Three Essays on Socio-economic Transitions: The Case of East and West Germany

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Contents

Zusammenfassung **1**

Summary **5**

1 Exploring the Determinants of Fertility: The Case of German Reunification **8**
1.1 Introduction 9
1.2 Changing Fertility in East Germany 11
1.2.1 A Cohort of Interest 14
1.3 Model 15
1.4 Data, Simulation, and Estimation Strategy 20
1.4.1 Data 20
1.4.2 Preference Structure 21
1.4.3 Maternal Leave and Childcare Costs 22
1.4.4 Household Income 24
1.4.5 Starting Values for the Simulation 26
1.5 Results 27
1.5.1 Benchmark Model: Fit of the Model 27
1.5.2 Counterfactual Experiments 27
1.6 Conclusions 33
Appendix 1.A The Iterative Form of the Quadratic Income Profile 33
Appendix 1.B Maternity Leave Payments in Germany 33
Appendix 1.C Probability of Maternal Re-entry into Employment 38
Appendix 1.D Working with the Microcensus 39
1.D.1 The Deterministic Profile of Spousal Income 40
1.D.2 The Starting Values for Spousal Income after 1991 41
Appendix 1.E Working with the GSOEP 41
1.E.1 Stochastic Components of the Income Processes 42
1.E.2 Saving Level 43
Bibliography of Chapter 1 44

2 Job Displacement and Training Activities: Human Capital Accumulation during the East German Transition **46**
2.1 Introduction 47
2.2 Related Literature 48
2.3 Data 50
2.3.1 Variables 51
2.3.2 Matching 52

2.4 Methods and Assumptions . . . 55
2.4.1 Baseline Model . . . 55
2.4.2 Transition versus Stable Economy . . . 56
2.4.3 Before and after Re-entry into Employment . . . 57
2.4.4 Young versus Old East Germans . . . 58
2.5 Results . . . 58
2.5.1 The Displacement Effect on Training Activities . . . 58
2.5.2 The Effect on Training under Re-employment . . . 60
2.5.3 The Effect on Training for Young and Old Workers . . . 61
2.6 Limitations and Robustness . . . 62
2.6.1 Limitations of the Data . . . 62
2.6.2 Further Limitations and Robustness Checks . . . 63
2.7 Summary and Conclusion . . . 67
Appendix 2.A Regression Tables . . . 68
Bibliography of Chapter 2 . . . 76

3 Sources of German Income Inequality across Time and Space 80
3.1 Introduction . . . 81
3.2 A Brief Review of Methodical Approaches . . . 83
3.3 Data and Descriptive Statistics . . . 84
3.4 Analytical Framework . . . 91
3.4.1 Household Categorization . . . 91
3.4.2 Counterfactual Income Distributions . . . 92
3.4.3 Inequality Evaluation . . . 96
3.5 Results . . . 97
3.5.1 West Germany across Time: 1976 versus 2011 . . . 97
3.5.2 Germany in 2011 across Space: East versus West . . . 102
3.5.3 Limitations . . . 106
3.6 Discussion and Conclusion . . . 106
Appendix 3.A Detailed Description of the Counterfactual Exercises . . . 108
Appendix 3.B Derivation of the Income Levels . . . 115
Appendix 3.C Sample Size Reduction . . . 116
Bibliography of Chapter 3 . . . 117

Complete Bibliography 123

Acknowledgements – Danksagung 133

Abgrenzung 135

List of Figures

1.1 The Total Fertility Rate in West and East Germany 12
1.2 Fertility Rates in West and East Germany, by Birth Cohort 13
1.3 Children ever Born: Average Number of Children at the Age of 40 14
1.4 Detecting Cohorts of Interest 15
1.5 Fit of the Model 27
1.6 Counterfactual Exercises 29

2.3.1 Share of Displaced People Aged 25 to 55 51
2.5.1 Displacement Effect on Training 59
2.5.2 Displacement Effect on Training in East Germany, by Current Employment . . 61
2.5.3 Displacement Effect on Training in East Germany, by Age Group 62
2.6.1 East-West-Difference of the Displacement Effect on Employment 67

3.3.1 Normalized Age Distribution of Household Heads and Their Partners 86
3.3.2 Employment 90
3.5.1 Distributions of Net Household Income 98

List of Tables

1.1 Parameterization, Preference Structure . . . 22
1.2 Parameterization, Maternal Leave and Childcare Costs . . . 22
1.3 Parameterization, Household Income . . . 24
1.4 Parameterization, Starting Values . . . 26
1.5 Model Fit of Average Female Income . . . 28
1.6 Simulated Births from 1992 to 2008 . . . 29
1.7 Simulated Births from 1992 to 2008, by Birth Order . . . 31
1.B.1 Overview of the Changes in Legal Regulations . . . 34
1.B.2 Child-rearing Benefits per Child (before Grant Reduction) . . . 35
1.B.3 Underlying Parental Income . . . 35
1.B.4 Yearly Income Limits and Monthly Payment Reduction . . . 36

2.3.1 Sample Characteristics . . . 54
2.6.1 Industry Prior to the Plant Closure . . . 64
2.6.2 The Effect of Displacement on Living in West Germany . . . 66
2.A.1 The Effect of Displacement on Training of East and West Germans . . . 69
2.A.2 The Effect of Displacement on Training of East Germans . . . 70
2.A.3 The Effect of Displacement on Training, Robustness Checks: Industry (East) . 71
2.A.4 The Effect of Displacement on Training, Robustness Checks: Industry (All) . . 72
2.A.5 The Effect of Displacement on Training, Robustness Checks: Firm Size (East) . 73
2.A.6 The Effect of Displacement on Training, Robustness Checks: Firm Size (All) . 74
2.A.7 The Effect of Displacement on Employment of East and West Germans . . . 75

3.3.1 Household Size . . . 87
3.3.2 Education . . . 88
3.4.1 Categorization of Households . . . 91
3.5.1 Mean Income and Income Inequality . . . 98
3.5.2 Income Inequality Change when West Germans in 2011 Have the Household Characteristics from 1976 . . . 99
3.5.3 Differences in Inequality under Distinct Mating Schemes . . . 101
3.5.4 Income Inequality Change when West Germans in 2011 Have the Household Characteristics from the East . . . 104
3.5.5 Income Inequality Change when East Germans in 2011 Have the Household Characteristics from the West . . . 105
3.C.1 Descriptive Statistics before and after the Sample Size Reductions . . . 116

Zusammenfassung

Diese Doktorarbeit besteht aus drei Kapiteln, die jeweils eigenständige Forschungsarbeiten darstellen. Alle drei Arbeiten habe ich während meines Doktorandenstudiums an der Graduiertenschule Entscheidungswissenschaften an der Universität Konstanz verfasst. Die ersten zwei Kapitel untersuchen, wie der wirtschaftliche Umbruch, der in Ostdeutschland mit der deutschen Wiedervereinigung verbunden war, das Verhalten der ostdeutschen Bevölkerung veränderte. Das dritte Kapitel befasst sich mit der Fragestellung, wie Einkommensungleichheit mit der sozio-ökonomischen Zusammensetzung eines Landes in Verbindung steht. Im Rahmen dieser Forschungsarbeite nutze ich unter anderem aus, dass die einstige Spaltung Deutschlands weiterhin die sozio-ökonomische Entwicklungen in Ost- und Westdeutschland beeinflusst.

Wieso ist es noch immer von Interesse, Effekte der deutschen Wiedervereinigung zu studieren?
Die deutsche Wiedervereinigung im Jahr 1990 ist für die ostdeutsche Bevölkerung mit einem umfangreichen wirtschaftlichen Wandel einhergegangen. Dieser Umbruch beeinflusste nicht nur das Leben der Ostdeutschen in den 1990er Jahren, seine Folgen sind noch immer sichtbar. Viele Ostdeutsche erlebten Karrierebrüche, die sich noch in den Altersrenten Jahrzehnte später widerspiegeln. Der demografische Schock, der mit dem Geburtenrückgang Anfang der 1990er Jahre verbunden ist, wird ebenfalls die Zukunft prägen.
Unerwartet fiel im November 1989 die Mauer zwischen der Bundesrepublik Deutschland und der Deutschen Demokratischen Republik. Innerhalb kurzer Zeit erfolgte die Wiedervereinigung: Bereits im Oktober 1990 wurde das westdeutsche rechtliche, politische und institutionelle System auf Ostdeutschland übertragen. Die ostdeutsche Bevölkerung musste sich schnell an die neuen Gegebenheiten anpassen. Mit dieser Geschwindigkeit des Transformationsprozesses bietet die deutsche Wiedervereinigung ein einzigartiges Beispiel für die Erforschung, wie Menschen auf neue politische und ökonomische Rahmenbedingungen reagieren. Damit haben Studien, die die Effekte der Wiedervereinigung untersuchen, eine Bedeutung, die weit über Deutschland hinausgeht. Ich nutze dieses “natürliche Experiment” der Wiedervereinigung in den ersten zwei Kapiteln der Dissertation.
Da demographische und sozio-ökonomische Entwicklungen sowie auch Änderungen kultureller Normen langwierige Prozesse sind, unterscheiden sich die sozio-ökonomischen Zusammenset-

zungen der ostdeutschen und der westdeutschen Bevölkerung noch immer. Selbst nach mehr als 20 Jahren im selben politischen Umfeld sind, beispielsweise, verheiratete Frauen in Ostdeutschland wesentlich öfter erwerbstätig als verheiratete Frauen in Westdeutschland. Diese einzigartige Spaltung der Bevölkerung innerhalb eines Landes ermöglicht die Durchführung kontrafaktischer Experimente unter zwei sozio-ökonomisch unterschiedlich zusammengesetzten Bevölkerungsteilen, die unter dem gleichen politischen System leben. Im dritten Kapitel nutze ich diese Gelegenheit und führe kontrafaktische Experimente mit den unterschiedlichen Bevölkerungszusammensetzungen in Ost- und Westdeutschland durch.

Kapitel 1 beschäftigt sich mit der Fragestellung, wie wirtschaftliche und institutionelle Rahmenbedingungen Geburtsentscheidungen beeinflussen. Im Vergleich zu Frauen in der Bundesrepublik Deutschland hatten Frauen in der Deutschen Demokratischen Republik (DDR) mehr Kinder. Außerdem waren Mütter in der DDR wesentlich jünger. Mit der Wiedervereinigung und dem damit einhergehenden wirtschaftlichen, institutionellen und politischen Wandel haben ostdeutsche Frauen ihr Geburtenverhalten den westdeutschen Frauen angepasst. Da die ostdeutschen Frauen zum Zeitpunkt der Wiedervereinigung bereits mehr Kinder hatten als westdeutsche Frauen des gleichen Alters, gingen die Geburtenzahlen für ostdeutsche Frauen jeden Alters zunächst stark zurück. Manche ostdeutsche Frauen – meist ältere - bekamen keine (weiteren) Kinder mehr, andere schoben Geburten auf. Im Rahmen dieses Geburtenaufschubs stiegen die Geburtenzahlen ab 1994 wieder. In Zusammenarbeit mit Georgi Kocharkov simuliere ich das fertile Leben ostdeutscher Frauen in der neuen, durch die Wiedervereinigung geschaffenen Situation. Die Simulation wird genutzt, um eine Reihe kontrafaktischer Experimente durchzuführen. Die Ergebnisse dieser Experimente zeigen, dass die längere Elternzeit und die gestiegene Humankapitalentwertung während der Elternzeit den Geburtenrückgang in den 1990er Jahren erklären. Das starke Einkommenswachstum des Partners, der nicht in Elternzeit geht, ist verantwortlich für den Anstieg der Geburten ab dem Alter von 30 Jahren.

Kapitel 2 behandelt die Auswirkung von Entlassungen nach der Wiedervereinigung auf Humankapitalakkumulation. Mit dem Übergang von der Planwirtschaft zur Marktwirtschaft am Anfang der 1990er Jahre wurden viele ostdeutsche Betriebe geschlossen. Viele Menschen verloren ihre Arbeit. Gleichzeitig wurde ihr firmenspezifisches Humankapital wertlos. Zudem war ihr Humankapital an einer Planwirtschaft ausgerichtet und noch nicht an die moderne Marktwirtschaft angepasst. Mittels eines dreifachen Differenzen-Schätzers (triple difference estimator) untersuche ich, wie die entlassenen ostdeutschen Arbeiter auf diese doppelte Entwertung ihres Humankapitals reagierten. Ich vergleiche den Effekt des Jobverlusts auf Schulungs- und Ausbildungsaktivitäten zwischen Ost- und Westdeutschen. Im Einklang mit der Humankapitaltheorie finde ich, dass Ostdeutsche signifikant mehr Zeit in Schulungs- und Ausbildungsaktivitäten investieren, falls sie ein oder zwei Jahre zuvor entlassen wurden. Dieser Anstieg an Schulungs- und Ausbildungsaktivitäten ist geringer für ältere Arbeitnehmer und nicht beobachtbar für Westdeutsche. Außerdem weisen die Schätzungen darauf hin, dass die entlassenen Ostdeutschen die zusätzlichen Schulungs- und Ausbildungsaktivitäten dann durchführen, wenn sie keiner Beschäftigung nachgehen. Sobald sie eine neue Arbeit aufnehmen, reduzieren sich ihre Schulungs- und Ausbildungsaktivitäten auf ein Niveau, das niedriger liegt als ohne die betriebsbedingte Entlassung. Infolgedessen könnten Betriebsschließungen in wirtschaftlichen Umbruchsituationen sogar positive Nebeneffekte haben, indem sie den Arbeitern ermöglichen, der mit dem Umbruch einhergehenden Humankapitalentwertung früher entgegenzuwirken.

In *Kapitel 3* untersuche ich die Interaktion von Einkommensungleichheit und sozio-ökonomischen Veränderungen. Seit den 1970er Jahren ist die Einkommensungleichheit zwischen deutschen Haushalten signifikant gestiegen. Um die Einflüsse sozio-ökonomischer Trends auf Einkommensungleichheit zu quantifizieren, konstruiere ich kontrafaktische Verteilungen über Netto-Haushaltseinkommen mit Hilfe eines umfangreichen deutschen Datensatzes. Ich verwende eine Methodik, die es mir erlaubt, indirekte Einflüsse, wie beispielsweise den Einfluss des Bildungsstandes auf die Wahrscheinlichkeit einer Vollzeitbeschäftigung, zu berücksichtigen. Außerdem ermöglicht es der verwendete methodische Ansatz, dass, bezüglich des Bildungsstandes des Haushaltes, der kontrafaktische Bildungsstand von Männern und Frauen getrennt vom kontrafaktischen Aufeinandertreffen (Matching) der Bildungsstände innerhalb der Haushalte untersucht werden können. Im Gegensatz zu vorangegangenen Studien untersuche ich eine Reihe verschiedener sozio-ökonomischer Faktoren und vergleiche diese detailiert in Hinblick auf ihre Beziehung zur Einkommensungleichheit. Zunächst analysiere ich, wie diverse sozio-ökonomische Trends mit dem Anstieg an Einkommensungleichheit einhergehen. Danach untersuche ich, soweit mir bekannt erstmalig, wie sozio-ökonomische Angleichungen zwischen Ost- und Westdeutschland Einkommensungleichheit beeinflussen können. Die Ergebnisse zeigen, dass der Anstieg an Single-Haushalten einen großen Anteil des Anstiegs an Einkommensungleichheit seit den 1970er Jahre erklären kann. Der Anstieg an Einkommensungleichheit ist ebenfalls verbunden mit Änderungen im Beschäftigungsverhältnis von Männern und alleinstehenden Frauen. Für das Jahr 2011 suggerieren meine Ergebnisse, dass die stärkere Arbeitsmarktbindung ostdeutscher verheirateter Frauen verbunden mit der höheren Arbeitslosigkeit in Ostdeutschland mehr Ungleichheit erzeugt als die westdeutsche Arbeitsmarktsituation. Außerdem weisen die Ergebnisse darauf hin, dass kleinere Haushalte, welche häufiger in Ost- als in Westdeutschland zu finden sind, zusätzlich verstärkend auf Einkommensungleichheit wirken; nur der homogene Bildungsstand in der ostdeutschen Bevölkerung wirkt diesen ungleichheitsfördernden Bedingungen entgegen. Ich finde keine signifikanten Auswirkungen der alternden Bevölkerung und auch keine Auswirkungen bezüglich des Matchings unterschiedlicher Bildungsstände innerhalb der Haushalte.

Eine mögliche Erklärung dafür ist, dass das deutsche Steuer- und Transfersystem bereits den größten Teil der Ungleichheit, die durch Matching unterschiedlicher Bildungsstände innerhalb der Haushalte entsteht, ausgleicht.

Summary

This thesis comprises three chapters. Each chapter represents an independent research paper. The three papers are the outcome of my doctoral studies at the Graduate School of Decision Sciences at the University of Konstanz. In the first two chapters, I investigate how the economic transition associated with the German reunification changed the behavior of East Germans. The third chapter focuses on the question how the socio-economic composition of a country relates to income inequality. In this work, I exploit, besides societal trends over time, the fact that the former division of Germany still influences the socio-economic composition of East and West Germany.

Why is it still interesting to study effects of the German reunification? The German Reunification in 1990 came with enormous economic changes for the East German population. These changes influenced not only the life of East Germans in the 1990s, its consequences are still visible today. The East Germans' career breaks from the 1990s are reflected in the pension levels decades later. The demographic shock associated with the low fertility during the transition will also be recognizable in the future.

The Wall between the Federal German Republic (FRG, West Germany) and the German Democratic Republic (GDR, East Germany) fell unexpectedly in November 1989. The reunification evolved fast. In October 1990, the legal, political, and institutional system of West Germany was fully extended to East Germany. The East German population was forced to assimilate quickly. The speed of this transition makes the German reunification a unique environment to study how people's behavior adapts to a new political and economic environment. In doing this, the studies on the German reunification are of high relevance - not only for Germany. In the first two chapters, I use the exogenous shock of the German reunification as a "natural experiment" to study how several determinants of the economic transition affect birth rates and human capital accumulation after job losses.

Since demographic and socio-economic processes, as well as cultural norms, are long–lasting, the East Germans' socio-economic composition still differs substantially from that of their West German peers. Even after sharing the political and institutional environment for more than 20 years, the labor force participation of married females, for instance, is much higher in the East

than in the West. This unique split in the country's population allows to conduct counterfactual exercises with two different socio-economic parts of the population that live under the same political and institutional regime. In the third chapter, I utilize this opportunity and conduct counterfactual exercises with the two different socio-economic compositions of the East and West German population to study how income inequality relates to different socio-economic factors.

Chapter 1 considers economic and institutional determinants of fertility decisions. Before the reunification, East German women were having more children than West German women. Moreover, East German mothers were significantly younger. With the reunification, the economic, institutional, and political environment changed and East German females adapted their child-bearing behavior to that of their West German peers. Given that, at the time of the reunification, East German females had already more children than West Germans of the same age, fertility rates of East German women declined across all ages. Some East German females, mostly older females, decided not to have anymore children, while others postponed (further) births. In the scope of this postponement process, total fertility rose again from 1994 onward. In collaboration with Georgi Kocharkov, we construct a life-cycle model to simulate the fertility decisions of East German females in the new environment which these females faced after the reunification. The simulation is used to conduct a series of counterfactual experiments. The results of these experiments show that longer maternal leaves and the increased human capital depreciation during maternity can explain the fertility drop observed in the 1990s. The strong growth of spousal income is responsible for the postponement of fertility after the age of 30.

Chapter 2 focuses on job displacement and human capital accumulation after the reunification. With the East German transition to a market economy in the early 1990s, many East German plants closed; a significant share of the East German population lost their job. This, combined with the fact that human capital in East Germany was not yet aligned to the modern market economy, creates a double effect of human capital depreciation. Using a difference-in-difference-in-difference set-up, I study how displaced East German workers reacted to this double depreciation and compare the effect of displacement on training activities between East and West German workers. I find that East Germans increased their time investment in adult training significantly when they were displaced one or two years earlier. This increase in adult training is lower for older workers and not observable for West Germans. Moreover, the results suggest that when East Germans lose their job due to a plant closure, they do more training as soon as they are not employed anymore; but when they find a new employment, they invest significantly less time in training as they would have done without the job displacement. In that sense, plant closures may have a useful side-effect in a transition period as they allow people to counteract the human capital depreciation associated with the transition sooner.

Chapter 3 focuses on the interaction of income inequality and socio-economic changes. Income inequality rose in Germany since the 1970s. To quantify the impact of socio-economic trends on inequality, I construct counterfactual distributions of net household income with rich German data. I utilize a methodology which controls for marital sorting in education and allows for indirect influences such as the influence of education on employment. In contrast to previous studies, I analyze a set of various socio-economic factors and compare them in detail regarding their relation to income inequality. First, I investigate how different socio-economic trends are associated with the rise in income inequality over time. Then, I conduct counterfactual exercises, as far as I know for the first time, to analyze how socio-economic convergence between East and West Germany would influence income inequality. I find that the prevalence of singlehood accounts for the observed increase in inequality to a vast extent. The inequality increase is also associated with a change of employment among males and single females. For 2011, my results suggest that the stronger labor market attachment of East German married females combined with the high East German unemployment produces even more income inequality than West German employment, smaller households boost East German inequality, but the East Germans' level of education works against it. Neither across time nor across space, I find a significant impact of the aging society. Moreover, positive assortative mating in the levels of education appears to be irrelevant for inequality in the German households' net income. One explanation for this finding could be that the German tax and transfer system already equalizes the vast extent of income inequality created by assortative mating in the spouses' education levels.

CHAPTER 1

Exploring the Determinants of Fertility: The Case of German Reunification

1.1 Introduction

The fall of the Berlin Wall and the reunification of East and West Germany is one of the most important historical events in 20th-century Europe. It brought about the end of the Communist era in Central and Eastern Europe and reunited the two divided parts of today's largest European economy. Fertility behavior in East and West Germany was very different before the reunification. In particular, the total fertility rate (that is, the hypothetical number of births that a woman would have over her life estimated in a given year) in the East was around 1.76 in the last decade before the reunification.[1] On the other hand, the fertility rate in the 1980s in West Germany was around 1.37. One of the most striking socio-economic developments due to the reunification was the dramatic fertility response observed in East Germany in the 1990s and the 2000s. The total fertility rate started decreasing immediately after the fall of the Berlin Wall and reached a record-low level of 0.77 in 1994.[2]

Our empirical analysis on the cohort-specific fertility of East German females points out that upon reunification all East German cohorts who have started their fertile life had more children than their West German counterparts. All of these cohorts reduced their per-period fertility which led to the observed fertility drop. In the later stages of their fertile life, these transitioning cohorts started adapting to the fertility behavior of West German females. Younger East German cohorts who started their fertile life after the reunification exhibit very similar age-specific fertility rates to their West German peers.

The demographic development presented above gives a unique opportunity to study the economic determinants of fertility behavior. Females who have started their fertile life under the communist regime reacted strongly to the new economic situation after 1989. We choose to analyze the determinants of the post-unification fertility for the cohort of females born in 1968. This cohort represents very well the fertility transition behavior in East Germany in the 1990s and the 2000s. They started their fertile life in the former German Democratic Republic (GDR). Upon reunification, they were 22 years old, and have achieved an average fertility of 0.447 which was above the fertility of their West German counterparts of 0.141. This was followed by a very abrupt fertility drop which was most pronounced in 1994. Later on, their age-specific fertility stopped declining and even increased when they turned 30. Their complete fertility of 1.509 (at age 40) was lower than the previous East German cohorts but still higher than the corresponding West German cohort (1.430).

We construct and estimate a life-cycle model of female fertility in order to analyze the determinants of the fertility transition of the 1968 birth cohort in East Germany. In our model, females

[1]Fertility numbers are taken from the Human Fertility Database (Max Planck Institute for Demographic Research (Germany) and Vienna Institute of Demography (Austria), available at www.humanfertility.org, data downloaded on January 8, 2015).

[2]See Figure 1.1a for further details.

derive utility out of consumption and the number of children present in the household. Their income and the income of their spouse rise with age and are subject to idiosyncratic shocks. Thus, they make decisions over consumption, savings, and whether or not to have a child at each stage of their life-cycle. The new-born children require them to leave the labor market (maternity leave). The labor market re-entry happens stochastically and it depends on the age of their youngest child. When all their existing children are at least six years old, they return for sure in the labor market. Active mothers in the labor market face childcare costs which depend on the age of their children under six years of age.

We simulate the model using estimated parameters for the spousal income process, external childcare costs, maternity leave payments, and the maternal re-entry probability. The simulation of the model starts in 1991 when the females are 23 years old and finishes when they are 40 years old. The starting values for the simulation in terms of income, female employment status, the number of children born, and the age of these children are taken from the data. The parameters for the female income process cannot be estimated directly from the data because of the unobserved depreciation during maternal leaves. These parameters along with the preference parameters for fertility are estimated by the method of simulated moments so that the model matches the life-cycle evolution of female income and their age-specific fertility rates. The overall fit of the estimated model is good.

The model is used to gauge the economic factors that determine the fertility transition of the 1968 birth cohort after the reunification. We perform a series of counterfactual experiments using the model in which we *(i)* mute the depreciation of human capital during maternal leave, *(ii)* shorten maternity leaves to pre-unification levels, *(iii)* switch off income risk, or *(iv)* income growth. The experiments show that the maternal human capital depreciation and the longer maternal leaves after reunification can explain the fertility drop observed in the 1990s. The mechanism behind this result is related to the fact that human capital depreciation after the reunification led to a sharp rise in the cost of children, especially at a younger age. The growth of the spousal income, on the other hand, is the main driver behind the postponement of fertility after the age of 30. Rising income in the model produces an income effect which boosts fertility up when income levels are high. The other factors play a secondary role in shaping the fertility decisions of females from the 1968 birth cohort in East Germany.

Episodes of rapid demographic change have attracted the attention of economists for a long time. Our paper relates to this literature. Several existing papers have focused their attention on the rapid expansion of fertility after the World War II. The so-called "baby boom" era was an episode of large fertility expansion in the aftermath of the war. Greenwood et al. (2005) challenge the conventional wisdom that the baby boom occurred as a consequence of the gloomy years of the Great Depression and the World War II throughout which starting a family was difficult. Instead, they propose that the technological progress in the household sector made it easier for households to raise children. An alternative explanation for the occurrence of the baby boom is supplied by Doepke et al. (2015). They argue that the rapid expansion of fertility in the 1950s was due to the increased labor-force participation of females throughout the war mobilization. Women who reach adulthood in the 1950s would then face an increased competition on the labor market which would drive them to exit and have children earlier.

Another episode of fast fertility change was the dramatic decline in birth rates in the years of the World War I. It is estimated that between 1915 and 1919 1.4 million children were not born in France due to the large drop in births. This amounts to 3.5% of the population of France in those years, and to the total amount of the military losses due to the war (1.4 million). Similar was the situation in Germany. The estimated loss in terms of children was 3.2 million (5% of the population) which exceeds the war losses of 2 million lives. Vandenbroucke (2014) develops a fertility theory in which French wives face *(i)* uncertainty about the survival of their husbands at war, *(ii)* a temporary labor productivity drop followed by a post-war expansion, and *(iii)* a compensation scheme for mobilization of husbands. His model generates most of the slow down in births throughout the war. The quantitative analysis points out that the increased probability of the husband dying in the war is the leading factor behind the reduced fertility levels in war-time France.

Unlike the existing work, we concentrate on a more recent period of fast fertility change due to a large economic shock. In addition, our structural model is estimated to a particular cohort which clearly exhibits the transitional fertility behavior of East German females.[3]

The paper proceeds as follows. Section 1.2 describes the fertility changes in East Germany after the reunification. Section 1.3 presents the structural model. In Section 1.4, we discuss data and estimation work. Section 1.5 outlines the model fit and the counterfactual experiments and their results. In the final section, we draw conclusions.

1.2 Changing Fertility in East Germany

In this section, we first describe in detail the available fertility data for Germany. Then, we provide a description of East and West German fertility before and especially after the reunification in 1990. In particular, the East German drop in total fertility and the subsequent catch up is compared to the mostly stable West German fertility rates.

Fertility rates in East Germany changed dramatically after the reunification in 1990. Total and age-specific fertility rates finally adjusted to West German patterns in 2010. Here we utilize data

[3]Using the German reunification as an exogenous economic shock in structural economic models is not new. Fuchs-Schündeln (2008) takes the German reunification as a natural experiment and builds a life-cycle model which matches the observed patterns of the saving rate in East and West Germany. The quantitative analysis points out that the precautionary motive is essential in replicating the observed pattern of the saving rate in East and West Germany.

from the Human Fertility Database to describe this adjustment process.

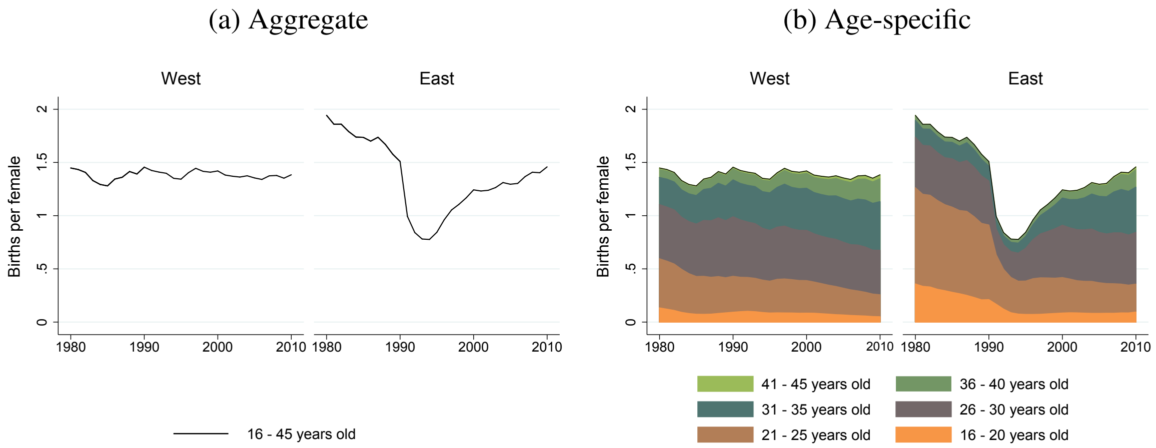
Fertility Data

Before 1990, all East German data has been collected by the State Central Administration for Statistics (*Staatliche Zentralverwaltung für Statistik*) of the German Democratic Republic (GDR). In the Federal Republic of Germany (FRG) data collection is governed by the Federal Office of Statistics (*Statistisches Bundesamt*). Nowadays, all live births delivered within the borders of Germany, East or West, and after reunification, are registered in the Human Fertility Database (HFD). There, aggregated fertility rates per year and cohort are available for East and West Germany separately since 1952.[4]

History of German Fertility

The total fertility rate (TFR) is a constructed measure of yearly fertility. It states how many children a woman would bear throughout her life if the number of children that she bears at each age equals the current age-specific fertility rate. Shortly, the TFR is the sum of age-specific fertility rates (AFR). Figure 1.1a shows that East and West German women gave birth to the same number of children on average in 1990. The TFR in both parts of Germany was about 1.5. After the reunification, total fertility decreased slowly to approximately 1.4 children per woman in West Germany in the course of the next 20 years, whereas in East Germany fertility declined by 50% within four years (to 0.77 in 1994) and recovered only slowly to pre-unification levels in 2010.

Figure 1.1: The Total Fertility Rate in West and East Germany



The drop in East German fertility is unique. As Goldstein & Kreyenfeld (2011) point out that,

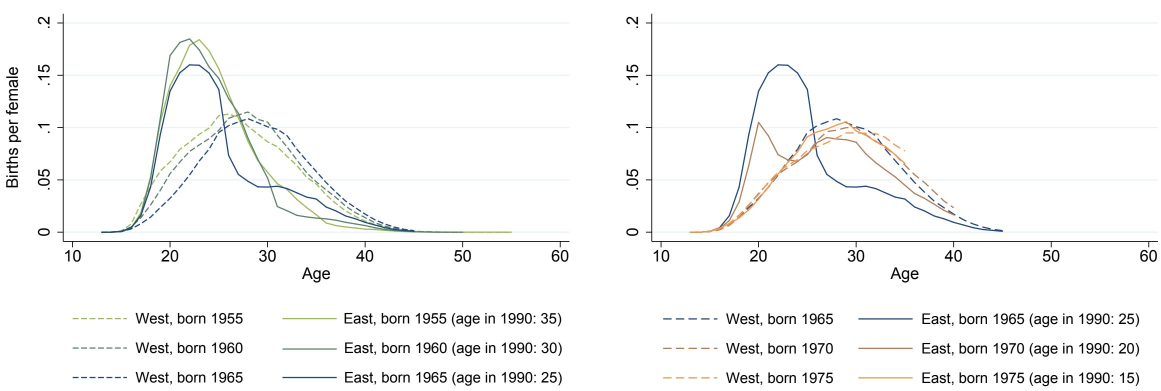
[4]From 1958 to 1989, live births in East and West Germany are defined slightly differently. The definition of live births has been more restrictive in the GDR. For more details, see Kreyenfeld et al. (2016) (Table 2).

if the former German Democratic Republic still existed, the fertility drop in the early 1990s would have been the lowest fertility rate ever recorded for a country. Figure 1.1b shows how age-specific fertility rates contribute to the decline of the total fertility rate. Females of every age group from the East had fewer children during the fertility drop. Moreover, since 1990 they gave birth to fewer children when they were younger than 25 years of age, while, for females older than 25 years, childbearing became more popular since 2000. In 2010, the contribution of the different age groups to the TFR is very similar for East and West Germany. This pattern indicates that East German females postponed childbearing in the 1990s and, thereby, adapted the West German fertility behavior.

Figures 1.2a and 1.2b depict the cohort-specific fertility rates for females who had been in the end, in the middle and in the beginning of their fertile period at the time of the reunification. Three important facts can be derived from these data. First, fertility in the former GDR peaked when females were in their early 20s whereas in West Germany fertility is more spread out over the life-cycle with a peak in the late 20s. Second, compared to the older East German cohorts, younger cohorts get fewer children early in life and more children later in life. Third, East German females who have been 15 years old when the Berlin Wall fell, and thus, have not started their fertility life before the reunification have very similar fertility rates as their West German peers.

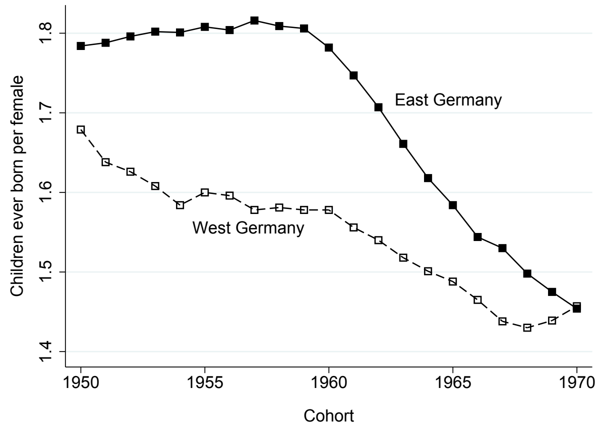
Figure 1.2: Fertility Rates in West and East Germany, by Birth Cohort

(a) Cohorts Born 1955, 1960 and 1965 (b) Cohorts Born 1965, 1970 and 1975



The TFR drop documented above implies that the number of children ever born to a woman in East Germany decreased to West German levels after the reunification (from 1.78 in 1990 to 1.48 in 2010). Figure 1.3 depicts this convergence by plotting the average number of children born to a 40-year-old female in East and West Germany by year of birth. To sum up, the facts point out that at the time of the reunification East German females of any cohort had more children than their West German peers. East German fertility declined afterwards because it adapted to the West German cohort fertility and timing of childbearing. Females who started their fertile life

Figure 1.3: Children ever Born: Average Number of Children at the Age of 40



after the reunification have very similar fertility behavior in both parts of Germany.[5]

1.2.1 A Cohort of Interest

In this paper, we are mostly interested in the East German female cohorts which exhibit a transitional fertility behavior. They have starting conditions similar to previous East German cohorts but upon transition change dramatically their fertility decisions. The East German birth cohort of women born in 1968 represents the transitional fertility process that followed the German reunification very well. First, women from this East German birth cohort started their fertile life in East Germany. Until 1990, i.e. until they turned 22 years old, they represent the typical childbearing behavior of the former GDR. Their age-specific birth rate is comparably large in their early fertile life. In 1989, when these women turned 21, they gave birth to 0.129 children on average (see Figure 1.4a). Second, immediately after the reunification, their age-specific fertility rate dropped strongly - even under the rate of their West German counterparts. In 1994, this fertility drop was most pronounced. The cohort born in 1968 gave birth on average to 0.068 children in this year. For West German females born in 1968, the number was approximately 25% larger (0.085) (see Figure 1.4b). Thirdly, the East German fertility rate of the 1968 cohort stopped declining and even increased again in the late 1990s. From the age of 30 onward, the age-specific fertility rate of the 1968 birth cohort even overstates the fertility rate of older East German cohorts (see Figure 1.4a). As the cohort of 1968 did not bear more children than older East German cohorts (see Figure 1.3), the high fertility rates at older ages represent a postponement of fertility decisions.[6]

Why pick exactly the cohort of 1968? A second look at Figures 1.2a and 1.2b reveals that the transitional fertility behavior of East German women starts showing in the life cycle fertility

[5]This in line with the results of Conrad et al. (1996).

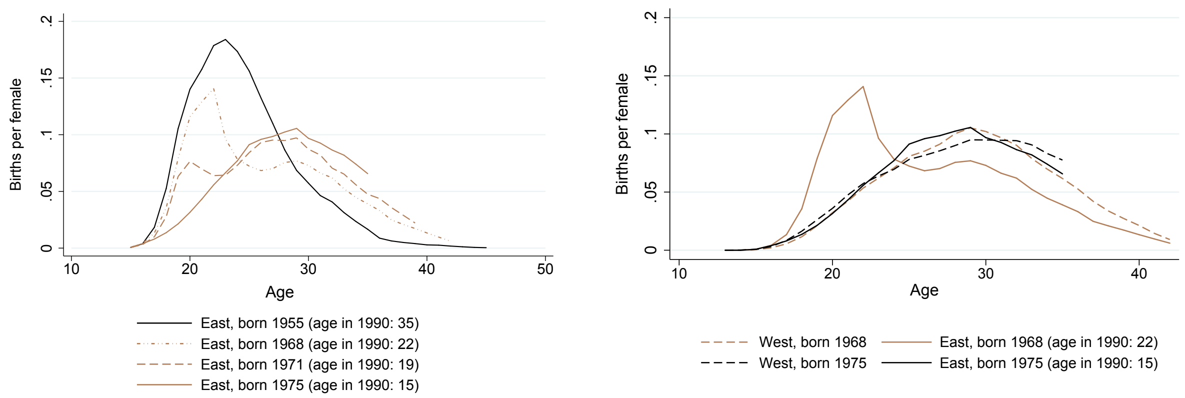
[6]The cumulative fertility rate at age 40 amounts 1.498 for the females born in 1968; the last cohort who turned 40 in the GDR, i.e. in 1989, had on average 1.797 children at the same age.

profile of the 1960 birth cohort. The behavior described in the previous paragraph is still pronounced in the 1970 birth cohort. As Figure 1.4b points out, this behavior completely disappears in the 1975 East German birth cohort. We have inspected the life cycle fertility profiles of each cohort between 1960 and 1970 and found out that the 1968 birth cohort exhibits the clearest pattern of the fertility transition of East German women upon reunification.

As outlined in the introduction, analyzing the determinants of the fertility behavior of this transitioning cohort through the prism of a structural model hinges on the assumption that the fertility preferences of the 1968 cohort are already formed before the event of the reunification. This is a plausible assumption in this case. The East German women from this cohort were 22 years old when the communist regime was overthrown. They have already started their fertility process and had approximately 0.447 (1990) of their lifetime fertility rate of 1.498 (at age 40).

Figure 1.4: Detecting Cohorts of Interest

(a) Fertility of Selected Cohorts in East Germany (b) Fertility of Selected Cohorts in East and West Germany



1.3 Model

We propose a structural model to describe the fertility decisions of the 1968 cohort of East German women. The fertility decisions are made by a female whose life-cycle lasts for T periods. Each model period corresponds to a year. In the first T_f periods, the female is fertile. Afterwards, the female is sterile but may be unemployed in order to care for her children.

Household's Preferences and Decision Making

It is assumed that the female is the sole decision maker of the household and that her preferences represent the preferences of the household. Her preferences are defined over the number of children n_t attached to her in each period t and consumption levels c_t. The preferences are represented by the expected life time utility,

$$\sum_{t=1}^{T} \beta^{t-1} \boldsymbol{E} \left[U \left(\frac{c_t}{\phi(2, n_t)} \right) + \theta W(n_t) \right],$$

where $\beta \in (0, 1)$ is a discount factor, and the parameter θ weights the per period utility out of children $W(n_t)$ versus the per period utility of consumption $U\left(\frac{c_t}{\phi(2,n_t)}\right)$. The function $\phi(2, \cdot)$ is the OECD–modified adult equivalence scale assuming two adults in the household. Thus, the equivalence scale is defined as

$$\phi(2, n) = 1.5 + 0.3n.$$

The utility functions U and W are of constant relative risk aversion (CRRA),

$$U\left(\frac{c}{\phi(2, n)}\right) = \frac{\left(\frac{c}{\phi(2,n)}\right)^{1-\rho_U} - 1}{1 - \rho_U} \text{ and } W(n) = \frac{(n + \kappa)^{1-\rho_W} - 1}{1 - \rho_W},$$

where the presence of the parameter $\kappa > 0$ ensures that having no child endows finite utility. In every period $t = 1, \ldots, T$, the female makes decisions about household consumption c_t and savings s_t. In the first $T_f < T$ periods, she chooses whether she wants to become pregnant ($I_t = 1$) or not ($I_t = 0$). If pregnancy occurs, the birth occurs with probability 1 at the start of the next period.[7] Therefore, next period number of children is given by

$$n_t = n_{t-1} + I_{t-1}.$$

Note that I_{t-k} signifies whether the household features a $k - 1$ years old child in period t.

Maternity Leave and Childcare

When a birth occurs in a period, the female exits the labor market and receives maternity leave payments M for up to two years. These payments are modeled after the German maternal leave programs *Erziehungsgeld* and *Elterngeld*. The paid amount depends on the number of children, their age and the parental income. Moreover, the payment structure might change over time. A detailed description of the maternity leave programs in Germany is presented in Appendix 1.B. Women in Germany can get up to two years of paid maternity leave. Mothers re-enter the labor market with some exogenous probability p_{empl}. This can happen even before the end of their paid maternity leave period. This re-entry probability summarizes both the availability of childcare facilities and the situation in the labor market in the time period. It depends on the age of the

[7]We assume that there is no uncertainty about the number of pregnancies and births. See Cavalcanti et al. (2017) for a model environment in which fertility is stochastic.

youngest child and the female's employment status in the last period. We assume that if there are no children younger than six years of age in the household, the female is always active. In addition, labor market participation is also sure when the female has worked in the previous period and does not have a birth in the current period. The re-entry probability for mothers with children who are less than six years old is conditional on the age of the youngest child in the family and is given by $p_{\text{age youngest kid}}$. This probability of re-entry applies to mothers who have stayed home in the previous period due to the presence of children or have a birth in the current period. Suppose that the indicator function $\mathbf{1}_{\text{empl},t}$ takes the value of one if the female is employed in the current period, and zero otherwise. Then, the function below summarizes the probabilistic structure of labor market re-entry of mothers,

$$p_{\text{empl}}(\mathbf{1}_{\text{empl},t-1}, (I_{t-i})_{i=1}^{6}) = \begin{cases} p_{\text{age youngest kid}}, & \text{if } I_{t-1} = 1 \\ p_{\text{age youngest kid}}, & \text{if } \mathbf{1}_{\text{empl},t-1} = 0, \sum_{i=2}^{6} I_{t-i} > 0 \\ 1, & \text{if } \mathbf{1}_{\text{empl},t-1} = 1, I_{t-1} = 0 \\ 1, & \text{if } \sum_{i=1}^{6} I_{t-i} = 0 \end{cases} . \tag{1.1}$$

Although, in reality, some females are never returning to the labor market and some childless females are non-employed, we do not model long-term non-employment here. Instead, we focus on the transition back to employment of mothers with young children and how this effects fertility decisions. The variation in the income process realizations (described next) allows for low income paths which correspond to the long-term non-employed females.

It is assumed that children younger than six years of age require childcare provided either by childcare facilities or by their mothers staying at home full-time.[8] Non-employed mothers care for their young children at home and do not utilize external childcare whereas employed mothers face fixed childcare costs which depend on the age and the number of the children. The monetary childcare costs $care_t$ are given by

$$care_t = \mathbf{1}_{\text{empl},t} \left(\gamma_{\text{baby}} \sum_{i=1}^{3} I_{t-i} + \gamma_{\text{kindergarten}} \sum_{i=4}^{6} I_{t-i} \right), \tag{1.2}$$

where $\gamma_{\text{baby}} > 0$ and $\gamma_{\text{kindergarten}} > 0$ are the costs per child for children younger than three years and for pre-school children. If the female is not employed in period t, $\mathbf{1}_{empl,t} = 0$, there are no childcare costs incurred.

[8]Of course, also older children may require childcare after school in the afternoon. However, including this option in our model would enlarge the state space and, hence, increase the computational complexity of the model.

Household Income Structure

Household income y_t is the sum of the female's own income y_t^f, maternity leave payments M, and residual household income y_t^m,

$$y_t = \begin{cases} \mathbf{1}_{\text{spouse},t}\, y_t^m + y_t^f, & \text{if } \mathbf{1}_{\text{empl},t} = 1 \\ \mathbf{1}_{\text{spouse},t}\, y_t^m + M, & \text{if } \mathbf{1}_{\text{empl},t} = 0 \text{ and } I_{t-1} + I_{t-2} > 0 \\ \mathbf{1}_{\text{spouse},t}\, y_t^m, & \text{if } \mathbf{1}_{\text{empl},t} = 0 \text{ and } I_{t-1} + I_{t-2} = 0 \end{cases}, \tag{1.3}$$

where $\mathbf{1}_{\text{spouse},t}$ is an indicator signifying the presence of a spouse in the household. The conditions $\mathbf{1}_{\text{empl},t} = 0$ and $I_{t-1} + I_{t-2} > 0$ represent the requirements for maternity leave payments, that is, that the mother is unemployed and the youngest child is either in the first or second year of life. The spousal household income y_t^m can be viewed as the income of a present spouse.[9] The probability of having a spouse at age t conditional on not having one at age $t-1$ is given by $p_{\text{spouse},t}$. We assume that once a spouse is present in the family, he never disappears. Therefore, the indicator for the presence of a spouse is

$$\mathbf{1}_{\text{spouse},t} = \begin{cases} 1, & \text{with prob. } p_{\text{spouse},\,t} \quad \text{if } \mathbf{1}_{\text{spouse},t-1} = 0 \\ 0, & \text{with prob. } 1 - p_{\text{spouse},t} \quad \text{if } \mathbf{1}_{\text{spouse},t-1} = 0 \\ 1, & \quad \text{if } \mathbf{1}_{\text{spouse},t-1} = 1 \end{cases}. \tag{1.4}$$

The income levels of females and their spouses are the sum of a deterministic and a stochastic component,

$$\log y_t^{j} = \log \xi_t^j + \log \omega_t^{j}, \tag{1.5}$$

where $j \in \{m, f\}$. The deterministic parts of both income processes, ξ_t^f and ξ_t^m, depend on the age of the female. The spousal income deterministic component ξ_t^m is given by

$$\xi_t^m = \xi_{t-1}^m + \beta_0^m + \beta_1^m t. \tag{1.6}$$

This formulation imposes a quadratic age profile of male's deterministic income. The female income process has a the deterministic component ξ_t^f which takes into account potential depreci-

[9]Note that in Germany a divorced male has the obligation to pay alimony to his ex-wife and his children if the female's income is insufficient. This payment is ensured until the female is remarried.

ation of human capital due to motherhood. It is represented by

$$\xi_t^f = \begin{cases} \xi_{t-1}^f + \beta_0^f + \beta_1^f t & \text{if } \mathbf{1}_{\text{empl},t} = 1 \\ \delta \xi_{t-1}^f & \text{else} \end{cases}, \tag{1.7}$$

where the depreciation rate is given by δ. The parameters β_0^f and β_1^f drive the income process in case of employment. Note that in case the female does not bear any children, the age profile of her deterministic income is again a quadratic function of age.
The stochastic components of income $\log \omega_t^j$ follow a bivariate AR(1) process,

$$\begin{pmatrix} \log \omega_t^m \\ \log \omega_t^f \end{pmatrix} = \varphi \begin{pmatrix} \log \omega_{t-1}^m \\ \log \omega_{t-1}^f \end{pmatrix} + \begin{pmatrix} \varepsilon_t^m \\ \varepsilon_t^f \end{pmatrix}, \quad \begin{pmatrix} \varepsilon_t^m \\ \varepsilon_t^f \end{pmatrix} \sim N\left(0, \Sigma_\varepsilon\right) \tag{1.8}$$

with a common persistence parameter φ and a variance-covariance matrix Σ_ε.
We allow in the model social benefits S to ensure positive household income after childcare costs. Household income after childcare costs is denoted by

$$y_t^{AC} = \max(y_t - care_t, S). \tag{1.9}$$

Household Problem

Females chose how much to consume and save, and whether to have a child in each period of their fertile life. At each point of the life-cycle, these choices should satisfy the simple household budget constraint

$$y_t^{AC} + ra_t = c_t + a_{t+1}, \tag{1.10}$$

which states that consumption c_t and savings for the next period a_{t+1} should equal household income and interest rate payments on the savings, $y_t^{AC} + ra_t$.
The decision-making process ensures that the choices made at any age t maximize the total discounted future utility out of consumption and children. The household maximization problem is formulated recursively with the use of a vector of state variables

$$s_t = \left(n_t, a_t, \mathbf{1}_{\text{spouse},t}, \omega_t^m, \xi_t^m, \omega_t^f, \xi_t^f, \mathbf{1}_{\text{empl},t}, \{I_{t-k}\}_{k=1}^{6} \right).$$

The recursive formulation of the problem for each age $t = 1, \cdots, T$ is given by

$$V_t(s_t) = \max_{a_{t+1}, I_t} U\left(\frac{c_t}{\phi(2, n_t)}\right) + \theta W(n_t) + \beta \boldsymbol{E}_t[V_{t+1}(s_{t+1})]$$

subject to

$$n_{t+1} = n_t + I_t,$$

and subject to the expressions for the maternity leave probability (1.1), the childcare costs (1.2), the income processes (1.3)-(1.9), and the budget constraint (1.10).

1.4 Data, Simulation, and Estimation Strategy

Using the model outlined in the previous section, we simulate the fertile life cycle of 45,000 of females from the 1968 birth cohort from 1991 onward. We start the simulation when these women are 23 years old and finish it when they are 40 years old.[10] Therefore, the fertile life span in the model is $T_f = 17$.[11] For the simulation, we need starting values describing the household situation of these females in 1991. These starting values include household income level, income composition, employment status of the female, the number of children born to the family, and the age of these children.

Besides the starting values, the income process, external childcare costs, maternity leave payments, the maternal re-entry probability, and the probability of having spousal income are required for the simulation. Most of these are determined by parameters which are set exogenously. These parameters are either provided by previous work or can be estimated from the data. The parameters which describe the female income profile cannot be estimated directly because of the unobserved depreciation during (maternal) leaves and the sorting into maternal leave (motherhood). We use the method of simulated moments (MSM) to estimate the female income process. The unknown preference parameters for fertility are also inferred by the method of simulated moments.

The following subsection describes the data used and its limits. The estimation of the parameters as well as the derivation of the starting values is introduced in the subsequent subsections.

1.4.1 Data

We utilize three different databases: the Human Fertility Database, the German Microcensus, and the German Socio-Economic Panel. Each data set has its own advantages and limitations, which are described below.

The Human Fertility Database (HFD) collects data of all registered (live) births within Germany since 1952.[12] The HFD provides aggregate fertility rates and no information on the parental background. Birth order-specific fertility rates are not available between 1990 and 2008, but age-specific fertility rates are available for each cohort in this time span. These age-specific

[10]The first detailed data which is available for East German households dates back to 1991.

[11]We simulate six additional of years of life after the end of the fertile life-cycle to allow for children born in the last fertile period to go through childcare, and all mothers to return to their active labor market status.

[12]If a German citizen delivers a child outside of Germany, the birth is not automatically registered, but the parents can apply for registration.

fertility rates are used as data targets when we utilize the method of simulated moments to infer the parameters characterizing the preferences for children.

The German Microcensus (MC) is the largest household survey in Europe. It covers 0.7% of all German households. The survey includes all persons in Germany who have the right of residence and are living in private households or collective households either at their main or secondary residence. We focus on the data of private households with at most two adults (one female and at most one male) and at most two generations (household head and, if existing, spouse and children) living at the main residence in East Germany. We use the MC data for the years 1991, 1996, 2001, 2006 and 2011 to estimate the deterministic male income profile and to derive data targets for inferring the female income profile. Moreover, we use the detailed microdata of the MC to generate starting values for the simulation. The variables of interest are the female net income, the net household income, the number of children in the household, and the age of all children.[13]

The longitudinal data of the German Socio–Economic Panel (GSOEP) dates from 1984. For 1990 (2005), about 14,000 (21,000) persons have been interviewed successfully which makes it hard for our complex analysis to derive input data based only on the GSOEP. An advantage of the GSOEP is that it provides information on savings. Moreover, contrary to the MC, it is a longitudinal survey; this longitudinal information is used to estimate the parameters characterizing the stochastic parts of the income processes.[14]

Monetary information in the data sets is provided in different currencies and in nominal terms. In 1990, the West German Deutsche Mark (DM) also became the official currency for East Germany. Twelve years later, in 2002, the Deutsche Mark was abolished and the Euro (EUR) was introduced. Therefore, we express all income levels in 2011 EUR values.

1.4.2 Preference Structure

The household's preference structure is characterized by the discount factor β, and the parameters θ, ρ_U, ρ_W, and κ. The discount factor and the coefficient of relative risk aversion with respect to consumption are set to 0.96, and 2, respectively. These values have been used before by Fuchs-Schündeln (2008). The real interest rate, $r = 0.0184$, is also taken from Fuchs-Schündeln (2008). The weighting parameter θ, the coefficient of relative risk aversion with respect to fertility ρ_W, and the parameter κ which determines the utility of having no children are estimated by applying the method of simulated moments (MSM). For every year between 1991 and 2008, the targeted data moments are derived from East German fertility data of the HFD. In particular,

[13]Data before 2005 do not include the concrete age of a child but how many children are in a specific age group. The length of these age groups differ between 3 to 5 years. More details on the preparation of the MC data is provided in the beginning of Appendix 1.D.

[14]Information on the preparation of the GSOEP data is provided in the beginning of Appendix 1.E.

we target 17 age-specific fertility rates for the female cohort born in 1968. Table 1.1 summarizes the parameters characterizing the preference structure, their values, and source.

Table 1.1: Parameterization, Preference Structure

Parameters	Symbol	Value	Source / Estimation
Risk-free rate	r_U	0.0184	Fuchs-Schündeln (2008)
Discount factor	β_j	0.96	Fuchs-Schündeln (2008)
CRRA coefficient, consumption	ρ_U	2.0	Fuchs-Schündeln (2008)
Weighting parameter, kids	θ	0.32	MSM, target: age-specific fertility (HDF)
CRRA coefficent, kids	ρ_W	4.20	
No-child parameter	κ	4.80	

1.4.3 Maternal Leave and Childcare Costs

The model presented in Section 1.3 includes exogenously determined maternal leave payments, probability of female re-entry into employment, and external childcare costs. Table 1.2 provides a summary of the parameters and the corresponding sources. The following subsections describe in detail the derivation of the parameters.

Table 1.2: Parameterization, Maternal Leave and Childcare Costs

Parameters	Symbol	Value	Source
Maternal leave payment	M	(endogenous)	German law: BErzGG, BEEG
Probability maternal LFP	p_0	9.19 %	Grunow & Müller (2012)
	p_1	35.67 %	Grunow & Müller (2012)
	p_2	42.61 %	Grunow & Müller (2012)
	p_3	43.01 %	Grunow & Müller (2012)
	p_4	19.89 %	Grunow & Müller (2012)
	p_5	14.11 %	Grunow & Müller (2012)
External childcare costs	γ_{baby}	EUR 253.80	Müller et al. (2013)
	$\gamma_{\text{kindergarten}}$	EUR 152.20	Müller et al. (2013)

Maternal Leave Payment

Maternal leave payments M are computed according to the law *Gesetz zum Erziehungsgeld und zur Elternzeit (Bundeserziehungsgeldgesetz, BErzGG)* and the law *Gesetz zum Elterngeld und zur Elternzeit (Bundeselterngeld- und Elternzeitgesetz, BEEG)*.[15] The former law was substituted

[15]The translation of these legal acts are the Federal Child-raising Allowance and Parental Leave Act and the Federal Parental Allowance and Parental Leave Act, respectively.

by the later from the beginning of 2007. Moreover, the laws have been subject to several changes and adjustments which are considered in the computation of the maternal leave payments. In Germany, childrearing benefits depend on the number of children, their age, the income of the parents, their employment status, and the number of parents living with the child. An overview of the derivation of childrearing benefits and their changes over time can be found in Appendix 1.B. Households in the upper tail of the income distribution may be not eligible or may receive reduced transfers. Table 1.B.4, Appendix 1.B, provides an overview of these reductions and income limits.

Probability of Maternal Re-entry into the Labor Market

Grunow & Müller (2012) perform a Kaplan-Meier survival analysis on the number of months mothers are staying out of employment in East Germany. We utilize their monthly estimates $\hat{s}(m)$ for the first 66 months after the childbirth, i.e. for $m = 0, \cdots, 66$, to compute yearly estimates on the probability of maternal re-entry into the labor market,

$$p_{yy} = \text{Pr}\left[\mathbf{1}_{empl,yy} = 1 | \mathbf{1}_{empl,yy-1} = 0\right] = \begin{cases} 1 - \frac{\hat{s}(12yy+6)}{12yy-6} \text{ if } yy \geq 1 \\ 1 - \hat{s}(6) \text{ if } yy = 0 \end{cases}$$

where $yy = 0, \cdots, 5$ represents the number of the child's full years of live. Within this conversion, we consider the females who enter into employment up to 6 months before and up to 6 months after the child's yy-th birthday as those who enter into employment after yy years of the child's birth. The resulting estimates are the basis for the values of $p_{\text{age youngest kid}}$ in the simulation. These values are listed in Table 1.2.[16]

External Childcare Costs

Costs of public childcare vary dramatically across German federal states; they are strongly subsidized in some regions, but very expensive in other regions. Moreover, since public childcare availability differs strongly across regions, private childcare costs may play a major role for the estimation of overall average childcare costs and, thus, need to be estimated additionally. Müller et al. (2013) follow an approach which takes the special German circumstances of the childcare system into account to estimate childcare costs for East and West Germany separately (see Müller et al., 2013, Table A2-7). We use their estimates for full-time childcare in East Germany. The numbers are presented in Table 1.2.

[16] A more detailed derivation can be found in Appendix 1.C.

1.4.4 Household Income

This section provides an overview of the estimation of the parameters describing the income processes. Table 1.3 summarizes the parameters of interest together with the underlying data set for the estimation or the source of the estimates.

Table 1.3: Parameterization, Household Income

Parameters	Symbol	Value	Source / Estimation
Spousal income profile	$p_{\text{spouse},\,t}$	0.217 - 0.232	GSOEP
	β_0^m	52.558	Microcensus
	β_1^m	-1.689	Microcensus
AR(1) process	φ	0.690	GSOEP
	$\sigma^2_{\varepsilon^m}, \sigma^2_{\varepsilon^f}$	0.279	GSOEP
	ρ_ε	0.000	Harkness (2013)
Social security benefit	S	EUR 735.69	OECD statistics
Female income profile	β_0^f	48.678	MSM, target: age-specific average female income (MC)
	β_1^f	-1.212	
	δ	0.96	

Spousal Income Profile

The probability $p_{\text{spouse},\,t}$ of a present spouse is estimated from the GSOEP. Among all households with a female adult and no spousal income in the last period, we compute the relative frequency of households who have positive spousal income in the current period. This relative frequency is computed conditional on the age of the female.[17]

The age-dependent income profile can be formulated in a quadratic way, such that

$$\xi_t^m = B_1 + B_2 t + B_3 t^2,$$

and the parameters of interest are given by

$$\beta_0^m = B_2 - B_3, \quad \beta_1^m = 2B_3. \tag{1.11}$$

Therefore, to determine the estimates for the parameters β_0^m and β_1^m, we estimate B_1, B_2, and B_3 by applying the method of weighted least squares on average age-specific income levels. The estimation is based on MC data from 1991, 1996, 2001, 2006, and 2011. We use squared standard errors of the mean age-specific income levels as weights. Then, we derive the estimates

[17] Due to the small sample size of the GSOEP, these relative frequencies have been computed using information on households with females aged 21 to 50 between 1992 and 2011.

of the parameters β_0^m and β_1^m according to the equations (1.11).[18]

Female Income Profile

The parameters $\beta_0^f, \beta_1^f, \delta$ are estimated by applying the method of simulated moments (MSM) to the model. We use average income levels of employed females, as data targets. These are derived from the MC data in the years 1996, 2001, and 2006. We increase the number of targets by considering additionally, for 1996, the average income levels of employed females with no children and with exactly one child in the household. We do not use data from 2001 onward to generate income targets conditional on the number of children because in the later years of the life of the 1968 birth cohort children may move out of the household such that the births of the female may not longer coincide with the number of children observed in the data.

Stochastic Components of the Income Processes

For the stochastic component of the income processes, we need three sets of parameters: first, the coefficient of the AR(1) process φ; second, the parameter ρ describing the correlation between the residuals in the stochastic income processes of the female and the spousal income; third, the variances σ_{ε^m} and σ_{ε^f} of the residuals. For the correlation parameter ρ, we follow Harkness (2013) who argues that ρ equals zero. For the estimation of the AR(1) process, we first subtract the deterministic spousal income profile $\log(\xi_t^m)$ from the observed log–income values in the GSOEP. Thereby, we create data on the stochastic component of the residual income process, i.e. observations of $\log(\omega_t^m)$. Using the longitudinal observations of $\log(\omega_t^m)$, we then estimate the AR(1) process for the stochastic component of the residual income process. The estimated coefficient φ is assumed to be the same for the female income processes. Using predictions of the AR(1) process, an empirical distribution of the residuals ε_t^m is generated. The sample variance of these ε_t^m's are taken as estimates for $\sigma^2_{\varepsilon^m}$. We then assume that $\sigma_{\varepsilon^m} = \sigma_{\varepsilon^f}$. For more details, see Appendix 1.E.1.

Social Benefits

In Germany, the social benefits a household receives relies on several factors: the place of living, the number of household members, the number of children, their age, the willingness to find a new job, and other criteria. Moreover, the benefit transfer system has also changed slightly over the time. The OECD.Stats website provides statistics on the net income of unemployed / not working married couples in East Germany.[19] As this data is not available for all years of interest,

[18] The relation between the quadratic form of the income profile and the iterative form, as presented in equation (1.6), is described in Appendix 1.A. For more details on the estimation of the parameters, see Appendix 1.D.1.

[19] URL: http://stats.oecd.org/index.aspx?data setCode=FIXINCLSA, accessed on January 23, 2017, Table: *Benefits, Taxes and Wages - Net Incomes*.

we use an average value of EUR 735.69.

1.4.5 Starting Values for the Simulation

The simulation of a household from 1991 to 2008 requires knowledge of the household situation in 1991. These starting values for the household are created with data from the MC and the GSOEP. In the starting period, we neglect the stochastic income component by assuming $\log\ \omega_t^f = \log\ \omega_t^m = 0$. Hence, $\xi_t^j = y_t^j$ for $j \in \{f, m\}$.

In the first step of the derivation of the starting values for East German females born in 1968, we derive from the MC an empirical joint distribution of these females "employment" status, their income, the spousal income, and the number of children living in the household in 1991. Then, we make a draw from this joint distribution in terms of the female employment and income, the spousal income and the number of children. If our draw for the spousal income is zero for household i, $\mathbf{1}_{spouse,t,i}$ is set to zero. In the second step, we derive from the MC a set of empirical joint distributions for the age structure of the present children. These distributions are conditional on the number of children younger than six years in the household and the employment status of the female. Then, we make random draws from these distributions and assign randonmly the children's age structure within households with the corresponding numbers of children and employment status.[20,21] Hence, exploiting the MC data from 1991, we can obtain a set of starting values for the simulation for all state variables apart from savings.

The starting values on savings are generated using the GSOEP data. The 1992 data of the GSOEP provides information which allows to infer saving levels in 1991. We follow the approach by Fuchs-Schündeln (2008) and compute an average wealth level for our cohort of interest.[22]

Table 1.4: Parameterization, Starting Values

Starting Values	Symbol	Source
Income	$\xi_t^{f,h}$	Microcensus
	$\xi_t^{m,h}$	Microcensus
	$\mathbf{1}_{spouse,t}$	Microcensus
Employment	$\mathbf{1}_{empl,t}$	Microcensus
Fertility	n	Microcensus
	$(I_{t-k})_{k=1}^{6}$	Microcensus
Savings	a_t	GSOEP

[20]The two-step procedure is designed to ease the computational problem of generating starting values for each household in the simulation. Note that for the starting values, we assume that the number of children living in a household coincide with the number of births of the female.

[21]The starting values for spouses who enter the household after 1991 are generated in a similar fashion. They are drawn from an empirical distribution which is conditioned on the year of entry, the female's employment status, the female's income level, and the number of children. For more information see Appendix 1.D.2.

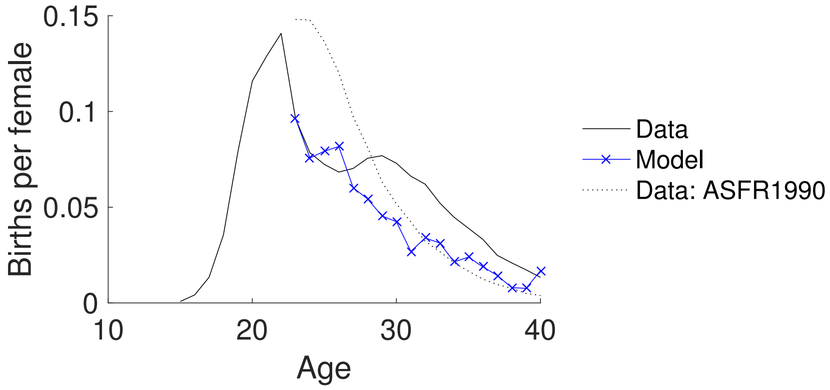
[22]For the detailed description of the procedure for generating the starting saving levels, see Appendix1.E.2.

1.5 Results

1.5.1 Benchmark Model: Fit of the Model

Figure 1.5 shows the observed fertility of the East German females born in 1968 (*Data*), the fertility of the same cohort simulated from age 24 onward (*Model*), and, as a reference, the last observed age-specific fertility rates for the GDR (*Data: ASFR 1990*).[23] Although the line representing the model and the line representing the observed fertility do not lie on top of each, the major characteristic of the transition is matched by the model: a strong drop in fertility, followed by a period of increasing fertility, before fertility declines at a slower pace than what has been observed last for the GDR. The model produces fewer children than observed, but similar to the data, it generates more old mothers than the age-specific fertility rates of the GDR.

Figure 1.5: Fit of the Model



The income targets and the income moments generated by the model are listed in Table 1.5. Average female monthly income is slightly overestimated at the end of their fertile life, but except for that, the average income in the model fits the observed income quite well.

1.5.2 Counterfactual Experiments

With the reunification, the life of East Germans changed. Family policies from West Germany came into effect, wages increased but became more affected by maternity leaves, and in general, household income became more volatile. How important are these changes in the East Germans' life for the fertility transition? Using the life-cycle model, we conduct several counterfactual experiments to answer this question. Here is a list of these experiments, which are described in more detail later:

1. We shut down the depreciation of human capital during maternity leaves by setting the depreciation parameter $\delta = 0$.

[23] Because fertility decisions are generally made 9 months before the birth, the age-specific fertility rates from 1990 represent fertility decisions made before the reunification on October 3, 1990.

Table 1.5: Model Fit of Average Female Income

Year	Age	Children	Target	Model
1996	28	-	1049.65	1123.83
1996	28	0	1191.77	1186.57
1996	28	1	1046.80	1116.02
2001	33	-	1280.19	1274.62
2006	38	-	1260.84	1405.07
2011	43	-	1353.64	1513.38

Notes: Average monthly income in real EURO value of 2011. Entries in the column *Children* denote whether the moments are conditioned on the female's number of children. If the entry is 0 (1), the moment represents only the average income of females with no (one) child.

2. We set the maternity leave to at most one year. This implies that females return to the labor market for sure after the initial maternity period.

3. We shut down the income risk stemming from the stochastic components of income. We do that sequentially; first, we set $\sigma^2_{\varepsilon^f} = 0$, then we set $\sigma^2_{\varepsilon^m} = 0$.

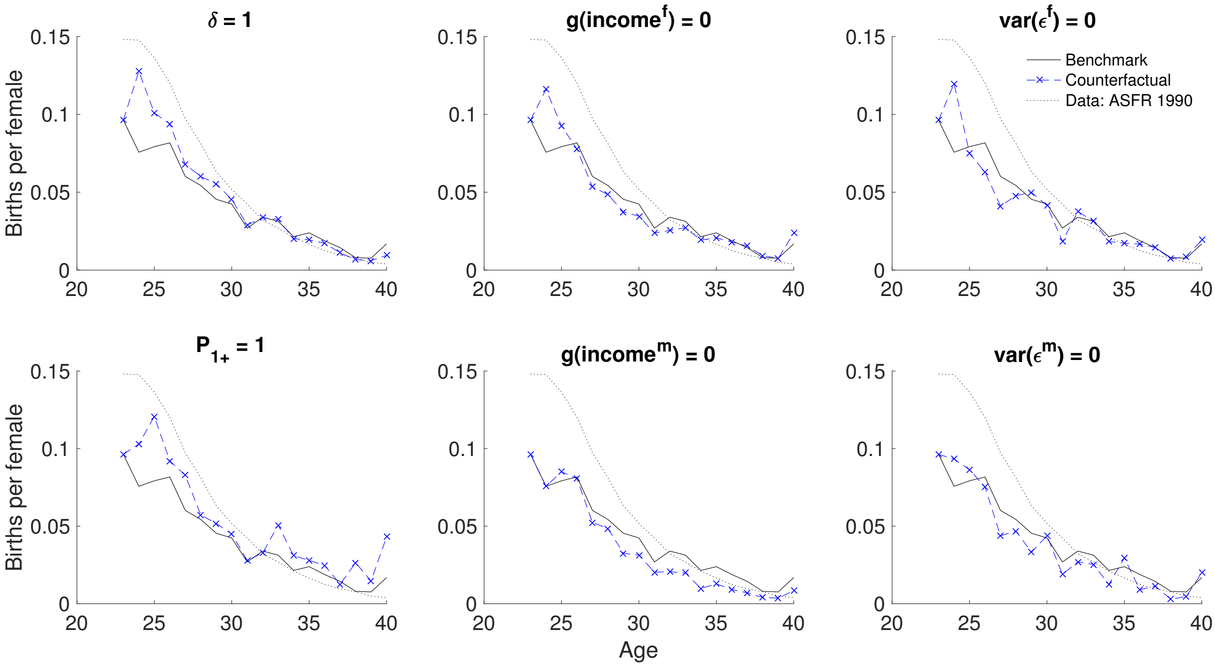
4. Finally, the income growth is shut down by setting $\beta_0^j = \beta_1^j = 0$ for $j = m$ or $j = f$.

To sum up, it turns out that increased human capital depreciation during maternity leaves has a large potential to explain the fertility drop as well as the postponement of childbearing. The increase in the larger number of births at old age can also be associated with the strong rise in spousal income and its volatility. The simulations also suggest that the females' income growth, increased volatility in the females' income, and longer maternity leaves are related to the fertility drop in the early fertile life; at the same time larger maternity leaves seem to reduce fertility at later ages, and thereby, counteracts the effect associated with changes in the male income profile. The following subsections provide a detailed discussion of each counterfactual simulation.

Human Capital Depreciation during Maternal Leaves

We simulate a world in which females experience no human capital depreciation during maternity leaves. When they re-enter the labor market after their maternal leave, the income process continues at the same point at which they left the labor market. Although this scenario appears quite extreme, it is not so far from life in the GDR (Trappe & Rosenfeld, 2000).
If human capital depreciation is low, the penalty for having children decreases; more children are born. Moreover, income grows the most in the early years of life and stagnates at later years. When there is human capital depreciation during maternity leaves, it is not beneficial to give up growth of income and get children earlier. When depreciation is not present, females start their fertility life earlier.

Figure 1.6: Counterfactual Exercises



The upper left plot in Figure 1.6 shows how the age-specific fertility in the model changes if human capital depreciation is shut down during maternity leaves. Females get more children before the age of 30. Particularly in their mid-twenties, fertility increases; for the age group from 24 to 27, fertility increases from 0.297 to 0.390 (see Table 1.6). Thereby, the characteristic drop and catch-up of the transitioning cohort vanishes. In addition to that, fertility decreases only slightly at later ages (see Table 1.6). The overall number of children simulated raises from 0.642 to 0.736. Altogether, the effects of lower human capital depreciation are as expected: more children are born and the postponement of childbearing is reduced.

Table 1.6: Simulated Births from 1992 to 2008

	Age 24 - 27	Age 28 - 31	Age 32 - 35	Age 36 - 40	All ages
Benchmark	0.297	0.169	0.111	0.066	0.642
No human capital depr. ($\delta = 1$)	0.390	0.190	0.106	0.051	0.736
Shorter maternal leave ($P_{1+} = 1$)	0.398	0.182	0.142	0.122	0.844
No male income growth ($g(income^m) = 0$)	0.294	0.133	0.063	0.032	0.522
No female income growth ($g(income^f) = 0$)	0.340	0.144	0.093	0.074	0.650
No male income volatility ($var(\epsilon^m) = 0$)	0.299	0.143	0.094	0.048	0.584
No female income volatility ($var(\epsilon^f) = 0$)	0.299	0.158	0.105	0.066	0.627

Duration of Maternal Leaves

We decrease the time of maternal leaves to the standard duration of maternity leaves in the GDR. In the GDR, the maternity leave did not last longer than a year until June 1989.[24] Moreover, as unemployment was basically non-existent, females did not have to search for a new job after their maternal leave.[25] Therefore, the probability to enter the labor market is set to 1 when the youngest child is at least one year old, i.e. $p_{\text{age youngest kid}} = 1$.
When mothers stay out of labor for a shorter period of time, they have to give up less income, and the wage penalty through human capital depreciation during maternal leaves reduces. Therefore, shortened maternity leaves can be interpreted as a reduction in the costs of children. One might expect that more children are born when maternity leaves are shorter.[26] Besides, when maternity leaves are short and females can enter the labor market earlier, foregone income reduces and spacing births is penalized less. Therefore, we expect both more births and larger gaps between the births.
The left plot in the lower panel of Figure 1.6 shows how the simulated number of births changes if the maternity leave is shortened to one year. Fertility increases at almost all ages, but particularly strong in the beginning and in the end of the simulation. Again, the characteristic fertility drop vanishes. Compared to the benchmark, when the females are between 24 and 27 years old, fertility increases by a third. Fertility almost doubles for the age group 36 to 40 (see Table 1.6).[27] Late childbearing is on the rise in this experiment. Moreover, females rather postpone the birth of the second child: compared to the benchmark, more first children are born at the age of 24 to 27 and more females have two or three children, but fewer mothers get a second child at the age 24 to 27 (see Table 1.7); these numbers suggest a postponement of second births and more spacing between births despite the larger number of children born.

Income Risk

In order to evaluate the potential of changes in income volatility on the East German fertility transition, we perform two counterfactual exercises. The counterfactual scenarios are extreme: first, the riskiness of the spousal income process is shut down completely and, second, the income risk in the female income process is shut down.

[24]According to Kreyenfeld (2004, Table 2), maternal leaves had been enlarged to 15 months in June 1989; before, the duration of maternal leaves had been increased from 6 months in 1979 to 12 months in 1988.
[25]For more details, see Sørensen & Trappe (1995).
[26]If a female's income understates the costs for childcare, it may rather be optimal for the female to stay at home and care for the children herself. Although it appears rather unlikely, childcare costs sum up to a significant amount of income if the female has several small children. Then, reduced maternity leaves may cause a rise in the costs of children.
[27]The pronounced increase in fertility in the last period may be consequence of neglecting biological limitations. Incorporating a non-zero probability of non-conception, may reduce the last periods fertility and spread it out across several years in which the females are in the end of their fertile life. However, fertility in the end of the fertile life would still experience an increase in this counterfactual scenario.

Table 1.7: Simulated Births from 1992 to 2008, by Birth Order

	Age 24 - 27	Age 28 - 31	Age 32 - 35	Age 36 - 40	All ages
			First child		
Benchmark	0.179	0.125	0.085	0.043	0.941
No human capital depr. ($\delta = 1$)	0.243	0.131	0.069	0.025	0.977
Shorter maternal leave ($P_{1+} = 1$)	0.324	0.100	0.049	0.015	0.996
No male income growth ($g(income^m) = 0$)	0.195	0.106	0.051	0.023	0.884
No female income growth ($g(income^f) = 0$)	0.213	0.107	0.070	0.042	0.940
No male income volatility ($var(\epsilon^m) = 0$)	0.168	0.113	0.083	0.038	0.909
No female income volatility ($var(\epsilon^f) = 0$)	0.190	0.119	0.081	0.043	0.942
			Second child		
Benchmark	0.116	0.040	0.023	0.020	0.258
No human capital depr. ($\delta = 1$)	0.145	0.054	0.033	0.023	0.314
Shorter maternal leave ($P_{1+} = 1$)	0.074	0.078	0.088	0.100	0.400
No male income growth ($g(income^m) = 0$)	0.098	0.024	0.011	0.008	0.202
No female income growth ($g(income^f) = 0$)	0.123	0.033	0.021	0.028	0.266
No male income volatility ($var(\epsilon^m) = 0$)	0.130	0.026	0.009	0.009	0.234
No female income volatility ($var(\epsilon^f) = 0$)	0.107	0.035	0.021	0.021	0.245
			Third child		
Benchmark	0.0027	0.0028	0.0024	0.0022	0.0090
No human capital depr. ($\delta = 1$)	0.0023	0.0035	0.0028	0.0026	0.0112
Shorter maternal leave ($P_{1+} = 1$)	0.0011	0.0025	0.0046	0.0065	0.0146
No male income growth ($g(income^m) = 0$)	0.0010	0.0015	0.0003	0.0006	0.0034
No female income growth ($g(income^f) = 0$)	0.0035	0.0023	0.0017	0.0032	0.0107
No male income volatility ($var(\epsilon^m) = 0$)	0.0012	0.0024	0.0013	0.0010	0.0059
No female income volatility ($var(\epsilon^f) = 0$)	0.0017	0.0019	0.0015	0.0015	0.0065

The right plots of Figure 1.6 show how age-specific fertility changes when income risk is not present. When spousal income risk is muted, the number of births decreases from 0.642 to 0.584 and, instead of the characteristic drop and rebound, fertility decreases slowly in the early years (see the lower right plot of Figure 1.6 and, for the numbers, see Table 1.6). Thus, the results of the simulation suggest that increased volatility in the males income process does not explain the fertility drop. However, it has some potential to explain later childbearing; without volatility in the spousal income, fertility after the age of 27 declines from 0.345 to 0.285. One explanation for the decreased fertility in the absence of income risk may be that, precautionary savings are not necessary, and therefore, households receive enough utility out of consumption; the additional utility out of another child does not justify the costs for children.
If the female income process has no risky component, the number of births goes down. However, in the first year of the simulation, fertility is much larger in the absence of income risk and is much lower in the following years. In the absence of female income risk, the riskiness of the costs of children (in terms of forgone income) declines too; therefore, a lower amount of precautionary savings is to be accumulated before the childbirth and childbearing can be preponed. To sum up, an increase in the female income risk has only limited potential to explain the fertility transition observed for the females born in 1968. The results suggest that, if females income is less risky, fertility increases at young age but drops strongly in the subsequent years whereas fertility at older ages barely changes, and in total fertility even slightly decreases.

Income Growth

We do two counterfactuals on income growth. Once we fix the spousal income to the levels from 1991, and once we fix female income to the level of 1991.
Figure 1.6 (lower panel, second plot) shows how the age-specific fertility in the model changes if spousal income is fixed. Fertility barely changes early in life. For ages 27 and older, fertility decreases. This fertility decline is due to the income effect. In the absence of income growth, household income is low, children become relatively expensive, and therefore, fewer children are born.
If female income is fixed (Figure 1.6, upper panel, second plot), females have more children early in life; the fertility drop vanishes. Additionally, fertility decreases slightly for ages 27 and older, but a marginal catch-up occurs in last fertile period. Similar to the argument on the impact of male income, the income effect may explain the decreasing fertility at older ages. However, as females do not only contribute to the household income, but also take time off to care for the child, the income effect is reduced by the substitution effect. Lower income reduces the costs of children as the female foregone income during maternity leaves decreases. As income is not growing, human capital depreciation during maternal leaves has, on average, the same impact in earlier than in later years. The utility out of children can be collected over a longer horizon when

children are born earlier. Postponing childbearing to reduce the long-lasting effect of human capital depreciation during maternal leaves is not optimal anymore.

1.6 Conclusions

Our paper sheds more light on the economic determinants of fertility. We use the German reunification as an exogenous factor which produces a large drop in fertility in East Germany. We estimate our structural model to the 1968 birth cohort of East German females. The results point out that human capital depreciation during maternity along with the duration of the maternity leave is responsible for this large fertility decline. Male income growth is responsible in shaping fertility at the late stages of the fertile life-cycle.

Understanding the response of fertility to changes in the economic environment is important when it comes to constructing quantitative models for policy evaluation. Such models of fertility and female labor supply decisions can be used for assessing policies related to female participation, fertility, childcare, child subsidies, parental leaves, and poverty reduction.

Appendix 1.A The Iterative Form of the Quadratic Income Profile

The quadratic income profile in age t given as $\xi_t^m = B_1 + B_2 t + B_3 t^2$, $t \geq 0$, can be rewritten for all $t \geq 1$ as

$$\begin{aligned}
\xi_t^m &= \xi_{t-1}^m + (B_1 + B_2 t + B_3 t^2) - (B_1 + B_2(t-1) + B_3(t-1)^2) \\
&= \xi_{t-1}^m + B_2 + (B_3 t^2) - (B_3(t^2 - 2t + 1)) \\
&= \xi_{t-1}^m + B_2 - B_3 + 2B_3 t.
\end{aligned}$$

With $\beta_0^m = B_2 - B_3$ and $\beta_1^m = 2B_3$, we receive the iterative form

$$\xi_t^m = \xi_{t-1}^m + \beta_0^m + \beta_1^m t, \quad t \geq 1, \quad \text{given } \xi_0^m,$$

which is completely characterized by the two parameters β_0^m and β_0^m and the income ξ_0^m in the starting period $t = 0$.

Appendix 1.B Maternity Leave Payments in Germany

Between 1991 and 2008, the legal regulations which determine maternity leave payments in Germany changed several times. Table 1.B.1 summarizes the resolution date of the major changes, the type of change, and where it has been published (the page of the Bundesgesetzblatt, Teil I). In this study, the amendments of interest are those who affect the level and duration of maternity leave payments. Since maternity leave payments can be cut, if parental income is too high, changes of the corresponding parental income limits and the size of the potential grant reduction are also necessary information.

Table 1.B.1: Overview of the Changes in Legal Regulations

Date of the resolution	Page of the Bundesgesetzblatt (Teil I)	Type of change in the law			
		Grant level	Grant duration	Income limit	Grant reduction
Federal Child-raising Allowance Act (BErzGG)					
25.07.1989	1550 - 1555	-	-	-	-
06.12.1991	2142 - 2145		x		
21.12.1993	2365			x	x
12.10.2000	1426 - 1432	x	x		
30.11.2000	1638 - 1644	x		x	x
07.12.2001	3358 - 3365	x		x	
29.12.2003	3087 - 3093	x		x	x
Federal Parental Allowance and Parental Leave Act (BEEG)					
05.12.2006	2748 - 2758	x	x	x	x

Table 1.B.2 displays the maximum monthly grant level and the maximum grant duration per child. Between 2001 and 2006, monthly maternity leave payments were larger when maternity leave lasted at most a year. From 2007 onward, the grant level was directly determined by parental net income. The underlying income concept is presented in Table 1.B.3. It also lists the underlying income definitions used to determine whether and by how much child-rearing allowances have been cut before 2007. Table 1.B.4 presents the amount of the reductions as well as the income limits which the yearly parental income needs to exceed for being affected by the reductions.

Using the following assumptions and adjustments, we reduce the complexity in implementing the different child-raising regulations: Before 2001, couple households are assumed to be married. We neglect the fact that parental leaves can be extended by two months, i.e. to 14 months, if the father takes parental leave as well. The date on which the law enters into force is used for determining the maternal leave benefits; potential birth date thresholds are neglected. If the income limit which determines whether parents are eligible for child-raising benefits differs depending on the duration of the grant, we only consider the more restrictive limit independent of the grant duration. When the child is in its first year, we assume only a one year grant. The grant in the second year will then take into account the excess payments in the previous year. For the computation of the grant reduction in the first 6 months, we abstract from a distinction in the income limits for 1 and 2-year grants. We consider the excess with respect to the income limit for the 2-year grants also for the 1-year grant. For the computation of the grant in the second year, the reduction from the first year is taken into account. Inflation within this one year is neglected.

Table 1.B.2: Child-rearing Benefits per Child (before Grant Reduction)

Validity	Grant level	Duration, in years
07/1990 – 12/1992	DM 600	1.5
01/1993 – 12/2000	DM 600	2.0
01/2001 – 12/2001	DM 600 for 2 years / DM 900 for 1 year	2.0 / 1.0
01/2002 – 12/2003	EUR 307 / EUR 460	2.0 / 1.0
01/2004 – 12/2006	EUR 300 / EUR 450	2.0 / 1.0
01/2007 – 12/2010	$\max(\text{EUR } 300, \min(\tilde{M}, \text{EUR } 1800))^{\dagger}$	1.0^{+}

Notes: † Parental income (Y) determines $\tilde{M}$ as follows:

$$\tilde{M} = \begin{cases} \min\left(100\%, \left(0.67\% + 0.1\% \frac{1000-Y}{2}\right)\right) Y, & Y < \text{EUR } 1000 \\ 67\% Y, & Y \geq \text{EUR } 1000. \end{cases}$$

Child-rearing allowance increases by 10%, at least by EUR 75, if the granted person lives with 2 or more children (younger than 6) in the same household; in case of multiple births, EUR 300 are granted for each additional child.
$^{+}$ The duration of child-raising benefits increases by 2 months, if both parents take parental leaves for at least two months.

Table 1.B.3: Underlying Parental Income

Validity	Income concept (Y)
07/1989 – 12/1993	Yearly parental income from employment two years before the birth (e.g. the 1990 income if the child was born in 1992) reduced by church taxes, transfer payments, and special expenses (Considering the year in which the child turns 7 months old is allowed if the income of that year is lower than the income two years before the birth.)
01/1992 – 12/1993	Yearly parental income from employment two years before the birth (e.g. the 1990 income if the child was born in 1992) reduced by church taxes, transfer payments, and special expenses. (Considering the year in which the child turns 7or 19 months old is allowed if the income of that year is lower than the income two years before the birth.)

Continued on next page ...

... Table 1.B.3 continued

Validity	Income concept (Y)
01/1994 – 12/2003	If the parents are emplyoed, 73% of the anticipated income the parents earn in the year of the payment reduced by church taxes, transfer payments, and special expenses (If the income cannot be anticipated, the previous year income and the income of the year before can be taken into account.)†
01/2004 – 12/2006	If the parents are emplyoed, 76% of the income the parents earned in the year before the year of the grant payment, reduced by church taxes, transfer payments, and special expenses (If that income is unknown, the income of the year before is taken into account. If the income in the year of the grant payment is lower by at least 20%, the income of the year of the grant payment is taken into account.)$^{+}$
01/2007 – 12/2010	Average parental income of the 12 months before the month of the birth, after taxes and obligatory social insurances

Notes: † In some special cases, 78% of the parental income are considered. For the simulation, we use the 73% threshold.
$^{+}$ In some special cases, 81% of the parental income are considered. For the simulation, we use the 76% threshold.

Table 1.B.4: Yearly Income Limits and Monthly Payment Reduction

Validity	Income limit (L)	Reduction
07/1989 – 12/1993	*From 7th month onward:*	
	Married couples who live together: DM 29,400 / singles: DM 23,700 + DM 4,200 for each additional child	$\frac{12}{40}\frac{(Y-L)}{100}$
01/1994 – 12/2000	*Within first 6 months*:	
	Married couples who live together: DM 100,000 / singles: DM 75,000 + DM 4,200 for each additional child	No grant
	From 7th month onward:	
	Married couples who live together: DM 29,400 / singles: DM 23,700 + DM 4,200 for each additional child	$\frac{12}{40}\frac{(Y-L)}{100}$

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... Table 1.B.4 continued

Validity	Income limit (L)	Reduction
01/2001 – 12/2001	*Within first 6 months*:	
	Couples who live together: DM 100,000 / singles: DM 75,000 + DM 4,200 for each additional child	No grant
	From 7th month onward:	
	Couples who live together: DM 32,200 / singles: DM 26,400 + DM 4,200 for each additional child	2 year grant: 4.2% $(Y - L)$, 1 year grant: by 6.2% $(Y - L)$
01/2002 – 12/2003	*Within first 6 months*:	
	Couples who live together: EUR 51,130 / singles: EUR 38,350 + EUR 2,454 for each additional child, resp.	No grant
	From 7th month onward:	
	Couples who live together: EUR 16,470 / singles: EUR 13,496 + EUR 2,454 for each additional child	2 year grant: 4.2% $(Y - L)$, 1 year grant: 6.2% $(Y - L)$
01/2004 – 12/2006	*Within first 6 months:*	
	EUR 30,000 / EUR 23,000 for a 2 year grant + EUR 3,140 for each additional child, resp.	No grant
	EUR 22,086 / EUR 19,086 for a 1 year grant + EUR 3,140 for each additional child, resp.	No grant
	From 7th month onward:	
	Couples who live together: EUR 16,500 / singles: EUR 13,500 + EUR 3,140 for each additional child	2 year grant: 5.2% $(Y - L)$, 1 year grant: 7.2% $(Y - L)$
01/2007 – 12/2010	No income limit	No reduction

Notes: Only those children who receive "Kindergeld" are considered. Since 2001: Non-married parents have the same rights are married couples.

Appendix 1.C Probability of Maternal Re-entry into Employment

Grunow & Müller (2012) do Kaplan-Meier survival analysis of maternal re-entry into the labor force. The survival analysis considers the time after the first birth on a monthly basis. Grunow & Müller compare East German, West German and East-West mobile mothers.
We apply their data on maternal re-entry computed (Grunow & Müller, 2012, Abbildung 2).[28] Their analysis uses data on mothers from 1992 till 2009. It is restricted in the following sense: It covers only women who were employed 6 months before the child was born. The regional affiliation depends on employment history. Berlin has been excluded. It is not controlled for younger siblings. Many mothers have more than one child; therefore the probability of a mother re-entering the labor force may be underestimated (overestimated) when the older (youngest) sibling is young (old).
The given Kaplan-Meier survival estimates are defined as follows:

$$\hat{s}(m) = \prod_{m(i) \leq m} \frac{n_i - d_i}{d_i}, \quad \hat{s}(0) = 1,$$

where n_i stands for the number of survivors just prior to time $m(i)$, i.e., number of mothers out of the labor force, and d_i denotes the number of deaths at time $m(i)$, i.e. number of mothers re-entering into the labor force. Consequently, $\frac{n_i - d_i}{d_i}$ represents the relative frequency of mothers who do not re-enter the labor force (given that they have not been employed in the previous period).
We are interested in the probability that a mother will re-enter the labor market when her youngest child is yy years old. Therefore, we convert the monthly Kaplan-Mayer survival estimates, $\hat{s}(m)$ into yearly estimates. As

$$\text{Pr}\left[1_{empl,m} = 0\right] = \text{Pr}\left[1_{empl,m-k} = 0, \forall k = 0, \ldots, m-1\right],$$

and $\hat{s}(m)$ is an estimator for

$$s(m) = \prod_{k=0}^{m-1} \text{Pr}\left[1_{empl,m-k} = 0 | 1_{empl,m-k-1} = 0\right],$$

[28] We thank Daniela Grunow for providing the output file of their analyses.

the following rearrangement holds:

$$\begin{aligned}
\Pr\left[1_{empl,m}=1|1_{empl,m-i}=0\right] &= 1-\Pr\left[1_{empl,m}=0|1_{empl,m-i}=0\right] \\
&= 1-\frac{\Pr\left[1_{empl,m}=0,1_{empl,m-i}=0\right]}{\Pr\left[1_{empl,m-i}=0\right]} \\
&= 1-\frac{\Pr\left[1_{empl,m-k}=0,\forall k=0,\dots,m-1\right]}{\Pr\left[1_{empl,m-k}=0,\forall k=i,\dots,m-1\right]} \\
&= 1-\frac{\prod_{k=0}^{m-1}\Pr\left[1_{empl,m-k}=0|1_{empl,m-k-1}=0\right]}{\prod_{k=i}^{m-1}\Pr\left[1_{empl,m-k}=0|1_{empl,m-k-1}=0\right]} \\
&= 1-\frac{s(m)}{s(m-i)}. \qquad (1.C.1)
\end{aligned}$$

This rearrangement can be applied to any period of time points which are multiples of months. Utilizing the results of Grunow & Müller (2012) and equation 1.C.1, we compute estimates for the probability of maternal re-entry into the labor market on a yearly (yy) basis:

$$\Pr\left[1_{empl,yy}=1|1_{empl,yy-1}=0\right]=\begin{cases}1-\frac{\hat{s}(12yy+6)}{12yy-6} \text{ if } yy\geq 1\\ 1-\hat{s}(6) \text{ if } yy=0\end{cases}.$$

Within this conversion, we consider the females who enter into employment up to 6 months before and up to 6 months after the child's yy-th birthday as those who enter into employment after yy years of the child's birth. We only use the data until the child is 5 years old and assume that all mothers re-enter into the labor force when the youngest child is 6 years old. This simplification is necessary as the computational time of the model doubles with every additional year in which we keep track of children's age.

Appendix 1.D Working with the Microcensus

For the derivation of the starting values and female income targets, and also for the estimation of parameters characterizing spousal income, we utilize information from the Microcensus. In order to do so, we restrict the households surveyed to those with the main place of living in East Germany. We exclude all households who have not been surveyed at the main place of living and those whose household head and partner are no German citizens. Moreover, we restrict the sample to households which consist of one or two generations, a female adult, children, and if existing, a male adult who is the female's spouse. While doing this, we also exclude communal accommodations, households with same-sex couples, single male households, and households with no or more than one reference person. Additionally, we exclude households with divorced or widowed adults who live with a partner in the same household. Households with implausible or missing information regarding the household's income, the female's income, and the female's employment status are also not considered for the following analysis.

Before we utilize the information on income, employment, and the number of children provided by the Microcensus to derive starting values, income parameters, and income targets, we adjust the corresponding variables such that they represent the structure of the model. Therefore, a female is re-coded as employed (in the labor force) independent of her true employment status if she has no child younger than 6 years. If she is unemployed and has children younger than six, her income is set to zero and becomes a part of the spouse's income.

The spouse's income is re-defined as the monthly net household income reduced by the female's monthly net income and, if the female is not employed, maternity leave benefits. Since Microcensus data provides no information on the level of maternity leave benefits, we impute maternity leave benefits based on the information provided and the legal regulations described in Section 1.B. For this imputation, information on the female's income in the year prior to the birth is required. As this is not available, we use the average female income of the employed females who are one year younger and have one child less.[29] Using this information, we impute the parental income which is used to determine whether the parents are eligible for child-raising allowances; the parental income then equals the sum of the imputed female income and, if a male adult is present in the household, the current monthly net income of this male.

Since we assume a maximum number of 4 children within the model, households with more than 4 children are re-coded as households with 4 children; we neglect the oldest children. The model restricts the number of children born within a calendar year to one. If several children were born in the same year, the additional children are made one year older until either one or no child is born in each year.

1.D.1 The Deterministic Profile of Spousal Income

Using Microcensus data, we apply the method of weighted least squares to estimate the spousal income profile which is assumed to be quadratic in age. For each year $yr = 1991, 1996, \ldots 2001$, we compute age-specific means $\xi^{m,yr}_{t,obs.}$ and standard errors $s^{yr}_{\xi_t}$ of spousal income for females who are between 20 and 50 years old. Utilizing the diagonal weighting matrix $\Sigma = \left(\left(s^{yr\,2}_{\xi_t}\right)^{2011}_{yr=1991}\right)^{31}_{t=1}$,

[29]In the rare case, that no female with these characteristics is represented in the Microcensus, we use the average income of employed females who are of the same age and have one child (two children) less.

we then solve the following minimization problem:

$$\min_{\beta_0^m,\beta_1^m} \begin{bmatrix} \xi_{1,obs.}^{m,1991} - (B_1 + \ \ 1B_2t + \ \ 1^2B_3) \\ \cdots \\ \xi_{1,obs.}^{m,2011} - (B_1 + \ \ 1B_2 + \ \ 1^2B_3) \\ \cdots \\ \xi_{31,obs.}^{m,1991} - (B_1 + 31B_2 + 31^2B_3) \\ \cdots \\ \xi_{31,obs.}^{m,2011} - (B_1 + 31B_2 + 31^2B_3) \end{bmatrix}^T \Sigma^{-1} \begin{bmatrix} \xi_{1,obs.}^{m,1991} - (B_1 + \ \ B_2 + \ \ 1^2B_3) \\ \cdots \\ \xi_{1,obs.}^{m,2011} - (B_1 + \ \ B_2 + \ \ 1^2B_3) \\ \cdots \\ \xi_{31,obs.}^{m,1991} - (B_1 + 31B_2 + 31^2B_3) \\ \cdots \\ \xi_{31,obs.}^{m,2011} - (B_1 + 31B_2 + 31^2B_3) \end{bmatrix}$$

subject to

$$\beta_0^m = B_2 - B_3$$
$$\beta_1^m = 2B_3.$$

1.D.2 The Starting Values for Spousal Income after 1991

If spousal income emerges in a household for the first time, this spousal income level needs to be generated. We draw it from an empirical distribution constructed with Microcensus. The empirical distribution of the spousal income level is conditioned the year of entry, the employment status of the female, the female's income level, and the number of children.[30]
For all the years without Microcensus observations, we first draw which year of observed Microcensus data to use and, then, proceed as above. In this process, only the two closest years surveyed are taken into account. The relative distance to the survey years determines the counter-probability of drawing the corresponding survey year.

Appendix 1.E Working with the GSOEP

For the derivation of the starting values for savings and the parameters characterizing the stochastic components of the income processes, we utilize information from the GSOEP. In order to do so, we restrict the households surveyed to those living in East Germany and not in Berlin. Moreover, we restrict the sample to households which consist of one or two generations, a female adult, children, and if existing, a male adult who is the female's spouse. While doing this, we also exclude communal accommodations, households with same-sex couples, single male

[30] If, in a specific year in the Microcensus, there is no spousal income observed for a specific combination of female employment, female income, and number of children, the restriction regarding the female's income is neglected; the spousal income is then drawn from the empirical distribution which is only conditioned on the female employment, the number of children, and the observation year.

households, and households with no or more than one reference person. Besides, we exclude households in which more than two different adult females were living between 1992 and 2011. The household is split into two different households when the former female adult leaves it and the new female is entering the household. Households with implausible or missing information regarding the household's income, the female's income, and the female's employment status are also not considered for the following analysis.

We re-define that females are employed if they had been working in full-time, part-time, or short-time work, or if they have no child younger than 6 in the household. Female income is set to zero if the female is not employed and has a child younger than 6. All variables regarding income and employment are surveyed in the previous year and on a yearly basis. We adjust them to represent monthly data. Utilizing information on last year maternal benefits and last year income from 1992 to 2011, we recover the income structure from 1991 to 2010. For the estimation of income-related parameters, individual income after taxes and transfers are of interest. However, individual income after taxes and transfers are not surveyed; we use the relative share of female-to-household labor income and the received maternity leave benefits to estimate the females share of the post-government household income. The remaining part of the post-government household income is considered as the spousal income.

Cross-sectional weights are set according to the female adult weight when the household was surveyed the first time; to create longitudinal weights, these weights are multiplied with the reversed yearly staying probability of the household.

The sample size of the GSOEP is relatively small; cohort-specific analyses are not possible. Therefore, we keep all females at age 20 to 50 who were born between 1952 and 1990 and use estimated parameters smoothed across cohorts or age.

1.E.1 Stochastic Components of the Income Processes

Assuming that the AR(1) process which describes the stochastic component of the income process has the following two properties:

$$\log(\omega_{-1}^{m,h}) = 0 \quad \text{and} \quad \mathbb{E}[\varepsilon_t] = 0,$$

the stochastic component of individual i's spousal income profile can be obtained by subtracting the deterministic component from individual i's spousal income. Therefore, we first estimate the deterministic spousal income profile with the GSOEP data, and afterwards, derive the innovation process $\log(\omega_{t,i,obs.}^{m})$ for each individual i. We compute the difference between the logarithm of fitted values and the logarithm of the observed spousal income:

$$\log(\omega_{t,i,obs.}^{m}) = \log(y_{t,i,obs.}^{m}) - \log(\xi_{t,i}^{m}).$$

Using the longitudinal observations of $log(\omega^m_{t,i,obs.})$, we then estimate the AR(1) process for the stochastic component of the spousal income process. The estimated coefficient φ is assumed to be the same for the female income processes. Using the mean predictions of the estimated AR(1) process, we derive for each individual i values for the $\varepsilon^m_{t,i,obs.}$'s:

$$\varepsilon^m_{t,i,obs.} = \log(\omega^m_{t,i,\text{predicted}}) - \log(\omega^m_{t,i,\text{obs.}}).$$

For each female birth cohort, the sample variance of the corresponding $\varepsilon^m_{t,i,obs.}$'s is computed. The sample variance is then smoothed over the cohorts and the fitted value for the cohort born in 1968 is used as an estimate for σ_{ε^m} and σ_{ε^f}.

1.E.2 Saving Level

Following the procedure by Fuchs-Schündeln (2008), but neglecting the wealth of cars owned, we compute average household wealth levels. We use the values computed with the 1992 survey questions as a proxy for 1991 because most values taken for the computation of the wealth level describe the situation of the household in the last year, i.e. in 1991. As the sample size of the GSOEP is too small to compute reliable estimates for each cohort separately, we first compute the wealth level of all 20 to 50-year-old females in 1991, and then use a quadratic fit to smooth the wealth levels across cohorts; the fit for the cohort born 1968 is taken as the estimate of the starting value of savings.

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CHAPTER 2

Job Displacement and Training Activities: Human Capital Accumulation during the East German Transition

2.1 Introduction

The most important investments in human capital are education and training (see Becker, 1993, p.17). Both education and training can either be specific or general. As the opposite of general training and education, specific training and education provide knowledge which are specific to a firm, industry, occupation, country, or political system. As outlined by Schmid-Schönbein (1997, p.57), in the former German Democratic Republic (GDR, in the following also called East Germany), many components of human capital were completely system-specific (juridical knowledge etc.). All other (learnable) components – as well as technical components – were also to some extent system-dependent. The technology in the GDR was outdated. When the Berlin Wall fell in November 1989, the existing human capital was not fully suitable for the modern technology which was implemented in the process of transition. Consequently, the East German's transition was necessarily combined with huge human capital depreciation - a depreciation in both specific and general human capital.

In this paper, I study how people reacted to this human capital depreciation and compare their time investment in training activities to the investment of peers who lived in the rather stable market economy of West Germany. Thereby, I test the theory on the time-profile of investment in human capital in a non-standard setting - in a transition from a command to a market economy. The theory on the time-profile of human capital investment has been developed by Mincer (1958, 1962), Becker (1962, 1964) and Ben-Porath (1967). Here, three claims from the seminal book by Becker (1964) are of main interest. First, with a constant rate of return, "a considerable incentive would exist for everyone to invest immediately rather than waiting. (...) [Second,] the number investing would tend to decline rapidly with age even if the rate of return did not (Becker, 1964, p.50)." [Third,] "younger people have greater incentive to invest because they can collect the return over more years" (Becker, 1964, p.50). Following these predictions, East Germans are expected to invest in their human capital as soon as possible and younger people are expected to invest more on average. Assuming that the human capital of West Germans was not affected by the reunification, all else equal, West Germans are expected to invest less in training. Even when they lose a job, they are expected to invest less in training because they only lose firm-specific human capital; general human capital investments have not depreciated. West Germans could nevertheless undergo training in order to increase their labor market options, but their incentives would be smaller than for East Germans.

This study focuses on people who experienced a job loss due to a plant closure within the very first years of the East German transition process. A plant closure is an exogenous shock that affects everyone within the plant independent of personal characteristics or skills. I argue that the characteristics of displaced workers and (matched) non-displaced workers only differ randomly and, therefore, use the non-displaced workers as the counterfactuals of the displaced workers.

By investigating the effect of job displacement on training activities, this study provides new insights on the process of human capital accumulation during economic transitions. Moreover, contrary to the existing literature, I analyze the impact of different economic environments; this is done by comparing the displacement effect on training activities between East and West German workers in the first years after the German reunification.

The aim of this paper is to answers the following questions: Does job displacement increase adult training activities? Is this rise in training activities stronger for people from the transitioning East German economy than for West Germans? And, after displacement, do young East Germans invest more time in training than older East Germans?

In order to answer these questions, an exact matching technique is used to compare the treatment group of displaced workers with a control group of non-displaced workers. Within the matched sample, I make use of a difference-in-difference model introduced by Jacobson et al. (1993), the common approach to study the treatment effect of a plant closure (see e.g. Stevens, 1997; Couch, 2001; Schmieder et al., 2010; Ichino et al., 2017). I then extend the model by another difference-in-difference set-up to compare the displacement effects between East and West Germans (and between young and old East Germans). In order to rule out limitations of the natural East-West-German experiment, I conduct several robustness checks and discuss, among others, how East-West migration might affect the results.

In line with the theory on the timing of human capital investments, I find that East Germans increase their time investment in adult training significantly when they were displaced one or two years earlier; this increase in adult training is lower for older workers and not observable for West Germans. Moreover, the results suggest that, when East Germans lose their job due to a plant closure, they increase their training activities as soon as they are not employed anymore and, thereby, counteract the human capital depreciation associated with the transition earlier.

The paper proceeds as follows: In the next section, I present a brief literature review and the paper's contribution to the existing literature. In Section 2.3, I introduce the data, the main variables of interest, and the matching procedure. The estimation approach is presented in Section 2.4. The results are shown in Section 2.5. In Section 2.6, I discuss limitations and how they might influence the results. The paper closes with a summary and conclusion.

2.2 Related Literature

This paper contributes to several branches of the literature: the literature on outcomes of job displacements, the literature on the transition of socialist command economies, and the literature on adult training. A wide range of outcomes of job displacement have already been studied; among them, labor market outcomes like unemployment spells, earnings losses, and sectoral mobility (see, e.g., Ruhm, 1991; Jacobson et al., 1993; Stevens, 1997; Couch, 2001; Bender et al., 2002; Kletzer & Fairlie, 2003; Schmieder et al., 2010), outcomes on regional mobility (see, e.g., Bailey & Turok, 2010; Fackler & Rippe, 2017), health (see, e.g., Gallo et al., 2004; Browning et al., 2006; Browning & Heinesen, 2012; Sullivan & Wachter, 2009) and family life (see, e.g., Charles & Stephens, 2004; Del Bono et al., 2012).[1] Despite the extensive research on displacement outcomes, almost nothing is known about the effect of job displacement on adult education or training. To my knowledge, only one study on post-displacement human capital investments exists: Chapman et al. (2003) investigate displaced workers' credit constraints for human capital investments using Canadian data. The present paper attempts to close this gap.

The displacement literature focuses mainly on industrialized countries and market economies. Some studies consider the effect of displacement in a rather stable economic period (e.g., Couch, 2001; Burda & Mertens, 2001; Bender et al., 2002; Kletzer & Fairlie, 2003; Gallo et al., 2004) while others investigate a specific recession period (Appelqvist, 2007; Schmieder et al., 2010; Farber, 2011). However, less is known about how the displacement effect depends on the economic environment. Only a few studies compare displacement outcomes across different economies. One exception is the book *Losing Work, Moving On* edited by Kuhn (2002). It provides standardized results and compares them across several industrialized Western countries and Japan. Displacement effects in transitioning East European economies are even less considered. By focusing my analysis on Germany in the early 1990s, I am able to compare the effect sizes of job displacement between the rather stable West German market economy and the transitioning East German economy. As described in previous studies (Fuchs-Schündeln & Schundeln, 2005; Alesina & Fuchs-Schündeln, 2007; Fuchs-Schündeln, 2008; Rainer & Siedler, 2009), the advantage of focusing on Germany is that, in 1989, the Berlin Wall fell unexpectedly; and moreover, with the reunification, both parts of Germany fell under the same legal and institutional setting while their economic backgrounds still differed. This environment provides a unique opportunity to investigate the historical impact on socio-economic outcomes.

For the Eastern part of reunified Germany, there is now a substantial body of research on retraining and continuing education that took place in the 1990s. The focus of this research lies on the effects of retraining and continuing education on labor market outcomes. Their findings have no clear evidence for a positive employment effect of training in the short run (see Speckesser (2004, Chapter 1) for an extensive review); however, in the medium and long run, several training programs were found to improve the participants' labor market outcomes (Lechner et al., 2007; Fitzenberger & Speckesser, 2007; Fitzenberger & Völter, 2007).[2] To study the treatment effect of training activities, these studies have a control group representing the counterfactual. As training outcomes are considered in these studies, the individuals' ability should not differ between treated individuals and counterfactuals. However, this might not be the case since observable characteristics like formal education, occupational positions, and tenure provided no

[1]For a recent literature review, see Baumann (2016, Chapter 1). Earlier reviews on the extensive research on displacement costs in the U.S. have been provided by Hamermesh (1989), Fallick (1996).

[2]See Wunsch (2005, Table A.3) for a summary of earlier findings.

clear evidence of ability, but were also consequences of political conformity and dis-conformity. Hence, all studies on training effects in East Germany may strongly suffer from endogeneity due to an unobserved ability bias. In the present study, this bias is reduced by focusing on the effects of a plant closure which occurred independently of individual characteristics. Furthermore, I exploit a matching approach to compare displaced workers only with matched non-displaced workers with the same characteristics.

In this paper, I investigate how job displacement affects training activities of East Germans and West Germans in the early 1990s. Workers displaced in the early 1990s had no reason to doubt that further training improves future labor market outcomes. Although training programs have already been developed for unemployed workers in West Germany before the reunification, a lack of data and a lack of an appropriate methodology made it impossible for researchers to study how further training affects future employment and earnings before the 1990s (Wunsch, 2005, Section 6.5). Contrary to research on the effect of training on labor market outcomes, research on the opposing effect, i.e. the effect of labor market outcomes on training, has been studied little. By focusing on the effect going in the less prominent direction, the paper provides new insights on human capital accumulation.

2.3 Data

The German Socio–Economic Panel (GSOEP) is a yearly, longitudinal survey, conducted on a yearly basis since 1984. East Germans were surveyed for the first time in 1990. In this study, the distinction between East and West Germans are based on whether they lived in the East or in the West prior to 1990.[3] In 1990, the GSOEP covers a total of about 14,000 successfully-interviewed individuals, of which 95% are still surveyed in 1998. To ensure that attrition is not driving the results, I keep only those individuals who have been surveyed from 1990 until 1998.[4,5]

Moreover, I restrict the sample to people who were at working age prior to the transition. All individuals who were younger than 25 in 1990 are excluded to ensure that the East Germans finished their education under the socialist regime and before the transition process started. People are excluded as soon as they become older than 55 because, then, they may retire early.

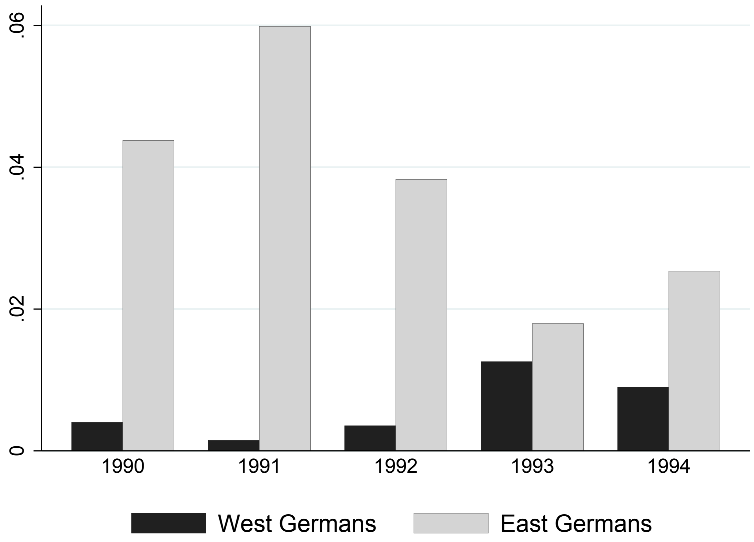
[3] The GSOEP covers a question about the *place of living in 1989*. Berlin is divided into East Berlin and West Berlin. I adjust implausible answers: People who responded to the GSOEP before 1990 are re-coded as West Germans and people who were living in East Germany in 1990, were not interviewed before 1990, and received their education from the GDR are re-coded as East Germans. I also repeat the analysis excluding the individuals with implausible declarations of their place of living. The results do not change.

[4] Employment and training spells are always collected with one year of delay. Therefore, the data on 1998 is required for the training and employment spells in 1997.

[5] Some gaps exist in the spell data. These gaps are coded as missings. I also conduct the analysis by completely excluding individuals with such missing values at any month and another analysis without excluding any individuals with gaps or incomplete information. In both cases, the effects are less significant but the effect patterns do not change.

Those who turn 55 before the year of the plant closure are also dropped from the sample.[6]
The study focuses on plant closures between 1990 and 1994. In each of these years, among the remaining individuals, between 1.5% and 6% of the East Germans and less than 1.5% of the West Germans lost their job because of a plant closure (see Figure 2.3.1).

Figure 2.3.1: Share of Displaced People Aged 25 to 55



Notes: GSOEP, own calculations, weighted according to the cross-sectional weights.

2.3.1 Variables

For the analysis, information on human capital investments, employment, and job displacement are needed. The following subsections explain in detail how these are obtained.

Training and Employment

One advantage of the GSOEP is that it provides information on training and employment spells for East Germans since January 1990. The respondents are asked for each month of the previous year, among others, whether they have been in vocational training, whether they have been full-time employed, whether they have been part-time employed, whether they have been working short hours, and whether they have been unemployed. Using this information, I construct a variable on the number of months in which the respondent has undergone some vocational training. Hence, this training variable takes the values $0, 1, \ldots, 12$. Although the intensity of this human capital investment is not observed, it is straightforward to assume that the more months

[6] In a robustness test, all people are dropped from the sample completely when they turn older than 55 before the last year of interest, i.e. in the third year after the plant closure. The main results remain unchanged.

someone does training, the more time is invested in human capital accumulation.[7]
The employment variable is constructed using the same information as the training variable. An individual is coded as employed for that year, if she states that she has been employed part-time or full-time in more than 6 months of the year.[8]

Job Displacement

In 1991, the GSOEP started asking the survey respondents whether they have lost their *last* job in the current or in the last calendar year, in which month the job loss occurred, and how they lost their job. One of the options for the job loss is *a plant closure*.[9] People who check the box for this option are coded as being displaced if the displacement occurred between January 1990 and December 1994. All other people - employed, unemployed, in the labor force, or out of the labor force - are coded as not being displaced, and are potential members of the control group.

2.3.2 Matching

In the East German subsample, I identify 236 workers who experienced a job loss due to a plant closure between 1990 and 1994; in the West German subsample, 97 displaced workers are identified. These displaced workers might not represent a random sample of the (GSOEP) population; the GSOEP population also covers housewives and long-term unemployed, and plant closures may be more prevalent among firms which do not promote training activities of their employees.
Therefore, I restrict the potential control group of non-displaced people by applying an exact matching technique for each displacement year within the East and West German subsamples. Potential control group members are kept if, first, they are at most 55 years old in the year of the plant closure and, second, if they match with a displaced worker in all of the following criteria in the pre-displacement calendar year: sex, age group (old: older than 40 in 1990, young: 40 at most in 1990), formal education (3 categories: low - no job qualification degree, middle, high - job qualification degree from university or similar institution), number of months with training, unemployment, and employment.[10] Applying this matching procedure, 13 displaced workers

[7] To additionally test the robustness of the training variable, I re-code training in two different ways. First, I evaluate the number of months with vocational training on a quarterly basis. Second, I evaluate for each quarter the extensive margin of vocational training, i.e. I take a dummy for *whether* the respondent was in vocational training in the specific quarter. Then, the estimated effects are less significant, but point in the same direction.

[8] As this cutoff of 6 months is chosen arbitrarily, I also re-run the analysis with the cutoff at 5 and 7 months but results do not change. The specification of this variable is also tested by considering, first, the employment from the last December and, second, full-time employment in more than 6 months of the current year. Again, the results are robust to these changes.

[9] The original answer in the German survey is “Wegen Betriebsstillegung / Auflösung der Dienststelle”.

[10] For East Germans in 1990, some criteria are unknown. To not lose these observations, a displaced worker with an unknown characteristic is matched with controls who have the same unknown characteristic.

remain unmatched and, therefore, are excluded from the sample. In the end, the East (West) German subsample covers 228 (92) displaced workers in the treatment group which are matched with 4,014 (8,497) controls.

For the analysis, both displaced workers and workers in the control group are weighted. The displaced workers are weighted according to the longitudinal weights provided by the GSOEP. Considering, for each year t, the number of displaced workers and controls which coincide in their matching criteria in the year prior to the plant closure, the new longitudinal weights of the controls are set as follows:

$$\textit{new weight}_{i,t} = \textit{old weight}_{i,t} \frac{\sum_{j \in \textit{Displaced}} \textit{old weight}_{j,t}}{\sum_{j \in \textit{Controls}} \textit{old weight}_{j,t}}.$$

Thereby, the weights of the controls are adjusted twofold: by the weighted number of displaced workers matched and, reciprocally, by the weighted number of controls matching the same displaced workers.

Treatment versus Control Group

For each regional subsample, Table 2.3.1 summarizes observable characteristics of the treatment and control group prior to the plant closure. Differences between displaced and non-displaced workers are negligible regarding the exact-matched variables: sex, education in 1990, months in training, etc. It is reassuring that other variables like age, tenure, and employment, which were not among the matching variables, are also almost perfectly matched in the last interview prior to the plant closure; mean values of age and tenure and the size of the employment categories differ barely between the control and treatment group. It is also reassuring that, prior to the plant closure, education levels of the control and the treatment group differ only marginally, although the matching took place on formal education in 1990, i.e. on education which had mostly been received prior to reunification. Control and treatment group only vary slightly in terms of plant size. Displaced workers had worked in middle size firms more often than workers in the control group. For the West German subsample, this discrepancy diminishes.

Table 2.3.1: Sample Characteristics

	East Germans		West Germans	
	Displaced	Non-displ.	Displaced	Non-displ.
General sample characteristics				
Female	0.60	0.60	0.38	0.38
Age, plant closure year	42.28	42.45	42.62	41.90
Older than 40, 1990	0.53	0.53	0.47	0.47
Education, 1990				
low	0.05	0.05	0.22	0.22
middle	0.69	0.69	0.69	0.69
high	0.26	0.26	0.07	0.07
unknown	0.00	0.00	0.01	0.01
Sample characteristics: year before the plant closure†				
Months in training	0.11	0.11	0.02	0.02
Months unemployed	0.02	0.02	0.00	0.00
Months employed	11.83	11.83	11.88	11.88
Sample characteristics: last interview before the plant closure+				
Education				
low	0.05	0.05	0.22	0.23
middle	0.70	0.69	0.70	0.69
high	0.25	0.26	0.08	0.07
unknown	0.00	0.00	0.00	0.01
Employment				
full-time	0.85	0.86	0.86	0.80
part-time	0.12	0.12	0.10	0.16
marginal	0.00	0.00	0.01	0.03
none	0.02	0.02	0.02	0.02

Continued on next page ...

Notes: †Not available for East Germans in 1989.
+For the control group of non-displaced workers, the numbers refer to the interview in the treatment year if the interview month lies before the median displacement month; otherwise, the answers of the previous survey year are evaluated. For 12 West Germans controls of the 1990 plant closures, a 1989 survey is not available and 10 East Germans who were displaced in 1990 were not interviewed before the displacement.
GSOEP, own calculations using cross-sectional weights adjusted by the number of treated workers and matched controls.

... Table 2.3.1 continued				
	East Germans		West Germans	
	Displaced	Non-displ.	Displaced	Non-displ.
Firm size				
1-19	0.14	0.15	0.21	0.20
20-199	0.38	0.33	0.28	0.24
200-1999	0.33	0.27	0.24	0.24
$\geq$2000	0.13	0.21	0.23	0.27
non-applicable	0.02	0.02	0.02	0.02
unknown	0.00	0.01	0.01	0.01
Tenure				
mean	13.15	13.66	11.79	13.02
unknown	0.02	0.02	0.04	0.03
Observations				
Plant closure 1990	61	992	11	1814
Plant closure 1991	74	924	7	1184
Plant closure 1992	47	789	15	1575
Plant closure 1993	18	697	36	1984
Plant closure 1994	28	612	23	1940
N, total	228	4014	92	8497

Notes: †Not available for East Germans in 1989.
+For the control group of non-displaced workers, the numbers refer to the interview in the treatment year if the interview month lies before the median displacement month; otherwise, the answers of the previous survey year are evaluated. For 12 West Germans controls of the 1990 plant closures, a 1989 survey is not available and 10 East Germans who were displaced in 1990 were not interviewed before the displacement.
GSOEP, own calculations using cross-sectional weights adjusted by the number of treated workers and matched controls.

2.4 Methods and Assumptions

2.4.1 Baseline Model

The baseline estimation is applied to the East and West German subsample separately as well as to a subsample of young East Germans and a subsample of old East Germans. I use the following model by Ichino et al. (2017), which combines plant closures of several years by adjusting the approach of Jacobson et al. (1993):[11]

$$Y_{it} = \theta_t + \sum_{k=-2}^{3} PC_{it}(k)\ \psi^k + \sum_{k=-3}^{3} (DP_i \times PC_{it}(k))\ \delta^k + \varepsilon_{it}. \tag{2.4.1}$$

The treatment variable DP_i indicates whether an individual i has been displaced; it is a dummy variable, which equals 1 if the individual has been displaced due to a plant closure between 1990 and 1994. The value k represents the time since the plant closure. As I match treated and non-treated workers in the year prior to the treatment, for both treated workers and their (matched) counterfactuals, the dummy variable $PC_{it}(k)$ indicates whether the plant closure occurred k years ago; it equals 1 if individual i is observed in year t at a distance of k years from the plant closure. Note that, also for the non-treated counterfactuals, $PC_{it}(k)$ equals 1 if the plant closure happened k years ago (although only the treated workers actually experienced the plant closure). The outcome variable Y_{it} represents the number of months of calendar year t in which individual i does some training. Variations over the business cycle are captured by calendar year fixed effects θ_t. The ε_{it}'s denote the individual and time-specific residuals.
The parameters $\delta^0, \delta^1, \ldots, \delta^3$ capture the effect of interest. They are interpreted as the increase in the likelihood of investing in training in one more month per year when being displaced k years earlier; the counterfactual is the investment in training without the displacement k years earlier.
The identification assumption emerges with the difference-in-difference model formulated in (2.4.1). For each region and for each East German age group, the counterfactual of the displaced workers are the non-displaced workers. A necessary, although clearly not sufficient condition is the common trend of the pre-treatment outcome between the control and treatment group. Moreover, non-displaced workers cannot be interpreted as the counterfactual of the displaced workers if there is some kind of selection into treatment or control group, e.g. through the industry of the worker, or through workers with lower ability being more likely to experience a plant closure. These and other threats to the identification assumption are discussed in Section 2.6.

2.4.2 Transition versus Stable Economy

In order to estimate the difference of the effects between the East and the West German subsample, the following difference-in-difference-in-difference (DDD) approach is applied to the pooled

[11] Contrary to Jacobson et al. (1993), individual-fixed effects cannot be incorporated due to the small number of observations. However, I test the robustness of the results by including age and gender dummies; the results remain unchanged.

sample of East and West subsamples:[12]

$$Y_{it} = \theta_t + \sum_{k=-2}^{3} PC_{it}(k)\ \psi^k + \sum_{k=-3}^{3} (DP_i \times PC_{it}(k))\ \delta^k \qquad (2.4.2)$$
$$+ \sum_{k=-3}^{3} (PC_{it}(k) \times East_i)\ \psi^{k,E} + \sum_{k=-3}^{3} (DP_i \times PC_{it}(k) \times East_i)\ \delta^{k,E} + \varepsilon_{it},$$

where $East_i$ is a dummy variable for being an East German.[13] For each period k since the plant closure, $\delta^{k,E}$ represents how the displacement effect on training differs between East and West Germans.

Comparing training activities of workers from the stable West German economy with training activities of workers from the transitioning East Germans economy underlies the following assumption: training opportunities were available and the supply of training opportunities was demand-induced, and not limited for either East or West Germans. This assumption particularly needs to hold for West Germans, for whom I find a smaller displacement effect on training participation. With the reunification in 1990, the West German institutional and legal settings were extended to East Germany. Part of this new institutional environment is the Bundesanstalt für Arbeit (the Federal Labor Office); it provides support for further training and continuing education. Whereas West Germany was already equipped with an established infrastructure of regional labor offices and training facilities, this infrastructure still had to be built in East Germany. Hence, it is rather East Germany which suffered from an under-supply of training opportunities. Due to this under-supply, any training effect of displacement in such transitioning economies could be underestimated. However, it is well known that the Federal Labor Office focused on providing enough training opportunities in the East. For instance, in 1992, it spent 50% more on vocational training in East Germany, although its labor force was almost 75% smaller than the West Germans' (Hujer & Wellner, 2000). Besides, there is no evidence for a lack of training opportunities in the West. Therefore, the East-West difference in the supply of training opportunities is assumed to be demand-induced.

2.4.3 Before and after Re-entry into Employment

As soon as displaced workers find a new job, they have less time and higher opportunity costs for training activities. Neglecting their accumulation of new firm-specific human capital, their training activities may decline to the level of non-displaced workers. Moreover, with increased training activities during their post-displacement unemployment spell, they may have

[12] This DDD approach has been used by Ichino et al. (2017, equation (3)) to evaluate the difference in displacement effects of young and old Austrian workers.

[13] I also tested whether different business cycles in East and West Germany affect the results by including region-specific calendar-year effects. However, the results do not change.

accumulated human capital which is more up-to-date than what they would have acquired without the displacement. As a consequence, the re-employed may invest even less time in training than without the displacement.

I provide some information on this employment-training trade-off by splitting the per-period effect on training δ^k, for each $k > 0$, by the employment status; the regression equation becomes

$$Y_{it} = \theta_t + \sum_{k=-2}^{3} PC_{it}(k)\ \psi^k + \sum_{k=-3}^{0} (DP_i \times PC_{it}(k))\ \delta^k \\ + \sum_{k=1}^{3} (DP_i \times PC_{it}(k)) \left(Empl_{it}\ \delta^{k,empl} + (1 - Empl_{it})\ \delta^{k,no\ empl}\right) + \varepsilon_{it},$$

where $Empl_{it}$ is a dummy variable for individual i's employment. It equals 1 if i is employed in most of the months of period t.

2.4.4 Young versus Old East Germans

Human capital theory suggests that young people have stronger incentives to invest in human capital. I test this prediction in the special scenario of the East German transition.

In order to compare the effects between two East German age groups, I split the East German sample by their age in 1990: People who are at most 40 are called young and form the base group. The remaining people are called old and are indicated by the dummy variable Old_i. For the estimation, I use the regression model by Ichino et al. (2017, equation (3)):

$$Y_{it} = \theta_t + \sum_{k=-2}^{3} PC_{it}(k)\ \psi^k + \sum_{k=-3}^{3} (DP_i \times PC_{it}(k))\ \delta^k \\ + \sum_{k=-3}^{3} (PC_{it}(k) \times Old_i)\ \psi^{k,Old} + \sum_{k=-3}^{3} (DP_i \times PC_{it}(k) \times Old_i)\ \delta^{k,Old} + \varepsilon_{it}.$$

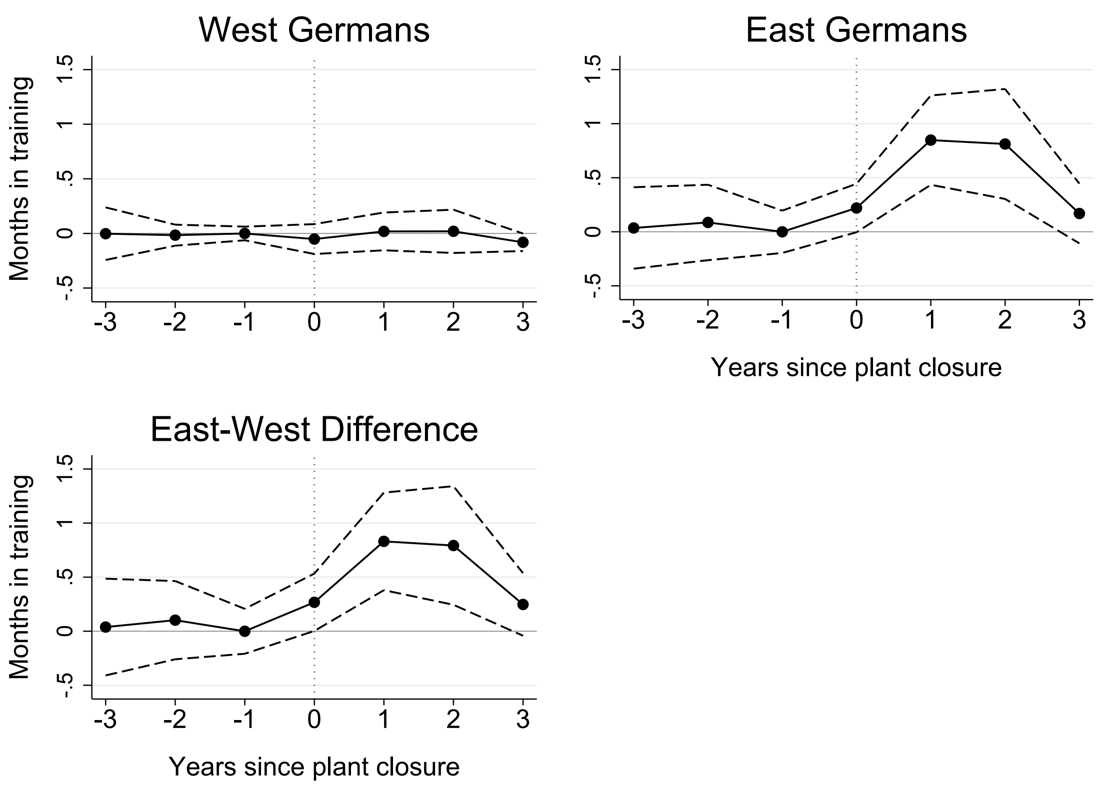
The parameter $\delta^{k,Old}$ captures the difference of the displacement effects between old and young East Germans for each period k after the plant closure.

2.5 Results

2.5.1 The Displacement Effect on Training Activities

Figure 2.5.1 displays the effect of job displacement in the rather stable West German economy, in the transitioning East German economy, and the East-West difference of the effects. For the exact numbers of the coefficients see Table 2.A.1, Columns (1) - (3), of the Appendix. The upper panel of Figure 2.5.1 shows that, before the plant closure, displaced workers and the counterfactual non-displaced workers do not differ in the number of months in which they train. This holds for both East and West German workers. After the plant closure, displaced West German workers do not invest significantly more in training as they would without the displacement. If at all, in the third year after the displacement they spend marginally less time on training. In contrast, East Germans have an increased likelihood to invest in training activities after displacement. Particularly, in the first two years after displacement, the effect on training is stronger for East Germans (lower panel of Figure 2.5.1). With a probability of approximately 80% in both years, a displaced East German does some training in one more month than without displacement (right plot, upper panel of Figure 2.5.1). In the third year after displacement, the probability of additional training activities falls again to a level insignificantly different from that of the control group.

Figure 2.5.1: Displacement Effect on Training



Notes: Point estimates with 95% confidence intervals. GSOEP, own calculations.

The East-West-difference in the displacement effect can be interpreted in the following way: East Germans understand that they are living in a transition process. As soon as they lose their job, they notice that their skills have become obsolete and that they lack skills required in the market economy and for the modern technology; they have a strong incentive for continuing

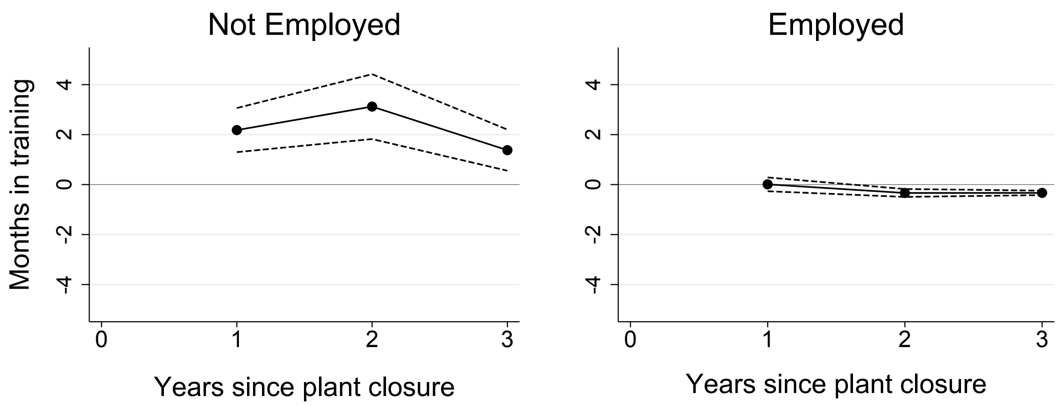
training in order to increase their chances on the labor market in the future. In East Germany, displaced workers immediately try to mitigate this human capital depreciation by exploiting the low opportunity costs of training during unemployment. In comparison, the West Germans' human capital did not depreciate that much; in general, only the firm-specific knowledge became obsolete. In the 1990s, the West German economic situation was rather stable for decades. Hence, West Germans had been trained in and for the same economic system as they are living in the 1990s. Incentives for adult training are, therefore, weak.
In the third year after the plant closure, displaced East German workers spend on average as much time in training as without the displacement (see Figure 2.5.1). For displaced West Germans, the effect is even marignally negative. One possible explanation for these lower training activities is re-employment. The re-employed workers may be fully occupied with their new jobs. As long as displaced workers are unemployed, their opportunity costs of training are low, but when they find a new job, opportunity costs rise again. The displaced East Germans may increased their training activities in the time of unemployment and, thereby, did planned training activities earlier than without the displacement. A negative displacement effect of re-employed East German workers would strengthen this argument. Therefore, in the next subsection, I study how the significant displacement effect on the East Germans' training activities is associated with post-displacement employment.

2.5.2 The Effect on Training under Re-employment

Figure 2.5.2 shows how the effect of displacement on training is related to the employment status of the displaced East German worker:[14] If the displaced worker is not employed for at least 6 months in the first (second, third) year following the year of displacement, then, on average, that worker undergoes training in about 2 (3, 1) more months of that year - compared to what she would do without the displacement. For a displaced worker who is employed in more than 6 months per year the positive displacement effect on training vanishes. In particular in the first year after displacement, the number of months in which a displaced but employed worker does some training is indistinguishable from the months she would do some training in case of no displacement. In the second and third year after displacement, displaced workers who are mostly employed, invest even less in training than they would invest without the displacement: On average, in one month per year, displaced workers who are employed most of the year do less training compared to what they would have done without the displacement. This negative effect on training activities combined with the strong positive effect under non-employment suggests that East Germans make the highly necessary investment in training activities as soon as possible by bringing it forward to the time immediately after displacement - a time in which they are not employed and have low opportunity costs of training.

[14]The exact numbers of the coefficients are displayed in Table 2.A.1, Column (4), in the Appendix.

Figure 2.5.2: Displacement Effect on Training in East Germany, by Current Employment



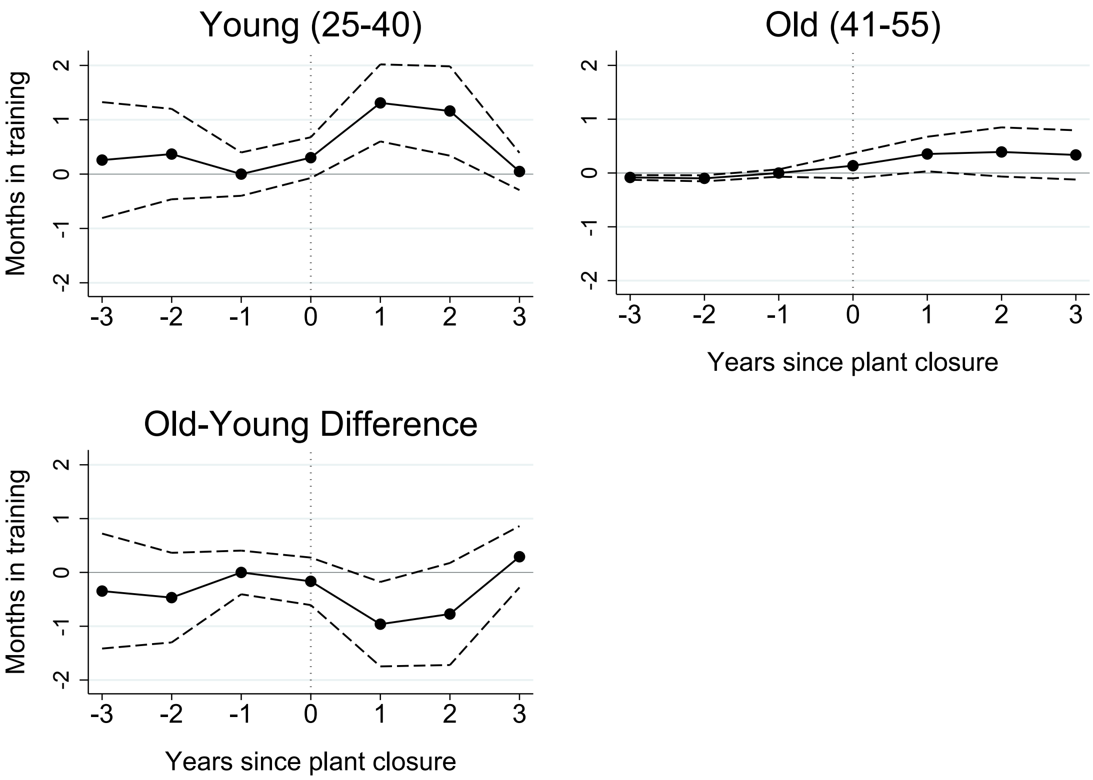
Notes: The header *Not Employed* refers to the estimate for people who are not employed in at least 6 months in $k = 1, 2, 3$ years after the plant closure; The estimate for those who are employed in more than 6 months are displayed under the header *Employed*. Point estimates with 95% confidence intervals. GSOEP, own calculations.

2.5.3 The Effect on Training for Young and Old Workers

Figure 2.5.3 displays the effect of job displacement for young and old East Germans separately. First, it confirms the common trend assumption between the control and the treatment group for the subsample of young East Germans (see the upper left panel). The common trend assumption for the subsample of old East Germans is slightly violated as, contrary to the treatment group, the control group includes some old East Germans who did some training in the third and second year before the plant closure. I repeat the analysis with counterfactual workers matching the displaced workers additionally in the amount of training months two and three years before the plant closure. Thereby, the number of displaced workers matched falls from 228 to 226, the common trend assumption is fulfilled, and changes in the displacement effects are negligible; see Table 2.A.2 in the Appendix.

Second, the upper panel of Figure 2.5.3 shows that both young and old East Germans invest more in training relative to their counterfactuals. For old workers, the displacement effect on training is only weakly significant in the first year after the displacement. On average, each young displaced worker increases her training activities one month more than older workers in the first two years after the displacement (lower panel, Figure 2.5.3); however, only in the first year after displacement, this difference between the two age groups is weakly statistically significant. Later, for both young and old East Germans, displacement does not significantly affect the likelihood to alter time investments in training activities. The larger effect on training activities for young workers is in line with human capital theory: Young people can collect returns from human capital investments over a longer time horizon and, thus, their incentive for training is larger.

Figure 2.5.3: Displacement Effect on Training in East Germany, by Age Group



Notes: Point estimates with 95% confidence intervals. GSOEP, own calculations.

2.6 Limitations and Robustness

2.6.1 Limitations of the Data

As all survey data, the GSOEP provides self-reported information. Sometimes, this information is incomplete or implausible. Whenever possible, incomplete or implausible information has been replaced by imputed data; if imputation was not possible, such observations were dropped from the sample.[15] However, when I drop all individuals who have incomplete information on the matched variables within the time of the matching, the results in Section 2.5 still point in the same direction.[16]

One might argue that the GSOEP does not provide enough information on the history of East

[15]Imputation affects information on monthly employment and training activities as well as information on the place of living.

[16]Administrative data would be clearly preferable for the research question at hand; besides the absence of missing information, it would also cover more workers. To my knowledge, the only administrative data with all the information required is a combination of the IAB Employment Subsample (IABS) and the training participants data (FuU). It has been utilized, for instance by Bender et al. (2005), to evaluate training programs. However, the relevant information on East Germans is not included before 1992. Excluding 1990 and 1991 in the analysis would mean to exclude the two most important years - the first two years of the transition, which show the highest displacement rates in East Germany.

German workers as it only covers East Germany from 1990 onward and 1990 is already the first year in which the treatment, the plant closure, may occur. First, although pre-displacement information is scarce for the East Germans whose plant closed in 1990, these displaced East Germans are matched according to their sex, age in 1990 (older than 40, at most 40), education in 1990, and also to their employment and training activities in January 1990. This is possible as the earliest displacement observed in the GSOEP in 1990 took place in February 1990. Second, in the socialist GDR, equality was a major policy goal; unemployment was basically non-existent. Hence, additional information on the history of East German workers may have little added value.

Following the displacement literature, I identify involuntary job separations by focusing on the exogenous shock of plant closures. This shock is assumed to be independent of the workers' characteristics; however, the fact that a worker switches to a new job before the plant closure may not be exogenous. In line with the findings of Schwerdt (2011), one might expect that workers with higher skill levels are more likely to find a new job early. Such workers would be neglected in the treatment group, whereas workers with lower skill levels, who may have a larger need for further training, may be over-represented. As a consequence, the displacement effect estimated would be biased upwards for all the subsamples: West Germans, East Germans, young East Germans, and old East Germans. To explain the identified East-West difference in training activities, the skill level of displaced East Germans must fall well below the skill level of displaced West Germans; this, however, appears unlikely.

2.6.2 Further Limitations and Robustness Checks

There are certain questions that the baseline results may not have addressed. Is it conceivable that the estimated displacement effect stems from specific industries which were affected more often by plant closures and, thus, are over-represented in the treatment group? Could it be that the estimated East German displacement effect is driven by unproductive small firms where workers are less skilled and therefore require more training? Is East-West-German migration influencing the estimated displacement effect? May spill-over effects from the East German transition to the West German economy explain the insignificant effect on the West Germans' training activities? The next subsections focus on these questions.

Industry-specific Displacement

Plant closures may be more common in some industries than in others. In such cases, the displacement effect found may be due to specific industries which are over-represented among displaced workers and under-represented in the control group.

Unfortunately, the GSOEP does not provide direct information on the industry of the plant

closed; but it provides information on the industry the worker is working in at the time of each interview. Therefore, I impute the industry of the plant closure using the month of the interview, the month of the displacement, and the industry mentioned at the last interview before the plant closure. As the GSOEP covers East Germans only since 1990 and some West Germans also entered the GSOEP in or after 1990, the last industry worked in is unknown for some workers with a plant closure in 1990. For the control group, the month of the median displacement is considered as the displacement month. The month of the median displacement is computed for each year and regional subsample separately.
Table 2.6.1 shows that, given the information from the last interview before the plant closure, displaced and non-displaced workers do not match exactly regarding the industry branch. Among both the displaced East Germans and the displaced West Germans, manufacturing is much stronger represented as within the control groups. The opposite holds for the bank, insurance, and service industry. Moreover, compared to the control group, displaced East Germans used to work more often in agriculture or retail, and less in the transport industry.

Table 2.6.1: Industry Working for Prior to the Plant Closure+

	East Germans		West Germans	
	Displaced	Non-displ.	Displaced	Non-displ.
Agriculture	0.12	0.07	0.00	0.01
Energy	0.03	0.02	0.00	0.01
Mining	0.04	0.02	0.00	0.01
Manufacturing	0.30	0.20	0.40	0.26
Construction	0.10	0.12	0.15	0.15
Retail	0.18	0.11	0.14	0.12
Transport	0.03	0.10	0.05	0.05
Bank, insurance	0.00	0.02	0.02	0.07
Services	0.17	0.30	0.19	0.27
Non-applicable	0.02	0.02	0.02	0.02
Unknown	0.02	0.01	0.03	0.03

Notes: +Information from the last interview prior to the plant closure. For the control group of non-displaced workers, the numbers refer to the interview in the treatment year if the interview month lies before the median displacement month; otherwise, the answers of the previous survey year are evaluated. For 12 West Germans controls of the 1990 plant closures, a 1989 survey is not available and 10 East Germans who were displaced in 1990 were not interviewed before the displacement.
GSOEP, own calculations using cross-sectional weights adjusted by the number of treated workers and controls matched.

To rule out that the displacement effect found is due to specific industries which are under-represented in the control group, I conduct several robustness checks regarding the last industry observed prior to the plant closure. First, I add industry fixed effects using the last industry

observed prior to the plant closure. If information on the industry is unknown, this is taken into account with an additional dummy variable. Moreover, I repeat the analysis without the workers with unknown information on the industry. This reduces the number of displaced workers to 210 East and 84 West Germans. In both cases, the main effects remain at a similar level (compare, in the Appendix, Columns (2) and (3) with Column (1) in each of the Tables 2.A.3 and 2.A.4).
Second, I instead expand the matching procedure by the industry the workers worked in before the plant closure. In doing so, workers with missing industry information are matched with each other. I then end up with 210 (87) displaced East (West) German workers. Dropping workers with no information on the industry result in only 196 (82) people in the East (West) treatment group. In both the samples with and without the workers with unknown industry information, the main result does not change significantly (see Tables 2.A.3 and 2.A.4in the Appendix); there is no evidence that the estimated displacement effect in the baseline results is driven by the treatment group representing workers from different industries than the control group.

Firm Size-specific Displacement

The plant closure of a small firm may not be as independent of the workers characteristics as a plant closure of a big firm. If the firm is very small, the workers skills may be highly correlated with the likelihood of a plant closure. Hence, displaced workers from small firms may have lower unobserved skills than the non-displaced counterfactuals from small firms; these displaced workers may require more training and, therefore, may drive the estimated displacement effect. Like industry, the size of the firm with a plant closure is not explicitly given in the GSOEP. Therefore, I use the same procedure applied to the industry to infer the firm size.[17]
I check whether the results are driven by displaced workers in small firms by excluding all workers working in small firms before the plant closure. An additional robustness check uses only workers with a known firm size of 20 and more employees; the number of displaced East (West) German workers shrinks to 195 (69) and 181 (63), respectively. The results are robust to both changes in the sample (see Tables 2.A.5 and 2.A.6 in the Appendix).

Migration between East and West Germany

The fall of the Berlin Wall initiated a migration flow from East to West Germany. It peaked in 1990 and fell sharply until 1997 (Heiland, 2004). Until 1997, the outmigration amounted to about 10% of the GDR population from 1988; more than a third of them migrated before 1991.[18]
One might argue that the East-West migration may influence the estimated displacement effect

[17]In Section 2.6.2, it is described in detail how the industry branch is inferred with the information available in the GSOEP.
[18]Own calcuation, given information provided by Heiland (2004), (Grünheid, 2009) and the Statistical Yearbook of the GDR (Statistisches Jahrbuch der DDR, 1989).

on training. First, I assume that the effect on training is associated with a person's previous human capital accumulation and, thus, with her stock of human capital and not with the place of living. Second, the institutional background is the same in both parts of Germany and, in both parts, training opportunities are available. However, one might still argue that displaced East Germans are less constrained and, therefore, are more likely to move to the West. There, they compete for a new job with West Germans whose stock of human capital is already aligned to the modern West German market economy; to increase their chances in the labor market, displaced East German migrants may increase their training activities. The displacement effect found would not stem from displacement per se, but from its impact on East-West migration. To test whether displacement initiates East Germans to move to the West, I estimate the baseline model with the outcome variable indicating that the individual is living in West Germany. Table 2.6.2 presents the coefficients of interest; none of them is significantly different from zero. In fact, only 3 of the 228 displaced East Germans moved to West Germany after the displacement. The sample size is too small to test whether East-West movers increase their training activities, but it strengthens the main results as it is unlikely that the East-West migration triggers the East Germans' displacement effect on training.

Table 2.6.2: The Effect of Displacement on Living in West Germany

	East Germans
DP X PC(0)	0.000
	(0.005)
DP X PC(1)	0.002
	(0.008)
DP X PC(2)	0.006
	(0.014)
DP X PC(3)	0.002
	(0.015)

Notes: Regression according to equation (2.4.1), where the outcome variable indicates that a worker is living in West Germany.
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Spill-over Effects between the East German Transition and the West German Labor Market

As a result of the reunification, West Germany experienced a demand-induced boom in the early 1990s (see e.g. Müller, 1998) whereas the East German economy underwent an extensive

Figure 2.6.1: East-West-Difference of the Displacement Effect on Employment

Notes: Point estimates with 95% confidence intervals. GSOEP, own calculations.

transformation. Finding a new job may have been easier for displaced West Germans. If costs of displacement are lower, investments in additional training may have been less necessary. To check whether the estimated East-West difference in the displacement effect on training may stem from lower displacement costs for West Germans, I test whether employment costs of displacement differ between East and West Germans. I conduct a DDD estimation similar to equation (2.4.2), but using the number of months with employment as the outcome variable. Figure 2.6.1 shows that despite its higher magnitude for West Germans the displacement effect on employment differs only weakly from the effect estimated for East Germans in the second year after displacement (For the exact numbers, see Table 2.A.7 in the Appendix.).[19] Therefore, I argue that the booming West German economy may have reduced the training activities of displaced West Germans but it appears unlikely that it is large enough to explain the whole East-West-German gap of the displacement effect on training.

2.7 Summary and Conclusion

Following the German reunification in 1990, the East German economy underwent a transition from a command to a market economy. Many East Germans lost their jobs because of plant closures while their human capital was not yet aligned to a modern market economy. Hence, displaced workers from East Germany lost all the three firm-specific, regime-specific, and technology-specific human capital. In contrast, displaced workers from West Germany lost, in general, only firm-specific human capital. In this paper, I study how displaced East German workers reacted to the stronger human capital depreciation. Using a difference-in-difference-in-difference set-up, I compare the effect of displacement on training activities between East and

[19] Moreover, considering quarterly data, the East-West difference on the costs of displacement in terms of employment are insignificant for all quarters.

West German workers.
I find that East Germans increase their time investment in adult training significantly when they were displaced one or two years earlier. This increase in adult training is not observable for West Germans. Moreover, the displacement effect on training is more pronounced for young relative to old East Germans. These findings are in line with the human capital theory developed by Becker (1962, 1964), Mincer (1958, 1962), Ben-Porath (1967). Besides that, the results suggest that when East Germans lose their job due to a plant closure, they increase their training activities as soon as they are not employment anymore; but when they find a new employment, they invest significantly less time in training than they would have done without the job displacement. In that sense, plant closures may have a useful side-effect in a transition period because they allow people to counteract the human capital depreciation associated with the transition sooner.

Appendix 2.A Regression Tables

Table 2.A.1: The Effect of Displacement on Training of East and West Germans

	(1) West	(2) East	(3) All	(4) East
DP X PC(-3)	-0.002	0.036	-0.002	0.035
	(0.123)	(0.192)	(0.123)	(0.192)
DP X PC(-2)	-0.016	0.086	-0.016	0.086
	(0.049)	(0.178)	(0.050)	(0.178)
DP X PC(-1)	-0.000	0.000	0.001	0.000
	(0.032)	(0.100)	(0.035)	(0.100)
DP X PC(0)	-0.051	0.220	-0.048	0.220
	(0.070)	(0.114)	(0.073)	(0.115)
DP X PC(1)	0.019	0.848^{***}	0.017	
	(0.088)	(0.211)	(0.090)	
DP X PC(2)	0.019	0.812^{**}	0.020	
	(0.101)	(0.259)	(0.104)	
DP X PC(3)	-0.081^{*}	0.169	-0.081	
	(0.041)	(0.141)	(0.043)	
DP X PC(-3) X East			0.038	
			(0.228)	
DP X PC(-2) X East			0.102	
			(0.185)	
DP X PC(-1) X East			-0.001	
			(0.106)	
DP X PC(0) X East			0.268^{*}	
			(0.135)	
DP X PC(1) X East			0.831^{***}	
			(0.230)	
DP X PC(2) X East			0.793^{**}	
			(0.280)	
DP X PC(3) X East			0.248	
			(0.148)	
DP X PC(1) X No Empl.				2.182^{***}
				(0.450)
DP X PC(2) X No Empl.				3.121^{***}
				(0.662)
DP X PC(3) X No Empl.				1.378^{**}
				(0.420)
DP X PC(1) X Empl.				0.011
				(0.141)
DP X PC(2) X Empl.				-0.334^{***}
				(0.080)
DP X PC(3) X Empl.				-0.331^{***}
				(0.045)
Observations	47288	22497	69785	22497
R^2	0.006	0.042	0.052	0.154

Notes: Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.A.2: The Effect of Displacement on Training of East Germans

	(1) Young	(2) Young Match	(3) Old	(4) Old Match	(5) East	(6) East Match
DP X PC(-3)	0.259 (0.544)	0.000 (0.009)	-0.082^{***} (0.023)	0.000 (0.004)	0.264 (0.545)	0.000 (0.006)
DP X PC(-2)	0.369 (0.424)	-0.000 (0.579)	-0.099^{***} (0.028)	-0.000 (0.003)	0.369 (0.424)	-0.000 (0.585)
DP X PC(-1)	0.000 (0.203)	0.000 (0.048)	-0.000 (0.035)	-0.000 (0.035)	0.000 (0.204)	0.000 (0.042)
DP X PC(0)	0.303 (0.191)	0.344^{*} (0.161)	0.136 (0.120)	0.134 (0.120)	0.302 (0.190)	0.342^{*} (0.159)
DP X PC(1)	1.311^{***} (0.362)	1.351^{***} (0.368)	0.354^{*} (0.164)	0.349^{*} (0.164)	1.316^{***} (0.366)	1.357^{***} (0.372)
DP X PC(2)	1.162^{**} (0.419)	1.203^{**} (0.426)	0.391 (0.233)	0.390 (0.233)	1.162^{**} (0.422)	1.203^{**} (0.429)
DP X PC(3)	0.049 (0.175)	-0.205 (0.336)	0.337 (0.233)	0.338 (0.233)	0.049 (0.176)	-0.205 (0.337)
DP X PC(-3) X Old					-0.346 (0.545)	0.000 (0.009)
DP X PC(-2) X Old					-0.468 (0.425)	0.000 (0.585)
DP X PC(-1) X Old					-0.000 (0.207)	-0.000 (0.053)
DP X PC(0) X Old					-0.165 (0.225)	-0.208 (0.200)
DP X PC(1) X Old					-0.961^{*} (0.400)	-1.008^{*} (0.407)
DP X PC(2) X Old					-0.773 (0.484)	-0.816 (0.489)
DP X PC(3) X Old					0.291 (0.291)	0.547 (0.408)
Observations	13065	12462	9432	9144	22497	21606
R^2	0.062	0.074	0.027	0.028	0.064	0.074

Notes: The term *Match* denotes that the control and treatment group are additionally matched regarding the months of training in the third and second year before the plant closure.
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.A.3: The Effect of Displacement on Training, Robustness Checks: Industry (East)

	(1) Base	(2) Dummy	(3) Dummy	(4) Match	(5) Match
DP X PC(-3)	0.036	0.042	0.035	0.082	0.081
	(0.192)	(0.202)	(0.201)	(0.221)	(0.221)
DP X PC(-2)	0.086	0.097	0.096	0.184	0.187
	(0.178)	(0.187)	(0.187)	(0.191)	(0.194)
DP X PC(-1)	0.000	−0.022	−0.023	0.000	0.000
	(0.100)	(0.102)	(0.103)	(0.006)	(0.006)
DP X PC(0)	0.220	0.225	0.221	0.235*	0.259*
	(0.114)	(0.121)	(0.122)	(0.116)	(0.115)
DP X PC(1)	0.848***	0.852***	0.853***	0.694**	0.727***
	(0.211)	(0.223)	(0.223)	(0.218)	(0.219)
DP X PC(2)	0.812**	0.897**	0.900**	0.893**	0.920**
	(0.259)	(0.278)	(0.277)	(0.294)	(0.299)
DP X PC(3)	0.169	0.156	0.182	0.139	0.162
	(0.141)	(0.145)	(0.144)	(0.179)	(0.182)
Unknown Industry	In	In	Out	In	Out
Observations	22497	21903	21887	11994	11863
R^2	0.042	0.049	0.050	0.046	0.048

Notes: Column (1) with the header *Base* presents the estimates discussed in Section 2.5. The term *Dummy* denotes that the dummy variables is included for each potential industry the worker may have worked for before the plant closed. The term *Match* denotes that the control and treatment group are additionally matched regarding the industry the worker was working for before the plant closure. If workers with unknown industry categorization are included in (excluded from) the estimation, this is denoted as *In* (*Out*).
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.A.4: The Effect of Displacement on Training, Robustness Checks: Industry (All)

	(1) Base	(2) Dummy	(3) Dummy	(4) Match	(5) Match
DP X PC(-3)	-0.002	0.017	0.020	0.026	0.031
	(0.123)	(0.132)	(0.136)	(0.132)	(0.138)
DP X PC(-2)	-0.016	0.005	0.004	-0.056^{**}	-0.057^{**}
	(0.050)	(0.050)	(0.051)	(0.019)	(0.019)
DP X PC(-1)	0.001	0.020	0.021	0.000	0.000
	(0.035)	(0.032)	(0.033)	(0.005)	(0.005)
DP X PC(0)	-0.048	-0.087^{*}	-0.069	-0.037^{*}	-0.041^{*}
	(0.073)	(0.043)	(0.041)	(0.016)	(0.017)
DP X PC(1)	0.017	0.046	0.046	-0.051^{**}	-0.057^{**}
	(0.090)	(0.095)	(0.096)	(0.019)	(0.019)
DP X PC(2)	0.020	0.047	0.041	0.043	0.046
	(0.104)	(0.115)	(0.118)	(0.111)	(0.120)
DP X PC(3)	-0.081	-0.064	-0.071	-0.078^{**}	-0.080^{**}
	(0.043)	(0.044)	(0.045)	(0.025)	(0.026)
DP X PC(-3) X East	0.038	0.026	0.017	0.056	0.050
	(0.228)	(0.242)	(0.243)	(0.258)	(0.261)
DP X PC(-2) X East	0.102	0.095	0.094	0.240	0.244
	(0.185)	(0.194)	(0.193)	(0.191)	(0.195)
DP X PC(-1) X East	-0.001	-0.041	-0.043	-0.000	-0.000
	(0.106)	(0.107)	(0.108)	(0.006)	(0.006)
DP X PC(0) X East	0.268^{*}	0.311^{*}	0.290^{*}	0.271^{*}	0.300^{**}
	(0.135)	(0.128)	(0.128)	(0.116)	(0.115)
DP X PC(1) X East	0.831^{***}	0.805^{***}	0.808^{***}	0.745^{***}	0.784^{***}
	(0.230)	(0.243)	(0.244)	(0.219)	(0.221)
DP X PC(2) X East	0.793^{**}	0.848^{**}	0.859^{**}	0.848^{**}	0.873^{**}
	(0.280)	(0.300)	(0.302)	(0.315)	(0.322)
DP X PC(3) X East	0.248	0.216	0.251	0.215	0.241
	(0.148)	(0.152)	(0.151)	(0.181)	(0.184)
Unknown Industry	In	In	Out	In	Out
Observations	69785	67905	67215	32770	32545
R^2	0.052	0.060	0.061	0.060	0.061

Notes: Column (1) with the header *Base* presents the estimates discussed in Section 2.5. The term *Dummy* denotes that the dummy variables is included for each potential industry the worker may have worked for before the plant closed. The term *Match* denotes that the control and treatment group are additionally matched regarding the industry the worker was working for before the plant closure. If workers with unknown industry categorization are included in (excluded from) the estimation, this is denoted as *In* (*Out*).
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.A.5: The Effect of Displacement on Training, Robustness Checks: Firm Size (East)

	(1) Base	(2) Employers 20+ / unknown	(3) Employers 20+
DP X PC(-3)	0.036	-0.210^{***}	-0.213^{***}
	(0.192)	(0.042)	(0.043)
DP X PC(-2)	0.086	-0.128	-0.128
	(0.178)	(0.094)	(0.095)
DP X PC(-1)	0.000	-0.000	0.000
	(0.100)	(0.115)	(0.117)
DP X PC(0)	0.220	0.245	0.256
	(0.114)	(0.132)	(0.140)
DP X PC(1)	0.848^{***}	0.941^{***}	0.965^{***}
	(0.211)	(0.244)	(0.256)
DP X PC(2)	0.812^{**}	0.972^{**}	1.054^{**}
	(0.259)	(0.302)	(0.321)
DP X PC(3)	0.169	0.208	0.226
	(0.141)	(0.161)	(0.164)
Observations	22497	17188	16965
R^2	0.042	0.051	0.055

Notes: Column (1) with the header *Base* presents the estimates discussed in Section 2.5. The header *Employers 20+ / unknown* denotes that sample includes only workers who worked in a firm with at least 20 employers before the plant closure or for whom the firm size is unknown. The header *Employers 20+ / unknown* denotes that sample includes only workers who worked in a firm with at least 20 employers before the plant closure; workers without information on the firm size are excluded from the estimation.
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.A.6: The Effect of Displacement on Training, Robustness Checks: Firm Size (All)

	(1) Base	(2) Employers 20+ / unknown	(3) Employers 20+
DP X PC(-3)	-0.002	-0.009	-0.010
	(0.123)	(0.148)	(0.153)
DP X PC(-2)	-0.016	-0.023	-0.023
	(0.050)	(0.060)	(0.062)
DP X PC(-1)	0.001	0.001	0.001
	(0.035)	(0.042)	(0.045)
DP X PC(0)	-0.048	-0.054	-0.105
	(0.073)	(0.093)	(0.057)
DP X PC(1)	0.017	0.042	0.048
	(0.090)	(0.116)	(0.125)
DP X PC(2)	0.020	0.046	0.047
	(0.104)	(0.136)	(0.148)
DP X PC(3)	-0.081	-0.107^{**}	-0.112^{**}
	(0.043)	(0.039)	(0.041)
DP X PC(-3) X East	0.038	-0.201	-0.202
	(0.228)	(0.154)	(0.159)
DP X PC(-2) X East	0.102	-0.105	-0.105
	(0.185)	(0.111)	(0.113)
DP X PC(-1) X East	-0.001	-0.001	-0.001
	(0.106)	(0.123)	(0.126)
DP X PC(0) X East	0.268^{*}	0.298	0.361^{*}
	(0.135)	(0.161)	(0.151)
DP X PC(1) X East	0.831^{***}	0.899^{***}	0.918^{**}
	(0.230)	(0.271)	(0.286)
DP X PC(2) X East	0.793^{**}	0.925^{**}	1.007^{**}
	(0.280)	(0.331)	(0.354)
DP X PC(3) X East	0.248	0.313	0.337^{*}
	(0.148)	(0.167)	(0.169)
Observations	69785	50512	47813
R^2	0.052	0.061	0.065

Notes: Column (1) with the header *Base* presents the estimates discussed in Section 2.5. The header *Employers 20+ / unknown* denotes that sample includes only workers who worked in a firm with at least 20 employers before the plant closure or for whom the firm size is unknown. The header *Employers 20+ / unknown* denotes that sample includes only workers who worked in a firm with at least 20 employers before the plant closure; workers without information on the firm size are excluded from the estimation.
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.A.7: The Effect of Displacement on Employment of East and West Germans

	(1) West	(2) East	(3) All
DP X PC(-3)	-0.051	-0.142	-0.051
	(0.347)	(0.328)	(0.346)
DP X PC(-2)	-0.016	-0.020	-0.015
	(0.266)	(0.133)	(0.269)
DP X PC(-1)	0.001	-0.000	0.002
	(0.150)	(0.113)	(0.150)
DP X PC(0)	-1.968^{***}	-1.922^{***}	-1.971^{***}
	(0.419)	(0.262)	(0.427)
DP X PC(1)	-2.213^{**}	-3.112^{***}	-2.215^{**}
	(0.735)	(0.409)	(0.749)
DP X PC(2)	-0.649	-1.929^{***}	-0.644
	(0.473)	(0.419)	(0.476)
DP X PC(3)	-0.992	-1.011^{*}	-0.993
	(0.520)	(0.417)	(0.518)
DP X PC(-3) X East			-0.091
			(0.477)
DP X PC(-2) X East			-0.005
			(0.300)
DP X PC(-1) X East			-0.002
			(0.187)
DP X PC(0) X East			0.050
			(0.503)
DP X PC(1) X East			-0.898
			(0.853)
DP X PC(2) X East			-1.281^{*}
			(0.633)
DP X PC(3) X East			-0.021
			(0.666)
Observations	47288	22497	69785
R^2	0.100	0.147	0.143

Notes: Regression according to equation (2.4.1), where the outcome variable are the number of months with employment.
Robust standard errors in parentheses, * $p < 0.5$, ** $p < 0.01$, *** $p < 0.001$.

Bibliography of Chapter 2

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CHAPTER 3

Sources of German Income Inequality across Time and Space

3.1 Introduction

Similar to most industrialized countries, the net income of German households has become more unequal since the 1970s.[1] Recent literature emphasizes, among other reasons (e.g. changes in the tax and transfer system, capital income, or workplace heterogeneity; see Card et al., 2013, Schmid & Stein, 2013, Biewen, 2012, and Rehm et al., 2014), societal trends as determinants for this rise in income inequality (Peichl et al., 2012; Martin, 2006; Burtless, 2011; Greenwood et al., 2014; Kollmeyer, 2013; Gregorio & Lee, 2002; Reed & Cancian, 2012). Such societal trends are changes in the demography, education, preferences for marital sorting, and labor force participation. Take, for example, the rising share of single parents. Single parents are more likely to live in poverty than couples without children (see Buscher & Parys, 2006). When the number of single parents increases, the share of poor households also rises, and income becomes more unequal across the households. From a political perspective, before counteracting these societal trends or their effects on income inequality, it is important to understand whether and by how much each specific socio-economic trend influences income inequality.

The first contribution of my paper is to elaborately disentangle and compare the contribution of several societal trends on the German rise in income inequality. Germany has one advantage over other industrialized countries. Although facing the same political system for 20 years, in 2011, East and West Germany still differ substantially in their socio-economic characteristics.[2] These differences allow a cross-regional comparison of the societal impacts on income inequality. In the second part of the paper, I observe how these East-West-differences in socio-economic household characteristics influence income inequality in East and West Germany and, thereby, provide new insights on the relation between the socio-economic convergence between East and West Germany and income inequality.[3]

I apply the idea of the reweighting procedure by Di Nardo et al. (1996) in a non-parametric fashion and extend it by marital sorting algorithms. I construct counterfactual income distributions by adopting the composition of the population with respect to a specific attribute from another year or region. Attributes are the household head's age, the cohabitation status, the number of children, the adults' gender, their educational degree and their working status. The procedure

[1] For details on the rise in income inequality in industrialized countries, see, for example, Gottschalk & Smeeding (2000), and OECD (2008, 2011). For details on the rise in German income inequality, see, for instance, Hauser & Becker (1998), Becker (2012), Biewen (2000), and Bach et al. (2014).

[2] For a documentation on the distinct age distributions in East and West Germany, see Grünheid (2009) and Brenke (2014). For the evolution of East and West German household size, see Grünheid (2009) and Ebert & Fuchs (2012). For development of male and females education as well as assortative mating in both German regions, see Grave & Schmidt (2012), Wirth (1996) and Wirth (2014). For a documentation on German employment, see, for example, Ebert & Fuchs (2012) or Holst & Wieber (2014).

[3] I am not interested in the reason why these differences still exist or whether people with specific characteristics migrated to the East or to the West. If these East-West-movers (West-East movers) face the same conditional income distribution as their West (East) German peers, it is irrelevant whether parts of the West (East) German workforce is originally from the East (West).

indirectly takes the tax and transfer system into account as the adult-equivalent net income is held constant conditional on the household attributes. Moreover, unlike most decomposition approaches, the sequential approach proposed by Di Nardo et al. (1996) allows for holding some household characteristics constant while taking indirect effects into account. For example, when adjusting the composition of the population with respect to education, the age composition of the population is fixed, but a change in female education may affect the overall number of children and female employment. As a consequence, the reweighting procedure depends on causality assumptions, and like other decomposition techniques (e.g. the Oaxaca-Blinder and the RIF decomposition), it neglects general equilibrium effects.

Within the reweighting procedure, marital sorting can easily be controlled for. I control for marital sorting in formal education in three different ways: fixing marital sorting while adjusting gender–specific education (algorithm by Sinkhorn & Knopp, 1967), randomizing marital sorting while fixing gender-specific education, and perfectly sorting males and females regarding education while fixing their gender-specific education (algorithm by Gale & Shapley, 1962).[4] To my knowledge, this is the first study on German data combining a reweighting procedure and sorting algorithms.

I use data from the German Microcensus. The Microcensus is several times larger than the German Socio-Economic Panel (GSOEP), which is usually used in empirical studies.[5] The rich Microcensus allows for a finer categorization of household attributes. With this finer categorization, the present study provides detailed information on the sources of income inequality. Moreover, all relevant information is available in the German Microcensus since 1976. Because the time span surveyed is longer than in the GSOEP, I may observe more demographic and educational variation between the first and the last survey year. This larger variation could provide results which have not been found significant in previous studies.

For the comparison *across time*, I find that changes in the household size, education, and employment account for the rise in West German income inequality to a significant extent. Among these factors, the rising prevalence of singlehood plays the most important role. Exercises on the effects of employment show that the working status of males and single females does, but the working status of married females does not contribute to the rise in income inequality. These results augment the findings by Biewen & Juhasz (2011, 2012), Peichl et al. (2011), and Peichl et al. (2012) which reveal the importance of declining employment and smaller households for the rising German income inequality. Besides, in line with the findings on earnings inequality by Pestel (2017), I find that marital sorting in education has no potential to influence income

[4] Controlling for changes in marital sorting is necessary, as an increase in female or male education may drive the growing likelihood that males and females with the same educational degree marry each other or may offset this trend of increased positive assortative mating.

[5] See, for example, Pestel (2017), Rehm et al. (2014), Schmid & Stein (2013), Biewen & Juhasz (2012), Peichl et al. (2012). One exception is the study by Buscher & Parys (2006) on poverty in East and West German households, but they only consider Microcensus data from 1996 to 2002.

inequality in West Germany. Faik (2012) forecasts that population aging will cause more income inequality in the future. Although the workforce exhibits the aging trend already since 1976, I cannot find a significant impact of changes in the household head's age on income inequality.
By comparing the influence of household characteristics *across space*, I find that the high unemployment among East German males and single females makes income more unequally distributed. Fewer children in couple households combined with a stronger presence of children in single households, like in East Germany, also increases the income gap. These findings are in line with the studies on the East German inequality increase by Biewen (2001) and Peichl et al. (2012). Their studies link the growth in the income gap in the early 1990s and 2000s to rising unemployment, declining female labor force participation, and smaller households. Moreover, my results suggest that both the rather equal education across East German households and smaller variations in the conditional income distributions offset the inequality generated by employment and household size. Like for West Germany, for East Germany, I cannot confirm the hypothesis that marital sorting in education promotes income inequality. My results indicate that the German tax and transfer system counteracts the disequalizing effect which arises from marital sorting in education (see Fuchs-Schündeln et al., 2010; Pestel, 2017) or marital sorting occurs in terms of something else than formal education, e.g. in terms of occupation or industry.
In the following section, I briefly discuss methods for studying income inequality. In Section 3.3, I inform about the data set used and describe the socio-economic background of German households. The analytic framework is introduced in Section 3.4. Section 3.5 presents the results of the counterfactual exercises. In the final section, I discuss the main results and conclude.

3.2 A Brief Review of Methodical Approaches

In order to understand differences in inequality, an extensive spectrum of methods has been used in previous studies.[6] A range of descriptive papers exist. They link changes in policy and demography to shifts in economic inequality (see e.g. Gottschalk & Smeeding, 2000; Weick, 1995). However, these studies cannot provide a quantification of how much a specific demographic or political factor contributes to inequality.
Another branch of the literature utilizes regression models, in which the Gini coefficient is regressed on household or regional characteristics (e.g. Kollmeyer, 2013; Li et al., 1998; Gregorio & Lee, 2002). As the Gini coefficient is a non-linear and bounded measure, effects quantified by simple regression analysis provide only limited information. The recentered influence function (RIF) approach by Firpo et al. (2009) does not suffer from this caveat because it regresses the RIF of the Gini coefficient, and not the Gini coefficient itself, on the covariates. However, Rothe

[6]For a discussion of popular empirical strategies to determine the underlying sources of inequality, see Fortin et al. (2011).

(2015) argues that the RIF method is not always applicable, as it relies on strong assumptions. If the assumptions are not fulfilled, the RIF method can lead to arbitrarily large errors. For example, when it comes to the distributions of formal education in East and West Germany, the assumptions are not satisfied: The distributions of education are no location-shifted versions of each other. The variance in formal education is larger in the West whereas education is on average similar in both regions. The RIF method is not applicable.
For a better understanding of how inequality is affected by changes in the population composition or the income structure, the goal of many studies is to decompose changes in inequality. Thereby, the method used to decompose generalized entropy indices or other inequality measures may vary substantially.[7] A path-dependent decomposition has been proposed by Di Nardo et al. (1996). They analyze the impact of the labor market and institutional factors on changes in wage inequality. Changes in the population characteristics and in the conditional wage distribution are both taken into account. This semi-parametric approach has been adopted for the analysis of income inequality growth in the US (Daly & Valletta, 2006), Norway (Eika et al., 2014), New Zealand (Hyslop & Maré, 2005), Germany (Biewen & Juhasz, 2012; 2011; Peichl et al., 2012), and East Germany (Biewen, 2001). I also apply the idea introduced by Di Nardo et al., but incorporate martial sorting algorithms without estimating Kernel densities.[8]

3.3 Data and Descriptive Statistics

The German Microcensus is the largest representative household survey in Europe. It covers 1 percent of the German population. I utilize the scientific-use files of the Microcensus from 1976 and 2011 (FDZ der Statistischen Ämter des Bundes und der Länder, 2014).[9] The first survey year in which formal educational levels are reported is 1976. Since 1991 the survey also covers East German households. Whereas in the 1970s cohabiting males and females used to be married, non-married couples are more common nowadays. In the Microcensus of 1976, it was not considered that non-married males and females run a household together, and so I abstract from such households in 1976. Only since 1996, households which are run by a non-married couple are reported. As I do not focus on tax effects of marriages, all married and cohabiting

[7] Three examples are: Inequality change is split into the effect of income growth and reranking (e.g. Jenkins & van Kerm, 2006); Income is decomposed by its sources and their contribution to overall income inequality is quantified (e.g Lerman & Yitzhaki, 1985; Becker, 2000; Aslaksen et al., 2005; Karoly & Burtless, 1995; Cancian & Reed, 1998); The population is separated into pairwise disjoint subgroups, and within-group as well as between-group effects, and in some studies even group size effects, are measured (e.g Schwarze, 1996; Shorrocks, 1984; Peichl et al., 2011; 2012; Western et al., 2008; Bönke et al., 2015).

[8] The German Microcensus observes income within given intervals, but the data is rich so that I directly use the categorized income distribution and abstract from estimating kernel densities. This simplification does not influence the findings. For the West German inequality increase, it provides results in line with Biewen & Juhasz (2012) and Peichl et al. (2012). Both are reweighting studies which use the Kernel density estimates to smooth the income distribution as it is introduced by Di Nardo et al. (1996).

[9] The scientific-use files encompass 70 percent of the data, i.e. 0.7 percent of all German households.

couples refer to *married* households in 2011 and the term *married* is used as a synonym for not being single.[10]

For the household income, I apply the reported monthly net income.[11] It is divided by the OECD-modified scale to receive an adult-equivalent income for each household. The scale assigns a value of 1 to single households, 1.5 to couple households and, additionally, 0.3 for each child.

Households with more than two adults are not considered. Households including adult children or same-sex couples are excluded as their sample size is too small for the analysis.[12] Because my study does not focus on evaluating the income transfers to pensioners, I restrict the data to households with a household head of working age; that means that the male adult or, if absent, the single female adult is younger than 60 and at least 25 years old. For a useful categorization of households by age, I abstract from couples whose age difference is larger than 10 years. Thereby, the sample diminishes by less than 5 percent. In the end, the sample consists of approximately 137,000 households: 55,109 for West Germany in 1976, 67,749 for West Germany in 2011, and 14,055 for East Germany in 2011.[13]

How do West German households differ across time and compared to East German households? To answer this question, I present and discuss the age distribution, the cohabitation, education, and employment situation of German households in 1976 and 2011 in the following.

Aging Society

It is well-known that the German population is aging. This trend of an aging population is present in both parts of Germany. Since the 1990s, it is even more pronounced in the East (Grünheid, 2009). For my sample, Figure 3.3.1 illustrates the age distribution of West German household heads and their partners in 2011 compared to 1976 and compared to East Germany.[14] The left-hand panel shows that, in West Germany in 2011, the fraction of people who are older than 40 is larger than in 1976. The right-hand panel of Figure 3.3.1 shows that, in 2011, the share of people older than 50 is even larger in East Germany than in West Germany.

[10]Besides, social norms change. In 2010, 27 percent (61 percent) of all West (East) German babies are born to an unmarried mother (Pötzsch et al., 2012). Hence, there is no reason to restrict the analysis to married couples.

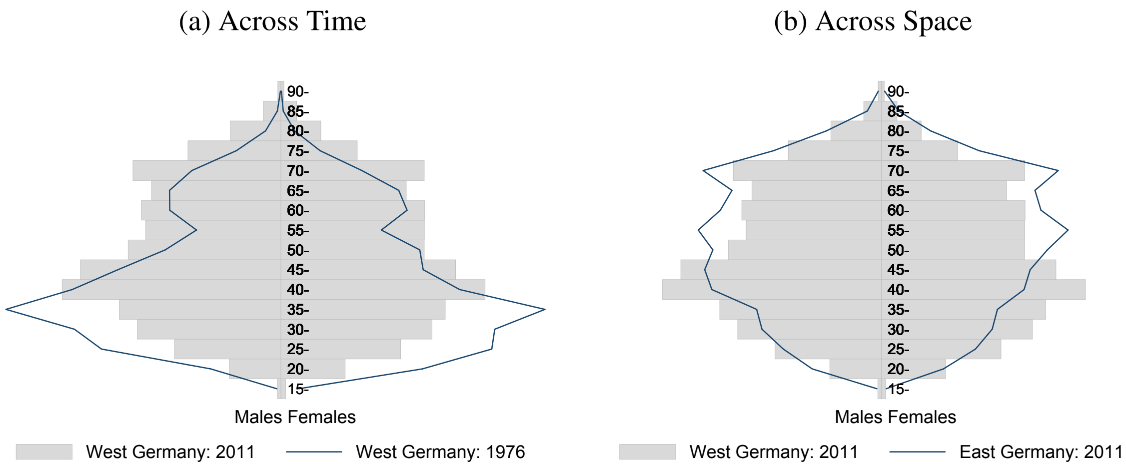
[11]Appendix Section 3.B documents how the reported income categories from the Microcensus are used to derive income levels.

[12]Most children older than 19 who live with their parents are either students at a university, or they finished education and work. They may work part-time, full-time, or not at all. Covering all these different types of adult children in the analysis results in an inflated categorization. Same-sex couples are not surveyed before 1996, and in the recent surveys there are too few same-sex couples to categorize them by age, gender, and their educational degrees simultaneously.

[13]Berlin is excluded from the sample.

[14]The figure represents the sample before restricting the age of the household head, but after introducing all other restrictions mentioned.

Figure 3.3.1: Normalized Age Distribution of Household Heads and Their Partners



Notes: Aged 15 to 95.

Household Size

In Germany, household size declines steadily since the 1970s. There are two main reasons for this trend: the rise in singlehood and the decline in fertility (see Table 3.3.1). Ebert & Fuchs (2012) document this rise in singlehood and the decline in the households with children for both East and West Germany. They also show that, since 2002, the prevalence of singlehood and households without children are more pronounced in the East than in the West. In the West, the share of couples with children has decreased, while the stronger prevalence of singlehood led to a rising share of singles with children. As presented in Table 3.3.1, this increase in single parents has occurred, although it has become less common among singles to have children in the households. In East Germany in 2011, compared to West Germany, the share of single parents is larger because single households are more prevalent and it is more common among singles to have children.

Buscher & Parys (2006) have shown that the risk of poverty is larger for single than for couple households and increases in the number of children living in the household. Hence, if there are more singles, the share of poor households grows and inequality rises. If single (couple) parents tend to have more children or the share of households with children increases among the singles (couples), income inequality may also grow. However, if the share of (couple) households with children increases, (couple) households may also become more alike; the inequality gap may decline.

Education and Marital Sorting

In Germany, formal education can be classified into three categories: school education, vocational training (apprenticeship), or university (college) education. People with a vocational training

Table 3.3.1: Household Size

	Average number of children in households	
West 1976	1.24	
West 2011	0.66	
East 2011	0.45	
	Couple households	Single households
West 1976	84.15 %	15.85 %
West 2011	49.32 %	50.68 %
East 2011	45.60 %	54.40 %
	Couple households with children	Single households with children
West 1976	62.37 %	3.22 %
West 2011	31.92 %	6.40 %
East 2011	21.23 %	7.96 %
	Childlessness rate among couples *	Childlessness rate among singles*
West 1976	25.88 %	79.70 %
West 2011	35.28 %	87.37 %
East 2011	53.45 %	85.38 %

Notes: Households of workforce age, children under 20. **Childless* refers to households with no children (younger than 20 years old) living with them; the household members may have children who live outside the household.

have a decent education, better than a school degree, but, in general, vocational training results in lower labor income than a university degree. As Table 3.3.2a shows, in West Germany, university education is rare in 1976. Males are on average better educated than females.[15] In 2011, West Germans are on average better educated, but also more unequal regarding their educational degrees. The gender differences in education have declined. In East Germany, women and men differ even less in their education. Moreover, the East German population is rather equally educated; more than three-quarter of the East German males and females have an apprenticeship degree.

If both partners have the same level of education, a couple is called *educational homogamous*. In 2011, the predominance of apprenticeships in East Germany creates strong educational homogamy (see Tables 3.3.2b, 3.3.2c). In West Germany, educational homogamy is still less pronounced than in the East, although it has increased since the 1970s (Grave & Schmidt, 2012; Wirth, 1996; 2014).

Educational homogamy is not only driven by gender-specific education, but also by *marital sorting*. In particular, in West Germany in 2011, marital sorting plays an essential role. If West

[15]For an overview of the evolution of education within marriages from 1976 to 2005, see Grave & Schmidt (2012).

Table 3.3.2: Education

(a) Educational Attainment

	Females			Males		
	University	Apprenticesh.	School	University	Apprenticesh.	School
West 1976	3.56	50.28	46.15	9.11	71.15	19.74
West 2011	20.02	66.07	13.91	23.82	65.02	11.15
East 2011	16.76	77.87	5.37	16.09	78.75	5.16

Notes: Fraction of all males and females, respectively, in percent.

(b) Contingency Tables of Couples' Education

WEST GERMANY 1976		Females			Males total
		University	Apprenticeship	School	
Males	University	2.42	4.88	1.60	*8.90*
	Apprenticeship	0.52	41.57	29.72	*71.81*
	School	0.14	3.64	15.52	*19.30*
Females total		*3.08*	*50.09*	*46.84*	

WEST GERMANY 2011		Females			Males total
		University	Apprenticeship	School	
Males	University	12.86	11.23	1.19	*25.28*
	Apprenticeship	5.13	52.73	8.03	*65.90*
	School	0.73	3.92	4.17	*8.82*
Females total		*18.73*	*67.88*	*13.39*	

EAST GERMANY 2011		Females			Males total
		University	Apprenticeship	School	
Males	University	9.88	8.47	0.41	*18.76*
	Apprenticeship	6.48	69.92	2.36	*78.76*
	School	0.37	1.16	0.95	*2.48*
Females total		*16.73*	*79.55*	*3.72*	

Notes: Fraction of all married households, in percent.

German males and females were matched randomly, 49 percent of the couples would have the same educational degree. However, the observed share of homogamous couples is larger by 38 percent (see Table 3.3.2c). Compared to West Germany in 2011, marital sorting is less important for educational homogamy in 1976 and plays an even subordinate role for the East.

The idea of how education affects income inequality is straightforward. The skill-premium

(c) Homogamy (Table 3.3.2 continued)

	Fraction of homogamous couples	Fraction of homogamous couples relative to random matching
West 1976	59.50 %	+ 31 %
West 2011	69.76 %	+ 38 %
East 2011	80.76 %	+ 23 %

makes income strongly correlated with education. Low inequality in education is associated with low income inequality.[16] For West Germany, this means that the education from the 1970s may equalize income across households because the expansion of education made West Germans more dispersed in their education.

The idea of how marital sorting affects income inequality is equally straightforward. When marriages occur between low-educated and well-educated people, their different income levels balance out within the household; but marriages among low-educated (highly educated) people produce relatively poor (rich) households. If the number of marriages among high-educated (low-educated) people were increasing, the number of relatively rich (poor) households would rise, as well as income inequality across households.

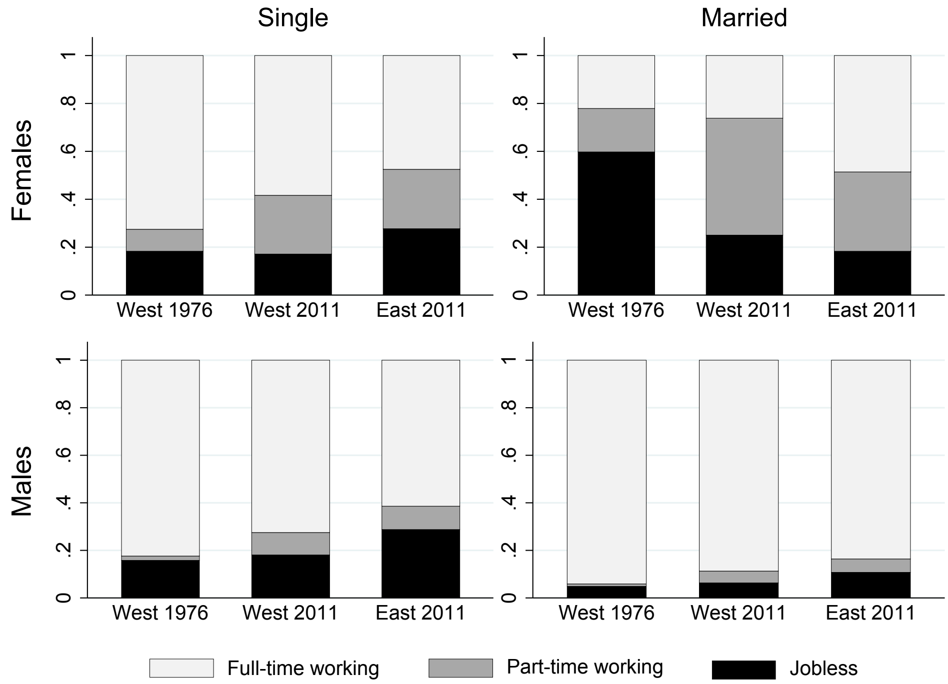
Employment

Figure 3.3.2 illustrates the employment of single and married men and women in Germany across time and space. Here, adult household members are categorized as either jobless, full-time working, or part-time (between 0 and 35 hours) working. Thereby, unemployed people are not distinguished from people who are not in the labor force. The terms *jobless*, *unemployed* and *not in the labor force* are used interchangeably.

Between 1976 and 2011, part-time employment gained importance in West Germany. In 2011, married females are less often jobless in favor of part-time work. In contrast, single females work fewer hours in favor of part-time work. Among males, part-time work has also increased since 1976. However, the joblessness rate among males has increased as well. This rise in jobless and part-time working males goes along with a decline in full-time working males which produces more inequality in the employment of West German men.

[16]The channel through which the skill-premium works depends on the employment of highly educated, medium, and low-educated people. If highly-educated people do not work but low-educated people work, the mechanism may not apply. However, education and employment are positively correlated in Germany which may even amplify the effect. Moreover, when education and employment are positively correlated, an increase in female education may also boost income inequality. Suppose the following extreme case: Most females are low-educated, and only the highly educated females are working. In the presence of positive assortative mating, highly educated females are more likely to marry highly educated males (see Table 3.3.2b for the contingency tables), and both together are likely to face a household income far above median levels. Then, a rising share of highly educated females, and not the dispersion in education per se, would boost income inequality across households.

Figure 3.3.2: Employment



Compared to the development of the West German employment until 2011, the East German employment in 2011 can be viewed as going one step further in time. Males and single females are more often jobless than in the West; their employment is lower and more dispersed. Moreover, compared to West Germany in 2011, married females are less often jobless and less often part-time working in favor of full-time work.

When the conditional employment of the household members changes, the same demographic pattern may generate more or less income inequality. Through the impact of labor income, low inequality in the households' employment may produce relatively low income inequality. Moreover, when single females work more hours, their labor income is lifted, and the income gap to single male households as well as to couple households shrinks. Inequality in adult-equivalent income is expected to shrink.

The impact of a rise in married females' employment is ambiguous. On the one hand, employment of married females may offset a disadvantage in the husbands' income. On the other hand, employment of married females' can amplify the income inequality arising by the husbands.[17]

[17]See Lam (1997) for details on the correlation of the income of husbands and wives and their impact on income inequality across households. If, for example, the variance of the wives' and the husbands' income is the same ($\sigma_W = \sigma_H$), the average income of the wives is smaller than that of the husbands ($\mu_W < \mu_H$), and marital sorting in terms of income occurs ($\rho > 0$), then the wives' average income amplifies inequality across the households. This amplifying effect becomes particularly apparent if ρ is large, i.e., if educational and employment homogamy are strong.

3.4 Analytical Framework

In order to analyze the impact of several socio-economic factors on income inequality, I use a non-parametric version of the reweighting method by Di Nardo et al. (1996) and extend it by sorting algorithms. The framework is introduced in three stages: First, households are categorized by specific characteristics like age, size, education, etc. Then, the share of households with a specific characteristic is adjusted to a counterfactual scenario. This adjustment is, for example, a decrease in the share of single households to the levels of 1976. By adjusting the size of specific subgroups of the population, the overall income distribution in the population changes. Finally, the resulting change in income inequality is evaluated.

3.4.1 Household Categorization

For the analysis, weighted households are categorized by the age (H) of the household head, marital or cohabitation status (C), gender (G), the number of children under 20 years old (K), the adults' educational levels (E), and the adults' working status (W).[18,19] Households which cannot be categorized are excluded from the sample. See Table 3.4.1 for a list of the categories and their characteristics.

Table 3.4.1: Categorization of Households

Abbreviation	Description
H	Age of the household head: 25-34, 35-44, 45-54, 55-59
C	Cohabitation status: single, couple household
G	Gender: male & female, female, male
E	Highest educational degree of the adults in the household $= E^m \times E^f$ if couple household $= E^m$ if single male household $= E^f$ if single female household
E^f, E^m	Educational degree by gender: university, apprenticeship, school
K	Children younger than 20 in the household: 0, 1, 2, 3 or more
W	Working status of the adults in the household $= W^m \times W^f$ if couple household $= W^m$ if single male household $= W^f$ if single female household
W^f, W^m	Working status by gender: full-time working (≥ 35 hours), part-time working (> 0 hours, < 35 hours), jobless

Household characteristics are summarized in a household type $x = (x_W, x_K, x_E, x_G, x_C, x_H)$.

[18]The results remain the same if the age category for couple households is determined according to the average age of the couple.

[19]Note that every household possessing the gender *male & female* belongs to the category *couple*, and vice versa.

The set of all possible household types is denoted by $X = W \times K \times E \times G \times C \times H$. These are 1,584 potential household types, out of which no more than 1,208 are surveyed in the Microcensus. For instance, there are no 55 to 59 year old, highly educated, but jobless single males with three or more children in the household.

3.4.2 Counterfactual Income Distributions

For each year and region, the income distribution function of the whole population is denoted by F_Y^i. The i stands for the year and the region: either West Germany in 1976, West Germany in 2011, or East Germany in 2011. In the specific year and region, the income for households of type x is distributed according to the density $f_{Y|X}^i(\cdot, x)$. The share of households who belong to a specific household type x is given by $\mathbb{P}_X^i(x)$. To construct a counterfactual income distribution function F_Y for year and region i, the income densities $f_{Y|X}^i(\cdot, x)$ conditional on household types $x \in X$ are weighted by counterfactual shares of the household types $\mathbb{P}_X(x)$:

$$F_Y(I) = \int_0^I \sum_x f_{Y|X}^i(y, x)\ \mathbb{P}_X(x)\ dy. \tag{3.4.1}$$

In order to construct the counterfactual shares of household types $\mathbb{P}_X(x)$, household characteristics X are decomposed into 3 parts:

X_{fix}: regarding these characteristics the population is held constant,

X_{ex}: characteristics which are changed conditionally on X_{fix}, and

X_{ind}: the rest.[20] Regarding the characteristics X_{ind}, the population may change due to the conditionality on $X_{ex} \times X_{fix}$.

For example, when I consider the impact of the overall increase in education from 1976 to 2011, I hold the age distribution and the fraction of single and couple households constant ($X_{fix} = G \times C \times H$); I change the fraction of well-educated and less-educated households conditionally on age and gender ($X_{ex} = E$); the employment and the number of children in the households are fixed conditionally on the households' age, cohabitation status, gender, and education ($X_{ind} = W \times K$). Then, the adjustment of male and female education might have an effect on overall employment as well as on the overall number of children.

In all exercises, I assume that the distribution of the household's age is independent of any other household characteristic. It is well-known that females get older than men, and males are older when they start cohabiting. Therefore, I condition the share of couple, single male, and single female households on the households' age.

[20] By definition, everything which is not explicitly controlled for in either X_{ex} or X_{fix} is held constant conditional on $X_{ex} \times X_{fix}$, because $F_Y(I) = \int_0^I \sum_x f_{Y|X}(y,x)\, \mathbb{P}_X(x)\, dy = \int_0^I \sum_{x \in X} \sum_{z \in Z} f_{Y|Z,X}(y,z,x)\, \mathbb{P}_{Z|X}(z,x)\, \mathbb{P}_X(x)\, dy$ and $\mathbb{P}_{Z|X}\ \mathbb{P}_X = \mathbb{P}_{Z|X}\ \mathbb{P}_{(X_{ind}|X_{ex},X_{fix})}\ \mathbb{P}_{X_{ex}|X_{fix}}\ \mathbb{P}_{X_{fix}}$ $= \mathbb{P}_{(Z,X_{ind}|X_{ex},X_{fix})}\ \mathbb{P}_{X_{ex}|X_{fix}}\ \mathbb{P}_{X_{fix}}$. The known framework follows with $\tilde{X}_{ind} := Z \times X_{ind}$.

By construction, the either two-dimensional or one-dimensional educational level of the household depends on the cohabitation status and the household members' gender. Because I condition the adults' gender on the household head's age, education is also conditioned on age. Besides, assuming that the behavior of different generations across time generates the societal trends observed, it appears reasonable to condition all other household characteristics on the household head's age.

In Germany, the educational degree is to a vast extent predetermined by the school track chosen at the age of ten. Fertility decisions are made later in life; therefore, I condition the number of children on the household's education. I assume that the number of children living in the household has an effect on the working status of the adult household members. Moreover, I assume that married females adjust their working status depending on their husbands' employment.

For the sake of simplicity, in the following A and B describe two distinct subsamples, which are categorized according to X. A and B may stand for West Germany in 1976, West Germany in 2011, or East Germany in 2011.

How would income inequality change if households in sample A (e.g. West Germany in 2011) were characterized in terms of their characteristic X_{ex} as in sample B (e.g. West Germany in 1976)? The corresponding counterfactual shares of household types $\mathbb{P}_X(x)$ are implemented by exchanging the conditional distribution $\mathbb{P}^A_{X_{ex}|X_{fix}}$ by $\mathbb{P}^B_{X_{ex}|X_{fix}}$ in the Bayes' formula, that is

$$\mathbb{P}_X = \mathbb{P}_{(X_{ind},X_{ex},X_{fix})} = \mathbb{P}^A_{(X_{ind}|X_{ex},X_{fix})}\mathbb{P}^B_{X_{ex}|X_{fix}}\mathbb{P}^A_{X_{fix}}. \tag{3.4.2}$$

Given the counterfactual shares of household types as constructed in equation (3.4.2), the following assumption ensures that the counterfactual income distribution function F_Y in equation (3.4.1) is well-defined.

Assumption 3.4.1. *For all $x \in X$: $\mathbb{P}^A_X(x) = 0$ if and only if $\mathbb{P}^B_X(x) = 0$.*

The assumption is satisfied when each household type which is represented in sample A also occurs in sample B, and vice versa. In order to generate well-defined counterfactual income distribution functions for the exercises across time (space), I include only those household types which are present in West Germany in both years 1976 and 2011 (in 2011 in both regions East and West Germany).[21] For a detailed description of each exercise, see the Appendix, Section 3.A.

[21] Omitting all these households decreases the number of observations by less than 4 percent (see the Appendix, Table 3.C.1a). It does not affect the inequality across households (see the Appendix, Table 3.C.1b). To generate well-defined counterfactual income distribution functions, a restriction of the subsample is not necessary in the exercises on age, singlehood, and education. I constructed these exercises also before excluding the household types which do not exist in the other year or region; the findings do not change.

Marital Sorting in Education

When a counterfactual exercise on education is conducted, educational sorting in marriages needs to be fixed. Adjusting the education within the household's without fixing marital sorting provides no clear results on whether changes in gender-specific education or changes in marital sorting affect income inequality. If X_{fix} characterizes married households of specific age groups, $\mathbb{P}^i_{E|X_{fix}} = \mathbb{P}^i_{(E^m,E^f)|X_{fix}}$ represents contingency tables of male and female educational levels. In the exercises on education, these contingency tables are adjusted for every age group. Similar to Greenwood et al. (2014), I apply the Sinkhorn-Knopp algorithm (Sinkhorn & Knopp, 1967) to fix the mating scheme. This mechanism fixes marital sorting in terms of the local log odds ratio in the contingency tables.[22] The local log odds ratio is a typical measure for assortative mating (see, for example, Siow, 2015). It is defined as

$$log\left(\frac{\mathbb{P}^i(E^m_k, E^f_l)\,\mathbb{P}^i(E^m_{k+1}, E^f_{l+1})}{\mathbb{P}^i(E^m_{k+1}, E^f_l)\,\mathbb{P}^i(E^m_k, E^f_{l+1})}\right),$$

where $k, l \in \{1, 2\}$, and $E^m_1 = E^f_1 = university$, $E^m_2 = E^f_2 = apprenticeship$, and $E^m_3 = E^f_3 = school$. With the 3-by-3 contingency table of male and female education levels, a 2-by-2 matrix of local log odds ratios results. This matrix can be seen as a generalization of the odds ratio, which is only defined for 2-by-2 contingency tables.[23] An advantage of the local log odds ratio is its scale-invariance. The Sinkhorn-Knopp algorithm exploits the scale-invariance by fixing the sorting pattern when adjusting the marginal distributions of male and female education.[24]

How would income inequality change if, in sample A, marital sorting across couple households is random, perfect, or the same as in sample B? I conduct several counterfactual exercises on marital sorting. In the first exercise, I test whether random matching would diminish income inequality. In the second exercise, I assume an educational sorting pattern from another year or region B and test whether marital sorting differs so much that it has a significant impact on income inequality. Finally, I test whether perfect positive assortative matching, in the sense of the Gale-Shapley matching algorithm (Gale & Shapley, 1962), would increase income inequality significantly.

[22] Fixing another measure of assortative mating may provide different results because two different measures of assortative mating are generally not equivalent; so, the share of homogamous couples relative to random matching varies, although the local log odds ratios are fixed. For an overview of measures for association analysis, see Tan et al. (2004).

[23] However, this matrix of local log odds ratios is not the generalized odds ratio as defined by Agresti (1980). (The generalized odds ratio can be traced back to the association measure of Goodman and Kruskal (see Goodman & Kruskal, 1954) which is a non-scale-invariant generalization of Yules' Q.)

[24] The convergence of the Sinkhorn-Knopp algorithm is only ensured if the contingency tables have no zero entries. With the given data set, there exists only one case in which a contingency table has a zero entry. However, the Sinkhorn-Knopp algorithm still works.

The counterfactual exercises are implemented by adjusting the conditional distribution of the households' education $\mathbb{P}^A_{E|X_{fix}}$ in the formula

$$\mathbb{P}^A_X = \mathbb{P}^A_{(X_{ind},E,X_{fix})} = \mathbb{P}^A_{(X_{ind},|E,X_{fix})}\mathbb{P}^A_{E|X_{fix}}\mathbb{P}^A_{X_{fix}}. \tag{3.4.3}$$

If X_{fix} characterizes singles, $\mathbb{P}_{E|X_{fix}}$ equals $\mathbb{P}^A_{E|X_{fix}}$. Otherwise, matching algorithms are used to create counterfactual contingency tables $\mathbb{P}_{E|X_{fix}}$ for $\mathbb{P}^A_{E|X_{fix}}$ in equation (3.4.3). When applying these matching algorithms, the marginal distribution of male and female education, $\mathbb{P}^A_{E^m|X_{fix}}$ and $\mathbb{P}^A_{E^f|X_{fix}}$, respectively, remain unchanged. For the exercise on random sorting, the entries of the contingency tables are replaced by

$$\begin{aligned}\mathbb{P}_{E|X_{fix}}(x_E, x_{fix}) &= \mathbb{P}_{(E^m,E^f)|X_{fix}}(x_{E^m}, x_{E^f}, x_{fix}) \\ &= \mathbb{P}^A_{E^m|X_{fix}}(x_{E^m}, x_{fix})\, \mathbb{P}^A_{E^f|X_{fix}}(x_{E^f}, x_{fix}).\end{aligned}$$

In order to adopt the educational sorting pattern from a different year or region B, the contingency tables $\mathbb{P}^B_{E|X_{fix}}$ are transformed with the Sinkhorn-Knopp algorithm. The sorting pattern of B is fixed, but male and female marginal conditional education form A is incorporated. The transformed contingency tables replace $\mathbb{P}^A_{E|X_{fix}}$ in equation (3.4.3). For the exercise on perfect sorting, the Gale-Shapley algorithm is applied on $\mathbb{P}^A_{E|X_{fix}}$, and the resulting contingency tables are incorporated in equation (3.4.3). The exercises on random and perfect matching only use information from sample A. Restricting the sample to cover the same household types as in another year or region (sample B) is therefore not necessary; Assumption 3.4.1 is not required. However, in order to ensure that the conditional income distributions for the newly matched couples exist and the created overall income distribution function is well-defined, the following assumption needs to be satisfied in all exercises which use sorting algorithms.

Assumption 3.4.2. *For all $x = (x_{E^m}, x_{E^f}, x_{fix}) \in E^m \times E^f \times X_{fix}$: $\mathbb{P}^A_{E^m,E^f|X_{fix}}(x) > 0$ if and only if $\mathbb{P}_{E^m,E^f|X_{fix}}(x) > 0$.*

For the exercises on random and perfect sorting, the assumption is fulfilled when all conditional contingency tables $\mathbb{P}^A_{E|X_{fix}}$ of male and female education have positive entries. When the counterfactual mating pattern is taken from another year or region B, Assumption 3.4.2 is sufficient for generating a well-defined counterfactual income distribution. It states that a contingency table of male and female education has only a zero entry for A when its counterpart in B is zero as well, and vice versa.[25,26]

[25] In the East German subsample, there is no couple household in the age group 55 to 59 with a low-educated male (school) and a highly educated female (university). I overcome this problem by dropping all households for that age group in the exercise of interest.

[26] As the exercise becomes more comparable to the other exercises across time (space) when the sample is also restricted in order to fulfill Assumption 3.4.1, I conduct the exercise in which the counterfactual mating pattern is

3.4.3 Inequality Evaluation

The non-parametric framework produces a counterfactual income distribution for each exercise conducted. Because the whole counterfactual income distribution is known, any inequality measure can be used to evaluate the changes in the income distribution. Here, I utilize the Gini coefficient, the Theil index, and the Atkinson index.[27] The three different inequality measures exhibit different properties which enables a comprehensive analysis.[28]

The Gini coefficient (Gini, 1921) is defined as

$$\mathrm{G} := \frac{1}{2} - \int_0^1 \tilde{l}(y)dy,$$

where $\tilde{l} : [0,1] \to [0,1]$ denotes the piece-wise linear approximation of the Lorenz curve. It has the advantage that it is independent of the income scale and population size. Its size is rather easy to interpret as it always ranges between 0 and 1. For the interpretation, note that the Gini coefficient puts most weight on the median.

In contrast, the Theil index (Theil, 1967) is more sensitive to the top of the distribution. It is also income scale-invariant. The upper bound of the Theil index depends on the sample; it amounts to 100 times the logarithm of the number of distinct income levels. The Theil index considers the proportional relation between the income levels in the population. It is defined as

$$\mathrm{T} := \int \frac{y}{\bar{y}} \log\left(\frac{y}{\bar{y}}\right) dF_Y(y),$$

where $\bar{y} = \int y dF_Y$.

The Atkinson's index (Atkinson, 1970) is based on the difference of marginal social utilities. Defined as

$$\mathrm{A}_\varepsilon := 1 - \left[\int \left(\frac{y}{\bar{y}}\right)^{1-\varepsilon} dF_Y(y)\right]^{\frac{1}{1-\varepsilon}},$$

the Atkinson index features income scale independence and ranges between 0 and 1. If the inequality aversion parameter ε is large, the Atkinson index is sensitive to changes at the bottom of the income distribution.

For improving the legibility, all three the Gini coefficient, the Theil index, and the Atkinson index are multiplied by the factor 100. This up-scaling lifts the upper bound of the Gini coefficient and

taken from another year twice: once, to compare it to the exercises of random and perfect matching, and again, to compare it to the other exercises across time by omitting the household types which are not observed in either sample A or sample B. The results remain unchanged.

[27] Other inequality measures, which could also be applied, are percentile-ratios, coefficient of variation, Dalton's index, or other generalized entropy indices.

[28] For a detailed description of the properties, please see Cowell (2011).

the Atkinson index to 100.
By bootstrapping, I compute p-values for testing whether income inequality under the counterfactual scenario differs significantly from the inequality observed. I use bootstrapped p-values instead of standard errors, because the confidence intervals of the inequality measures are in general non-symmetric. Mills & Zandvakili (1997) show that statistical inference by bootstrapping performs well for the Gini coefficient and Theil's entropy measures. I follow their approach of the 'percentile method' which directly exploits the bootstrap distribution for the confidence intervals. For an extensive derivation of bootstrap methods, please see Efron & Tibshirani (1994).
I also evaluate the economic significance of the change in the Gini coefficient. I apply an approach presented in Blackburn (1989). He argues that an increase in the Gini coefficient can be linked to a lump sum tax k taken from every household below median income and given to all households above median income. The lump sum tax is given by

$$k = 2\bar{y}\left(\mathrm{G}^{\mathrm{data}} - \mathrm{G}^{\mathrm{counterfactual}}\right),$$

where $\bar{y} = \int y dF_Y^{\mathrm{data}}$. The transfers are given in adult-equivalent income. For example, a decrease of the Gini coefficient from 0.30 to 0.23 accrues when every household above the median gives a lump sum of 14 percent of the mean income to all households below the median. Hence, in 2011, West Germany ($\mathrm{G}^{2011} = 0.30$) would reach an inequality level from 1976 ($\mathrm{G}^{1976} = 0.23$), if every household above the median income (EUR 1600) gives about EUR 250 to the households below the median income.

3.5 Results

3.5.1 West Germany across Time: 1976 versus 2011

Since 1976 income inequality has risen strongly in West Germany. After 35 years, the Gini coefficient is larger by around 7 points, the Atkinson index increased by more than 12 points and the Theil index almost doubled from 8.4 to 16.7 (see Table 3.5.1).[29] To a vast extent, changes in the socio-economic background of the society account for this increase in inequality. Income inequality would be lower by around 4 Gini points if the socio-economic background of the households had remained unchanged since the 1970s, but the households' income conditional on its socio-economic background were as in 2011. As the Lorenz curves in Figure 3.5.1a present, in particular, the share of poor households would diminish.
Table 3.5.2 summarizes to what extent a change in a specific household characteristic, with all

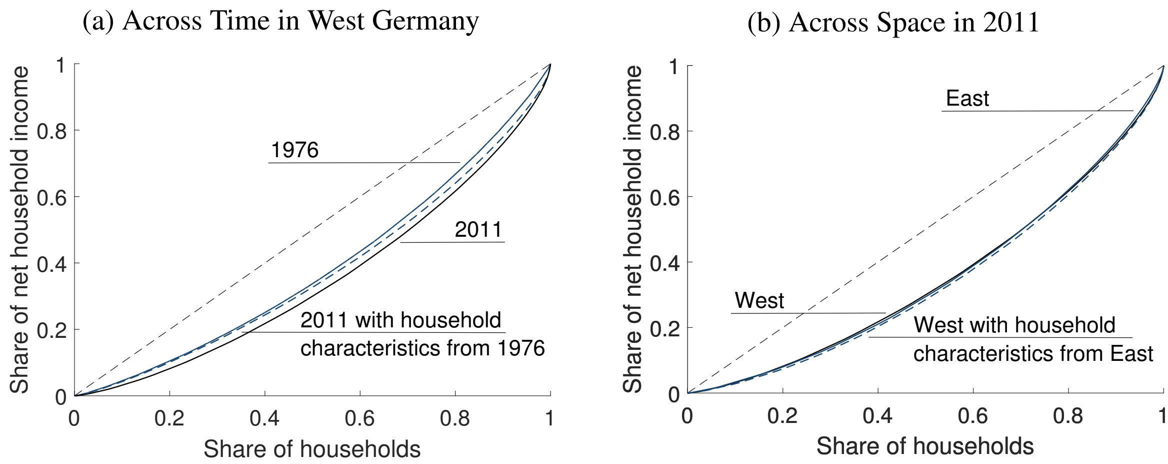
[29]Here, and in all exercises which compare the impact of socio-economic characteristics from 1976 and 2011, household types are omitted if they are not observed in West Germany for either 1976 and 2011.

Table 3.5.1: Mean Income and Income Inequality

	Mean income	Income inequality		
		Gini coefficient	Theil index	Atkinson index ($\varepsilon = 2.0$)
West 1976†	1305.41	22.98 (22.87, 23.11)	8.43 (8.33, 8.53)	16.49 (16.20, 16.78)
West 2011†	1808.45	29.92 (29.67, 30.19)	16.69 (16.21, 17.12)	29.01 (28.50, 29.52)
East 2011‡	1384.68	30.03 (29.52, 30.49)	15.59 (14.88, 16.32)	27.38 (26.57, 28.22)
West 2011‡	1824.96	29.99 (29.74, 30.26)	16.77 (16.33, 17.21)	29.25 (28.73, 29.76)

Notes: 95% confidence intervals in parentheses. Mean income: in EURO, inflation-adjusted to 2011 levels and adjusted by the OECD-modified adult-equivalent scale.
† Household types are excluded if they are not observed in West Germany either in 1976 or 2011.
‡ Household types are excluded if they are not observed in 2011 for either East or West Germany.

Figure 3.5.1: Distributions of Net Household Income



Notes: After omitting all household types which do not exist in either the factual or the counterfactual year and region. Income: adjusted by the OECD-modified adult-equivalent scale.

its indirect effects, contributes to that decline in income inequality.[30] Take, for example, the *age* distribution of the workforce. If, in 2011, the population were as young as in 1976, income inequality would barely drop; the Gini coefficient would decrease by only 0.23.

[30]The entries in the table do not add up to the overall change in the Gini coefficient, i.e. 4.19, because of indirect effects; e.g. increasing the fraction of young households leads also to an increase in the number of children and may, therefore, affect the working status of married women which itself influences income inequality.

Table 3.5.2: Income Inequality Change when West Germans in 2011 Have the Household Characteristics from 1976

Counterfactual characteristics from 1976	Gini coefficient	Theil index	Atkinson index ($\varepsilon = 2$)
All household characteristics	-4.19***	-4.14***	-9.11***
Age	-0.23	-0.26	-0.24
Household size			
Children	-0.09	-0.14	-0.31
Cohabitation incl. gender	-1.76***	-2.07***	-4.99***
+ Children cond. *single*, gender, education	-1.72***	-2.04***	-4.95***
+ Children cond. cohabitation, gender, education	-2.11***	-2.42***	-5.61***
Education and educational homogamy			
Marital sorting	0.09	0.13	0.06
Marginal male and female education	-1.26***	-1.40***	-1.90***
Male and female education + marital sorting	-1.25***	-1.37***	-1.89***
Working status			
Married females working status	0.34*	0.41	0.03
Single females working status	-0.68***	-0.63**	-1.04***
+ Married females working status	-0.31	-0.21	-0.94**
Males working status	-0.76***	-0.69**	-1.42***
+ Females working status	-1.03***	-0.86***	-2.35***
Working status + education incl. sorting	-2.47***	-2.25***	-4.46***
Overall difference in income inequality between 1976 and 2011	-6.94***	-8.26***	-12.51***

Notes: Difference: counterfactual minus factual inequality measure. Two-sided significance test: *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$.

Contrary to the household heads' age distribution, the diminishing *household size* accounts for the rise in income inequality to a vast extent. If West German households were as rarely male single-headed or female single-headed as in 1976, income inequality would be lower by 1.76 Gini points. This decline in inequality is statistically and economically significant. Following the argument by Blackburn (1989), transfers of EUR 63.66 from households above the median income to households below the median income would generate the same decline in inequality. The particularly strong change in the Atkinson index by 4.99 points out that this decline is pushed by a reduction of poor households. If, additionally, the conditional number of children in the households were as large as in 1976, the effect would be slightly amplified by further reducing the number of poor households.[31] Hence, the increase in single households drives the rise in inequality which is associated with declining households.[32]

Although, in 2011, almost half of all West German households are run by singles, educational homogamy, within the other half of the households, could have the potential to influence income inequality. First, in order to test whether positive assortative mating boosts inequality, suppose cohabiting males and females *sort into marriages* regarding their education in the same way as they did in the 1970s.[33] Then, income inequality across West German households would not differ from the observed inequality in 2011. Second, suppose the more extreme case in which males and females in 2011 are matched randomly in terms of education. Then, income inequality would be lower than observed in 2011, but this decline in inequality would still not be statistically nor economically significant (see Table 3.5.3, "data vs. random matching"). Only in the more extreme case in which the scenario of randomly matched couples is compared to the scenario of perfectly matched couples, the Gini coefficient changes statistically significantly (see Table 3.5.3). However, the increase in inequality associated with the change from random to perfect matching is not economically significant. The same effect on income inequality would occur if 1 percent of the mean income, that is EUR 18.08, were taken from every household below the median income level and transferred to the households above the median income level.

Contrary to marital sorting in education, changes in the population's *education* significantly contribute to the rise in income inequality. Changes in male and female education account for approximately a fifth of the inequality increase between 1976 and 2011. In the 1970s, education

[31] This additional decline in inequality is only weakly statistically significant for the Gini coefficient and the Atkinson index.

[32] All the findings on the household size, here and in the comparison across space, are independent of the adult-equivalent scale used; the square root scale and the old OECD equivalence scale (also called Oxford scale) provide the same results.

[33] The influence of marital sorting might be different when all single and non-single adults are re-matched. In practice, there is minor sorting into marriage by education. For example, in 2011, low-educated males and highly educated as well as low-educated females are more likely to be single (compare Table 3.3.2a and Table 3.3.2b). Including these people from the tails of the educational distribution in the exercises makes education among married males (married females) more unequally distributed. Then, under random matching, the share of educational homogamous couples declines. As a consequence, the relative impact of marital sorting on income inequality would be overestimated.

Table 3.5.3: Differences in Inequality under Distinct Mating Schemes

	West 2011	East 2011
Data vs. random matching		
Gini coefficient	0.27	0.26
Theil index	0.34	0.43
Atkinson index with parameter 2.0	0.25	0.08
Perfect matching vs. data		
Gini coefficient	0.23	0.21
Theil index	0.32	0.39
Atkinson index with parameter 2.0	0.21	0.04
Perfect vs. random matching		
Gini coefficient	0.50***	0.47
Theil index	0.66**	0.83
Atkinson index with parameter 2.0	0.46	0.12

Notes: Before omitting any household type. Inequality measures: multiplied by 100. One-sided significance test with p-values: *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$.

is very pronounced at the lower levels. Because education and income are highly correlated, the unilateral distribution of education from the 1970s is associated with less variation in the population's income distribution. The counterfactual exercise suggests that if West Germans in 2011 had the same education as their ancestors in 1976, income inequality would diminish by 1.26 Gini points.

The *employment* situation of 1976 also produces less income inequality than the employment situation in 2011. If the West German households of 2011 faced the same employment as the households of 1976, then income inequality would shrink by 1.03 Gini points. In particular, the reduced employment of males widens the income gap; income inequality would already shrink by 0.76 Gini points if only the males faced the same employment as in 1976. The counterfactual analysis on females' employment suggests that, first, raising the female labor supply among singles to the levels of 1976 reduces income inequality by lifting the household income of single females. Second, if at all, the employment of married females marginally equalizes income more in 2011 compared to 1976. It appears that, if the increased (part-time) employment of married females has any effect, it marginally offsets the increased inequality arising from their husbands' incomes. However, the stable Atkinson index shows that the rise in the employment of married females has not reduced the number of poor households, but only rearranged income in the middle-income households.

3.5.2 Germany in 2011 across Space: East versus West

At first sight, in 2011, income inequality in East and West Germany are very similar. For both regions, the Gini coefficient lies around 30 points (see Table 3.5.1). However, there are some deviations at the tails. Both a lower Atkinson index and a lower Theil index indicate less income inequality in the East. Socio-economic factors may account for such mismatches in the income distribution. Can the variations in the socio-economic background of East and West German households also account for the lower Atkinson index and the lower Theil index in the East? The answer is no. Both indices would increase for West Germany if West German households faced the same socio-economic background as East Germans. The Atkinson index would increase strongly by 3.43 points, and also the Gini coefficient would increase by significant 1.88 points (for a visualization, see Figure 3.5.1b).[34] Hence, the socio-economic background of the East German households produces more income inequality than the socio-economic background of the West German households. This discrepancy is more than offset by the East German conditional income distribution.

Knowing that the East German household characteristics make income more unequally distributed whereas the West German household characteristics equalize income, the following question comes to mind: How does each socio-economic characteristic account for the different consequences on income inequality? Several counterfactual exercises on West German income inequality are conducted to answer this question. The results of these exercises are summarized in Table 3.5.4. The table lists the differences between the counterfactual and actual Gini coefficients, Theil indices, and Atkinson indices.

Analogous exercises on East German income inequality are also conducted. The results are presented in Table 3.5.5. They show similar effects but of reversed sign and smaller magnitude.[35] Since the results of the exercises on East and West German inequality are similar, the following discussion focuses on the results for West Germany.

The results suggest that the distinct *age* distributions across East and West German households do not account for different levels of income inequality; for income inequality in the West, it does not matter whether the working age population is as young as West Germans or as old as East Germans. Income inequality would decline by insignificant 0.19 Gini points if West German household heads were as old as the East Germans' (see Table 3.5.4).

The smaller *household size* in East Germany has a minor disequalizing effect. If both the share of male and female single-headed households and the number of children living in the households were the same in West as in East Germany, then income inequality in West Germany would increase by 0.65 Gini points. The impact of the children dominates this change in income

[34] Here, and in all exercises which compare the impact of socio-economic characteristics from East and West Germany, household types are omitted if they are not observed in 2011 for both sample regions East and West.

[35] Due to the lower sample size, the results are less statistically significant.

inequality. More children in single households may lead to an increase in poor households, and fewer children in couple households may lead to an increase in high-income households. Both changes boost income inequality.

In line with the results of the analysis on assortative mating in the previous subsection (Section 3.5.1, Table 3.5.3), income inequality among West German households does not change significantly, when I impose the *marital sorting* structure from East German households. Besides that, marital sorting in formal education has also no potential to influence income inequality in East Germany (see Section 3.5.1, Table 3.5.3, column "East 2011"). Even in the extreme scenario in which income inequality in the case of random matching is compared to the case of perfect matching, the surplus of inequality is not significantly different.

The small variation in East German *education* leads to a lower level of income inequality across households. If West Germans were, to the favor of a larger share of vocationally trained people, as rarely low-educated and as rarely highly educated as their East German peers, the Gini coefficient would diminish by 1.38 points. Following the argument by Blackburn (1989), this reduction in inequality is the same as when taking EUR 50.37 from each household above the median income level and giving it to the households below the median income level. This equalizing impact of education is opposed to a heavily disequalizing employment situation in East Germany.[36]

In fact, among all household characteristics studied, the *working status* has the strongest impact on income inequality. If West Germans faced the same working status as their East German peers, then income inequality would increase substantially by 2.32 Gini points. The Atkinson index would even rise by 4.11 points indicating a strong increase in low-income households. This rise in low-income households can be explained by the relatively large share of jobless males and single females in East Germany, who are associated with low income. Because the difference in the share of jobless people is larger between East and West German males than between East and West German females, the Atkinson index is more influenced by male than by female employment. Moreover, an exercise on the employment of married females indicates that inequality would rise if the West German wives increased their employment attachment to the level of East Germans. This result stands in contrast to the findings across time (see Section 3.5.1). Whereas the increased employment attachment of West German females over time is rather interpreted as an attempt to offset the inequality arising by the husbands' income, East German females seem to work more than their West German peers because of another reason than equalizing income variations across households. However, the driving forces behind female employment decisions are beyond the scope of this paper.

[36]For the joint impact of the East German employment, education, and marital sorting, see line "Working Status + education incl. sorting" in Table 3.5.4. As outlined before, the impact of marital sorting is negligible.

Table 3.5.4: Income Inequality Change when West Germans in 2011 Have the Household Characteristics from the East

Counterfactual characteristics from the East	Gini coefficient	Theil index	Atkinson index ($\varepsilon = 2$)
All household characteristics	1.88***	1.77***	3.43***
Age	0.19	0.19	0.28
Household size			
Children	0.54***	0.54*	0.58
Cohabitation incl. gender	0.25	0.32	0.70*
+ Children cond. *single*, gender, education	0.43**	0.45	0.76**
+ Children cond. cohabitation, gender, education	0.65***	0.72**	1.06**
Education and educational homogamy			
Marital sorting	0.02	0.03	0.03
Marginal male and female education	-1.38***	-1.43***	-2.08***
Male and female education + marital sorting	-1.38***	-1.42***	-2.08***
Working status			
Married females working status	0.44**	0.48	0.75**
Single females working status	0.65***	0.60*	1.08***
+ Married females working status	1.10***	1.09***	1.85***
Males working status	1.18***	1.11***	2.36***
+ Females working status	2.32***	2.29***	4.11***
Working status + education incl. sorting	0.93***	0.77**	1.99***
Overall difference in income inequality between East and West	0.04	-1.18**	-1.87***

Notes: Difference: counterfactual minus factual inequality measure. Two-sided significance test: *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$.

Table 3.5.5: Income Inequality Change when East Germans in 2011 Have the Household Characteristics from the West

Counterfactual characteristics from the West	Gini coefficient	Theil index	Atkinson index ($\varepsilon = 2$)
All household characteristics	-1.15***	-0.89*	-1.97***
Age	-0.17	-0.15	-0.17
Household size			
Children	-0.34	-0.38	-0.42
Cohabitation incl. gender	-0.24	-0.27	-0.46
+ Children cond. *single*, gender, education	-0.31	-0.33	-0.39
+ Children cond. cohabitation, gender, education	-0.68**	-0.72	-0.96
Education and educational homogamy			
Marital sorting	0.02	0.01	0.02
Marginal male and female education	1.32***	1.37***	1.90**
Male and female education + marital sorting	1.41***	1.46***	1.97***
Working status			
Married females working status	-0.29	-0.17	-0.58
Single females working status	-0.46	-0.42	-0.58
+ Married females working status	-0.74**	-0.58	-1.14**
Males working status	-1.21***	-1.08**	-1.75***
+ Females working status	-1.93***	-1.62***	-2.94***
Working status + education incl. sorting	-0.59*	-0.32	-1.01*
Overall difference in income inequality between West and East	-0.04	1.18**	1.87***

Notes: Difference: counterfactual minus factual inequality measure. Two-sided significance test: *** $p < 1\%$, ** $p < 5\%$, * $p < 10\%$.

3.5.3 Limitations

Similar to the Oaxaca-Blinder approach or the RIF method, the counterfactual exercises of the reweighting procedure neglect general equilibrium effects. Changes in the composition of the population may affect the conditional income distribution which a specific household type faces. One may argue that the income of a person with a university degree is larger when fewer people have a university degree. In the counterfactual exercises on education, the conditional income distribution from West Germany in 2011 is held constant. This income distribution represents the largest share of university educated people among all three populations studied. Thus, in the counterfactual scenario, the few highly-educated household members may face an income too close to the mean; and the change in inequality may be underestimated. In contrast, the change in inequality may be overestimated when the share of jobless people is reduced in a counterfactual scenario.

The study focuses on the years 1976 and 2011 because of two reasons. First, the German Microcensus only provides such detailed information since 1976. Second, without differences in the socio-demographic composition of the population, counterfactual exercises on the population's composition are useless. The socio-demographic composition of a population changes slowly. Therefore, a large time span between the two observed years is desirable. With the survey years lying 35 years apart and restricting the exercises to household heads at working age (i.e. within a 35 years age range between 25 and 59), the comparison of West Germans from 1976 and 2011 can be viewed as a comparison of two different populations.

Besides, one may question whether 1976 and 2011 represent extreme years in the overall rise of inequality. The studies by Becker (2012) and Albig et al. (2017) show that 1976 and 2011, respectively, are no outliers and represent the overall trend of rising income inequality.

3.6 Discussion and Conclusion

The aim of this paper is a better understanding of the connection between the socio-economic characteristics of households and net income inequality across the households. I apply German Microcensus data from 1976 and 2011 for a reweighting analysis which includes transformations in marital sorting. First, I quantify by how much changes in the households' socio-economic characteristics, like age, household size, education, and employment are related to the West German income inequality rise since the 1970s. Then, I investigate how these household characteristics differently influence income inequality in East and West German in 2011.

In the analysis over time, I find that the prevalence of singlehood is strongly associated with the rise in income inequality. Besides, changes in education and employment are linked to the rise in income inequality, although by a smaller magnitude. I could not find a significant effect of the older population suggesting that the age distribution of the workforce changed too little since the

1970s to influence income inequality significantly.
The analysis on East and West Germany shows that overall income inequality in 2011 is similar in both regions. However, the results suggest that the East German employment pattern promotes income inequality stronger than the West German employment pattern. The main reason is the presence of many jobless males and jobless single females. Creating full-time jobs may reduce the income inequality in the East.
Besides employment, the smaller household size in East Germany is associated with slightly higher income inequality. Contrary to the findings on the temporal comparison, here, the inequality effect of the declining household size is driven by the difference in the number of children. Fewer children in couple households and more children in single households widen the income gap. Special support for single parents may be able to diminish such a gap.
In East Germany, two factors work against the amplification of income inequality related to employment and household size. First, education among East German households is rather similar. I argue that this low variation in education creates less variation in income by influencing labor income. Second, conditional on the household characteristics, East German income is less dispersed than in the West.
My detailed exercises reveal the importance of differentiating between married and single female employment. In particular, the employment of married females may affect income inequality in two ways: either their income offsets the income inequality arising by their husbands or it amplifies the income inequality across households. My results indicate both effects: if the West German rise in married females' employment is related to income inequality, then it most likely has an equalizing effect. In contrast, the results of my exercises across space suggest that inequality would grow if the married females in West Germany increased their employment attachment to East German levels. These ambiguous effects allow for no policy implications; they emphasize the need for further research on the employment incentives of married females.
Neither across East nor across West German households, I could find a significant impact of marital sorting in formal education on net income inequality. For West Germany, Pestel (2017) provides an explanation for this finding. He argues that the low labor force participation of married females makes sorting in earnings potentials irrelevant for earnings inequality. However, for East Germany, he finds that sorting in earnings potentials strongly affects earnings inequality. My results suggest that either the German tax and transfer system works against that effect on earnings inequality (Fuchs-Schündeln et al., 2010) or East German couples sort not only in education, but also in other earnings potentials like, for example, occupation or industry. However, both an analysis of the effects of the German tax and transfer system and a decomposition of marital sorting in several earnings potentials is beyond the scope of this paper and left for future research.

Appendix 3.A Detailed Description of the Counterfactual Exercises

Exchanging All Household Characteristics

How strong would income inequality change if households in 2011 had the same characteristics as in the 1970s, but their household income conditional on the characteristics was distributed as in 2011? That is, the household head's age, her / his probability of being single, the number of children, education, and employment were as in the 1970s. With A standing for West Germany in 2011 and B being West Germany in 1976, the following income distribution takes into account both the conditional income of A and the households characteristics of B:

$$F_Y(I) = \int_0^I \sum_x f^A_{Y|X}(y,x)\ \mathbb{P}^B_X(x)\ dy.$$

Note that F_Y is only well-defined under the following assumption.

Assumption 3.A.1. *For all* $x \in X$*:* $\mathbb{P}^A_X(x) = 0$ *if and only if* $\mathbb{P}^B_X(x) = 0$.

The assumption is fulfilled when all household types which cover at least one household from region and year A are also represented by at least one household from region and year B, and vice versa.[37]

Exercises on Age

If the household heads in 2011 were as young as in the 1970s, would income inequality decline? Increasing the fraction of young households, without taking into account that young households differ in their number of kids, employment status, and cohabitation from old households might provide misleading results. A more intuitive counterfactual income distribution can be provided when the age of the household's head is adjusted while all other household characteristics are held constant conditional on the household head's age. With A standing for West Germany in 2011 and B being West Germany in 1976, the counterfactual income distribution is given by

$$F_Y(I) = \int_0^I \sum_{x_{-H}\in X_{-H}} \sum_{x_H \in H} f^A_{Y|X}(y,(x_{-H},x_H))\ \mathbb{P}^H_{X_{-H}|H}(x_{-H},x_H)\ \mathbb{P}^B_H(x_H)dy,$$

where $X_{-H} = W \times K \times E \times G \times C$ is the set of household types when it is not controlled for age. With $x_{-H} \in X_{-H}$ and $x_H \in H$, $\mathbb{P}^i_{X_{-H}|H}(x_{-H},x_H)$ denotes the conditional probability

[37] As it is summarized in Table 3.C.1b, deleting all households in the subsamples (West Germany 1976 and 2011, and East Germany 2011) which do not fulfill this assumption decreases the number of observations by less than 4%. Moreover, it does not change income inequality essentially.

that a household of year or region i ($i = A, B$) has the household type $x = (x_{-H}, x_H)$ given that that household head is from the age group x_H. The probability that the household belongs to age group x_H is given by $\mathbb{P}^i_H(x_H)$.
The following assumption ensures that F_Y is well-defined.

Assumption 3.A.2. *For all* $x_H \in H$*:* $\mathbb{P}^A_H(x_H) = 0$ *if and only if* $\mathbb{P}^B_H(x_H) = 0$.

For my data, the assumption is fulfilled because, for every age group, there exists a household which belongs to that age group.

Exercises on Singlehood, Single Parents, and Households Size

How would the income distribution change if singlehood in West Germany in 2011 were as low (high) as in 1976 (East Germany)? As the cohabitation status should not modify the age distribution across households, the household's age group is held constant. On the contrary, singles have fewer children than couples and couples, in particular married females, make different labor supply decisions such that their working status differs from single females. Ignoring these effects in a counterfactual exercise in which the share of single households is reduced may lead to strongly deviating results. To allow for the different indirect effects of singles by gender, not only the overall share of singles but the share of single females and single males is adjusted. A counterfactual income distribution function which considers all the above criteria follows with

$$
\begin{aligned}
F_Y(I) = \int_0^I \sum_{x \in X} & f^A_{Y|X}(y, (x_W, x_K, x_E, x_G, x_C, x_H)) \\
& \mathbb{P}^A_{W,K,E|G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H) \\
& \mathbb{P}^B_{G,C|H}(x_G, x_C, x_H) \\
& \mathbb{P}^A_H(x_H)\, dy,
\end{aligned}
$$

where $\mathbb{P}^A_{W,K,E|G,C,H}$ and $\mathbb{P}^B_{G,C|H}$ represent conditional shares of the population in A and B, respectively. Among all households of age x_H, the share of households with cohabitation status x_C and gender x_G is given by $\mathbb{P}^i_{G,C|H}(x_G, x_C, x_H)$ (for $i = A, B$). Here and hereafter, the interpretation of other conditional shares $\mathbb{P}^i_{\cdot|\cdot}$ follows analogously. For F_Y to be well-defined, a weak version of Assumption 3.A.1 is required.

Assumption 3.A.3. *For all* $x = (x_G, x_C, x_H) \in G \times C \times H$ *with* $\mathbb{P}^A_H(x_H) > 0 :$ $\mathbb{P}^A_{G,C|H}(x) = 0$ *if and only if* $\mathbb{P}^B_{G,C|H}(x) = 0$.

By applying the rich Microcensus data, Assumption 3.A.3 is satisfied as it states the following: Suppose in the categorization of household types, it is only controlled for age, cohabitation, and

gender. If there is any combination of gender, cohabitation status, and age group which cannot be found among the households for region and year A, then that combination should also not be represented for region and year B, and vice versa.
Among all the singles, the likelihood of having children in the household also differs between East and West Germany, as well as across time. Taking this into account might give a better answer to the question how single parenting affects income inequality. The resulting counterfactual income distribution is given by

$$\begin{aligned} F_Y(I) = \int_0^I \sum_{x \in X} & f^A_{Y|X}(y, (x_W, x_K, x_E, x_G, x_C, x_H)) \\ & \mathbb{P}^A_{W|K,E,G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H) \\ & \mathbb{P}^*_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H) \\ & \mathbb{P}^A_{E|G,C,H}(x_E, x_G, x_C, x_H) \\ & \mathbb{P}^B_{G,C|H}(x_G, x_C, x_H) \\ & \mathbb{P}^A_H(x_H)\, dy, \end{aligned}$$

where

$$\mathbb{P}^*_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H) = \begin{cases} \mathbb{P}^B_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H) & \text{if } x_C = \text{single} \\ \mathbb{P}^A_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H) & \text{if } x_C = \text{couple} \ . \end{cases}$$

Thereby, singlehood is still conditioned on the household head's age and the number of children is additionally conditioned on the household's gender and education category. Assumption 3.A.1 guarantees a well-defined counterfactual income distribution for all exercises in which the conditional number of children is adjusted. With

$$\mathbb{P}^*_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H) = \mathbb{P}^B_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H),$$

a counterfactual income distribution is generated for quantifying the impact of differences in the household size; that is quantifying the joint impact of differences in cohabitation and differences in children. Both the share of single households by gender and the conditional number of children living in single and married households are adjusted. To consider only the effect of the different number of children living in the households while simultaneously fixing the share of single households, $\mathbb{P}^{*}_{K|E,G,C,H} = \mathbb{P}^{B}_{K|E,G,C,H}$ is plugged into

$$F_Y(I) = \int_0^I \sum_{x \in X} f^A_{Y|X}(y, (x_W, x_K, x_E, x_G, x_C, x_H))$$
$$\mathbb{P}^A_{W|K,E,G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H)$$
$$\mathbb{P}^{*}_{K|E,G,C,H}(x_K, x_E, x_G, x_C, x_H)$$
$$\mathbb{P}^A_{E,G,C,H}(x_E, x_G, x_C, x_H)\, dy.$$

Exercises on Education and Marital Sorting

For both martial sorting and gender-specific education, I construct counterfactual exercises in which the population's age distribution, the share of single households, and their gender are held constant. For year or region A, the counterfactual income distribution is given by

$$F_Y(I) = \int_0^I \sum_{x \in X} f^A_{Y|X}(y, (x_W, x_K, x_E, x_G, x_C, x_H))$$
$$\mathbb{P}^A_{W,K|E,G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H)$$
$$\mathbb{P}^{*}_{E|G,C,H}(x_E, x_G, x_C, x_H) \qquad (3.A.1)$$
$$\mathbb{P}^A_{G,C,H}(x_G, x_C, x_H)\, dy,$$

where $\mathbb{P}^{*}_{E|G,C,H}(x_E, x_G, x_C, x_H)$ is the counterfactual share of households with educational level x_E among all households of age x_H, cohabitation x_C, and gender x_G. Compared to the factual data, conditional education of couples are replaced in such a way that either marital sorting is fixed or the marginal distributions of male and female education are fixed.

I conduct several counterfactual exercises on marital sorting. In the first exercise, I test whether random matching would diminish income inequality. In the second exercise, I assume an educational sorting pattern from another year or region B and test whether marital sorting differs so much that it has a significant impact on income inequality. Finally, I test whether perfect positive assortative matching, in the sense of the Gale-Shapley matching algorithm (Gale & Shapley, 1962), would increase income inequality significantly. For singles, conditional education in Equation (3.A.1) does not differ from the factual data, but the sorting algorithms affect the conditional joint education $x_E = (x^m_E, x^f_E) \in E^f \times E^m$ of couples:

$$\mathbb{P}^{*}_{E|G,C,H}(x_E, x_G, x_C, x_H) = \begin{cases} \mathbb{P}^{A,\text{ sort}}_{E|G,C,H}(x_E, x_G, x_C, x_H) & \text{if } x_C = \text{couple} \\ \mathbb{P}^{A}_{E|G,C,H}(x_E, x_G, x_C, x_H) & \text{if } x_C = \text{single .} \end{cases} \qquad (3.A.2)$$

$\mathbb{P}^{A,\text{ sort}}_{E|G,C,H}(\cdot, \cdot, \text{couple}, x_H)$ represents a contingency table for each age group x_H. Matching algorithms are used to create counterfactual contingency tables $\mathbb{P}^{A,\text{ sort}}_{E|G,C,H}$. When applying the matching algorithms, male and female conditional marginal education, $\mathbb{P}^{A}_{E^m|G,C,H}$ and $\mathbb{P}^{A}_{E^f|G,C,H}$, respectively, remain unchanged. For the exercise on random sorting, the contingency tables are replaced by

$$\mathbb{P}^{A,\text{ sort}}_{(E^m,E^f)|G,C,H}(x_{E^m}, x_{E^f}, x_G, x_C, x_H) = \mathbb{P}^{A}_{E^m|G,C,H}(x_{E^m}, x_G, x_C, x_H)$$
$$\mathbb{P}^{A}_{E^f|G,C,H}(x_{E^f}, x_G, x_C, x_H).$$

In order to adopt the educational sorting pattern from a different year or region B, the contingency table $\mathbb{P}^{B}_{E|G,C,H}(\cdot, \cdot, \text{couple}, x_H)$ is transformed with the Sinkhorn-Knopp algorithm for each $x_H \in H$. The sorting pattern of B is fixed but the males' and females' marginal conditional education from A is incorporated. The transformed contingency tables are inserted as $\mathbb{P}^{A,\text{ sort}}_{E|G,C,H}$ in equation (3.A.2).

For the exercise on perfect sorting, the Gale-Shapley algorithm is applied on the contingency table $\mathbb{P}^{A}_{E|G,C,H}(\cdot, \cdot, \text{couple}, x_H)$ for each $x_H \in H$. The resulting contingency tables are inserted as $\mathbb{P}^{A,\text{ sort}}_{E|G,C,H}$ in equation (3.A.2).

The exercises on random and perfect matching only use information from sample A. Restricting the sample to cover the same household types as in another year or region (sample B) is therefore not necessary; Assumption 3.4.1 is not required. However, in order to ensure that the conditional income distributions for the newly matched couples exist and the created overall income distribution function is well-defined, the following assumption needs to be satisfied in all exercises which use sorting algorithms.

Assumption 3.A.4. *For all $x = (x_{E^m}, x_{E^f}, x_G, x_C, x_H) \in E^m \times E^f \times G \times C \times H$ the following holds: $\mathbb{P}^{A}_{E^m,E^f|G,C,H}(x) > 0$ if and only if $\mathbb{P}_{E^m,E^f|G,C,H}(x) > 0$.*

For the exercises on random and perfect sorting, the assumption is fulfilled when all conditional contingency tables $\mathbb{P}^{A}_{E|X_{fix}}$ of male and female education have positive entries. When the counterfactual mating pattern is taken from another year or region B, Assumption 3.A.4 is sufficient for generating a well-defined counterfactual income distribution. It states that a contingency table of male and female education has only a zero entry for A when its counterpart in B is zero as well, and vice versa.[38]

Considering the overall increase in education from 1976 to 2011, how does this change in education is related to the rise in income inequality? Considering the rather equally distribution of education level in East Germany, how would such an distribution of education across the West German households alter income inequality in the West?

[38] In the East German subsample, there is no couple household in the age group 55 to 59 with a low-educated male (school) and a highly educated female (university). I overcome this problem by dropping all households for that age group in the exercise of interest.

For the counterfactual exercise, the marginal distributions of male and female education conditional on age are taken from another region or year. Then, the counterfactual share of households with education x_E given their age x_H, gender x_G, and cohabitation status x_C is given by

$$\mathbb{P}^*_{E|G,C,H}(x_E, x_G, x_C, x_H) = \begin{cases} \mathbb{P}^{B,\,\text{SK(A)}}_{E|G,C,H}(x_E, x_G, x_C, x_H) & \text{if } x_C = \text{couple} \\ \mathbb{P}^{B}_{E|G,C,H}(x_E, x_G, x_C, x_H) & \text{if } x_C = \text{single} . \end{cases}$$

$\mathbb{P}^{B,\,\text{SK(A)}}_{E|G,C,H}(\cdot, \cdot, \text{couple}, x_H)$ denotes the contingency table regarding conditional education of husbands and wives after the Sinkhorn-Knopp (SK) algorithm has been applied to the mating scheme of A with the marginal distributions of male and female education from B. Without the SK algorithm, that is, if

$$\mathbb{P}^*_{E|G,C,H}(x_E, x_G, x_C, x_H) = \mathbb{P}^{B}_{E|G,C,H}(x_E, x_G, x_C, x_H),$$

both the educational sorting within married households and the conditional distribution of male and female education are supposed to be the same as in B. In both the exercise with the SK algorithm and the exercise without the SK algorithm, Assumption 3.A.4 is sufficient for ensuring the construction of a well-defined counterfactual income distribution. It is satisfied when a contingency table of year and region A has only zero entries if its counterpart in B (after applying the SK algorithm) is zero as well, and vice versa.

Exercises on Employment

In the 1970s, most married females were jobless. Until 2011, this share more than halved. East German married females are by 20 percent more often full-time working than West Germans. How much does the shift in conditional employment affect income inequality? The influence of the different (female) employment situations in East and West Germany, and in the 1970s and 2011, is computed with the counterfactual income distribution given by

$$\begin{aligned} F_Y(I) = \int_0^I \sum_{x \in X} & f^A_{Y|X}(y, (x_W, x_K, x_E, x_G, x_C, x_H)) \\ & \mathbb{P}^*_{W|K,E,G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H) \\ & \mathbb{P}^A_{K,E,G,C,H}(x_K, x_E, x_G, x_C, x_H)\, dy. \end{aligned}$$

With $x := (x_W, x_K, x_E, x_G, x_C, x_H)$, conditional employment of married females is adjusted by applying

$$\mathbb{P}^{*}_{W|K,E,G,C,H}(x) = \begin{cases} \mathbb{P}^{B}_{W^f|W^m,K,E,G,C,H}(x)\mathbb{P}^{A}_{W^m|K,E,G,C,H}(x) & \text{if } x_C = \text{couple} \\ \mathbb{P}^{A}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single} \end{cases}.$$

Thereby, conditional employment of males and single females is held constant. Analoguously, with

$$\mathbb{P}^{*}_{W|K,E,G,C,H}(x) = \begin{cases} \mathbb{P}^{A}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{couple} \\ \mathbb{P}^{B}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single, } x_G = \text{female} \\ \mathbb{P}^{A}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single, } x_G = \text{male} \end{cases}$$

conditional employment of single females is adopted while the conditional employment of males and married females is fixed. Together,

$$\mathbb{P}^{*}_{W|K,E,G,C,H}(x) = \begin{cases} \mathbb{P}^{B}_{W^f|W^m,K,E,G,C,H}(x)\ \mathbb{P}^{A}_{W^m|K,E,G,C,H}(x) & \text{if } x_C = \text{couple} \\ \mathbb{P}^{B}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single, } x_G = \text{female} \\ \mathbb{P}^{A}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single, } x_G = \text{male} \end{cases}$$

takes the conditional employment of all females from region and year B into account. Analogously, a counterfactual exercise on male employment is conducted with

$$\mathbb{P}^{*}_{W|K,E,G,C,H}(x) = \begin{cases} \mathbb{P}^{A}_{W^f|W^m,K,E,G,C,H}(x)\ \mathbb{P}^{B}_{W^m|K,E,G,C,H}(x) & \text{if } x_C = \text{couple} \\ \mathbb{P}^{A}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single, } x_G = \text{female} \\ \mathbb{P}^{B}_{W|K,E,G,C,H}(x) & \text{if } x_C = \text{single, } x_G = \text{male} \end{cases}.$$

Applying

$$\mathbb{P}^{*}_{W|K,E,G,C,H}(x) = \mathbb{P}^{B}_{W|K,E,G,C,H}(x)$$

provides a counterfactual distribution which supposes the conditional employment of all household members from the counterfactual year and region B.

Is the effect of education amplified by the change in employment or reduced? Both together, the change in education (including marital sorting) and the different conditional working status, can reinforce income inequality or their impacts on income inequality can compensate each other. In order to find an answer to this question, the counterfactual income distribution

$$
\begin{aligned}
F_Y(I) = \int_0^I \sum_{x \in X} f^A_{Y|X}(y, (x_W, x_K, x_E, x_G, x_C, x_H))& \\
\mathbb{P}^B_{W|K,E,G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H)& \\
\mathbb{P}^A_{K|E,G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H)& \\
\mathbb{P}^B_{E|G,C,H}(x_W, x_K, x_E, x_G, x_C, x_H)& \\
\mathbb{P}^A_{G,C,H}(x_K, x_E, x_G, x_C, x_H)\, dy&
\end{aligned}
$$

is generated. Note that exercises on employment require Assumption 3.A.1 to hold.

Appendix 3.B Derivation of the Income Levels

In the Microcensus, net household income is given as an income interval. I assume the income to be uniformly distributed within these intervals. This is a common assumption which is also used for the implementation of the 2011 household income within the Microsensus (see the documentation provided by the Statistisches Bundesamt in 2014). Then, the mean household income (i.e. the middle of the income interval) is utilized for the analysis as the household's income level.

The derivation of the upper bound of the very top income interval bases on the approach used by the Statistisches Bundesamt (2014) for the Microsensus of 2011. The Microcensus provides auxiliary values for the net income; these auxiliary values are generated by drawing the income uniformly from the known income interval. For 2011 households with an income larger than the last upper bound known , i.e. larger than $18,000$, we compute the mean household income with the help of these auxiliary values. The mean income amounts EUR $21,256.33$. To compute a hypothetical upper bound for 1976 income levels, I assume that the upper tail of the 1976 income distribution behaves like the upper tail of the 2011 income distribution. In detail, I use the ratio of the mean income and the last upper bound known (i.e. $18,000$) and the assumption that the income levels are uniformly distribution within each income interval to generate the hypothetical upper bound for 1976. The ratio is $21,256.33/18,000 \approx 1.18$. and, for the very top income category, $4,085.44$ DM ($24,512.66$ EUR) is derived as an upper bound for 1976 (2011); the expected income in the highest income category amounts to $3,542.72$ DM ($21,256.33$ EUR).

Appendix 3.C Sample Size Reduction

Table 3.C.1: Descriptive Statistics before and after the Sample Size Reductions

(a) Share of Households Affected by the Sample Size Reduction

Households without a counterpart in the counterfactual region / year	West 2011	East 2011
Exercises across time	2.06 %	-
Exercises across space	3.96 %	0.14 %

(b) Impact on Income Inequality

Income inequality	West 2011	East 2011
Gini coefficient		
Before approximation: factual data	30.11	30.06
1st approximation: maximum number of children	30.09	30.04
2nd approximation across time (dropping households)	29.92	-
2nd approximation across space (dropping households)	29.99	30.03
Theil index		
Before approximation: factual data	16.88	15.62
1st approximation: maximum number of children	16.86	15.60
2nd approximation across time (dropping households)	16.69	-
2nd approximation across space (dropping households)	16.77	15.59
Atkinson index with parameter 2.0		
Before approximation: factual data	29.17	27.41
1st approximation: maximum number of children	29.14	27.39
2nd approximation across time (dropping households)	29.01	-
2nd approximation across space (dropping households)	29.25	27.38

Notes: In the first approximation, households with three or more children are made count as households with two children. In the second approximation, household types are omitted if they are not observed in the counterfactual year and region.

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Abgrenzung

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Ich versichere hiermit, dass ich das zweite Kapitel *Job Displacement and Training Activities: Human Capital Accumulation during the East German Transition* sowie das dritte Kapitel *Sources of German Income Inequality across Time and Space* ohne Hilfe Dritter verfasst habe.