____

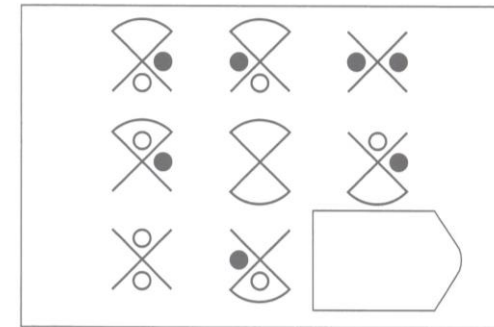
8 of 10



- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8

Which option completes the picture? ____

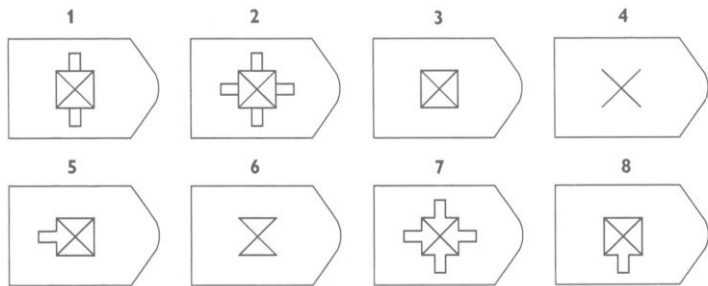
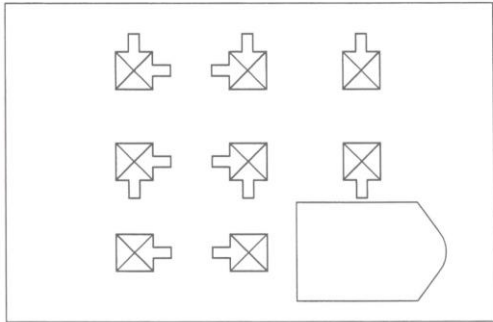
9 of 10



- 1
- 2
- 3
- 4
- 5
- 6
- 7
- 8

Which option completes the picture? ____

10 of 10



Which option completes the picture? _____

Please answer the following 2 questions. For each right answer you receive an additional 0.50€ at the end of the experiment.

How many of the 10 questions above do you think you answered correctly? (between 0 and 10 questions)

_____questions

On average, how many of the 10 questions asked above do you think your classmates answered correctly? (between 0 and 10 questions)

_____questions

Decision sheet L

Depending on the role of the dice you can now receive different amounts.

If you

role a 1 you receive 1€

role a 2 you receive 2€

role a 3 you receive 3€

role a 4 you receive 4€

role a 5 you receive 5€

role a 6/ a star you receive 0€

Please roll the dice in a manner that ensures only you can see the result (e.g. cover the dice with your hand). Remember the number rolled, and then turn the dice on the star (6).

Now fill in the number you rolled.

Which number did you roll? ____

- 13.) How old is your father? _____
- 14.) Does your mother work? Yes No I don't know
- 15.) Does your father work? Yes No I don't know
- 16.) Does your family have a migrant background? Yes No I don't know
- 17.) How would you rate the financial situation of your family relative to your fellow students'?
- much worse worse equal better much better
- 18.) How many cars does your family possess?
- 0 1 2 3 or more
- 19.) How many computers (tablets, laptops included) does your family possess?
- 0 1 2 3 or more
- 20.) How many books does your family possess?
- 0-10 11-25 26-100 101-200 201-500 more than 500
- 21.) Do you have an own room? yes no
- 22.) How often have you traveled as a family during the last two months?
- 0 1 2 3 or more
- 23.) Do you smoke? never rarely sometimes regularly
- 24.) Do you drink alcohol? never rarely sometimes regularly
- 25.) How much pocket money do you get each month? _____
- 26.) Do you work? Yes No
- 27.) If yes, how much do you earn each month?
- 0€-10€ 10€-50€ 50€-100€ more than 100€
- 28.) What do you spend most of your pocket money on?
- | | | |
|---|---------------------------------------|--|
| <input type="checkbox"/> mobile phone bills | <input type="checkbox"/> video games | <input type="checkbox"/> clothes |
| <input type="checkbox"/> magazines | <input type="checkbox"/> cinema | <input type="checkbox"/> going out |
| <input type="checkbox"/> food and beverages | <input type="checkbox"/> sweets | <input type="checkbox"/> beauty products |
| <input type="checkbox"/> music | <input type="checkbox"/> sports | <input type="checkbox"/> concerts |
| <input type="checkbox"/> cigarettes | <input type="checkbox"/> alcohol | <input type="checkbox"/> toys |
| <input type="checkbox"/> saving | <input type="checkbox"/> other: _____ | |

B. Robustness Checks

Regression models

To check whether our results are robust to the use of alternative regression models we redo our regression analysis for risk preferences and trust. We use an ordered Probit regression since the lottery number as well as the amount sent in the trust game is an ordinal variable. Table B. shows the results for risk preferences, while Table B.2 shows the results for trust. In both cases we can confirm the results found in our previous analysis.

TABLE B.1 ROBUSTNESS CHECK: RISK PREFERENCES (ORDERED PROBIT)

	(1)	(2)	(3)	(4)	(5)
Male	0.531*** (0.17)			0.555*** (0.17)	0.392** (0.19)
2 nd born		0.212 (0.14)		0.188 (0.14)	0.384** (0.15)
Mixed sex			0.221* (0.12)	0.263* (0.14)	0.315 (0.22)
Interaction 2nd born*Mixed sex					-0.615** (0.25)
Interaction Men * Mixed sex					0.568** (0.22)
Raven (std.)	0.160** (0.06)	0.151** (0.06)	0.156** (0.06)	0.168*** (0.07)	0.172** (0.07)
Pocket money (std.)	0.158* (0.09)	0.166* (0.09)	0.171* (0.10)	0.148* (0.09)	0.113 (0.09)
FAS (std.)	0.133** (0.06)	0.149*** (0.06)	0.139*** (0.05)	0.136*** (0.05)	0.135** (0.06)
Mother's age (std.)	-0.019 (0.07)	-0.088 (0.07)	-0.040 (0.07)	-0.065 (0.08)	-0.080 (0.08)
No. of Siblings	-0.066 (0.16)	0.013 (0.15)	0.016 (0.15)	-0.068 (0.16)	-0.058 (0.15)
Spacing	-0.058** (0.03)	-0.064** (0.03)	-0.069** (0.03)	-0.066** (0.03)	-0.073*** (0.03)
Cut 1constant	-0.410** (0.17)	-0.485** (0.19)	-0.538*** (0.18)	-0.247 (0.18)	-0.260 (0.20)
Cut 2constant	0.059 (0.17)	-0.029 (0.20)	-0.083 (0.18)	0.227 (0.18)	0.220 (0.20)
Cut 3constant	0.730*** (0.17)	0.623*** (0.20)	0.569*** (0.18)	0.907*** (0.19)	0.908*** (0.20)
Cut 4constant	0.880*** (0.19)	0.768*** (0.22)	0.714*** (0.20)	1.058*** (0.20)	1.062*** (0.22)
constant	1.282*** (0.22)	1.160*** (0.24)	1.106*** (0.21)	1.467*** (0.23)	1.483*** (0.24)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.040	0.025	0.025	0.047	0.056
Prob > chi2/F	0.000	0.000	0.000	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.280
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.000

Notes: Dependent variable is the risk level. Control variables are spacing, number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE B.2 ROBUSTNESS CHECK: TRUST (ORDERED PROBIT)

	(1)	(2)	(3)	(4)	(5)
Male	0.264** (0.13)			0.290** (0.13)	0.168 (0.14)
2 nd born		0.264** (0.13)		0.260** (0.13)	0.245** (0.12)
Mixed sex			0.137 (0.12)	0.156 (0.13)	-0.062 (0.18)
Interaction 2nd born*Mixed sex					0.060 (0.20)
Interaction Men * Mixed sex					0.417* (0.24)
Risk (std.)	0.088 (0.07)	0.107 (0.07)	0.112 (0.07)	0.067 (0.06)	0.058 (0.07)
Raven (std.)	0.101* (0.05)	0.099** (0.05)	0.096* (0.05)	0.110** (0.06)	0.121** (0.06)
Pocket money (std.)	-0.003 (0.05)	0.003 (0.04)	-0.002 (0.05)	-0.004 (0.04)	-0.018 (0.04)
FAS (std.)	0.011 (0.07)	0.027 (0.07)	0.016 (0.07)	0.023 (0.07)	0.017 (0.07)
Mother's age (std.)	0.123* (0.07)	0.053 (0.08)	0.112 (0.07)	0.060 (0.08)	0.048 (0.08)
No. of Siblings	0.098 (0.19)	0.128 (0.18)	0.138 (0.19)	0.086 (0.18)	0.085 (0.18)
Spacing	-0.054* (0.03)	-0.058* (0.03)	-0.059* (0.03)	-0.060* (0.03)	-0.058* (0.03)
Cut 1 constant	-1.605*** (0.23)	-1.581*** (0.23)	-1.659*** (0.23)	-1.456*** (0.24)	-1.523*** (0.24)
Cut 2 constant	-0.987*** (0.24)	-0.956*** (0.24)	-1.037*** (0.25)	-0.832*** (0.25)	-0.902*** (0.25)
Cut 3 constant	0.149 (0.23)	0.180 (0.24)	0.092 (0.24)	0.313 (0.25)	0.248 (0.24)
Cut 4 constant	0.509** (0.25)	0.538** (0.25)	0.448* (0.26)	0.677*** (0.26)	0.615** (0.26)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.022	0.022	0.018	0.028	0.031
Prob > chi2/F	0.002	0.000	0.005	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.145
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.013

Notes: Dependent variable is the amount send (trust).. Control variables are spacing, number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS), risk preferences and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Sample specifications

To check whether our results are robust to a more conservative splitting of the sample with respect to siblings' sex composition, we define single sex as only those cases where all siblings have the same sex also in families with three children. Single sex is here more strictly designed in this setting compared to the sample used in our main analysis. We re-do the analysis for all variables, time preferences, risk preferences and trust and we can confirm our main results.

TABLE B.3 ROBUSTNESS CHECK: TIME PREFERENCES

	(1)	(2)	(3)	(4)	(5)
Male	-0.045 (0.07)			-0.037 (0.07)	-0.115 (0.08)
2 nd born		0.218*** (0.07)		0.214*** (0.07)	0.213** (0.10)
Mixed sex			0.060 (0.10)	0.029 (0.09)	-0.080 (0.16)
Interaction					0.021 (0.17)
2nd born*Mixed sex					0.196 (0.15)
Interaction					0.196 (0.15)
Men * Mixed sex					0.196 (0.15)
Risk (std.)	-0.008 (0.06)	-0.023 (0.06)	-0.015 (0.05)	-0.020 (0.06)	-0.024 (0.06)
Raven (std.)	0.025 (0.05)	0.029 (0.05)	0.027 (0.05)	0.029 (0.05)	0.033 (0.05)
Pocket money (std.)	0.070* (0.04)	0.071* (0.04)	0.069* (0.04)	0.071* (0.04)	0.065* (0.04)
FAS (std.)	-0.173*** (0.05)	-0.165*** (0.05)	-0.174*** (0.05)	-0.165*** (0.05)	-0.165*** (0.05)
Mother's age (std.)	0.064 (0.05)	0.013 (0.05)	0.064 (0.05)	0.013 (0.05)	0.005 (0.05)
No. of Siblings	0.201* (0.10)	0.188* (0.10)	0.165 (0.11)	0.180 (0.11)	0.171 (0.11)
Spacing	0.009 (0.03)	0.008 (0.03)	0.008 (0.03)	0.007 (0.03)	0.009 (0.03)
constant	4.669*** (0.15)	4.551*** (0.15)	4.667*** (0.16)	4.573*** (0.15)	4.618*** (0.14)
Sigma constant	0.663*** (0.03)	0.657*** (0.03)	0.663*** (0.04)	0.656*** (0.03)	0.655*** (0.03)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.037	0.047	0.037	0.047	0.050
Prob > chi2/F	0.002	0.000	0.002	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.049
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.535

Notes: Dependent variable is the future equivalent. Control variables are spacing, number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS) and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE B.4 ROBUSTNESS CHECK: RISK PREFERENCES

	(1)	(2)	(3)	(4)	(5)
Male	1.444*** (0.42)			1.503*** (0.43)	1.080** (0.50)
2 nd born		0.583 (0.39)		0.477 (0.39)	0.827** (0.41)
Mixed sex			0.529 (0.33)	0.654* (0.38)	0.520 (0.60)
Interaction 2nd born*Mixed sex					-0.752 (0.49)
Interaction Men * Mixed sex					0.982 (0.63)
Raven (std.)	0.428** (0.18)	0.414** (0.18)	0.416** (0.18)	0.431** (0.18)	0.423** (0.18)
Pocket money (std.)	0.452* (0.26)	0.487* (0.27)	0.505* (0.28)	0.427* (0.24)	0.369 (0.22)
FAS (std.)	0.333** (0.16)	0.390** (0.16)	0.362** (0.15)	0.337** (0.15)	0.335** (0.15)
Mother's age (std.)	-0.037 (0.20)	-0.230 (0.20)	-0.103 (0.20)	-0.159 (0.20)	-0.196 (0.21)
No. of Siblings	-0.156 (0.44)	0.059 (0.43)	-0.193 (0.45)	-0.483 (0.49)	-0.485 (0.48)
Spacing	-0.159** (0.08)	-0.178** (0.08)	-0.186** (0.08)	-0.170** (0.07)	-0.167** (0.07)
constant	2.137*** (0.47)	2.383*** (0.57)	2.799*** (0.53)	2.013*** (0.56)	2.079*** (0.60)
Sigma constant	2.760*** (0.19)	2.839*** (0.17)	2.843*** (0.17)	2.729*** (0.19)	2.713*** (0.19)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.036	0.022	0.022	0.041	0.044
Prob > chi2/F	0.000	0.000	0.000	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.88
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.000

Notes: Dependent variable is the risk level. Control variables are spacing, number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

TABLE B.5 ROBUSTNESS CHECK: TRUST

	(1)	(2)	(3)	(4)	(5)
Male	0.240** (0.11)			0.269** (0.12)	0.116 (0.15)
2 nd born		0.226** (0.11)		0.211* (0.11)	0.301** (0.12)
Mixed sex			0.158 (0.11)	0.175 (0.11)	0.083 (0.16)
Interaction 2nd born*Mixed sex					-0.180 (0.19)
Interaction Men * Mixed sex					0.380* (0.22)
Risk (std.)	0.091* (0.05)	0.108* (0.06)	0.113* (0.06)	0.072 (0.05)	0.062 (0.05)
Raven (std.)	0.084* (0.05)	0.081* (0.04)	0.078* (0.04)	0.089* (0.05)	0.092** (0.05)
Pocket money (std.)	-0.005 (0.04)	0.001 (0.04)	-0.003 (0.04)	-0.005 (0.04)	-0.021 (0.04)
FAS (std.)	0.014 (0.06)	0.029 (0.06)	0.019 (0.06)	0.023 (0.05)	0.025 (0.06)
Mother's age (std.)	0.101* (0.06)	0.041 (0.07)	0.090 (0.06)	0.048 (0.07)	0.034 (0.07)
No. of Siblings	0.100 (0.16)	0.129 (0.15)	0.059 (0.15)	0.002 (0.15)	0.001 (0.16)
Spacing	-0.047* (0.03)	-0.051* (0.03)	-0.052* (0.03)	-0.052* (0.03)	-0.051* (0.03)
constant	1.387*** (0.20)	1.366*** (0.20)	1.506*** (0.20)	1.321*** (0.20)	1.355*** (0.20)
Sigma constant	0.884*** (0.06)	0.885*** (0.06)	0.889*** (0.06)	0.875*** (0.06)	0.870*** (0.06)
No. of Obs.	311	311	311	311	311
Pseudo R2	0.028	0.027	0.024	0.037	0.042
Prob > chi2/F	0.000	0.000	0.002	0.000	0.000
Wald tests for joint effects (p-values)					
H_0 : no birth order effect in mixed sex families ($\beta_{2nd} + \beta_{interaction1} = 0$)					0.484
H_0 : no gender effect in mixed sex families ($\beta_{gender} + \beta_{interaction2} = 0$)					0.003

Notes: Dependent variable is the amount send (trust).. Control variables are number of siblings, monthly pocket money, cognitive reflection (raven), socio-economic background (FAS), risk preferences and age of mother. Robust standard errors clustered at the classroom level are given below the coefficient in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

EIDESSTATTLICHE ERKLÄRUNG

Erklärung zum selbständigen Verfassen der Arbeit:

Ich erkläre hiermit, dass ich meine Doktorarbeit „Explaining Inequality in Economic Outcomes: An Empirical and Experimental Approach“ selbstständig und ohne fremde Hilfe angefertigt habe und dass ich als Koautor maßgeblich zu den weiteren Fachartikeln beigetragen habe. Alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen der aufgeführten Beiträge wurden besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert.

Lena Mareike Detlefsen

Kiel, 2018