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IRVINE

Market Disruption and Inequality: How Computerization and the Transition to Capitalism affect  
Wage and Gender Differentials

DISSERTATION

submitted in partial satisfaction of the requirements  
for the degree of

DOCTOR OF PHILOSOPHY

in Sociology

by

Joseph King

Dissertation Committee:  
Professor Matt Huffman, Co-Chair  
Associate Professor Andrew Penner, Co-Chair  
Chancellor's Professor David Neumark

2016

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Nina Bandelj, and Aleksandra Kanjua-Mrčela  
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# **DEDICATION**

To

my parents

for all their love and encouragement

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# CURRICULUM VITAE

## Joseph King

Department of Sociology  
University of California, Irvine  
Irvine, CA 92697-5100  
kingj2@uci.edu

### EDUCATION

#### University of California, Irvine

2016 Ph.D. Sociology

Dissertation: *“Market Disruption and Inequality: How Computerization and the Transition to Capitalism affect Wage and Gender Differentials”*

Committee: Andrew Penner (co-chair), Matt Huffman (co-chair), and David Neumark

Field Exams: Inequality, Demography

2015 M.A. Demographic and Social Analysis

#### Washington State University

2011 M.A. Sociology

#### University of Idaho

2007 B.S. Crime and Justice Studies, B.A. German

### AREAS OF INTEREST

Inequality, labor markets, organizations, demography, quantitative methods

## POSITIONS HELD

2013-2016 Graduate Research/Teaching Assistant, Department of Sociology, UC Irvine

### Previous

2015 Data Analyst Intern, Orange County Business Council

2011-2013 Research Associate (*Wissenschaftlicher Mitarbeiter*), Graduate School of Economic & Social Sciences and the Mannheim Centre for European Social Research (MZES), University of Mannheim (Germany)

2009-2011 Teaching Assistant, Department of Sociology, Washington State University

## PEER-REVIEWED PUBLICATIONS

2016 Matt Huffman, Joe King, and Malte Reichelt. "Equality for Whom? Organizational Policies and the Gender Gap across the German Earnings Distribution." Forthcoming in *Industrial and Labor Relations Review*.

2016 Joe King, Malte Reichelt, and Matt Huffman. "Computerization and Wage Inequality Between and Within German Work Establishments." In press at *Research in Social Stratification and Mobility*.

2016 Adams, Britni, Joe King, Andrew Penner, Nina Bandelj, and Aleksandra Kanjuro-Mrčela "Returns to Education and Labor Market Sorting in Slovenia, 1993-2007." In press at *Research in Social Stratification and Mobility*.

## WORKING PAPERS

King, Joe, Andrew Penner, Nina Bandelj, and Aleksandra Kanjuro-Mrčela "Market Transformation and the Opportunity Structure for Gender Inequality: A Cohort Analysis using Linked Employer-Employee Data from Slovenia." Under review at *American Sociological Review*.

"Computers and the Rise in Wage Inequality: A Cohort-Based Distributional Analysis using West German Data." In preparation.

## REPORTS

Winter, Nicole, Justin Chung, Melissa Niiya, Joseph King, Grace Lin, Erin Huges, Kelsey Collier, Justin O’Neill, Trevor Gamble, Wind Woods, Coral Wheeler, and Erica Heinrich. 2014. “AGS Internal Committee Report: Graduate Student Life Survey.” UC Irvine Associated Graduate Students.

## CONFERENCE PRESENTATIONS

- 2015 “Market Transition and the Opportunity Structure for Gender Inequality: A Cohort Analysis using Linked Employer-Employee Data from Slovenia.” Presented at the annual meeting of the American Sociological Association in Chicago.
- 2015 “Market Transition and the Opportunity Structure for Gender Inequality: A Cohort Analysis using Linked Employer-Employee Data from Slovenia.” Presented at the ISA Research Committee 28 meeting in Philadelphia.
- 2015 “Market Transition and the Opportunity Structure for Gender Inequality: A Cohort Analysis using Linked Employer-Employee Data from Slovenia.” Presented at the annual meeting of the Society for the Advancement of Socio-Economics in London.
- 2015 “Equality for Whom? Organizational Policies and the Gender Gap across the German Earnings Distribution.” Presented at a special-issue conference on Reducing Inequality in Organizations: What Works? What Doesn’t? hosted by Industrial and Labor Relations Review in New York.
- 2015 “Class-Based Technological Change and the Rise in Wage Inequality: A Workplace Analysis using Matched Employment Data from Germany.” Presented at the Organizational Stratification: Processes, Mechanisms and Institutional Contexts conference hosted by Research in Social Stratification and Mobility in Bielefeld, Germany.
- 2015 “Market Transition and the Opportunity Structure for Gender Inequality: A Cohort Analysis using Linked Employer-Employee Data from Slovenia.” Presented at the annual meeting of the Population Association of America in San Diego.
- 2014 “Computerization and the Rise in German Wage Inequality, 1979-2012: A New Look using Microdata.” Presented at the annual meeting of the American Sociological Association in San Francisco

- 2014 “Computerization and the Rise in German Wage Inequality, 1979-2012: A New Look using Microdata.” Presented at the TASKS III: Changing Tasks – Consequences for Inequality conference in Nuremberg, Germany
- 2013 “Technological Change, Union Decline, and the Rise in German Wage Inequality, 1979-2012.” Presented at the Research Committee on Social Stratification (RC28) in Trento, Italy
- 2011 “Labor Market Deregulation and Nonstandard Employment: Measuring the Effects of Atypical Work on Establishment-Level Sex Segregation in Germany.” Presented at the GESS Research Day in Mannheim, Germany.

### **GRANTS, HONORS, AND AWARDS**

- 2015 Travel Grant, ISA Research Committee 28 - Social Stratification and Mobility (RC28) (\$750)
- 2014 Pai Fellow, UC Irvine Center for Economics and Public Policy (\$1,000)
- 2014 Small Grant, UC Irvine Center for Organizational Research (\$1,000)
- 2014 Summer Research Fellowship, UC Irvine Department of Sociology (\$1,400)
- 2014 Travel Grant, Associated Graduate Students (AGS) UC Irvine (\$600)
- 2012-2013 Dissertation Research Grant, Mannheim Centre for European Social Research (MZES), University of Mannheim (€38,000)

### **TEACHING EXPERIENCE**

Spring 2015-TA  
 UCI, Social Science 10C: Probability and Statistics  
 Dr. Nick Noviello

Fall 2015-TA  
 UCI, Sociology 44: Births, Deaths, and Migration  
 Dr. Susan Brown

Spring 2014-TA  
 UCI, Sociology 10C: Probability and Statistics  
 Dr. Su Yang

Winter 2014-TA  
UCI, Social Science 10B: Probability and Statistics  
Dr. Nick Noviello

Winter 2013-TA  
University of Mannheim, Sociology: Empirical Research Practicum (in German)  
Dr. Thomas Gautschi

Fall 2010 – Summer 2011-TA  
WSU, Sociology 321: Quantitative Techniques in Sociology  
Dr. Kim Lloyd

Spring 2010-TA  
WSU, Sociology 320: Introduction to Social Research  
Dr. Arina Gertseva

Fall 2009-TA  
WSU, Sociology 101: Introduction to Sociology  
Dr. Lisa McIntyre

## **ABSTRACT OF THE DISSERTATION**

Market Disruption and Inequality: How Computerization and the Transition to Capitalism affect

Wage and Gender Differentials

By

Joseph King

Doctor of Philosophy in Sociology

University of California, Irvine, 2016

Professor Matt Huffman, Co-Chair

Associate Professor Andrew Penner, Co-Chair

This dissertation examines how two common types of market disruptions, technology-induced and government-induced disruptions, influence inequality. Specifically, it investigates how the spread of computers and the transition to capitalism are related to wage differentials and gender earnings differentials, respectively. Compared to prior work, this dissertation focuses particularly on how these disruptions influence inequality in heterogeneous ways across birth cohorts as well as between and within work establishments, using unconditional quantile regression and fixed effects regression. Results suggest that the spread of computers was related to greater inequality among older cohorts across the wage distribution in (West) Germany over time. Whereas computerization appears to have affected older cohorts more strongly, market transformation in Slovenia coincided with a greater rise in gender earnings inequality and changes to the organization of gender inequality in the labor market among younger cohorts. Furthermore, although results provide little indication of a causal effect of computers on establishment-level

inequality, computer investments tend to be higher in workplaces with greater heterogeneity in pay. Investments in computer technologies may also slightly contribute to between-establishment inequality in the long term, while appearing to have no long-term influence on within-establishment inequality. Overall, this dissertation highlights how disruptions shape inequality in nuanced ways and that cohorts and workplaces represent important structural boundaries that determine this effect.

## INTRODUCTION

Recent decades have seen a rapid increase in the popularity of the concept of ‘market disruption’ or simply “disruption” in both academic spheres and popular culture. Although its definition varies, ‘disruption’ can be generally understood as an exogenous shock to a single industry or even an entire economy, causing a change in how those markets function. Scholars have focused primarily on two types market-disrupting shocks. First, a government-induced shock. While countless investigations have considered how changes in policies at various levels of government affect a host of social outcomes, the term ‘disruption’ is often used in conjunction with large-scale policy changes, such as an increase in trade protectionism (Bhagwati and Srinivasan 1976) or trade liberalization (Dixon, Parmenter, and Powell 1984). Still others have identified the outbreak of state-sponsored war (e.g. Helkie 1991) as another form of government-induced disruption given the way this alters the functions of markets. This first, comparably more heterogeneous branch of market disruption has been conducted primarily by economists, and focuses on how these disruptions influence commodity prices or employment levels.

The second main branch of market disruption literature focuses on technology-induced shocks. While scholars across a multitude of disciplines including have examined how technology influences society, this particular approach distinguishes itself by analyzing how technological disruptions (i.e. information technology) affect the organization of markets and firms. This comparably better-known variant of disruption has emerged from within the discipline of management, and was pioneered chiefly by Clayton Christensen and his colleagues (Bower and Christensen 1995; Christensen 1997; Christensen and Raynor 2003). As they argue, dominant firms frequently lose their market position through disruptive technological innovations, meaning



that managers should embrace ‘disruption’ as management principle to remain relevant in the marketplace.

Aside from their consequences on strategy, commodity prices, and employment, technological and governmental disruptions matter because they influence inequality. In particular, the *spread of computers (i.e. computerization)* and the *transition to capitalism (i.e. marketization or market transformation)* are thought to affect earnings differentials. On the one hand, computers are argued to disrupt the relative productivity of particular types of labor tasks, contributing to rising wage inequality along the skill gradient (Autor, Levy, and Murnane 2003; Juhn, Murphy, and Pierce 1993; Krueger 1993; Levy and Murnane 1992). On the other hand, while marketization is also connected to a rise in earnings inequality (Bandelj and Mahutga 2010), this disruption importantly affects gender wage inequality through disrupting the existing gendered employment arrangement (Fodor 2002; Giddens 2002; van der Lippe and Fodor 1998). Computerization and the transition to capitalism are therefore highly socially disruptive processes; consequently, understanding their influences on earnings differentials remains critical.

Market disruptions are especially likely to have heterogeneous inequality consequences across the population. As life course research describes, individuals are embedded in social institutions in age-specific ways, which affect how they experience major societal events (Elder 1994; Settersten and Mayer 1997). Correspondingly, large-scale disruptions may yield birth cohort effects in which social change creates differences in the life patterns of successive cohorts (Elder 1974, 1994; Glenn 2005; Ryder 1965). In addition to cohort differences, disruptions may also produce heterogeneous effects along other dimensions. Sociologists have long recognized that work establishments are central to categorical inequalities, such as gender- and race-based differences in employment outcomes (e.g. Baron and Bielby 1980; Bielby and Baron 1986; Castilla

2008; Reskin 2003; Tomaskovic-Devey et al. 2006). Recent research has documented that workplaces are also fundamental to gradational inequalities, and have played an important role in the rise in wage inequality (Card, Heining, and Kline 2013; Song et al. 2015). Because the rise in inequality has transpired primarily between workplaces (Card et al. 2013), this suggests disruptions may have differential consequences on inequality between and within establishments. Together, cohorts and establishments represent two highly salient dimensions of effect heterogeneity from disruptions.

This dissertation considers how computerization (a government-induced disruption) and marketization (a technologically-induced disruption) affect inequality in heterogeneous ways. Compared to prior work, I approach disruption from a sociological standpoint, which recognizes that differentiation among individuals in society (e.g. power, prestige, and wages) stems from the structural positions that individuals occupy, rather than the characteristics of those individuals (Davis and Moore 1945; Sørensen 1996; Turmin 1953). I therefore examine how the influence of disruptions varies structurally, focusing particularly on their differential effects on cohorts and workplaces. Specifically, I analyze how computerization is related to wage inequality across cohorts and the impact of computer investments on between- and within-establishment earnings inequality. I also consider the cohort-specific ways market transition influences gender earnings inequality.

Following this introduction, chapter one offers a theoretical overview of how the spread of computers and the transition to capitalism are related to wage and gender differentials, correspondingly. To explain the relationship between computers and wage inequality, I draw particularly on the theory of skill-biased technological change (SBTC), but also class-biased technological change (CBTC) and unobserved heterogeneity. After this I describe how market

transformation is thought to alter gender inequality, concentrating on the organization of gender wage inequality in the labor market. Then I present the life course paradigm with a focus on how historical events impact individuals differently across cohorts. Although I leave the specific application of this paradigm to the respective empirical chapters, my goal is to briefly illuminate the utility of a cohort-based approach for understanding the heterogeneous impacts of computerization and marketization. Lastly, in this chapter, I offer some comments on the overall purpose of this dissertation.

Chapter two adopts a life course approach to evaluate how the diffusion of computers has influenced inequality in cohort-specific ways across the earnings distribution, using microdata from Western Germany. This chapter extends earlier studies by considering how computers affect inequality according to when individuals came of age and entered the labor market relative to the computer revolution. It therefore offers a more nuanced explanation for the relationship between computerization and inequality than skill-biased technological change. Results show that the spread of computers was more strongly related to inequality among older, compared to younger, cohorts. Although aggregate results suggest computers correlate with higher upper-tail inequality as predicted by SBTC in the mid-1980s and early-1990s, this is driven primarily by cohort differences in the returns to computer use. Cohorts also strongly moderated the computer wage premium in the 2000s, especially among low-wage workers.

The third chapter considers the influence of investments in information and communication technologies (ICT) on establishment-level wage inequality in Germany. Recognizing work establishments have been central to the rise in inequality (Card et al. 2013), this chapter extends existing research by considering how ICT simultaneously impacts between- and within-establishment wage differentials. Empirically, this chapter evaluates three explanations: SBTC,

CBTC, and unobserved heterogeneity. Fixed effects results provide little support for either skill- or class-biased technological change, suggesting the well-known association between computers and inequality is driven by unobserved establishment heterogeneity. This chapter therefore finds little evidence of a causal effect of computers on changes in establishment-level inequality. Rather than establishments that invest more greatly in ICT pay on average better wages and exhibit higher within-establishment inequality.

The fourth chapter assumes a life-course inspired, cohort-based approach to investigate how the transition to capitalism affects the male-female earnings gap. Although scholars have long been interested in the gender consequences of transition (e.g. Einhorn 1993; Fodor 2002; Giddens 2002; Hauser, Heyns, and Mansbridge 1993; van der Lippe and Fodor 1998; Rueschemeyer and Szelenyi 1995), few have considered how the impact of marketization may depend on individuals' life stage when this event occurred. This chapter also contributes to our understanding of the structure of gender inequality in establishments by investigating how transition alters the importance of allocative versus within-job gender inequality. Using Slovenian registry data, results show that gender differentials remained stable in older cohorts with well-established careers, but rose substantially among more recent cohorts. Slovenia's marketization also changed the structure of gender inequality, such that women in more recent cohorts receive lower pay than men for doing the same job for the same employer.

Finally, the fifth chapter summarizes these individual empirical chapters in slightly greater detail and offers some concluding remarks.

## **CHAPTER 1: Computerization, Marketization, and Inequality**

### **The Spread of Computers**

This dissertation first considers the disruptive influence of the spread of computers and how this affects wage inequality. An extensive and diverse literature has documented a strong relationship between computerization and inequality. Kuznets (1955) was among the first to systematically study changes in earnings inequality. Using data from the United States, England, and Germany, he found that inequality had declined in these countries between the late 1800s and the end of WWII, coinciding with major industrial developments. As he postulated, earnings inequality followed an inverted-U shaped pattern, increasing as countries first industrialized, and then decreasing again in the later stages of industrialization.

Until the early 1980s, earnings inequality received little scholarly interest due to its presumed stability (Lemieux 2008). Bluestone and Harrison (1982), however, were among the first to challenge Kuznets' (1955) long-standing theory; as they showed, wage inequality had been on the rise in the U.S. since the mid-1970s. Although their OLS estimates lacked a strong causal underpinning, they pointed to institutional changes (i.e. deunionization, firm restructuring, and managerial capitalism) as the likely cause of rising inequality. A few years later, in direct refutation of Kuznets (1955), Harrison and Bluestone (1988) coined the term “The Great U-Turn” to describe this trend in rising inequality.

At first, Bluestone and Harrison (1982) Harrison and Bluestone's (1988) findings about rising inequality were met with skepticism, as others argued these results could simply be due to business cycle fluctuations. Yet with the benefit of additional years of data, by the early 1990s a series of influential papers emerged (e.g. Bound and Johnson 1992; Juhn et al. 1993; Katz and Murphy 1992; Levy and Murnane 1992), documenting that inequality was indeed on the rise

(Lemieux 2008). As these studies showed, much of the growth had been between better- and less-skilled workers, though an even larger share had occurred within narrowly-defined skill groups (i.e. individuals with the same level of education and experience). Although these studies were initially hesitant to identify a cause, scholars eventually came to agree that the source of growing inequality was a rise in relative demand for all types of skill (i.e. education, experience, and unobserved abilities), which had outstripped the growth in the relative supply of skill. Skill-biased technological change (SBTC), as this theory came to be known, posits that recent technological changes, especially advancements in microcomputers, caused this rise in demand for skill. Given that computer technology is believed to complement human capital, the spread of computers was argued to lead to skill-based inequality (for more details, see Acemoglu 2002; Card and DiNardo 2002; Lemieux 2008).

Although these early studies lacked measures for computer technology, concentrating instead on supply-side changes in human capital, subsequent research has assessed the empirical relationship between computers and inequality. Perhaps the first and best known empirical investigations is Krueger (1993). Using individual-level CPS data from 1984 and 1989, he found that computer use predicts 10-15 percent higher wages on average. Moreover, Krueger discovered that better-educated workers are more likely to use computers at work, further supporting the belief that the spread of computers fuels demand for skill. Others have evaluated the influence of computers at the industry level, finding that investments in information and communication technologies (ICT) are related to a rising share of college-educated workers over time (Autor, Katz, and Krueger 1998; Berman, Bound, and Griliches 1994). Establishment-level research also links computer investments and skill-based inequality. A wealth of studies have shown that ICT investments predict a higher proportion of skilled workers and a lower share of unskilled workers

in establishments (Autor, Levy, and Murnane 2002; Bresnahan, Brynjolfsson, and Hitt 2002; Dunne and Schmitz 1995; Siegel 1998). Still other research suggests that ICT investments increase within-establishment wage differentials. For example, Fernandez (2001) reports that retooling in one large manufacturing plant amplified earnings dispersion through the hiring of new, highly skilled workers that commanded real wage increases compared to wage stagnation among low-skill workers.

But how exactly do computers enhance demand for skill? Addressing one of the most glaring problems of the original SBTC hypothesis, Autor et al. (2003) propose a “task-based” version of this theory, positing that tasks represent the missing causal mechanism behind computers’ influence on the labor market.<sup>1</sup> As they assert, workplace activities comprise two general types of tasks: routine and non-routine. On the one hand, routine cognitive tasks (e.g., bookkeeping, cashiering, calculating) and routine manual tasks (e.g. picking, sorting, repetitive assembly) involve methodically repetitive procedures which are liable to computer substitution since they can be easily defined by explicit programmed rules. On the other, non-routine cognitive tasks (e.g. managing, problem solving, and advising) are computer-complementary as computers enhance the productivity of individuals completing these activities. By contrast, the impact of ICT on non-routine manual tasks (e.g. truck driving, cleaning, and servicing) remains ambiguous as computers neither strongly complement nor substitute for these activities. Consequently, the task-based approach identifies two potential channels through which computers affect wages; first, through shifting work toward non-routine cognitive tasks and automating cognitive and manual routine tasks, ICT is argued to increase demand for skilled workers to perform non-routine cognitive tasks. In turn, wage changes depend on whether the supply of skilled workers keeps pace

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<sup>1</sup> This is also called the “nuanced” SBTC hypothesis or in the context of job polarization the “routinization” hypothesis.

with demand. Second, computerization may enhance the productivity (and therefore wages) of workers performing complementary tasks, contributing to inequality (Spitz-Oener 2008).

In addition to this direct, skill-based (and more recently task-based) mechanism, others have argued computerization enhances inequality indirectly as well. Specifically, class-biased technological change (CBTC) maintains that computerization boosts inequality through furthering the decline in collective bargaining institutions. Although trade union decline represents an important factor in rising inequality in its own right (for international comparisons, see DiNardo, Fortin, and Lemieux 1996; Dustmann, Ludsteck, and Schönberg 2009; Gosling and Lemieux 2001; Western and Rosenfeld 2011), Kristal (2013) and Kristal and Cohen (2015) argue that computerization increases inequality through deunionization by: (1) reducing the share of unionized manufacturing jobs, (2) heightening managerial anti-union tactics; and (3) skill polarization that weakens worker solidarity. Using a panel of U.S. industries, they demonstrate that ICT investment had a smaller effect on industries in which unions never had a significant presence, compared to ICT having a larger effect in industries that experienced strong declines in organized labor. As they contend, computerization exerted only a direct (i.e. skill-based) effect on inequality in industries with no historical union presence, while computerization had both a direct and indirect (i.e. union decline) effect on inequality among historically-unionized industries, leading to a greater inequality rise among the latter.

A third potential explanation between computerization and inequality is that the relationship stems from unobserved heterogeneity. One of the first studies to argue that the computer-wage relationship was endogenous was DiNardo and Pischke (1997). Using German microdata, they found that other job characteristics including pencils or calculators at work were associated with wage returns comparable in magnitude to the returns to computer use. As they



contend, due to the nonrandom assignment of computers in the labor market, any positive association could be due to unobserved differences between computer users and nonusers. For instance, white collar workers were among the first to use computers at work even though they earned on average more than their blue collar counterparts even prior to these technologies. Handel (2007) also finds that job characteristics account for the computer wage premium using CPS data, suggesting unobserved heterogeneity may likewise affect the relationship between computers and inequality in the U.S.

While unobserved heterogeneity may stem from a variety of sources (e.g. individuals, occupations, industries, or establishments), some have argued this arises primarily at the establishment level. Doms, Dunne, and Troske (1997) for example find that U.S. manufacturing plants that invested more greatly in computer technologies tended to employ better-educated workers and offered higher wages according to cross-sectional estimates; however, according to longitudinal models they found no evidence of wage changes. Indeed, Bresnahan (1999) argues computerization creates new ways of organizing work through routinizing and standardizing bureaucratic production processes within establishments. Accordingly, technological change may engender new, more unequal ways of organizing work, promoting the growth of heterogeneous workplaces (i.e. Card et al. 2013), which might serve as the proximal cause of rising inequality. Alternatively, another conceivable way computerization is related to unobserved establishment heterogeneity is that ICT investments are consistently higher in specific product markets that also tend to evince higher inequality, yet ICT has no actual impact on inequality in these particular markets (Bresnahan 1999). Based on this idea, ICT has no causal effect on wages, but is instead more useful in these unique markets, creating a spurious association between ICT and inequality.

## **The Transition to Capitalism and Gender Earnings Differentials**

In addition to the spread of computers, this dissertation also examines the influence of marketization on gender earnings differentials. The end of socialism and subsequent transition to capitalism in Central and Eastern Europe (CEE) presented a unique opportunity to witness how capitalism shapes inequality. Not only has this altered social exchange from a relatively centralized distributional system to a highly decentralized market system, but this fundamentally disrupted the existing gendered employment arrangement. Under socialism, women had to bear a double burden of being the primary caregiver in families while also typically working full-time (Corrin 1992). Many formerly socialist states in Central and Eastern Europe also had official gender egalitarian policies, though gender earnings inequality was large and persistent, and often comparable to levels among developed Western societies (Rosenfeld and Trappe 2002). Scholars therefore feared that women would bear the disproportionate costs of market transition (Einhorn 1993; Hauser et al. 1993). Surprisingly, however, women's socioeconomic situation did not drastically worsen in the years immediately following 1989 (Fodor 2002; Giddens 2002; van der Lippe and Fodor 1998; Rueschemeyer and Szelenyi 1995).

While marketization may be linked to small changes in gender inequality across most CEE countries, there are indications that this process may have importantly altered the *organization* of gender inequality. Petersen and Saporta (2004) identify three distinct types of gender pay inequality. First, due to a combination of worker preferences and employer practices, men and women are allocated to different occupations and establishments that offer differential rewards. This *allocative* inequality results from both distinctive patterns in hiring and in worker promotions and dismissals. Second, employers may systematically pay women less than men in the same occupation and establishment, resulting in *within-job* inequality. Third, majority female

occupations receive lower pay compared to majority male ones, net of skill requirements and work-related activities, yielding *valuative* inequality.

As Petersen and Saporta (2004) explain, the relative importance of these three types of inequality depends on their structural feasibility and cultural acceptance. Following the enactment of the Civil Rights Act in the U.S. and similar policies in other advanced developed countries (Ellis 1991), blatant employer discrimination according to ascriptive characteristics became more difficult and normatively less defensible. Hence, within-job inequality is structurally difficult and culturally unacceptable in these contexts. By contrast, documenting discrimination in allocative inequality is substantially more difficult to prove in court, making it structurally more feasible. Likewise, given that men and women are commonly presumed to have differing job preferences (Cjeka and Eagly 1999; Correll 2001, 2004; Fernandez and Friedrich 2011; Marini and Brinton 1984; Marini, Fan, and Finley 1996), allocative inequality is likely to be more socially palatable than within-job gender disparities. Finally, because *valuative* inequality is the product of discrimination against a particular class of jobs or occupations, this makes it the most difficult to prove in court. Although *valuative* inequality is also morally unacceptable, bias is often unconscious (Fiske 1998; Fiske et al. 1991), and therefore often unrecognized.

Together, these structural and normative influences make within-job inequality a relatively small component of total gender pay inequality among Western societies, with women earning on average 2-6 percent less than men doing the same work in the same establishment in Norway (Petersen et al. 1997), 1.4-5 percent less in Sweden (Meyersson, Petersen, and Snartland 2001), and 1-5 percent in the United States (Petersen and Morgan 1995). Accordingly, this comprises between 5-25 percent of the overall gender earnings gap in the U.S. (Petersen and Morgan 1995), and 10-30 percent in Norway (Petersen et al. 1997) and Sweden (Meyersson et al. 2001).

Allocative inequality, based on differential gender sorting into occupations and establishments, thus explains the vast majority of the gender pay gap in these contexts.<sup>2</sup>

However, patterns of gender inequality in transition societies appear to differ. Absent a similar legacy of gender equity legislation, the earnings differential within occupation-establishment units (i.e. within-job) remains a large component of the total gender pay gap among CEE societies. In their study of the Czech Republic, Křížková, Penner, and Petersen (2010) document that Czech women earn on average 10 percent less than their male counterparts for doing the same work for the same employer. As such, this within-job component comprises nearly half of the total gender pay gap. Jurajda (2003) and Sørensen and Trappe (1995) also find similar patterns in Slovakia and the former East Germany, respectively, suggesting that within-job inequality may be widespread among former socialist societies.

Nevertheless, the organization of gender inequality appears to have changed throughout market transition, suggesting marketization alters the organization of gender inequality. Although they do not study wage inequality, Sørensen and Trappe (1995) find that gender segregation was higher in the East and different in form than in West Germany. Compared to the West, female-dominated occupations in the East contained a higher proportion of women, though male-dominated occupations in the East were paradoxically less sex segregated. Still, they find that gender segregation patterns in the former East Germany have come to increasingly resemble those in Western Germany. Similarly, Penner et al. (2012) investigates patterns in gender pay inequality in Slovenia, finding that marketization has accompanied a shift towards Western-style forms of inequality with allocative inequality assuming increasingly more importance.

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<sup>2</sup> Research argues valiative inequality is also an important part of the gender pay gap (England 1992), though difficulties in empirically measuring this form of inequality make its contribution hard to assess.

## **Cohort Effects in the Life Course**

Chapters 3 and 5 employ the life course paradigm to show how computerization and marketization influence wage and gender differentials, respectively. “Life course” is the idea that human lives are embedded in social institutions (e.g. family, educational system, labor market, etc.) according to distinct biologically-patterned progressions and that these institutions shape human lives (Elder 1994; Settersten and Mayer 1997; Zhou and Moen 2001). Although this paradigm encompasses a wide body of literature (see Elder 1994), a life course application to disruptions focuses especially on how disruptions yield uneven consequences on individual life chances across the population based on their age when the disruption occurred. Major historical events affect individual life chances in part through altering social institutions. Yet because individuals are embedded these institutions in age-specific ways, birth year differences pose differential exposure and response options to individuals. Historical events in the life course produce cohort effects whereby social change creates differences in the life patterns of successive cohorts. In his classic study for instance, Elder (1974) highlighted the differential impact of the Great Depression on individuals between and within cohorts. A fundamental concept in life course analysis is the idea of cumulative advantage (or disadvantage), in which social advantages existing earlier in individuals’ lives provide the basis for later advantages (or disadvantages), contributing to social inequalities (DiPrete and Eirich 2006; Merton 1968). Alternatively, disruptions may also yield period effects, in which the impact of social change is fairly uniform across successive cohorts during the same time. Together, period and cohort effects proxy for exposure to historical change and reveal how disruptions affect a given population (Elder 1994).

Although the spread of computers has been widely recognized as a major social disruption, researchers have not yet approached this phenomenon from a life course perspective to understand

its cohort-specific consequences on earnings inequality. Instead, following primarily neoclassical economic tradition, scholars have primarily viewed computerization as a period effect (e.g. Autor, Katz, and Kearney 2006; Autor et al. 2003; Bound and Johnson 1992; Goos and Manning 2007; Juhn et al. 1993; Katz and Murphy 1992; Krueger 1993; Levy and Murnane 1992; Spitz-Oener 2008). While cohort investigations of computerization remain absent, a handful of studies have applied cohort methods to examine the rise in inequality. For instance, Card and Lemieux (2001) analyze the changing returns to education in the U.S., U.K., and Canada, finding significant cohort differences in the returns to education over time. As they explain, much of the well-known rise in the college-high school earnings gap (i.e. Goldin and Katz 2008) was driven by young workers in their early 30s, which was attributable to a slowdown in the growth of educational attainment among cohorts born in the early 1950s amidst technology-induced rises in the relative productivity of college workers (see Dooley and Gottschalk [1984] for a similar cohort approach to the returns to education). Scholars have likewise found marked cohort differences in intragenerational inequality in lifetime earnings. Using administrative data from West Germany, Bönke, Corneo, and Lüthen (2015) find a striking secular increase in lifetime earnings inequality among male cohorts, with men born in the mid-1960s experiencing 85% higher inequality than their fathers.

Likewise, little research has applied a life course lens to understand how marketization may influence gender inequality differently across cohorts. Mayer, Diewald, and Solga (1999) find significant age-related differences in the effects of German reunification across labor force cohorts. They document that after the fall of the Berlin Wall members of the oldest cohort in East Germany were pushed into early retirement in order to cope with rapid sectoral change. In contrast, middle-aged workers were among the most likely to retain their job, while members of the youngest cohort had the highest rates of downward and upward mobility. Cohort differences have also been

reported in China: Following the onset of reforms in the 1980s, younger cohorts experienced elevated job changes relative to older cohorts and benefitted more from working in quasi-marketized firms (Zhou and Moen 2001). Toro-Tulla (2014) also applies a cohort-based approach to economic development in Puerto Rico, finding major differences in the opportunity structure present across cohorts due to the rapidly changing industrial landscape.

### **Summary and Purpose of Dissertation**

In the words of John Stuart Mill (Mill 1843), this dissertation focuses on the effects of causes, rather than the causes of effects. In this case, these “causes” include the spread of computers and the transition to capitalism as they relate to wage and gender differentials, respectively. A larger discussion of the multitude of causes for wage and gender differences remains outside the scope of this dissertation. I concentrate particularly on these two disruptions as they represent arguably two of the largest and most important in recent times, which will continue to have far-reaching consequences in the future. By illustrating the heterogeneous effects of these disruptions, I hope to increase our understanding of how these phenomenon contribute to social stratification.

## **CHAPTER 2: Computers and the Rise in Wage Inequality: A Cohort-Based Distributional Analysis using West German Data**

### **Introduction**

In recent decades, computerization (i.e. the spread of computers and information technology) of the labor market has become arguably the dominant explanation for the growth in wage inequality. Particularly since the 1990s, a large body of economic research has emerged, supposedly documenting the sizable effect of computers on the wage structure. Dubbed skill-biased technological change (SBTC), this idea holds that the increase in computer technology has raised demand for highly skilled workers and decreased demand for low-skilled workers, producing inequality (Card and DiNardo 2002; Morris and Western 1999). In turn, elevated demand for skill is argued to have contributed strongly to the wage gap between college and non-college workers as well as the worsening economic situation of minorities (Acemoglu 2002; Wilson 1987). Given the widespread and growing influence of computers in the labor market, understanding their relationship with inequality is vital.

Despite abundant differences in computer use and proficiency across birth cohorts, research has not yet linked cohorts to the spread of computers and inequality. As life course research demonstrates, the consequence of major historical events, such as the spread of computers, varies in important ways depending on individuals' life stage in which these events occur (Elder 1974; Ryder 1965). The rapid diffusion of computer technologies subjects individuals to computers to different degrees, producing cohort-specific inequality patterns for two reasons. First, the spread of computers has meant that successive younger cohorts will have been exposed to these technologies to a greater cumulative extent at any given age relative to older cohorts. Younger cohorts will therefore possess greater generic computer skill endowments on average



(e.g., the ability to use various software programs, operating systems, programming languages, and hardware), increasing their likelihood of using a computer at work and depressing the returns to these skills across successive cohorts. Second, due to lower incentives to invest in learning computer skills, older cohorts will accrue these skills more slowly than younger cohorts, leading to a continuing skill divide. Accordingly, the returns to computer use – and the relationship between computers and inequality – should be on average larger among older cohorts. Moreover, the returns to computer use may differ by cohort across the earnings distribution. Greater relative computer skill endowments among younger cohorts should reduce the computer premium across the entire wage distribution among younger, as compared to older, cohorts. Thus computers should be related to inequality among high- and low-wage workers to different degrees across cohorts.

In this paper I adopt a life course approach to illuminate how the relationship between computer use and inequality varies across cohorts. This builds upon earlier studies by considering how computers affect inequality according to when individuals came of age and entered the labor market relative to the computer revolution. In doing so I offer a more nuanced explanation for the relationship between computerization and inequality than the dominant account, skill-biased technological change. Analytically, I employ unconditional quantile regression (Firpo, Fortin, and Lemieux 2009), which allows me to examine computers' influence across the earnings distribution. Given that much of the rise in inequality has occurred in the upper tail of the earnings distribution (Autor, Katz, and Kearney 2008; Card et al. 2013; Dustmann et al. 2009; Piketty and Saez 2003), where computers are predicted to have the largest effect (Card and DiNardo 2002; Krueger 1993), this method is advantageous for understanding how computers shape inequality across the distribution.

I apply this cohort-based approach to unique, individual-level data from West Germany containing consistent computer use measures. Although Germany<sup>3</sup> is often noted for its comparably strong employment protection, collective bargaining institutions, and relatively low earnings inequality (DiPrete and McManus 1996; OECD 2011a), wage inequality has risen markedly in recent decades, resembling U.S. trends (Dustmann et al. 2009). Understanding the relationship between computerization and inequality in Germany not only offers a useful comparative example but also furthers our appreciation of how computers shape inequality more generally.

## **A Life Course Approach to Computerization**

### *Historical Events in the Life Course*

I begin by recognizing that life course factors critically moderate the impact of major historical events, such as the spread of computers, on individual life chances. “Life course” is the idea that human lives are embedded in social institutions (e.g., the family, educational system, and the labor market) according to distinct biologically-patterned progressions and that these institutions shape human lives (Elder 1994; Settersten and Mayer 1997; Zhou and Moen 2001). Major historical events affect individual life chances in part by altering social institutions. Yet because individuals are embedded these institutions in age-specific ways, birth year differences pose differential exposure and response options to individuals. Historical effects on the life course produce cohort effects whereby social change creates differences in the life patterns of successive cohorts. In his classic study for instance, Elder (1974) highlighted differences in the impact of the Great Depression on individuals between and within cohorts. A fundamental concept in life course

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<sup>3</sup> Unless otherwise indicated, all references to Germany in this chapter apply only to West Germany.

analysis is the idea of cumulative advantage (or disadvantage), in which social advantages existing earlier in individuals' lives provide the basis for later advantages (or disadvantages), contributing to social inequalities (DiPrete and Eirich 2006; Merton 1968). Alternatively, history may also yield period effects, in which the impact of social change is fairly uniform across successive cohorts during the same time. Together, period and cohort effects proxy for exposure to historical change and reveal how major events affect a given population (Elder 1994).

### *Previous Studies*

Although the spread of computers has been widely recognized as a major historical occurrence, even demarcating the “third industrial revolution” (Liu and Grusky 2013), researchers have not yet approached this phenomenon from a life course perspective. Following primarily neoclassical economic theory, existing studies have treated the spread of computers implicitly as a period effect by concentrating on the aggregate relationship between computerization and rising inequality. Starting with the earliest computerization studies (i.e. Bound and Johnson 1992; Juhn et al. 1993; Katz and Murphy 1992; Levy and Murnane 1992), investigators found that much of the rise in wage inequality was among better- and lesser-skilled workers, though an even larger share of the increase was within narrowly-defined skill groups (i.e. among workers with the same level of education and experience). Although they were initially hesitant to identify a cause, because this rise coincided with the microcomputer revolution, scholars largely agreed that the spread of computers was the likely source, yielding the theory of skill-biased technological change (Lemieux 2008). Others have focused on the empirical relationship between computers and wage differentials. One of the first and perhaps best known studies to use individual-level computer measures is Krueger (1993). Using CPS data from 1984 and 1989, he finds that computer use

predicts 10-15 percent higher wages on average, with better-educated workers being particularly likely to use computers at work. Still others have investigated the relationship between IT and inequality within firms (Autor et al. 2002; Bresnahan et al. 2002; Doms et al. 1997) and industries (Autor et al. 1998; Berman et al. 1994; Kristal 2013; Kristal and Cohen 2015; Lin and Tomaskovic-Devey 2013) finding a robust link between computerization and inequality in these labor market units.

A more recent generation of studies has continued to tacitly approach computerization as a period effect, but cautioned against assuming a causal relationship. Using German microdata, DiNardo and Pischke (1997) show that other job characteristics including using pencils or calculators at work are associated with wage returns comparable to computer use. As they argue, due to the nonrandom allocation of computers at work, any positive association could be attributable to unobserved differences among computer users and non-users (King, Reichelt, and Huffman in press). In partial response to this and other critiques of the original SBTC hypothesis (for reviews see Card and DiNardo 2002; Lemieux 2008), Autor et al. (2003) offer a “task-based” version of SBTC, contending that tasks represent the missing causal mechanism behind computers’ influence on the labor market.<sup>4</sup> As they argue, computers affect the wage structure according to the tasks workers perform on the job, with computers complementing non-routine cognitive tasks (e.g. managing, problem solving, and advising) and substituting for routine cognitive and routine manual tasks (e.g. bookkeeping, cashiering, calculating, and sorting). By contrast, the impact of IT on non-routine manual tasks (e.g. cleaning and servicing) remains ambiguous as computers neither strongly complement nor substitute for these tasks. Numerous subsequent studies have used tasks to investigate changes in the occupational structure (e.g. Autor and Dorn 2009, 2013;

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<sup>4</sup> This is also referred to as the “nuanced” SBTC hypothesis or the “routinization” hypothesis in the context of job polarization.

Autor et al. 2006; Goos and Manning 2007; Goos, Manning, and Salomons 2009, 2014; Spitz-Oener 2006) and wage structure (e.g. Autor and Handel 2013; Firpo, Fortin, and Lemieux 2011).

### *Computerization in the Life Course*

To understand the relationship between the spread of computers and inequality I argue that computerization should be viewed through a life course perspective, and especially a cohort-based approach. While cohort investigations of computerization remain absent, a handful of studies have applied cohort methods to examine the rise in inequality. Evaluating the changing returns to education in the U.S., U.K., and Canada, Card and Lemieux (2001) find significant cohort differences in the returns to education over time. As they explain, much of the well-known rise in the college-high school earnings gap (c.f. Goldin and Katz 2008) was driven by young workers in their early 30s, which was attributable to a slowdown in the growth of educational attainment among cohorts born in the early 1950s amidst technology-induced rises in the relative productivity of college workers (see also Dooley and Gottschalk [1984] for a similar cohort-based approach to the returns to education). Scholars have likewise found marked cohort differences in intragenerational inequality in lifetime earnings. Using administrative data from West Germany, (Bönke et al. 2015) find a striking secular increase in lifetime earnings inequality among male cohorts, with men born in the mid-1960s experiencing 85% higher inequality than their fathers. Further, cohort differences have been particularly affected by growing differentials at the top and bottom of the distribution, with lower-tail inequality mattering more.

Computerization is likely to produce cohort effects for two reasons. First, due to the increased proliferation of computer technologies over time, successive younger cohorts will have been exposed to these technologies beginning at an earlier age and to a greater cumulative extent

by the time they reach the same age as older cohorts. Compared to older cohorts, individuals in younger cohorts will therefore possess larger average computer skill endowments (e.g. the ability to use various software programs, operating systems, programming languages, and hardware) thanks to this exposure.<sup>5</sup> On the one hand, given that better-skilled workers are more likely to use computers at work (Krueger 1993), a greater average stock of these skills will increase the likelihood of younger cohorts working in non-routine-task occupations that use computers than individuals in older cohorts (i.e. a selectivity effect; see for instance Autor and Dorn 2009).<sup>6</sup> On the other, assuming cohorts are imperfect substitutes for each other (i.e. Card and Lemieux 2001), economic theory dictates that a relative abundance of these skills among workers in a given cohort will depress the returns to computer use within this same cohort (i.e. a price effect). As a result, the average returns to computer use should decline across successive cohorts, thanks to a general reduction in selectivity and price for computer skills. Second, due to the costs associated with learning computer skills, workers in older cohorts are predicted to have less motivation to acquire these skills than younger workers. This follows from human capital theory (i.e. Becker 1964; Mincer 1974), which holds that rational individuals have greater incentives to invest in learning new skills when they are able to reap the benefits of these skills longer; consequently, the majority of skill acquisition occurs early in individuals' lives through formal schooling and on-the-job training. Yet because older workers must learn these skills later in life when their longer-term payout is less certain, these costs may be onerously high and serve as a deterrent for many. Older

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<sup>5</sup> There is a large body of literature on skill (and task) changes associated with computerization (see among others Autor, Levy, and Murnane 2003; Braverman 1974; Liu and Grusky 2013; Spitz-Oener 2006). Specifically, I am referring to a broad set of generic computer-related skills and competencies necessary to operate a computer at work. Although it has no bearing on my argument, individuals may conceivably acquire these skills through formal educational instruction, on-the-job training, or computer use at home (see DiMaggio and Bonikowski 2008; Krueger 1993).

<sup>6</sup> Selectivity in this sense can involve workers either possessing an adequate amount of these skills or applying these skills in a particular job by using computer.

workers that do choose to invest in these skills, however, should receive an especially large wage premium in order to compensate for this high opportunity cost (Becker 1964; Mincer 1974). As a result, older cohorts should accrue computer skills at a slower rate than younger workers, leading to a continuing skill divide over time. Overall, this implies that cohort differences in the returns to computer use will persist due to cumulative (dis)advantage in differential cumulative exposure to computer technologies (i.e. selectivity and price effects on computer skills) and differential incentives to invest in acquiring new computer skills. I thus expect that:

H1: *Ceteris paribus*, the returns to computer use are larger on average for older cohorts.

More importantly, computerization may produce cohort differences in the relationship between computers and inequality across the earnings distribution. Prior research has shown that high-skill workers are more apt to use computers use at work and garner a larger computer wage premium (Card and DiNardo 2002; Krueger 1993), which together are thought to contribute to rising upper-tail inequality (Autor et al. 2008; Dustmann et al. 2009). Prior to the advent of the personal computer (PC) and related technologies that kicked off the computer revolution in the early-1980s, workplace computer systems were mainframes used primarily in information-intensive divisions of large companies (e.g., payroll, accounting, inventory control, and financial services).<sup>7</sup> Although mainframe computer use eventually spread to more moderately-skilled individuals working via terminals, computer use before the early-1980s was often restricted to a highly skilled subset of workers (e.g., computer scientists and mathematicians). With the advent of the PC in the early-1980s, however, computers became substantially more powerful, cheaper,

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<sup>7</sup> While electric computing devices were first developed during World War II and the Apple II was released in 1977, many point to the computer revolution as beginning with the release of the IBM-PC in 1981 (Card and DiNardo 2002).

and easier to use, precipitating their rapid spread across workplaces and allegedly inciting skill-biased technological change (Bresnahan 1999; Card and DiNardo 2002).

This implies that in the early years of the computer revolution (i.e. the mid-1980s and early-1990s), computer skills may be limited to a small group of highly-skilled individuals among middle-aged and older cohorts, as these cohorts were born considerably before the start of the computer revolution and had relatively little exposure to computer technologies in their early lives. Expectantly, this will result in a large computer wage premium in the upper-tail of the earnings distribution among older cohorts during this time, due to selectivity and scarcity in these skills. By contrast, members of younger cohorts that came of age and entered the labor market nearer to the beginning of the PC revolution would have experienced relatively greater exposure to computer technology, as their peak years of skill acquisition occurred closer to the start of the PC revolution when computers were becoming rapidly more prevalent. Because computer skills would be more common among younger cohorts, this should mitigate selectivity and price effects of computer skills among these cohorts, reducing the computer wage premium across their earnings distributions. I therefore predict that:

H2: The computer wage premium is larger among high-wage workers in older cohorts than high-wage workers in younger cohorts in the mid-1980s and early-1990s.

Since the early-1990s, computerization and pace of technological innovation has accelerated by many accounts,<sup>8</sup> influencing the returns to computer use across the distribution.

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<sup>8</sup> For instance, after the abolition of commercial restrictions on Internet usage in 1991, the number of global Internet hosts grew from approximately 1 million in 1992 to 20 million by 1997, and reached 100 million by 2000 (Card and DiNardo 2002). Similarly, Jorgenson (2001: 10) calculates investments in information technology as a percentage of U.S. GDP grew annually by 2.36 percent from 1990-1995 and increased to 4.08 from 1995-1999.



Due to the selective nature of computer skills (DiNardo and Pischke 1997), as computers become increasingly ubiquitous in homes and workplaces (DiMaggio and Bonikowski 2008; Handel 2007), this enhances selectivity in who does *not* either possess adequate computer skills or implement these skills in a job by using a computer. Selectivity influences differ strongly across the distribution. As Autor et al. (2006, 2003) show, non-routine cognitive tasks are more common in the upper tail of the earnings distribution; hence, the spread of computers disproportionately increases computer use among high-wage workers, as these tasks lend themselves well to computers. Increasing computer use among high-wage workers, in turn, reduces the price of these skills in this segment of the labor market. Further, due to high unobserved abilities among high-skill workers (Angrist and Krueger 1991), regardless whether a given high-skill individual actually uses a computer at work, these individuals likely possess sufficient skills to use a computer. Thus as computers becoming increasingly common over time, the returns to generic computers skills should decline among high-skill (i.e. high-earning) workers as a result of decreased scarcity and selectivity in these skills. By contrast, job tasks in the lower tail of the earnings distribution are typically less well-suited to computers, such that computer use is rarer among low-wage jobs (Autor et al. 2006, 2003). More importantly, as compared to their high-skill counterparts, low-skill workers in low-wage jobs that do not use a computer are more prone to lack adequate computer skills given their slighter unobserved abilities (Angrist and Krueger 1991); thus, applying computer skills in low-wage jobs will command greater wages. For instance, Autor and Dorn (2009) analyze occupational mobility patterns among workers in primarily routine-task occupations that were becoming technologically obsolete. As they find, older, poorly-skilled workers were more apt to remain in declining occupations, while better-skilled, younger workers were more likely to enter non-routine task occupations, where computers are more abundant. The

continued spread of computers should therefore should result in comparably larger returns to computer use among low-skill workers given that computer skills remain select in this segment of the labor market.<sup>9</sup> Consequently, I predict that:

H3: The computer wage premium is larger among low-wage workers than high-wage workers across all cohorts in the early 2000s.

However, this period effect is unlikely to impact cohorts equally. Computerization can be expected to depress the returns to computer skills among high-wage workers in all cohorts as these individuals typically complete non-routine cognitive tasks and possess high unobserved abilities (Angrist and Krueger 1991; Autor et al. 2003). By contrast, cohort differences in computer skills should remain more pronounced among low-wage workers. In particular, low-skill individuals in older cohort should have especially marginal computer skills relative to their cohort members, as these workers were especially unlikely to become familiar with computer technologies during their formative years. By contrast, thanks to the comparably greater availability of computers during the early lives of younger cohorts, computer skills should be more common among all individuals in younger cohorts, including low-skill younger workers. The costs associated with learning computer skills are also likely to be particularly burdensome among low-skill older workers (Becker 1964; Mincer 1974), corresponding to high payout for individuals that elect to make this investment. In combination, I expect that:

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<sup>9</sup> In other words, I anticipate that changes in the computer wage premium is driven by a combination of price and selectivity effects among high-wage earners, while this premium is driven only by selectivity among low-wage earners.

H4: Compared to younger cohorts, the computer wage premium is especially large among low-wage workers in older cohorts in the 2000s.

### **Caveats and Alternative Explanations**

I am able to directly observe the cohort-specific returns to computer use, but cohort differences in computer skills represents the unobserved mechanism. Still, economic studies have moved away from examining the computer wage premium based on concerns about selectivity in computer use (e.g. DiNardo and Pischke 1997). Despite this, given that the spread of computers is thought to be one of the primary drivers of inequality, I believe investigating the returns to computer use is worthwhile. Because of these endogeneity concerns, this study does not adopt a causal perspective regarding the “true effect” of computers on wages, but rather focuses on how computerization is related to inequality over time. Still, I attempt to partly mitigate nonrandom computer assignment by controlling for occupations as a proxy for labor tasks.

Other factors may also contribute to cohort differences in the relationship between computers and inequality. Particularly in the German context, institutional changes have substantially affected the labor market. Following the collapse of the Soviet Union and subsequent German reunification in the early-1990s, 3.6 million immigrants came to West Germany, nearly doubling the immigrant labor force within half a decade (Statistisches Bundesamt 2012). Many of these immigrants were low-skill ethnic Germans returning from former Soviet bloc countries (Bauer, Dietz, and Zimmermann 2005). Similarly, nearly 900,000 former East German residents relocated to the West in the early 1990s, a trend which continued into the 2000s amidst stagnation in the Eastern German labor market (Burda 1993). In response to rising unemployment induced

by massive immigration, the German labor market underwent a series of deregulatory policies called the Hartz reforms in 2003-2005 (for details, see Gebel and Giesecke 2009; Jacobi and Kluge 2006).

Reunification likewise strongly impacted Germany's collective bargaining institutions. Unions have historically played a large role in shaping the German wage structure through high union coverage and by creating a de facto minimum wage across industries (Ebbinghaus and Visser 2000).<sup>10</sup> Traditionally, union bargaining in West Germany is conducted between employer associations and large unions, which negotiated broad sectoral agreements covering the majority of firms. In recent times, however, many firms have abandoned centralized bargaining in favor of regional, establishment-level, or individual contracts that provide greater flexibility but are associated with greater inequality (Fitzenberger, Kohn, and Lembcke 2013).

I attempt to account for these influences through a wide array of individual, firm, regional, and year controls. Still, omitted variable bias likely remains and influences these results.

## **Data, Models, and Measures**

### *Data*

I use data from the Qualification and Career Survey (BIBB/BAuA), a cross-sectional employee survey administered by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung, BIBB) and the Research Institute of the Federal Employment Service (Institut für Arbeitsmarkt- und Berufsforschung, IAB). These data are representative cross sections (i.e. non-panel) of the German population who work more than ten hours per week, containing approximately 20,000-35,000 individuals per wave. Although these data have been available at seven-year intervals since 1979, I use data from four waves (1985-86, 1991-92, 2006,

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<sup>10</sup> Germany has since implemented a statutory minimum wage, which took effect on January 1, 2015.

and 2012) in order to maximize the number of cohorts available in a given period.<sup>11</sup> This enables me to analyze cohort effects by differentiating between the early years of the computer revolution (through pooling the 1985-86 and 1991-92 waves) and the later years of this phenomenon (by pooling the 2006 and 2012 waves). Beyond a wide array of individual and organizational variables, the BIBB/BAuA is particularly unique for its individual workplace computer measures. Furthermore, compared to the CPS, which contains computer data only between the mid-1980s and early 2000s, computer measures in these data are available up to 2012. The quality and breadth of these data therefore allow for a longer-term estimation of how computers relate to inequality than previous studies. While the BIBB/BAuA is well known among economists (e.g. DiNardo and Pischke 1997; Spitz-Oener 2006; 2008), it has remained largely overlooked by sociologists (though see Giesecke and Verwiebe [2009] for a notable exception).

Over time, the survey sample design was modified, yielding a non-consistent target population across waves, particularly after reunification. I restrict the analysis to non-self-employed, non-civil-servant, private and public sector workers in West Germany between 21 and 60 years of age who were not in job training programs. Furthermore, while it is tempting to analyze Eastern Germans in later waves, given the sizable transitional changes in the 1990s and continual labor market differences between East and West, I restrict my analysis to Western Germany.<sup>12</sup> Unfortunately, information on race or ethnicity are not included in the data; although some waves include immigrant workers, this inclusion is inconsistent. As a result, I focus only on individuals with German citizenship.

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<sup>11</sup> Given the time span between waves, according to my coding strategy there were only two cohorts present in the 1979 and 1998-99 waves, compared to three in the other waves. Results were nevertheless substantially similar as those reported herein in the 1979 and 1998-99 waves.

<sup>12</sup> Supplementary analyses using computer use data from this same survey in 1991-92 and 2012 nevertheless suggested that computerization has a similar relationship with inequality in Eastern Germany, a point to which I return later.

### *Modeling Approach*

I use unconditional quantile regression (UQR) with bootstrapped standard errors (Firpo et al. 2009). Compared to conditional quantile regression (CQR), typically called “quantile regression,” UQR is particularly advantageous as estimated effects using this method are considerably more intuitive. The better-known CQR concentrates on conditional quantiles, which reflect an individual’s position in a virtual distribution that assumes all persons at that point have the same characteristics. For instance, assume individuals differ only with respect to using a computer. The conditional quantile of someone that does not use a computer would be their earnings relative to all observably similar workers that did not use a computer, while the conditional quantile of an individual that used a computer would be their earnings vis-à-vis all observably similar workers that also used a computer. CQR thus tells us about the relative effects of a covariate on earnings within a particular group, which may not be comparable to other groups. Group membership is determined by the covariates included in the model, meaning that the conditional quantile a given individual falls under may vary across models, depending on the covariates. Furthermore, conditional quantiles may not correspond to unconditional earnings percentiles, making it difficult to interpret the effects of a covariate at a particular conditional quantile (Fournier and Koske 2012; Killewald and Bearak 2014; Koenker 2005).<sup>13</sup> As a result, CQR only makes it possible to draw inferences about the influence of covariates on within-group dispersion by comparing estimated effects of a given regressor across the distribution (known as a location shift). In other words, CQR can only tell us whether the returns to computer use vary

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<sup>13</sup> Nevertheless, CQR results may resemble UQR results if conditional quantiles for a given variable closely approximate their respective unconditional quantile (Fournier and Koske 2012). As a robustness check I also estimated conditional quantile regression models, obtaining relatively similar findings (results available upon request).

across the earnings distribution, not how computers affect inequality among low- and high-earning individuals.

By contrast, UQR focuses on an individual's unconditional quantile, which is their earnings in the actual, observed distribution (Fournier and Koske 2012). Thus an individual's unconditional quantile is simply the proportion of individuals in the sample population that earn less than him or her, making UQR results more intuitive. Unconditional quantile regression estimates how a small change in a covariate influences absolute earnings inequality; for instance, UQR can be used to ask: how would using a computer affect individual earnings at the 90<sup>th</sup> quantile (or any other point in the distribution), holding all else constant? As with CQR, location shifts in UQR tell us how covariates influence within-group inequality. Additionally, because quantiles in UQR translate to unconditional percentiles, this method also tells us about how covariates affect between-group inequality, simply according to the size of point estimates at a given quantile (see Firpo, Fortin, and Lemieux [2007] for an illustration). Together, the ability to simultaneously investigate how computers affect between- and within-group inequality across the distribution make unconditional quantile regression an ideal method.

The central aspect of UQR involves a regression of the re-centered influence function (RIF) at a specific unconditional quantile. Influence functions have a long history in statistics and are commonly used to assess how particular observations affect distributional statistics of interest. The RIF represents a linear projection of a nonlinear distributional statistic (i.e. a quantile in our case), estimating how a change in the distribution of an explanatory variable affects that distributional statistic (Chi and Li 2008). This method is therefore much more general than standard linear regression as it can be applied to any distributional statistic including quantiles, the variance, or

other common inequality measures (Firpo et al. 2009). UQR is implemented in practice using ordinary least squares (OLS) using the RIF as the dependent variable, defined as:

$$\text{RIF}(Y; q_\tau, F_Y) = q_\tau + (\tau - \mathbf{1}\{Y \leq q_\tau\})/f_Y(q_\tau)$$

where  $\tau$  is a particular quantile,  $q_\tau$  is the value of the dependent variable,  $Y$ , at the  $\tau^{\text{th}}$  quantile,  $f_Y(q_\tau)$  is the density of  $Y$  at quantile  $\tau$ ,  $F_Y$  is the cumulative distribution function of  $Y$ , and  $\mathbf{1}\{Y \leq q_\tau\}$  is a dummy variable indicating whether the value of  $Y$  is below point  $q_\tau$ . Figures that follow depict the effect of computer use from the 10<sup>th</sup> to the 90<sup>th</sup> quantile. Finally, I use bootstrapped standard errors with 200 replications to account for uncertainty in estimating the RIF.<sup>14</sup>

### *Measures*

The dependent variable is the natural logarithm of gross hourly wage adjusted for inflation in 2005 Euros. To obtain this rate, I divide respondents' monthly gross wage by their reported average number of hours worked per week. Since data were often recorded over two years, inflation rates were averaged between years. Although wages were measured continuously in 2006 and 2012, gross monthly earnings was recorded in intervals in 1985-86 and 1991-92.<sup>15</sup> I therefore assign respondents wage interval midpoints to approximate a continuous distribution following previous work (e.g. DiNardo and Pischke 1997; Spitz-Oener 2008). The BIBB/BAuA censors individuals with high wages via top codes, which change across waves, affecting inequality estimates. To smooth across these changing top codes and account for censored wages, I impute the top two percent of wages separately for each year from the linear projection of a Tobit

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<sup>14</sup> Regressions were performed using Firpo, Fortin, and Lemieux's (2007) "rifreg" Stata ado file, available through Nicole Fortin's webpage (<http://faculty.arts.ubc.ca/nfortin/datahead.html>).

<sup>15</sup> In 1985-86 there were 21 categories and in 1991-92 there were 15. To ensure that the changing number of interval categories did not affect inequality estimates, I also recoded the dependent variable to the minimum number of categories available across all years. Despite this, estimates remained similar, suggesting that the interval number has little effect on the results.



regression using all covariates described herein combined with random noise from the normal distribution (Card et al. 2013; Dustmann et al. 2009). I also limit the analysis to respondents whose earnings were less than 100€ per hour. As in other studies, this analysis is not capable of investigating extreme right-tail wage dispersion.<sup>16</sup>

Given that measurements and questions pertaining to workplace computers changed across waves, I code for respondent use of a personal computer or computer terminal following prior research (e.g. Krueger 1993).<sup>17</sup> In later waves this question is asked in two ways: whether an individual uses a computer regularly (versus not at all) or whether they use any sort of computer technology regardless of the frequency (versus not at all). As a robustness check I compared results using these two separate measures; nevertheless, estimated effects differed little. For this reason, I focus on workplace computer use generally.

To attempt to account for unobserved heterogeneity in computer use I control for occupations as a proxy for tasks.<sup>18</sup> Occupations are not only suitable as they capture a multifaceted bundle of tasks (Autor 2013), but also represent unique labor markets for particular types of labor (Stolzenberg 1975). I code occupations into ten aggregated categories: agriculture and extractive, basic manufacturing, advanced manufacturing, non-durable manufacturing, construction,

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<sup>16</sup> Using administrative data Piketty and Saez (2006) find that earnings in the top percentiles have greatly increased since the 1990s in the United States. By contrast, earnings in the top percentile in continental Europe appear to have remained stable.

<sup>17</sup> Measures of computer use changed across waves, yet results were highly robust to a variety of coding strategies. In 1985-86, I code for use of a computer/terminal as a general tool as well as use of personal computer or computer system/terminal in an office setting. In 1991-92 I code for use of a computer/terminal as a general tool as well as use of a personal computer, computer system, or terminal in an office setting. In the 2006 and 2012 waves respondents were simply asked whether they use a computer on the job. As a further robustness check I also estimated regression models using a wider array of computer measures as in DiNardo and Pischke (1997), including PCs, computer terminals, word processors, computers on shop floors, office computers, and CAD systems. These results were also highly comparable. Program files available upon request.

<sup>18</sup> Another common strategy to deal with unobserved heterogeneity involves first differencing (Bell 1996; Entorf, Gollac, and Kramarz 1999); however, if the returns to unobserved skills are changing, panel methods will not eliminate the impact of these unobserved factors (DiNardo and Pischke 1997). As a result, proxying for tasks represents a preferable alternative.

operators and helpers, technical occupations, sales and services, managers and professionals, and health and human services. Admittedly, one limitation to proxying tasks with occupations is that this approach overlooks similarities in tasks between different occupations (Autor 2013). One particular strength of the BIBB/BAuA data, however, are their individual-level task measures, which have figured prominently in several previous studies (e.g. Spitz-Oener 2006; 2008). Unfortunately, tasks are not measured consistently over time, making comparisons across waves problematic. As a further robustness check, I tested models that controlled for individual tasks using Spitz-Oener's (2006; 2008) task measures.<sup>19</sup> These results closely resembled those I report below, indicating that occupation controls used in this study closely parallel BIBB/BAuA task measures (see Appendix A2.1).

To account for human capital characteristics, I control for individuals' educational attainment via dummy variables for individuals with no formal tertiary qualifications, graduates from vocational training programs, graduates from a university of applied sciences (*Fachhochschule*), and university graduates. Additional control variables include gender, dummies for 19 industries, public/private sector, year dummies, 10 dummies for federal state,<sup>20</sup> part-time work, experience,<sup>21</sup> experience squared, tenure, and seven dummies for establishment size. Unfortunately, these data contain no information on union status. I create four labor force cohorts, differentiated according to 20-year birth intervals, which covered those born between 1920 and 1991. Cohort proportions by wave as well as other descriptive statistics can be seen in Table 2.1.

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<sup>19</sup> I thank Alexandra Spitz-Oener for providing me with computer code used to construct these measures.

<sup>20</sup> Because later waves of the survey did not differentiate between eastern and western Berlin, respondents in Berlin are excluded from all analyses.

<sup>21</sup> Experience was relatively highly correlated with cohort (0.617); results, however, were nearly identical with the exclusion of experience and experience squared.

Examining Table 2.1, between 1985 and 1992 computer use increased from 15.9 percent to 33.6 percent of all workers. Rates of computer use accelerated throughout the 1990s, reaching over 80 percent of workers by 2006, and continuing to spread though at a slower rate until 2012. Over the 27 year period of observation, computer use at work increased about 440 percent.

Figure 2.1 decomposes aggregate trends in computer use by plotting cohort-specific computer use across wage percentiles in the early years of computerization from 1985-1992 (see panel A) and later years of computerization from 2006-2012 (see panel B). Both panels in this figure reveal marked cohort differences in computer use across the distribution; in the early years, computer use was consistently higher the younger the cohort across nearly the entire wage distribution. Although computer use increased fairly linearly up the earnings distribution, computer use surged above the 80<sup>th</sup> earnings percentiles in all three cohorts, suggesting that computers were relatively more common among better-paid workers at this time. By 2006-2012, cohort differences in computer use virtually disappeared above the median and shifted to the lower percentiles, denoting that cohort disparities in computer use were pronounced only among low-wage workers. At the 10<sup>th</sup> percentile for instance, compared to 72 percent of workers in the 1980-91 cohort using a computer at work, only 48.4 percent of workers in the 1940-59 cohort used a computer on the job. In these later years older workers were fully one-third less likely to use computers than younger workers. Figure 1 provides preliminary support for cohort differences in computer skills across the wage distribution, suggesting the returns to computer use may also vary by cohort across the distribution (see additionally Appendix A2.2 for age-specific differences in computer use in 1985-92 and 2006-12).<sup>22</sup>

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<sup>22</sup> Computer use followed similar cohort-specific patterns across the distribution within educational groups (results not shown), suggesting these trends were not driven simply by differences in general skill levels.

## Results

### *Cohort Differences in Average Returns to Computer Use*

To begin, I consider whether the returns to computer use differ significantly on average between cohorts and are larger among older workers. OLS estimates in Table 2.2 support this idea in both the early and later stages of the computer revolution, confirming Hypothesis 1. Whereas workers born between 1920 and 1939 earned on average 18.5 percent ( $e^{0.170} = 1.185$ ) higher wages relative to non-computer users in this same cohort net of covariates, the computer premium was 14.3 percent ( $e^{0.170-0.036} = 1.143$ ) among the 1940-59 cohort and 8.5 percent in the 1960-79 cohort according to Model 1. By 2006-2012, the computer wage premium for the 1940-59 cohort and the 1960-79 cohort had increased to 19.7 percent and 19.1 percent, respectively, while the 1980-91 cohort earned on average 12.0 percent higher wages for computer use. Thus, Table 2.2 suggests computers are generally related to higher inequality among older versus younger cohorts.

### *Cohort-Specific Returns to Computer Use across the Distribution*

While the previous results demonstrated that cohorts are rewarded to different degrees for using a computer at work, this does not show where in the earnings distribution these returns diverged. Figure 2.2 displays computers' relationship with inequality across the unconditional wage distribution separately by cohort in 1985-1992 (panel A) and 2006-2012 (panel B).<sup>23</sup> Focusing on the earlier period, in line with Hypothesis 2, the computer wage premium is larger among high-wage workers in older cohorts than among high-wage workers in younger cohorts.

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<sup>23</sup> Results were obtained by separate regressions for each cohort. I additionally conducted supplemental analyses to examine whether these differences were significant across cohorts. Cohort differences were frequently not distinguishable from each other in parts of the distribution where the returns to computers were similar (e.g. below the median in Fig. 2.2, panel A), though they were significantly different in parts of the distribution where the returns diverged considerably (e.g. above the 80<sup>th</sup> quantile in Fig. 2.2, panel A, and across most of the distribution for the 1980-91 cohort in Fig. 2.2, panel B).

Although the computer wage premium was similar among workers at the 10<sup>th</sup> quantile in the 1960-79 and 1920-39 cohorts, at the 90<sup>th</sup> quantile the computer wage premium was 17.1 percent and 31.3 percent in these same cohorts, respectively (see Appendix B2.1 and B2.2 for actual unconditional quantile regression estimates). In other words, the computer premium was nearly twice as large among older vis-à-vis younger workers at the 90<sup>th</sup> quantile at this time.<sup>24</sup> Larger returns to computers among high-wage workers increases inequality by enlarging the earnings gap between better- and lesser-paid workers. For instance, a 10 percent increase in computer use is predicted to increase the 90-10 wage gap by 1.1 percent among the 1960-79 cohort and 2.0 percent among the 1920-39 cohort.<sup>25</sup> This suggests that in the mid-1980s and early-1990s, computers are related to upper-tail inequality at the aggregate, providing evidence in favor of skill-biased technological change (e.g. Juhn et al. 1993; Krueger 1993; see Appendix A2.3 for aggregate computer influences in these two periods). While this suggests computerization has served as a period effect as researchers long assumed (e.g. Juhn et al. 1993; Krueger 1993), prior investigations have missed the fact that computers' relationship with inequality varies considerably across cohorts, with computer use influencing inequality to a greater degree among older workers. In other words, while computerization is related to aggregate inequality among high-wage workers in the mid-1980s and early-1990s, this is driven in large part by older cohorts.

As illustrated in Figure 2.2, panel B, by 2006-2012, the computer wage premium had reversed, such that the largest returns were among low-wage workers (confirming Hypothesis 3).

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<sup>24</sup> Part of this may be the product of older and younger cohorts working in different jobs that required different tasks, which may not be fully captured by aggregated occupations used in these regressions. Nevertheless, similar results were obtained when directly controlling for individual tasks (see Appendix A2.1).

<sup>25</sup> These results were obtained by multiplying the change in computerization (0.1) by the difference between coefficient estimates at the 90<sup>th</sup> and 10<sup>th</sup> quantiles and exponentiating this, i.e.  $e^{(0.158-0.053)*0.1} = 0.011$  and  $e^{(0.272-0.073)*0.1} = 0.020$ . As in linear regression, the coefficient on a dummy variable in UQR can be interpreted as a 100 percent increase in that covariate. In other words, assuming no equilibrium effects, this implies that a 100 percent increase in computer use at the 90<sup>th</sup> quantile is estimated to increase inequality 31.3 percent at this quantile. See Firpo et al. (2007) for further details.

While this contradicts the predictions of SBTC and may at first appear surprising, this finding is partly attributable to the non-random allocation of computers (DiNardo and Pischke 1997). The declining returns to computer use among high-wage workers is most likely the result of reduced scarcity and selectivity in computer skills among this segment of the labor market; by contrast, the growing returns to computer use among low-wage workers likely owes more to selectivity. Greater returns to computer use among low-wage workers reduces inequality by helping to close the gap between high- and low-wage workers. In the upper earnings quantiles even, computer use is non-significantly related to wage differences.<sup>26</sup> Lower returns to computer use among high-wage workers versus low-wage workers also indicates that computers are related to reduced within-group inequality in 2006-2012. Thus while the spread of computers was initially associated with elevated inequality given that the wage benefits to computer use were especially large among high-wage workers in the mid-1980s and early-1990s, the continued spread of computers into the 2000s is associated with *reductions* in inequality. For instance, averaging across all cohorts, a 10 percent increase in computer use is estimated to reduce the 90-10 wage gap by 3.7 percent. This equalizing impact is more than three times larger than the inequality-enhancing effect of computer use in 1985-1992.<sup>27</sup> These findings help reconcile earlier work that could offer little explanation for how the spread of computers is related to wage equalization in the U.S. (Handel 2007) and West Germany (Antonczyk, Fitzenberger, and Leuschner 2009). This finding also bolsters Autor and

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<sup>26</sup> This does not imply that all computer-related skills such as programming have experienced a decline in demand or reductions in the payoff to those skills. While there is little doubt that these skills are becoming increasingly valuable over time (see Liu and Grusky 2013), non-significance in the upper earnings quantiles indicates that the returns to generic “computer skills”, proxied by computer use, does not strongly covary with wages in this part of the distribution. This is likely because nearly all workers use computers in the upper quantiles.

<sup>27</sup> Auxiliary analyses revealed the aggregate log computer wage premium in 2006-2012 was 0.361 at the 90<sup>th</sup> quantile and -0.001 at the 10<sup>th</sup> quantile. By comparison, the aggregate premium in 1985-1992 was 0.170 at the 90<sup>th</sup> quantile and 0.059 at the 10<sup>th</sup> quantile, meaning a 10 percent increase in computers would increase the 90-10 gap by 1.1 percent in these years. See Appendix A2.3 for a graphical depiction of the aggregate returns to computer use across the distribution in both time periods.

Dorn's (2013) results that computer-related task shifts are associated with real wage increases among low-skill service occupations.

Comparing the returns across cohorts, similar to 1985-1992, the computer earnings premium was larger among low-wage workers in older cohorts in 2006-2012 (consistent with Hypothesis 4). Relative to 31.7 percent higher wages among computer users at the 10<sup>th</sup> quantile in the 1980-91 cohort, computer users in the 1960-79 and 1940-59 cohorts earned 47.8 and 54.2 percent higher wages at this same percentiles, correspondingly. The slope in returns to computer use also differed across cohorts; whereas the computer wage premium decreased sharply with increasing quantiles among 1960-79 and 1940-59 cohorts, the returns to computer use for the 1980-91 cohort is only steeply sloped between the 10<sup>th</sup> and 30<sup>th</sup> quantile and nearly flat above the 30<sup>th</sup> quantile. These findings are to be expected according to the idea that low-wage workers in older cohorts have especially paltry computer skills given the timing of the computer revolution in their lives, resulting in strong returns to these skills among individuals that invest in these abilities. Computers thus have a stronger association with inequality among low-wage workers in older cohorts. By contrast, the relatively small computer wage premium across much of the distribution among individuals in the 1980-91 cohort meshes with the idea that this cohort possesses superior computer skills thanks to the timing of their birth nearer to the computer revolution. On the whole, this illustrates that the spread of computers yielded varying influences on inequality across cohorts in both the early and later stages of computerization, with computers corresponding more strongly to inequality the older the cohort.

### *Additional Analyses*

Admittedly, one potential critique of these findings concerns the generalizability of the (West) German case. Although random survey data containing individual-level computer measures are rare, the CPS contains similar measures between 1984 and 2003, which have been used in other computerization studies (e.g. Krueger 1993; DiNardo and Pischke 1997). Creating identical 20-year birth cohorts and including a similar array of control variables, results in Figure 2.3 suggest that the computer-inequality relationship among high- and low-wage workers varies considerably by cohort in the U.S. as well. Although the shape of the computer wage premium across the distribution differs somewhat from Germany, this premium is generally lower across the distribution for younger workers in both time periods, reinforcing the idea that computers are more strongly associated with inequality among older cohorts due to their comparably smaller computer skill endowments. Results were also similar for East Germany using BIBB/BAuA data waves from 1992 and 2006-2012 (results available upon request).

### **Discussion and Conclusion**

Despite well-known differences in computer use and proficiency across birth cohorts, prior research has not yet linked these differences to the spread of computers and inequality. Drawing on life course theory, I adopt a cohort-based approach to show how the spread of computers influences inequality in cohort-specific ways using a unique West German data set. Due to the timing of the computer revolution in individuals' lives, I argue this exposes individuals to computers to different degrees across cohorts, producing cohort-based variation in computer skill endowments and incentives to learn these skills. In turn, this not only affects the average relationship between computers and inequality, but also the degree to which computers are



associated with inequality among high- and low-wage workers between cohorts. In this respect, I offer a more detailed explanation for the relationship between computerization and inequality relative to the dominant skill-biased technological change hypothesis.

I find significant cohort differences in the returns to computer use, with older cohorts receiving larger average returns compared to younger cohorts in the years of 1985-1992 and 2006-2012. While this suggests the spread of computers is typically more strongly related to inequality among older works, cohorts were particularly influential in moderating inequality across the earnings distribution. As I find, the returns to computer use were largest among high-wage workers in 1985-1992, supporting skill-biased technological change (e.g. Juhn et al. 1993; Levy and Murnane 1992; Bound and Johnson 1992; Katz and Murphy 1992; Krueger 1993); however, this aggregate period effect misses substantial between-cohort variation, with the returns to computer use being nearly twice as large among the oldest cohort compared to the youngest cohort at this time. In other words, while the spread of computers was related to aggregate inequality among high-wage workers in the mid-1980s and early-1990s, this was primarily attributable to older cohorts. The strong, direct link between computers and inequality posited by SBTC is therefore not supported as computerization is more greatly related to inequality among particular cohorts.

By the early 2000s, the returns to computer use had shifted across the distribution such that the computer wage premium was greatest among low-wage workers. Although this contradicts the predictions of SBTC, this may stem from the non-random allocation of computers in the labor market (DiNardo and Pischke 1997), with the increased spread of computers enhancing selectivity in who does *not* either possess adequate computer skills or implement these skills in a job that uses a computer. I expect the declining returns to computer use among high-wage workers is most likely attributable to reduced scarcity in these skills (since nearly every high-skill worker used a

computer at work by the 2000s) as well as diminished selectivity in these skills in this portion of the labor market. By contrast, I anticipate the increasing returns to computer use among low-wage workers is due to selectivity differences among computer users and non-users. Thus surprisingly, while computerization was related to higher aggregate inequality in the mid-1980s and early-1990s, the continued spread of computers into the 2000s is related to wage *equalization*. This equalizing impact is more than three times larger than the inequality-enhancing effect of computer use in 1985-1992, suggesting computers never had a very strong, direct relationship with elevated inequality. These findings help reconcile previous research that had difficulty explaining the changing influence of computerization in the U.S. (Handel 2007) and West Germany (Antonczyk et al. 2009), and also support Autor and Dorn's (2013) results that computer-related task shifts bolster the wages of low-skill service work.

Nevertheless, in the 2000s the computerization-inequality relationship varied considerably across cohorts, with larger returns among low-wage older workers than low-wage workers in younger cohorts. Thus, cohorts moderated the association between computerization and inequality in both the early and later stages of the computer revolution. This indicates that the spread of computers most strongly impacted workers born significantly before the beginning of the computer revolution in the early-1980s, at a time when these technologies were less common and individuals received less computer-specific training in their early lives. According to my results, individuals born between 1920 and 1959 were hardest hit by the timing of the computer revolution, especially those born between 1920 and 1939, relative to those born since the early-1980s. Moreover, because the computer wage premium is successively smaller among younger cohorts, this implies that the computer-inequality relationship will continue to dwindle over time as new cohorts with greater technological expertise come to replace current workers.

While these findings suggest that the influence of computerization has peaked and is now on the decline, we should not conclude that computers no longer shape inequality. As these results show, whereas using a computer at work once constituted a highly salient inequality divide in the labor market, this has shifted today to *not* using a computer. Clearly, computerization has contributed to a growing wage penalty against non-computer users, thanks to increasing disadvantage either against individuals that possess inadequate computer skills or work in a job that does not use this technology. Although it is possible these findings may be particular to the (West) German case, results were highly robust to a variety of model specifications, and similar findings were obtained using CPS computer supplement. Moreover, as others have shown, the spread of computers furthers occupational polarization (Autor and Dorn 2013; Goos and Manning 2007; Goos et al. 2014; Spitz-Oener 2006) and is linked to institutional changes such as financialization (Lin and Tomaskovic-Devey 2013; Tomaskovic-Devey and Lin 2011) and deunionization (Kristal 2013; Kristal and Cohen 2015). Consequently, this examination furthers the idea that computers have a diffuse influence that likely works through other proximate causes such as occupational polarization and institutional change. Particularly in the German context, deunionization appears to have played a major role in the rise in inequality (Card et al. 2013). More generally, these results highlight the utility of a cohort-based approach for understanding how macrostructural labor market shocks affect inequality.

## **CHAPTER 3: Computerization and Wage Inequality Between and Within German Work Establishments<sup>28</sup>**

### **Introduction**

The rise in wage inequality across many advanced societies has been dramatic, spurring considerable scholarly and public interest in its causes. Most existing studies have investigated rising inequality using individual-level data (e.g. Bound and Johnson 1992; Juhn et al. 1993; Katz and Murphy 1992; Krueger 1993; Western and Rosenfeld 2011), industry-level data (e.g. Autor et al. 1998; Berman et al. 1994; Kristal 2010, 2013; Lin and Tomaskovic-Devey 2013), or occupational-level data (e.g. Firpo et al. 2011; Goos and Manning 2007). Recently, Card et al. (2013) showed that establishments have also played an important role in rising wage inequality. Using West German administrative data, they demonstrated that a large proportion of growing earnings differentials across occupations, educational groups, and industries as well as the general increase in inequality is explained by rising establishment-specific wage premiums and increased worker sorting across workplaces. Given that considerable growth in inequality has transpired between workplaces, this suggests that establishment-level analyses may be particularly helpful in explaining rising inequality.

A leading explanation for growing inequality has been the spread of information and communication technologies (ICT). Although myriad studies report an association between ICT and inequality, the effect of computers on the wage structure remains elusive. According to the well-known skill-biased technological change hypothesis, spread of these technologies is believed to have increased demand for highly skilled workers and reduced demand for low-skilled workers,

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<sup>28</sup> Co-authored in collaboration with Malte Reichelt and Matt Huffman. Consequently, this chapter uses the pronoun “we” throughout.

leading to skill-based inequality (Card and DiNardo 2002; Morris and Western 1999). Much of the rise in inequality along the skill gradient has been attributed to ICT enhancing demand for certain job tasks, while reducing demand and ultimately displacing other tasks through automation (Autor et al. 2003; Firpo et al. 2011; Goos and Manning 2007; Spitz-Oener 2006). Alternatively, in addition to this direct, skill-based channel, class-biased technological change Kristal (2013) and Kristal and Cohen (2015) contends that ICT investments contribute to inequality indirectly through furthering the decline in collective bargaining. Still others (e.g. Bresnahan 1999; DiNardo and Pischke 1997; Doms et al. 1997; Handel 2007) argue that ICT has no influence on wages and that the observed relationship is driven by unobserved heterogeneity.

To address these issues, we use highly detailed longitudinal matched employer-employee data from Germany to provide new insights into how ICT affects establishment wage inequality. Because ICT investments are made at the establishment level, rather than the industry or individual level, workplaces are the relevant unit of analysis for evaluating the link between computerization and rising inequality. Moreover, given that computer investments may not only increase differentials in average wages between establishments but also earnings dispersion within them, we use an innovative approach to differentiate between computerization's influence on between- and within-workplace inequality over time. To date, no study has considered the simultaneous impact of ICT on earnings inequality between and within establishments, meaning that it is unclear exactly how computers might shape total workplace inequality. Using a variance function regression with establishment fixed effects, we are able to provide insights into the sources of rising workplace heterogeneity (Card et al. 2013), while also offering one of the most rigorous investigations of how computerization influences inequality to date.

As the dominant European economy and fourth largest in the world, evidence from Germany is an important addition to the largely U.S.-based wage inequality debate. Despite being known for its comparably strong employment protection, collective bargaining institutions, and relatively modest wage inequality (DiPrete and McManus 1996; OECD 2011a), earnings dispersion in Germany has increased significantly in recent decades, resembling U.S. trends (Dustmann et al. 2009). Understanding how computerization shapes inequality in a major economy such as Germany therefore not only provides a useful comparative example but also advances our knowledge regarding its link to larger patterns of inequality.

### **Computerization and the Rise in Inequality**

Considerable research has found a strong relationship between the spread of information and communication technologies (ICT) and the growth in inequality. We focus particularly on skill-biased technological change, class-biased technological change, and unobserved establishment heterogeneity as the primary explanations for this relationship, which we extend to the establishment level.

#### *Skill-Biased Technological Change (SBTC)*

A large body of predominantly economic literature has argued that ICT investments have a direct effect on wages through increasing skill-based inequality. Beginning with the earliest studies (e.g. Bound and Johnson 1992; Juhn et al. 1993; Katz and Murphy 1992; Levy and Murnane 1992), scholars observed that much of the rise in inequality was between better- and lesser-skilled workers, although an even larger portion of the growth transpired within narrowly defined skill groups. Although these early studies were cautious about causation, economists

largely agreed that computerization had likely driven much of the growth in inequality, yielding the theory of skill-biased technological change (Lemieux 2008). The idea that technological change, particularly advancements in microcomputers, is skill-biased is derived from the notion that computer technology complements human capital. Consequently, the spread of this technology is thought to raise demand for highly-skilled workers and decrease demand for low-skilled workers, producing inequality (Acemoglu 2002; Card and DiNardo 2002).<sup>29</sup>

Research on computerization has repeatedly demonstrated that the spread of ICT is related to skilled workers. Krueger (1993) was among the first to empirically evaluate the relationship between computers and wages. Using CPS microdata between 1984 and 1989, he found that computer use predicts 10-15 percent higher wages on average. Further, as he discovered, better-educated workers are more likely to use computers at work. Others have found that ICT investments are also related to a rising share of college-educated workers over time using longitudinal industry data (e.g. Autor et al. 1998; Berman et al. 1994).

Establishment-level research also links computer investments and skill-based inequality. A wealth of studies have shown that ICT investments predict a higher proportion of skilled workers and a lower share of unskilled workers in establishments over time (Autor et al. 2002; Bresnahan et al. 2002; Dunne and Schmitz 1995; Siegel 1998). Other research suggests that ICT investments increase within-establishment wage differentials. For example, Fernandez (2001) reports that retooling in one large manufacturing plant amplified earnings dispersion through the hiring of new, highly skilled workers that commanded real wage increases compared to wage stagnation among low-skill workers.

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<sup>29</sup> In addition to the technology-induced rise in demand for skill, growing skill-based inequality in the U.S. may have been also fueled by a slowdown in the growth of highly-educated workers (Goldin and Katz 2008).

But how do computers exactly enhance demand for skill? Addressing one of the most glaring problems of the original SBTC hypothesis, Autor et al. (2003) propose a “task-based” version of SBTC, positing that tasks represent the missing causal mechanism behind computers’ influence on the labor market.<sup>30</sup> As they assert, workplace activities comprise two general types of tasks: routine and non-routine. On the one hand, routine cognitive tasks (e.g., bookkeeping, cashiering, calculating) and routine manual tasks (e.g. picking, sorting, repetitive assembly) involve methodically repetitive procedures which are liable to computer substitution since they can be easily defined by explicit programmed rules. On the other, non-routine cognitive tasks (e.g. managing, problem solving, and advising) are computer-complementary as computers enhance the productivity of individuals completing these activities. By contrast, the impact of ICT on non-routine manual tasks (e.g. cleaning, and servicing) remains ambiguous as computers neither strongly complement nor substitute for these activities. Consequently, the task-based approach identifies two potential channels through which computers affect wages; first, through shifting work toward non-routine cognitive tasks and automating cognitive and manual routine tasks, ICT is argued to increase demand for skilled workers to perform non-routine cognitive tasks. In turn, wage changes depend on whether the supply of skilled workers keeps pace with demand. Second, computerization may enhance the productivity (and therefore wages) of workers performing complementary tasks, contributing to inequality (Spitz-Oener 2008).

In sum, skill-biased technological change predicts ICT investments increase the share of skilled workers in workplaces (Autor et al. 2002; Bresnahan et al. 2002; Dunne and Schmitz 1995; Siegel 1998) through task changes (Autor et al. 2003). Computer investments are also expected to amplify educational wage differentials by enhancing the relative productivity of individuals

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<sup>30</sup> This is also called the “nuanced” SBTC hypothesis or in the context of job polarization the “routinization” hypothesis.



performing complementary tasks (Spitz-Oener 2008). As a result, SBTC suggests that ICT investments increase between-establishment wage inequality through: (1) heightening educational sorting across workplaces, and (2) increasing wage differences between high- and low-educated workers. These implications likewise apply to within-establishment inequality. ICT is not only related to the hiring of better-skilled workers on average, but also the hollowing-out of mid-skill occupations, which tend to involve more routine tasks (Autor et al. 2003; Fernandez 2001). ICT is thus believed to contribute to a more polarized skill distribution within workplaces and thereby within-establishment dispersion. ICT investments should additionally enhance inequality within workplaces by magnifying educational wage differentials due to relative productivity gains among higher skilled workers performing complementary tasks (Fernandez 2001).<sup>31</sup> Together, this implies that if ICT affects between- and within-establishment inequality primarily through changing the skill distribution of establishments' workforces and altering the rewards to skill, accounting for skill (i.e. education) should significantly reduce the effect of ICT on between- and within-establishment inequality (Baron and Kenny 1986). This is because skill is the mechanism by which ICT affects between- and within-establishment inequality according to SBTC.

#### *Class-Biased Technological Change (CBTC)*

In contrast to the direct, skill-based channel predicted by skill-biased technological change, class-biased technological change views the spread of computers as indirectly enhancing inequality through furthering the decline in collective bargaining institutions. In both Western and

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<sup>31</sup> While this suggests that ICT contributes to *between*-group inequality within establishments, it is also possible that ICT may be related to higher *within*-group inequality within establishments (i.e. residual inequality among workers with the same observed educational and experience levels). For instance, Mincer (1974) and Western and Rosenfeld (2011) note higher earnings variability among better-educated workers. While we do not seek to disentangle these two types of inequality, it is important to note that they may both contribute to within-establishment earnings differentials.

Eastern Germany, trade unions have historically played an important role in pay negotiations (Ebbinghaus and Visser 2000). If a given firm belongs to their respective employers' association, central wage negotiations apply to all employees within all establishments of that firm regardless of individuals' membership status since employers typically do not discriminate between union and nonunion workers (Fitzenberger et al. 2013). In recent decades, the percentage of employees covered by sectoral agreements has declined drastically between 1996 and 2007 from approximately 66 percent to 50 percent in the West and from 48 percent to 33 percent in the East (Kohaut and Ellguth 2008). Amidst a declining share of sectoral or industry-level agreements, many employers have turned to regional or firm-level agreements, which allow for more local wage negotiations, or even abandoned all forms of collective wage agreements, instead negotiating pay on an individual basis.

Although trade union decline represents an important factor in rising inequality in its own right (for international comparisons, see among others DiNardo et al. 1996; Dustmann et al. 2009; Gernandt and Pfeiffer 2007; Gosling and Lemieux 2001; Western and Rosenfeld 2011), Kristal (2013) and Kristal and Cohen (2015) offer a new explanation for the relationship between ICT and deunionization on inequality. In addition to the direct skill-based channel of SBTC, they argue that computerization increases inequality indirectly through deunionization by: (1) reducing the share of unionized manufacturing jobs, (2) heightening managerial anti-union tactics; and (3) skill polarization that weakens worker solidarity. Using a panel of U.S. industries, they demonstrate that ICT investment had a smaller effect on industries in which unions never had a significant presence, compared to ICT having a larger effect in industries that experienced strong declines in organized labor. As they contend, computerization exerted only a direct (i.e. skill-based) effect on inequality in industries with no historical union presence, while computerization had both a direct

and indirect (i.e. union decline) effect on inequality among historically-unionized industries, leading to a greater inequality rise among the latter. Consequently, whereas skill-biased technological change assumes that skill is the primary mechanism through which computers enhance inequality, class-biased technological change contends union decline is an additional important mechanism behind computers' effect on rising inequality.

Although CBTC does not focus on the establishment-level, declines in unionized manufacturing jobs, heightened anti-union managerial tactics, and workforce skill polarization are ultimately processes that transpire within establishments. Milkman (1995) for instance illustrates how the introduction of automated production technology in one large automobile plant displaced manufacturing jobs. Numerous studies (e.g. Autor et al. 2002; Bresnahan et al. 2002; Dunne and Schmitz 1995; Siegel 1998) have shown that computer investments increase skill polarization within establishments. Although Kristal (2013) and Kristal and Cohen (2015) concede empirical evidence of enhanced managerial supervisory ability to combat unions is sparse, though they point to companies such as Wal-Mart undertaking technically-sophisticated efforts to educate managers on how to prevent union organizing drives.

Moreover, there are methodological reasons to evaluate the potential mediating influence of collective bargaining at the establishment level. As Card et al. (2013) show, much of the rise in inequality has been driven by the growth of new high-inequality workplaces. Consequently, any mediating influence of unions at the industry level may be due to establishment turnover within detailed industries, as union status depends primarily on the establishment (or firm) level. That is, if deunionization serves as an important channel by which ICT increases inequality, proper assessment of the role of deunionization requires a longitudinal *establishment-level* approach, rather than an industry-level approach. An establishment-level analysis is necessary to rule out the

possibility of a spurious mediating effect driven by the growth of new non-unionized workplaces offering more heterogeneous wages relative to older unionized establishments in the same detailed industry.

Conceptually, unions exert competing influences on inequality. On the one hand, trade unions raise the mean wage of their members compared to non-union workers. This between-establishment effect of unions increases inequality among otherwise similar workers in organized versus non-organized establishments. On the other hand, collective bargaining standardizes earnings among individuals within unionized establishments. This within-establishment effect of unions reduces inequality through decreasing the spread of wages among workers with similar attributes. Evaluating these influences, Freeman (1980, 1982) found that unions' within-establishment effect more than offset the between-establishment effect, such that unionization is related to lower overall inequality through standardizing pay among workers in the same establishment. Following this logic, if ICT investments contribute to deunionization as per CBTC, we should observe that computerization primarily increases within-establishment inequality over time, rather than affecting between-establishment inequality. Hence, controlling for changes in collective bargaining status should account for much of the relationship between ICT and changes in within-establishment inequality (Baron and Kenny 1986). Moreover, given the relatively stronger institutional foothold of collective bargaining in Western Germany (Burda 1993; Schnabel and Wagner 2003), ICT investments should precipitate larger increases in inequality in the West as unions have historically exerted greater compressionary effects on the wage structure compared to the East.

### *Unobserved Establishment Heterogeneity*

A third potential explanation is that the relationship between ICT and inequality stems from unobserved establishment heterogeneity. One of the first studies to argue that the computer-wage relationship was endogenous was DiNardo and Pischke (1997). Using German microdata, they found that other job characteristics including pencils or calculators at work were associated with wage returns comparable in magnitude to the returns to computer use. As they contend, due to the nonrandom assignment of computers in the labor market, any positive association could be due to unobserved differences between computer users and nonusers. For instance, white collar workers were among the first to use computers at work even though they earned on average more than their blue collar counterparts even prior to these technologies. Handel (2007) similarly finds that job characteristics account for the computer wage premium using CPS data.

Although selectivity in individual computer use is less of an issue when analyzing ICT's effect at the establishment level, research nevertheless suggests that even here the influence of ICT may be spurious. For example, Doms et al. (1997) found that U.S. manufacturing plants that invested more greatly in computer technologies tended to employ better-educated workers and offered higher wages according to cross-sectional estimates. However, according to longitudinal models they found no evidence of wage changes, although they do discover evidence of changes in workforce composition. Indeed, Bresnahan (1999) goes so far as to deny the complementarity between computers and individual human capital of computer users, arguing rather that complementarity between ICT and skill is an establishment outcome (for a similar argument see Bresnahan et al. 2002). According to this idea, computerization creates new ways of organizing work through routinizing and standardizing bureaucratic production processes within establishments. Due to the limited potential for substitution of computers for human decision-

making, this results in wholesale automation of some highly-routine occupations over the long term (e.g. telephone operators), and task changes among other occupations whose activities are only partly routine.<sup>32</sup>

Together, this implies that the relationship between ICT and rising inequality may be driven by unobserved establishment heterogeneity in two possible ways. First, thanks in part to technological changes that engender new, more unequal ways of organizing work, this promotes the growth of heterogeneous workplaces, which serves as the proximal cause of rising inequality (Bresnahan 1999). According to this idea, while ICT may be the distal cause of increasing inequality, its effects on between- and within-establishment wage differentials are highly diffuse and empirically unmeasurable. Although the reorganization of work may encompass a variety of changes, one commonly cited practice related to workplace heterogeneity is the rise in performance pay strategies. As Lemieux, MacLeod, and Parent (2009) argue, advances in information technology enhance managerial abilities to monitor and reward employees based on their performance. As they find, one-fifth of the total rise in inequality and nearly all of the growth in upper-tail inequality among U.S. men in recent decades is attributable to performance. Because these pay strategies are likely more attractive to more competitive (and typically better) employees, performance pay practices should increase both between- and within-establishment earnings inequality. Alternatively, another conceivable way ICT is related to unobserved establishment heterogeneity is that ICT investments are consistently higher in specific product markets that also tend to evince higher between- and within-establishment inequality, yet ICT has no actual impact on workplace inequality in these particular markets (Bresnahan 1999). Based on this idea, ICT has

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<sup>32</sup> Although this argument in many ways resembles Autor et al.'s (2003) task-based approach, it views ICT as primarily affecting workplaces, rather than occupations.

no causal effect on wages, but is instead more useful in these unique markets, creating a spurious association between ICT and inequality.

Altogether, this suggests that ICT either has an indirect and empirically unmeasurable impact on workplace inequality over time, or that computers have no causal effect on inequality. Either way, according to this idea we should observe a strong association between ICT and between- and within-establishment inequality according to cross-sectional estimates, which would not be present in longitudinal models that account for unobserved establishment heterogeneity.

### **Three Explanations**

Based on our review, we test the following explanations for the relationship between ICT investments and establishment wage inequality:

(1) *Skill-biased technological change*: Skill (i.e. education) mediates the effect of ICT investments on between- and within-establishment inequality. Compared to models without human capital controls, controlling for workers' human capital characteristics should reduce the estimated effect of ICT on between- and within-establishment inequality.

(2) *Class-biased technological change*: Deunionization mediates the influence of ICT investments on within-establishment inequality. Compared to models without collective bargaining controls, accounting for collective bargaining should reduce the estimated effect of ICT on within-establishment inequality. Changes in the

estimated impact of ICT with and without collective bargaining controls should be larger in Western Germany.

(3) *Unobserved establishment heterogeneity*: ICT investments have a non-significant effect on between- and within-establishment inequality. ICT investments should be related to between- and within-establishment inequality in cross-sectional models, but not in longitudinal models.

## **Data, Measures, and Statistical Models**

### *Data and Measures*

To address these questions we use longitudinal linked employer-employee data (LIAB) from the German Institute for Employment Research (IAB), which combine data from the IAB-Establishment Panel and the Employment Statistics Register. The IAB-Establishment Panel is an annual, stratified random sample of Eastern and Western German establishments that employ at least one worker who makes social security contributions<sup>33</sup> (for details, see Heining, Scholz, and Seth 2013). Based on this representative sample of establishments, the population of individuals working in these establishments on June 30<sup>th</sup> of each year are drawn from the Employment Statistics Register and matched to their respective workplaces. One key strength of these data is that they contain a wide variety of information on establishments as well as the characteristics of workers in these establishments. Unfortunately, one drawback is that these data do not include information on the precise number of hours an individual worked; we consequently limit the

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<sup>33</sup> Employees that do not contribute to social security include marginal workers and civil servants. In total, our sample frame comprises approximately 80 percent of the German labor force. We also excluded apprentices, trainees, interns, and family members in agriculture.



analysis to full-time men and women (those exceeding 30 hours worked per week)<sup>34</sup> aged 20-60 years old, using real log daily pay to calculate inequality. We also limit the analysis to establishment-years with 10 or more employees in order to mitigate the influence of small workplaces, which tend to have highly variable ICT investments and within-establishment inequality and may thereby bias our estimates. Likewise, to account for wage censoring, following prior studies (e.g. Card et al. 2013; Dustmann et al. 2009) we impute censored wages from an interval regression using sex, educational level, age, age squared, 3-digit occupation, industry, nationality, log establishment size, and a dummy for East Germany combined with random draws from the normal distribution (for a greater explanation see Reichelt 2015).<sup>35</sup> To account for clustering of individuals within establishments, we estimate all models using cluster-robust standard errors.

We use data from the 2001-2007 waves of the LIAB, which provides information on approximately 18,000 establishments and 3.6 million linked worker observations over time.<sup>36</sup> Establishments surveyed by the IAB Establishment Panel in these years were asked additional questions about their investments in information and communication technologies. The survey also asked about establishments' collective bargaining practices, which together were incorporated into the LIAB for these years. An ideal measure of ICT would capture change in the total capital stock of establishments' computer capital. Unfortunately, such information is not available in most data

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<sup>34</sup> Results were substantially similar for the entire sample of workers including both part- and full-time workers.

<sup>35</sup> Censoring affected approximately 15.1 percent of all observations for men and 4.7 percent of all observations for women in our sample.

<sup>36</sup> Whereas Card, Heining, and Kline (2013) use administrative data encompassing the entire German working population, we rely on an unbalanced panel of establishments and all linked workers therein. Compared to administrative data that contain only a handful of individual-level covariates, the benefit of our matched employment data are that they contain a large number of establishment attributes obtained via the IAB Establishment Panel (Heining, Scholz, and Seth 2013), in addition to individual-level covariates. ICT investment and collective bargaining information are only available for establishments contained in the LIAB, not across all establishments in the administrative records.

sets. Instead, we use the proportion of establishments' total investments dedicated to computer technology in a given year. This is a reasonable proxy for changes in share of total computer capital stock and matches measures used elsewhere (e.g. Berman et al. 1994; Doms et al. 1997; Kristal 2013; Kristal and Cohen 2015).<sup>37</sup> Similarly, we measure collective bargaining status with three dummy variables indicating whether an establishment abides by a sectoral wage agreement (*Tarifvertrag*), a firm-level agreement (*Haustarif/Firmentarif*), or no collective bargaining agreement (i.e. individual contracts). Individual-level control variables include gender, educational attainment (three dummies: no schooling completed, Hauptschule/Realschule, and (Fach)Hochschulreife), qualification level (three dummy variables: individuals with no vocational or academic training, individuals that completed vocational training, and university of applied sciences or college graduates), age (in years) and age squared, tenure in establishment (in years), nationality (3 dummies), and the natural logarithm of establishment size. Furthermore, we analyze Eastern and Western Germany separately to capture regional differences in collective bargaining strength.

Table 3.1 displays key descriptive statistics. On average, 16.4 percent of total establishment investments over the period were dedicated toward information and communication technologies, with similar shares among Eastern and Western establishments. Although 70.9 percent of all establishments in the sample over the period adhered to sectoral agreements, there were marked differences across regions, with 75.0 percent of Western workplaces covered by these arrangements compared to 58.5 percent in the East. By contrast, individual contracts and firm-level agreements remain considerably more common in the East at 22.7 percent and 18.8 percent, respectively, versus 10.6 percent and 14.4 percent in the West.

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<sup>37</sup> Similar results were obtained when using ICT investments in absolute terms (i.e. millions of Euros) and are available upon request.

### *Statistical Models*

To examine the relationship between ICT and establishment-level inequality we estimate a variance function regression with establishment fixed effects (Western and Bloome 2009). We adopt a modified version of Mouw and Kalleberg's (2010) estimation strategy that models how covariates affect average wages between workplaces (the between-establishment effect) as well as residual inequality within workplaces (the within-establishment effect).

We begin with the theoretical model,

$$y_{ijt} = x_{ijt}\beta_{FEt} + c_{jt} + \epsilon_{ijt} \quad (1)$$

$$i = 1 \dots N \text{ (individuals)}$$

$$j = 1 \dots N \text{ (establishments)}$$

$$t = 1 \dots N \text{ (years),}$$

which predicts the log daily wage,  $y_{ijt}$ , of individual  $i$  in establishment  $j$  in year  $t$  as a function of individual characteristics,  $x_{ijt}$ , and yearly establishment fixed effects,  $c_{jt}$ . For our estimates of between-establishment inequality we are primarily concerned with the yearly establishment fixed effects,  $c_{jt}$ , as it captures all unobserved invariant establishment characteristics that influence all workers' wages in that workplace and year, net of individual characteristics. For our estimates of within-establishment inequality we focus on the residual error term,  $\epsilon_{ijt}$ , which captures residual dispersion within establishments net of establishment fixed effects and individual characteristics.

Our empirical regression model of between-establishment inequality takes the form

$$\hat{c}_{jt} = \omega_{jt} + c_j + \epsilon_{jt} \quad (2)$$

where  $\hat{c}_{jt}$  is the estimated establishment fixed effect for year  $t$ ,  $\omega_{jt}$  captures all establishment-level variables of interest (including ICT investment and union status) in year  $t$ ,  $c_j$  is a pooled

establishment fixed effect for all years of observation that captures the general effect of all unobserved establishment characteristics on average wages, and  $\epsilon_{jt}$  is the residual. The pooled establishment fixed effect,  $c_j$ , allows us to evaluate the effect of a *change in ICT investment and collective bargaining status* on average wages within the establishment over time.<sup>38</sup> Introducing this pooled fixed effect, we control for all unobserved, invariant establishment characteristics that influence average pay, ICT investment, and union status.  $\omega_{jt}$  thus gives us an estimate for the effect of covariates on between-establishment wage differences, net of individual- and establishment-level characteristics.

To obtain estimated yearly fixed effects,  $\hat{c}_{jt}$ , for equation (2), we follow Wooldridge (2002: 273) and first calculate an OLS regression model in which every variable on the left- and right-hand side is demeaned according to establishment averages for that variable in that year, producing

$$y_{ijt} - \bar{y}_{jt} = (x_{ijt} - \bar{x}_{jt})\beta_{FET} + (c_{jt} - \bar{c}_{jt}) + (\epsilon_{ijt} - \bar{\epsilon}_{jt}), \quad (3)$$

where  $(c_{jt} - \bar{c}_{jt})$  will yield zero as  $\bar{c}_{jt}$  is constant for each establishment-year and  $\bar{\epsilon}_{jt}$  equals zero by construction. Rearranging the equation, we can see that  $(\bar{y}_{jt} - \bar{x}_{jt}\beta_{FET})$  is equivalent to the estimated establishment fixed effect,  $\hat{c}_{jt}$ , yielding

$$y_{ijt} = x_{ijt}\beta_{FET} + (\bar{y}_{jt} - \bar{x}_{jt}\beta_{FET}) + \epsilon_{ijt}. \quad (4)$$

Having now proved this to ourselves, we can obtain yearly estimates of the establishment fixed effect by first calculating

$$y_{ijt} - \bar{y}_{jt} = (x_{ijt} - \bar{x}_{jt})\beta_{FET} + \epsilon_{ijt}, \quad (5)$$

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<sup>38</sup> Alternatively, one could think of this as the “grand” establishment fixed effect over all year-specific establishment fixed effects. Although it is common to treat a unit of observation such as a person or establishment as having just one fixed effect (Wooldridge 2002), the multilevel structure of our data, with persons nested within establishments, enables us to distinguish between separate yearly establishment fixed effects (see for example Petersen, Penner, and Høgsnes 2014) and the overall “grand” establishment fixed effect. This differentiation provides year-to-year variation in establishment average wages and thereby allows us to look at how covariates affect this variation over time.

and subsequently using coefficient estimates,  $\hat{\beta}_{FET}$ , to retrieve the estimated establishment fixed effect for each year,  $\hat{c}_{jt}$ , according to equation (4)

$$\hat{c}_{jt} = \bar{y}_{jt} - \bar{x}_{jt}\hat{\beta}_{FET}. \quad (6)$$

The predicted year-specific establishment fixed effects obtained in equation (6) provide the unit of observation used for the dependent variable, between-establishment inequality, in equation (2). In other words, we generate a panel of yearly establishment fixed effects and regress these on all establishment-level variables and include a pooled establishment fixed effect.

To estimate the effects of ICT investment on within-establishment inequality, we begin by estimating the regression from equation (4),

$$y_{ijt} = x_{ijt}\beta_{FET} + (\bar{y}_{jt} - \bar{x}_{jt}\beta_{FET}) + \epsilon_{ijt},$$

using this regression to predict the logarithm of the squared residual,  $\hat{\epsilon}_{ijt}^2$ .  $\log(\hat{\epsilon}_{ijt}^2)$  provides an estimate of within-establishment wage inequality, as it measures the variability of individual wages after controlling for individual-level attributes and the establishment fixed effect,  $c_{jt}$ . We then perform a regression of the residual variance on individual- and establishment-level variables, again including the establishment fixed effect,  $c_j$ . We follow Western and Bloome (2009) and fit a gamma-distributed generalized linear model (GLM). We are using a non-linear model, which makes it analytically difficult to incorporate fixed effects by demeaning covariates and the dependent variable as is conventionally done. Therefore, we calculate the model

$$\log(\hat{\epsilon}_{ijt}^2) = x_{ijt}\beta + \omega_{jt}\eta + \bar{x}_{ij}\xi + \bar{\omega}_j\zeta + \epsilon_{ijt}, \quad (7)$$

where  $\bar{x}_{ij}$  is the establishment average of the individual variables,  $x_{ijt}$ , and  $\bar{\omega}_j$  is the establishment average of variables  $\omega_{jt}$ . As Chamberlain (1980) and Mundlak (1978) show, adding the average of each independent variable (in this case by establishment) removes the correlation between the

fixed effect,  $c_j$ , and the explanatory variables, providing us with the correct estimates for  $\beta$  and  $\eta$  (Wooldridge 2002). Conditioning on establishment averages, the coefficient for ICT investment can be interpreted as the mean effect of a change in ICT investment on the change in the level of wage dispersion among individuals within workplaces.

## Results

### *Between-Establishment Inequality*

Tables 3.2 and 3.3 display covariate estimates on between-establishment inequality in Western and Eastern Germany, respectively. In both tables, Model 1 captures the base ICT effect that includes all individual and establishment controls with the exception of human capital attributes (i.e. excluding educational attainment and formal qualification). Comparing the size and direction of this estimate to the ICT coefficient in Model 2, which includes human capital variables, tests whether ICT affects inequality via the direct skill-based channel as predicted by SBTC. Although CBTC has less to do with between-establishment inequality, comparing the estimated effect of ICT in Model 2 to the ICT coefficient in Model 3, which includes collective bargaining controls, reveals whether computerization influences inequality via the mechanism of collective bargaining differences.<sup>39</sup> Models 1-3 in these tables are estimated with pooled cross-sectional OLS regression that does not include establishment fixed effects. By comparison, Models 4-6 in these same tables incorporate establishment fixed effects, which hold constant all stable

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<sup>39</sup> Comparing nested models with and without collective bargaining controls in cross-section is admittedly an implicit test of class-biased technological change. The reason being that CBTC theorizes about the effect of changes in ICT investments and changes in collective bargaining on changes in inequality. Yet because pooled cross-sectional regression assumes establishment observations are independent of one another, these models only assess the influence of the presence or absence of covariates on the level of inequality. By comparison, establishment fixed effects models represent a very direct test of CBTC, as they analyze the influence of changes in covariates on changes in the dependent variable.

unobserved establishment attributes, evaluating whether the cross-sectional relationship among ICT and between-establishment inequality holds longitudinally, or whether this relationship is driven by unobserved heterogeneity across establishments.

According to cross-sectional estimates, workplaces that invest more greatly in ICT typically pay higher wages in Western and Eastern Germany, such that computerization is related to between-establishment inequality (see Model 1). *Ceteris paribus*, a 10 percent increase in ICT investment is associated with 0.85 percent ( $e^{0.085 \times 0.1} = 1.0085$ ) greater between-establishment in the West and 0.78 percent higher between-workplace inequality in the East. Incorporating human capital controls reduces the estimated effect of ICT in both regions, providing evidence for skill-biased technological change (c.f. Model 2 vs. 1). This reduction in the estimated impact of ICT is attributable to the fact that workplaces that invest more heavily in ICT also tend to employ more skilled workers that also command higher wages; hence accounting for this difference reduces the direct impact of ICT on between-establishment inequality. While the mediating effect of collective bargaining status in between-establishment inequality is unclear according to class-biased technological change, controlling for the influence of collective bargaining marginally increases the estimated effect of ICT in both Eastern and Western Germany (see Model 3 vs. 2). This indicates that unorganized establishments invest more greatly in ICT on average compared to collectively-bargained workplaces.<sup>40</sup> Altogether, we find evidence of skill-biased technological change according to pooled cross-sectional models in Western and Eastern Germany.

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<sup>40</sup> This masked effect in Model 3 arises from the fact that the reference collective bargaining category, workplaces with no collective bargaining, is negatively correlated with between-establishment inequality. Given the positive correlation between ICT and between-establishment inequality in Model 2, which increases when controlling for collective bargaining status in Model 3, this implies ICT investment is positively correlated with non-collectively bargained workplaces. By contrast, if ICT investments were lower on average among non-collectively-bargained workplaces (i.e. negatively correlated) controlling for collective bargaining would diminish the coefficient size of ICT.

Introducing establishment fixed effects in Models 4-6 of Tables 3.2 and 3.3, however, reduces the estimated effect of ICT investments to non-significance. This indicates the relationship between computerization and between-workplace inequality in pooled cross-sectional models is due to unobserved establishment heterogeneity. As a result, changes in ICT investments do not appear to be attributable to changes in between-establishment differentials in Eastern or Western Germany over time.

#### *Within-Establishment Inequality*

Tables 3.4 and 3.5 display the estimated effects of ICT on within-establishment inequality in Western and Eastern Germany, correspondingly. As with the previous between-workplace results, we compare the ICT coefficient in Model 1 to Model 2 to assess SBTC, estimated ICT effects in Model 2 to Model 3 to evaluate CBTC, and finally examine whether these relationships hold net of establishment fixed effects in Models 4-6.

Pooled cross-sectional estimates suggest that workplaces that invest more in ICT feature higher within-establishment inequality, denoting ICT is related to within-establishment inequality. According to Model 1, a 10 percent increase in ICT is related to 1.78 percent ( $e^{0.176 \times 0.1} = 1.0178$ ) higher within-workplace earnings dispersion in the West and 1.73 percent greater within-establishment inequality in the East, net of other factors. Conditioning on human capital attributes produces contradictory results in Western and Eastern Germany (see Model 2 in Tables 3.4 and 3.5, respectively). In the West, controlling for workplaces' educational distribution reduces the influence of ICT on within-establishment inequality, in line with the predictions of SBTC. In the East, however, conditioning on these same variables *enhances* the estimated effect of ICT, in contradiction to SBTC. In cross-section this implies that establishments that invest more greatly



in computer technology in the West tend to employ more heterogeneously-educated workers, while ICT-investing workplaces in the East tend to employ less heterogeneously-educated individuals. As Reichelt and Vicari (2014) describe, nearly all workers attained formal qualifications (i.e. a vocational or college degree) under the former socialist German Democratic Republic regime thanks to the availability of free education; however, this training often equipped workers with inapplicable skills for the modern economy. Today, overqualification is common in Eastern Germany due in part to the continued abundance of workers with high formal qualifications, but whose actual skills are highly heterogeneous. As a result, we suspect that this contradictory finding may be a result of the weak signal formal qualification provides employers in Eastern Germany regarding an individual's true ability.

Cross-sectional estimates also reveal that accounting for collective bargaining differences reduces the estimated effect of ICT on within-establishment inequality in both Western and Eastern Germany (compare Model 3 to Model 2 in Tables 3.4 and 3.5). In line with class-biased technological change, controlling for collective bargaining status partially accounts for some of the relationship between ICT and within-establishment inequality given that investments computer technology tend to be higher in non-collectively-bargained establishments. Despite this, contrary to the idea that ICT influences should be larger among labor market segments where collective bargaining has been historically stronger, estimated effects of ICT are smaller in Western Germany compared to the East (see Model 3 in Tables 3.4 and 3.5). To sum up, cross-sectional models provide evidence for CBTC on within-establishment inequality in Eastern and Western Germany, yet we do not find larger estimated effects in the West. Cross-sectional results also support SBTC, but only in Western Germany.

Nevertheless, as with between-establishment estimates, incorporating establishment fixed effects in Models 4-6 reduces the impact of ICT investments on within-workplace inequality to non-significance. The cross-sectional relationship between computerization and within-establishment differentials is therefore attributable to unobserved establishment heterogeneity, as suggested by Doms et al. (1997). Consequently, changes in ICT investments do not appear to be attributable to changes in between- *or* within-establishment inequality in either region of Germany over time.

#### *Lagged ICT Influences on Between-Establishment Inequality*

Thus far, we have demonstrated that the well-known association between ICT and inequality is spurious, and driven by unobserved establishment heterogeneity. In other words, we find little indication that computerization accounts for the rise in between-establishment inequality (i.e. Card et al. 2013) or changes in within-establishment wage dispersion over time. Although our fixed effects models evaluate the effect of a change in ICT investment on a change in the dependent variable from year  $t-1$  to year  $t$ , it is possible that ICT investments may have longer lagged effects that are not detectable over a one-year period.

Table 3.6 presents lagged results from a fixed effects model for Western and Eastern Germany. They estimate the impact of ICT investments made over the past four years on between-establishment inequality. These results were obtained by restricting the analysis to a subset of workplaces that remained in the panel for four or more consecutive years.<sup>41</sup> Correspondingly, changes in ICT investments made four years previously have a small but significant effect on

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<sup>41</sup> Similar results were obtained when estimating single year lags in separate models; however, these models ignore the correlation among ICT investments made across multiple years. We also tested models with five- and six-year lags, which produced comparable results, though the number of establishments dropped considerably the greater the number of lags warranting concern about the representativeness of these workplaces.

changes in inequality in the current panel year. Specifically, a 10 percent increase in ICT investment made four years ago is related to 0.06 percent higher between-establishment inequality in Western Germany and a similar rise in between-workplace inequality in the East. Conversely, we find no lagged effects of ICT on within-establishment inequality (results not shown). This indicates that while recent ICT investments appears to have no effect on between- or within-establishment inequality, ICT may have a minor influence on between-workplace inequality over a longer period.

## **Discussion and Conclusion**

Recent evidence suggests that a significant share of the rise in wage inequality has transpired at the establishment level (Card et al. 2013), requiring workplace-level analyses to understand the sources of growing inequality. Using a variance function regression with establishment fixed effects we provide the first analysis of how ICT investments influence earnings inequality between and within German establishments over time. Because establishments themselves invest in information and communications technologies, this makes workplaces, rather than industries or individual workers, the ideal unit of analysis for assessing computerization's role in rising inequality.

We find strong evidence that ICT is associated with higher between- and within-workplace inequality in Western and Eastern Germany. Examining the mechanisms for this effect, our cross-sectional models indicate that ICT investments are related to skill-based inequality between and within workplaces as predicted by skill-biased technological change. Cross-sectional results also indicate that ICT investments are related to differences in collective bargaining within workplaces, in accordance with class-biased technological change (i.e. Kristal 2013; Kristal and Cohen 2015).

Yet we do not observe stronger influences of ICT investments in Western Germany as this theory would expect. However, in contrast to cross-sectional results, net of establishment fixed effects, changes in ICT investments do not have a significant effect on changes in either between- or within-establishment inequality. As a result, we find little evidence for skill- or class-biased technological change over time; instead, our findings suggest that the well-known association between computerization and inequality is largely driven by unobserved heterogeneity across establishments.

Potentially, this spurious relationship between ICT and rising inequality may be attributable to two possibilities. One potential explanation is that ICT's effect on workplace inequality is highly diffuse and not directly empirically observable, but that computerization nevertheless drives new, more unequal ways of organizing work (Bresnahan 1999). An example of this is the rise in performance pay strategies, which have been shown to contribute strongly to growing inequality (see Lemieux et al. 2009). New organizational practices like these give rise to increasingly heterogeneous workplaces, which acts as the mechanism driving the takeoff in inequality. An alternative possibility is that ICT investments are consistently greater in specific product markets, which for various reasons have greater between- and within-establishment inequality, though ICT has no causal effect on inequality in these markets. For instance, auxiliary analyses suggested that ICT investments and inequality were particularly large in data management services, advertising, and legal services. This idea posits that the rise in inequality is driven by other factors correlated with, but not caused by, the spread of information and communication technology. This could include factors such as deunionization, globalization, or cultural shifts in attitudes about inequality. Unfortunately, we cannot adjudicate between these potential explanations, and so we encourage future scholarship to target this issue.

Importantly, the fact that we find no evidence that computerization affects earnings differentials in the ways predicted by skill- or class-biased technological change does not imply that ICT has no effect on inequality. As our lagged fixed effects analyses revealed, investments in ICT made four years prior to the current period did have a small, statistically significant effect on between-establishment inequality in both regions of Germany. Thus ICT may have a minor influence on workplace inequality over a longer period. Admittedly, our data do not allow us to meaningfully assess the long-term implications of computerization on educational sorting across establishments or the long-term rise in returns to skill (c.f. Card et al. 2013; Goldin and Katz 2008). Thus, although we resist making strong conclusions about how computerization affects demand for skill in the long term, in the short term ICT appears to have little influence on the rise in between-establishment inequality (i.e. Card et al. 2013).

Relatedly, although we find no evidence of class-biased technological change, there are two reasons why we cannot fully reject this explanation. First, although we offer a far more direct test of class-biased technological change than has been done, we rely on German establishment data from 2001-2007. In contrast, Kristal (2013) and Kristal and Cohen (2015) use U.S. industry data from 1969 to the 2000s. Given these large temporal differences, it is possible that labor organization played a more central role in the wage structure in earlier decades, or that technological investments differed markedly in earlier decades relative to those captured by our measures. Additionally, although our measure closely resembles those used in Kristal (2013) and Kristal and Cohen (2015), and other well-known studies, it is also conceivable that our relatively coarse indicator for ICT may not pick up on the subtle wage influences of computerization present in the population. Second, our non-significant findings may be attributable to divergent industrial relations structures between Germany and the U.S. As emphasized by the varieties of capitalism

literature (Hall and Soskice 2001), trade unions maintain a particularly influential role in coordinated market economies such as Germany by helping to standardize worker training and technology diffusion across establishments. Because trade union influence extends beyond the individual workplace in Germany, this may partly explain why changes in collective bargaining practices do not channel the influence of ICT investments in our study. Still, we take solace in the fact that collective bargaining differences mediate the influence of ICT on establishment inequality in cross-section, providing evidence for class-biased technological change in the German labor market. Nevertheless, because this effect is driven by unobserved establishment heterogeneity, this suggests that the theory of class-biased technological change may be vulnerable to workplace turnover within detailed industries over time.

Although we find few indications of a causal relationship between computerization and the rise in inequality, our findings nevertheless underscore the strong connection between these factors, particularly as it relates to the growth in workplace heterogeneity (i.e. Card et al. 2013). As our results show, information and communication technologies have flowed disproportionately to establishments that pay above-average wages, but also exhibit higher within-establishment earnings dispersion. More generally, these findings undergird the importance of using organizational data, such as linked employer-employee data, for both contextual understanding as well as illuminating potential causal factors driving inequality processes. Sociologists have long recognized workplaces as the primary site of production for categorical inequalities (Baron 1984; Baron and Bielby 1980; Tomaskovic-Devey et al. 2006). Increasingly, sociologists and other researchers must also look to establishments and other workplace organizations to explain gradational inequalities, such as earnings differentials.

## **CHAPTER 4: Market Transformation and the Opportunity Structure for Gender Inequality: A Cohort Analysis using Linked Employer-Employee**

### **Data from Slovenia<sup>42</sup>**

#### **Introduction**

Despite considerable scholarly and public interest in the effects of market transition among postsocialist countries, our knowledge regarding how market reforms have affected gender inequality remains limited. Although many formerly socialist states in Central and Eastern Europe (CEE) had official gender egalitarian policies, gender earnings inequality under socialism was large and persistent, and often comparable to levels among developed Western societies (Rosenfeld and Trappe 2002). While scholars feared that women would bear the disproportionate costs of market transition (Einhorn 1993; Hauser et al. 1993), most evidence has indicated that women's socioeconomic situation did not drastically worsen in the years immediately following 1989 (Fodor 2002; Giddens 2002; van der Lippe and Fodor 1998; Rueschemeyer and Szelenyi 1995). What has emerged, however, is that gender inequality among formerly CEE countries differs substantially in form from developed Western economies. Whereas gender earnings inequality among men and women who work in the same occupation for the same employer (i.e. occupation-establishment or within-job inequality) is relatively small in Western societies like the U.S., Sweden, and Norway (Meyersson et al. 2001; Petersen et al. 1997; Petersen and Morgan 1995), substantial levels of within-job gender inequality exist in CEE societies (Jurajda 2003; Křížková et al. 2010; Penner et al. 2012; Sørensen and Trappe 1995).

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<sup>42</sup> Co-authored in collaboration with Andrew Penner, Nina Bandelj, and Aleksandra Kanjuro-Mrčela. As a result, this chapter uses the pronoun “we” throughout.

As life course research has demonstrated, much of the gender pay differential originates early in the careers of young men and women, and is compounded by cumulative advantage processes over men's and women's working lives (DiPrete and Soule 1988; Gerhart 1988). Gender inequality is driven not only by differing preferences among men and women (Correll 2001, 2004; Fernandez and Friedrich 2011), but also by employer stereotypes and discrimination in the allocation, promotion, and rewarding of workers (England 1992; Petersen and Morgan 1995). In particular, structural conditions play a decisive role in determining how inequality is created. Petersen and Saporta (2004) contend that structural factors determine the "opportunity structure" for gender inequality and discrimination, i.e. the contexts in which employers are more or less able to discriminate. They argue that in today's post-Civil Rights era in the U.S., allocating men and women to differently-paid jobs is more feasible than paying them different rates within the same job, explaining why sorting across occupations and establishments comprises a much larger share of the gender gap today than within-job inequality.

In the context of market transition, the structural opportunities available for inequality are likely to vary significantly depending on one's birth cohort. Although few studies explicitly consider cohort-specific effects, one study of Eastern Germany found marked differences in the impact of market transition by cohort (Mayer et al. 1999). As societies transition from a centrally planned to a market economy, this creates new opportunities and risks, such as the development of new occupations and labor market sectors, organizational restructuring within firms (e.g. greater managerial discretion in firm operations, implementation of performance pay strategies, and changes in the intensity of work), and market and business cycle fluctuations. Yet individuals across cohorts face distinctive age-graded risks and options in experiencing these effects based on the timing of market transition in their lives, providing cohorts a unique character and outlook



reflecting their unique historical experiences (Ryder 1965). Due to previously-acquired cumulative advantages (or possibly disadvantages), the changing opportunity structure of marketization should have a relatively small impact on gender inequality among individuals in middle-aged and older cohorts, as their career trajectories have largely already been determined. By contrast, younger cohorts are a greater risk of new patterns of inequality inherent to the changing economic system, as their career trajectories (and resulting cumulative (dis)advantages) have not yet been well established. Younger workers may also be better positioned to capitalize on the changing opportunity structure due to the simultaneous changes in educational and training systems, which may better enable them to respond to the new demands of transition (Zhou and Moen 2001). As a result, in the context of market transition, we argue that the period in which a woman finishes schooling and enters the labor market may play an important role in shaping her labor market prospects vis-à-vis her male counterpart.

In this paper, we make two primary contributions. First, by adopting a life course approach, we shed new light on how market transformation affects gender inequality in cohort-specific ways. We extend previous work on the transition to a market-based system by considering how it may matter differently across birth cohorts: Those who have lived a significant part of their lives under socialism versus those who enter the labor market during major structural economic transformation. In this respect, we contribute to a growing body of literature spurred by Elder (1974), focusing on how events differentially affect people based on their life stage when the event occurred. Second, this cohort approach furthers our understanding of the structure of gender inequality in organizations by investigating how market transformation alters the relative importance of allocative versus within-job gender inequality. Our analyses therefore also extends Petersen and Saporta's (2004) notion of the opportunity structure for discrimination, generalizing

this idea to the organization of markets more broadly by examining how marketization changes the ways that gender inequality is organized as societies transition from one socio-economic configuration to another.<sup>43</sup>

We apply our life-course inspired cohort-based approach to an examination of the gender pay gap using matched employer-employee registry data from Slovenia between 1993 and 2007. Like other CEE countries, Slovenia has undergone significant social and economic change amidst transition, including rising gender inequality (Pollert 2003). Despite this, during the examined period, Slovenia was the strongest economic performer in the region and has managed to maintain high female labor force participation throughout transition. Using these high quality matched data, the Slovenian case provides an excellent context in which to observe the cohort-specific impact of market transformation on gender inequality.

## **The Opportunity Structure for Gender Inequality in Transition Societies**

### *The Sources of Gender Inequality in Organizations*

In capitalist societies scholars typically find that gender inequality arises from a combination of worker preferences and employer beliefs and practices. We argue that these factors are culturally determined and influenced by larger societal structures and norms. For workers, differences in cultural beliefs about gender task competencies (Cjeka and Eagly 1999; Correll 2001, 2004; Fernandez and Friedrich 2011), socialization patterns (Betz and O'Connell 1989; Marini and Brinton 1984; Marini et al. 1996), the gendered division of labor in families (Becker 1981, 1985; Mincer and Polachek 1974) , and social networks (Marsden 1987, 1988; Straits 1996) are argued to lead men and women to prefer different jobs and careers, contributing to gendered

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<sup>43</sup> We take an expansive view of the notion of the “opportunity structure” as encompassing both normative and structural (i.e. supply- and demand-side) factors.

educational sorting and sex segregation in the labor market (Charles 2011). For employers, these same gender expectations and cultural beliefs lead them to allocate women and men to different positions within establishments, and allow them to pay female-dominated or female-stereotypical work less (England 1992; Heilman 1980, 1984; Reskin and Roos 1990). As noted by Petersen and Saporta (2004), these factors produce three distinct types of gender inequality. First, due to a combination of worker preferences and employer practices, men and women are allocated to different occupations and establishments that offer differential rewards. This *allocative* inequality results from both distinctive patterns in hiring and in worker promotions and dismissals. Second, employers may systematically pay women less than men in the same occupation and establishment, resulting in *within-job* inequality. Third, majority female occupations receive lower pay compared to majority male ones, net of skill requirements and work-related activities, yielding *valuative* inequality.

The importance of different forms of inequality ultimately depends on their structural feasibility and cultural acceptance. In the United States, following the enactment of the 1964 Civil Rights Act, blatant employer discrimination according to ascriptive characteristics became more difficult and normatively less defensible. Within-job earnings inequality is straightforward to document, clear-cut, and likely to have a plaintiff, all factors which make it structurally less feasible for employers in the United States (Petersen and Saporta 2004). Consequently within-job gender pay inequality is comparably small in the U.S. (Petersen and Morgan 1995).

By contrast, allocative and valuative gender inequality remain much more widespread. Because documenting discrimination at the point of hire involves a multitude of factors including the quality of other applicants, inequalities in the recruitment process, who receives a job offer, and the quality of those offers, allocative discrimination at the point of hire is substantially more

difficult to prove in court (Petersen and Saporta 2004). Likewise, regardless of the source, if men and women have differing job preferences, allocative inequality is likely to be more socially palatable than within-job gender disparities. Given these challenges, few studies have empirically evaluated the impact of allocative inequality on the gender earnings gap. One of the rare exceptions is Petersen, Saporta, and Seidel (2000), which, using longitudinal data on job applicants to a single high tech firm, finds surprisingly no evidence of gender-based allocative inequality, though they do find indications of race-based inequality. By comparison, Fernandez and Friedrich (2011) and Fernandez and Sousa (2005) find evidence of significant gender differences in preferences and job networks in allocative inequality (see also Fernandez and Fernandez-Mateo [2006] for racial differences in job networks). Still, since these studies are based on examinations of single firms, their representativeness in the larger economy is unclear.

Finally, valuative inequality in the U.S. is perhaps the most challenging to demonstrate. In this case, inequality is the product of discrimination against a particular class of jobs or occupations, making it difficult to document, and a plaintiff is rarely forthcoming (Petersen and Saporta 2004). Although valuative inequality is also morally unacceptable, bias is often unconscious (Fiske 1998; Fiske et al. 1991), and therefore often unrecognized. Further, given that valuative discrimination acts by changing perceptions of what kinds of work are socially valuable, while it may be the case that most would agree that this type of inequality is reprehensible, in practice it becomes normative and any given valuation is not typically viewed as problematic. Research argues that valuative inequality plays a significant role in the gender pay gap (England 1992), though the precise size of this effect is difficult to estimate.

## *Gender Inequality in Comparative Perspective*

Scholars have documented patterns of gender inequality similar to the U.S. in other developed Western societies, suggesting that similar social structures and norms also influence allocative versus within-job inequality in these contexts. As in the United States, gender equity legislation outlawing discrimination was adopted by the majority of advanced developed countries in the second half of the 20<sup>th</sup> century, including in Australia and across Western Europe (Ellis 1991). Accordingly, pay disparities at the occupation-establishment (i.e. job) level are typically small, with women on average earning 2-6% less than men doing the same work in the same establishment in Norway (Petersen et al. 1997) and 1.4-5% less in Sweden (Meyersson et al. 2001). These rates are in line with Petersen and Morgan's (1995) estimate of a within-job gap of 1-5% in the United States. Sorting into occupations and establishments thus explains the vast majority of the gender pay gap in Norway, Sweden, and the U.S., with occupational segregation appearing to be particularly important.

However, patterns of gender inequality in transition societies appear to differ. Absent a similar legacy of gender equity legislation, the earnings differential within occupation-establishment units remains a large component of the total gender pay gap in former planned economies. In their study of the Czech Republic, Křížková et al. (2010) document that Czech women earn on average 10 percent less than their male counterparts for doing the same work for the same employer. As such, this within-job component comprises nearly half of the total gender pay gap.<sup>44</sup> Křížková et al. (2010) do find that occupational segregation plays an important role, and that sorting on occupations matters more than sorting into establishments. Jurajda (2003) and

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<sup>44</sup> By comparison, within-job gender inequality accounts for between 5-25 percent of the overall gender earnings gap in the U.S. (Petersen and Morgan 1995), and 10-30 percent in both Norway (Petersen et al. 1997) and Sweden (Meyersson, Petersen, and Snartland 2001).

Sørensen and Trappe (1995) also find similar segregation patterns in Slovakia and the former East Germany, respectively, suggesting that within-job inequality may be widespread among former socialist societies.

Moreover, the previous socialist legacy appears to have left a significant imprint on gender inequality in other ways as well. Gender inequality is systematically lower among publicly-owned establishments across CEE countries, suggesting that organizations with greater ties to the socialist past remain more egalitarian (Jurajda 2003; Křížková et al. 2010; Penner et al. 2012). Market transition and particularly the growth in private sector jobs thus not only affects the level of gender inequality in the labor market (Heyns 2005), but its organization (van der Lippe and Fodor 1998).

One major limitation to understanding how market transition shapes the male-female earnings gap has been a lack of suitable data. Because most studies rely on individual cross-sectional data from a single time point or have analyzed longitudinal patterns over a relatively short time period, little is known about how market transition has affected trends in the gender gap since the beginning of transition. Trapido (2007), however, represents a rare exception; using longitudinal data between 1992 and 1998 on a single birth cohort across four former members of the Soviet Union, he finds evidence of rising gender pay differentials among the economically expanding Baltic States of Latvia and Estonia and a decline in gender inequality in the economically stagnant regions of Russia and Ukraine. Trapido points to the increase of female-dominated “occupational ghettos” (i.e. Charles and Grusky 2004) in growing market economies as an important factor contributing to gender inequality, akin to service sector expansion in other developed market societies. Similarly, comparing patterns of occupational sex segregation in East and West Germany, Rosenfeld and Trappe (2002) find segregation was higher in the East and different in form than in West Germany. Compared to the West, female-dominated occupations in

the East contained a higher proportion of women, though male-dominated occupations in the East were paradoxically less sex segregated. Interestingly, patterns of gender segregation in Eastern Germany have increasingly come to resemble those in the West. Likewise, Penner et al. (2012) report gender pay inequality in Slovenia has gradually conformed to Western-style forms of inequality with allocative inequality becoming more important.

### *A Cohort-Based Approach to Market Transition*

To appreciate how market transition alters the organization (i.e. allocative vs. within-job) and level of gender inequality we argue that a life course perspective, and specifically a cohort-based approach, is necessary. In his classic study of the Great Depression, Elder (1974) highlighted the differential effects of the Great Depression on individuals between and within cohorts. Although relatively little research has applied this type of cohort-based approach to market transformation, Mayer et al. (1999) find significant differences in the effects of German reunification across labor force cohorts. They document that after the fall of the Berlin Wall members of the oldest cohort in East Germany were pushed into early retirement in order to cope with rapid sectoral change. In contrast, middle-aged workers were among the most likely to retain their job, while members of the youngest cohort had the highest rates of downward and upward mobility. Similar trends have also been reported in China: Following the onset of reforms in the 1980s, younger cohorts experienced elevated job changes relative to older cohorts and benefitted more from working in quasi-marketized firms (Zhou and Moen 2001). Toro-Tulla (2014) likewise applies a cohort-based approach to economic development in Puerto Rico, finding major differences in the opportunity structure present across cohorts due to the rapidly changing

industrial landscape (see also Noonan, Corcoran, and Courant [2005] for a cohort-based analysis of gender wage gaps among U.S. lawyers).

Taken together, these studies suggest that the timing of institutional changes in individuals' lives (i.e., their age) produces important differences in the effect of these changes, requiring a cohort-specific understanding of economic transformation. We follow Glenn (2005) and Ryder (1965) in defining a cohort as an assemblage of social actors that have experienced the same social, economic, or political event. Cohorts capture meaningful differences according to two temporal dimensions: biographical life stage and historical experience. To appreciate the impact of market transition, it is necessary to examine both the current structural constraints and opportunities facing individuals, and their past opportunities and constraints (Mayer and Schoepflin 1989; Ryder 1965; Zhou and Moen 2001). A central aspect to life course analysis is the concept of cumulative advantage, in which individual differences in social privilege earlier in life provide the basis for subsequent advantages, magnifying social differences across time (DiPrete and Eirich 2006; Merton 1968).

Building on this idea, we argue that individuals in different cohorts who enter the labor market when the opportunity structure for inequality differed, may have experienced distinct effects of transformation. Marketization alters the opportunity structure through creating new economic opportunities and risks, such as the development of new occupations and labor market sectors, organizational restructuring within firms (e.g. greater managerial discretion in firm operations, implementation of performance pay strategies, and changes in the intensity of work), and market and business cycle fluctuations among other aspects. Workers across different cohorts are at different stages of their career and locations in the stratification system and are hence differentially susceptible to these new opportunities and risks. Individuals in middle-aged and



older cohorts, for instance, have accrued particular advantaged (or possibly disadvantaged) positions in the labor market. For example, relative to younger workers, older workers in state and market sectors have greater authority within organizations thanks to their tenure and more extensive social network connections, advantages that are likely to endure throughout transition. Older workers may also perceive greater risk associated with new economic opportunities thanks to these cumulative (dis)advantages, making them less inclined to take part in these opportunities (Zhou and Moen 2001). Thus we would expect older cohorts to be less susceptible to large-scale changes in inequality, due to their well-established career trajectories and resulting preferences.

Or, viewed from the perspective of more recent cohorts, we would expect those having recently entered the labor market or those still in the early stages of their careers to be at greater risk of new patterns of inequality inherent to the changing economic system, thanks to their less-well-established careers and potentially differing preferences. Absent well-established career trajectories, younger workers not only have accrued comparably smaller cumulative (dis)advantage relative to older workers, making them structurally and behaviorally more disposed towards new economic opportunities and the potential risks therein. Younger workers may also be better positioned to capitalize on the changing opportunity structure due to the simultaneous changes taking place in educational and training systems (Plevnik and Lakota 2010), which may make them better able to respond to the new demands of marketization (Zhou and Moen 2001). Moreover, relative to older cohorts whose gender beliefs may have been more strongly influenced by socialism, newer cohorts might espouse less egalitarian gender beliefs as the transition to capitalism furthers a more traditional gendered division of labor (Corrin 1992; Frieze and Ferligoj 1995; Funk and Mueller 1993; Hartmann 1976). Hence newer cohorts may harbor different beliefs about gender typical work, suitable forms of gender inequality, and appropriate levels of gender

inequality. Beyond changing social norms, continual rises in female educational attainment have also furthered inter-cohort differences by reshaping the labor force supply (Mateju, Rehakova, and Simonova 2007; Pollert 2003). The effects of market transition are therefore moderated by cohort, as individuals across cohorts face distinctive age-graded risks and options that stem from the timing of economic transition in their lives. Consequently, cohorts-specific patterns of inequality provide insight into the opportunity structure (and resulting expectations) that were available to individuals at the time they entered the labor market.

### **The Slovenian Case**

We investigate the influence of the transition to a market-based economy on gender inequality in Slovenia. Although a postsocialist society, as part of the former Yugoslavia, Slovenia enjoyed considerable autonomy from Moscow under Communist rule. This meant the state was controlled by its own Communist party that espoused the official Marxist-Leninist ideology, and economic planning and decision-making was more decentralized than in Soviet satellites (Bandelj 2008). With approximately two million inhabitants, at the dawn of transition the region of Slovenia was the wealthiest region in Central and Eastern Europe,<sup>45</sup> and was the most developed and educated region in Yugoslavia. Further, market-based reforms implemented in the 1980s gave enterprise managers partial independence, so that Slovenia had a quasi-market-based system even prior to the onset of major economic restructuring (OECD 1997, 2011b).

Slovenia declared its independence from Yugoslavia in June 1991, embracing extensive economic reform. In contrast to the shock therapy reform programs in the Czech Republic, Latvia, and Romania that relied on mass, centralized distribution of ownership vouchers to expedite the

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<sup>45</sup> For instance, in 1991 Slovenia's per capita GDP was similar to that of Greece and Portugal (OECD 1997).

transition to capitalism, Slovenia built on its existing quasi-market structure to implement privatization and marketization programs that were comparably decentralized and gradual. In turn, this provided firms a more direct role in their conversion to private companies and ensured continuity in firm operations through preserving the interests of existing employees and managers (OECD 2011b). Aided by this ownership structure and the strong role of the state in overseeing economic transformation, market restructuring in the first two decades after independence had a comparably minor effect on unemployment and firm operations in Slovenia. Subsequently, Slovenia maintained strong and stable growth throughout much of the restructuring process, leaving Slovenia the most successful transition economy in Central and Eastern Europe prior to the global financial crisis (OECD 2011b).

Similar to many Western European economies, wage determination in Slovenia is highly coordinated. Slovenia's modern wage determination system originated from the 1996 Social Agreement, in which government and representatives of employers and employees established broad compensation guidelines at three distinct levels. At the top level, a general agreement is binding for all employees in the economy, indexing wage increases for the entire private sector to inflation. The second and third tiers of wage coordination comprise sector and enterprise-level agreements, which allow these respective levels to negotiate earnings increases according to productivity, performance, and other guidelines (Banerjee, Vodopivec, and Sila 2013). Despite this, earnings differ little across industrial sectors, suggesting a considerable degree of wage indexing across industries (OECD 1997). While this system has undergone several changes since the mid-1990s, collective agreements nevertheless covered 96 percent of workers in 2007, with the remaining 4 percent comprising managers who received individual contracts (Banerjee et al. 2013).

Compared to other EU member states, the raw gender pay gap in Slovenia is among the lowest. According to Eurostat (2014), the unadjusted male-female earnings gap was 16.7% in the EU27 and 2.5% in Slovenia in 2012. This is largely attributable to the high rate of full-time female employment, as well as women's overrepresentation in the public sector, which tends to pay better than the private sector (Eurostat 2014). However, one comparative study concluded that after controlling for individual characteristics, differences in the gender gap increased dramatically in Slovenia, so that the unadjusted pay gap may not provide a complete picture of gender inequality in pay (Plantenga and Remery 2006).

## **Data**

To examine the cohort-specific effects of market transformation on gender inequality we use longitudinal linked employer-employee administrative data from Slovenia between 1993 and 2007. These data are unique in two respects. First, they contain information on the entire Slovenian working population. Given the population-level nature of these data, they represent a significant improvement over standard survey data, which seldom contain observations of men and women working in the same establishment and occupation. Second, these data span a long temporal period, importantly including the early years of market transition and up to the beginning of the global financial crisis in 2009.

These data have two main limitations, however. First, we are unable to differentiate between regular and overtime pay, as earnings information is derived from individual tax records. However, as supplemental analyses suggest overtime is relatively uncommon in Slovenia, indicating this limitation is unproblematic. Analyses therefore focus on inequality in total pay. Second, like other registry data, these data have limited individual-level covariates. For instance,

the data contain no information on parental status, meaning we are unable to control for the influence of family responsibilities.<sup>46</sup> The data also contain no information on the number of hours individuals work. Fortunately, both overtime and part-time work are relatively uncommon in Slovenia (Eurostat 2015; OECD 2016), suggesting this poses few problems. Over the period of observation, labor force participation rates among individuals aged 15-64 slowly increased, from 65.4 percent to 75.9 percent among men and 56.7 percent to 66.8 percent among women (World Bank 2016); thus changes in labor market participation likewise pose few problems.

We restrict our investigation to workers between the ages of 17 and 66 who worked in mixed-gender establishments, occupations and occupation-establishment units, resulting in over 10 million person-years from 1.1 million different individuals nested within 128,000 establishments.<sup>47</sup> In any given year we observe an average of 667,000 individuals within 54,000 establishments and 1,500 occupations, totaling 222,000 occupation-establishment (job) units. The occupational scheme relies on Slovenia's national classification system, which roughly parallels the ISCO-88 code. Education is coded using 14 categories captured by dummy variables. Experience is measured continuously in years, calculated by subtracting years of education and school starting age from current age. We also include a term for experience squared in order to account for nonlinearity in the relationship between experience and pay. We construct five labor force cohorts, differentiated by 10-year birth intervals spanning individuals born between 1934 and 1983.<sup>48</sup> The size of each cohort, as well as other key descriptive information is reported in Table 4.1.

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<sup>46</sup> As a result, we are unable to test mechanisms related to parental status such as the motherhood penalty.

<sup>47</sup> Although units that are not mixed gender will not directly contribute to the estimation of gender differences, they will contribute to the estimation of the other coefficients and covariances, and can thus indirectly affect the estimates of the gender differences. As such, we report results from models restricted to mixed-gender units.

<sup>48</sup> We define cohorts according to birth year, rather than labor market entry year, as the data contain no measure of years of labor force experience and thus do not account for employment gaps over time. While differential labor force participation rates for men and women could potentially threaten the validity of this indicator variable, participation

Table 4.2 provides the ages of individuals in these five cohorts during recent milestones in Slovenian history. Individuals in the oldest two cohorts, born from 1934-43 and 1944-53, were infants to early adolescents at the time of the formation of Yugoslavia in 1945. By 1991, when Slovenia declared its independence and entered into transformation, these same cohorts were middle-aged and had spent a substantial share of their working lives under socialism. The careers (and associated cumulative (dis)advantages) of individuals in the 1934-43 and 1944-53 cohorts was therefore well-developed at the onset of transition due to their extensive labor market experience. By 2007, members of these cohorts were nearing or had reached our censored age limit. Still, because these cohorts were middle aged at the beginning of transition in 1991, we observe them working several years during transition, offering a glimpse into how gender inequality within these cohorts changed throughout marketization.

By contrast, at the beginning of transition in 1991, members of the 1964-1973 cohort had recently left school and were in the early stages of their working careers. Although individuals in this cohort experienced the bulk of their education and job-related training under socialism, they were uniquely positioned at the beginning of their careers when restructuring and privatization began. The 1964-1973 cohort therefore had little labor market experience at the start of transformation, meaning they had negligible cumulative (dis)advantage from the socialist era as they confronted a host of new economic opportunities and risks that would have implications on their future working lives. Similarly, individuals in the 1974-83 cohort were the first complete cohort to enter the labor market since the start of transition. While older members of this cohort were among the last to be educated and trained in the socialist era, younger members of this cohort received schooling and training under a newly-reformed education system (Plevnik and Lakota

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rates grew at approximately the same rate for women and men across the population as a whole, as well as among younger women and men (i.e. aged 15-24) during the period of observation (World Bank 2016).

2010). Having never worked in the pre-reform era, the 1974-83 cohort was the first cohort to be fully exposed to the changing opportunity structure of market transition in Slovenia.

## Methods

To analyze the cohort-specific nature of market transition on gender inequality we estimate a series of linear regressions that exploit the multilevel structure of the data. To first examine overall trends in gender inequality we estimate the model:

$$\ln(w_i) = x_i\beta + \varepsilon_i \quad (1)$$

where  $\ln(w_i)$  is log total pay for individual  $i$  ( $i = 1, 2, \dots, N$ ),  $x_i$  is a vector of covariates including a dummy variable for female, educational attainment dummies, experience, and experience squared, separately for each year in our data. This first equation does not control for individuals' establishment or occupation, thereby capturing the average level of gender inequality across the labor market. To understand how transition has altered the structural feasibility of various forms of inequality, we next investigate trends in the average levels of gender inequality found within establishments, occupations, and occupation-establishment units by estimating the model:

$$\ln(w_i) = x_i\beta + \gamma + \varepsilon_i \quad (2)$$

where  $\gamma$  represents fixed effects for either the establishment, occupation, or the occupation-establishment unit, respectively (for a similar approach see Petersen, Penner, and Høgsnes 2014).<sup>49</sup>

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<sup>49</sup> Typically, fixed effects regression models include fixed effects for individuals, and thus provide information about the within-person effects of covariates (Wooldridge 2002). Our analyses instead include fixed effects for either

Comparing results from models with and without various fixed effects allows us to examine the degree to which the processes creating gender inequality have changed throughout this period. Of particular interest is whether men and women who are in the same occupation-establishment unit receive different pay, or whether gender differences arise because men and women are sorted into different occupations-establishment units. These comparisons help us understand what kinds of gender inequality is considered acceptable, and how this has changed throughout transition.

Our primary goal – describing how the changing opportunity structure has produced cohort-specific effects – can be investigated by comparing cohort-specific gender gaps. We do this by estimating Equations (1) and (2) separately by cohort for each year. Results from these models provide cohort-specific information about the average earnings penalty associated with being female at each relevant level of analysis (e.g. population, occupation, establishment, or occupation-establishment) net of other covariates, for each year between 1993 and 2007. Gender differences are statistically significant in nearly all cases, with  $z$ -statistics typically ranging from 15 to 125. Occasionally, however, coefficients are not distinguishable from zero due to the relatively small number of observations, particularly among the youngest cohort in the early-1990s (when many individuals had not yet begun working). We represent these non-significant estimates with a hollow shape in our figures. Appendix B4.1-B4.4 contains the coefficients used to construct our figures. All coefficients are estimated with robust standard errors, which account for clustering at the respective establishment, occupation, or occupation-establishment levels.

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establishments, occupations, or occupation-establishment units to assess within-unit gender differences (e.g. the difference in pay between men and women in the same occupation and establishment).



## Results

### *Aggregate Changes in Gender Earnings Inequality*

Figure 4.1 depicts aggregate changes in population, within-establishment, within-occupation, and within-occupational-establishment (i.e. job-level) gender inequality. Since the beginning of transition, total population gender inequality increased nearly two-and-a-half times: Women earned 10.1 percent ( $1 - \exp^{-.106} = .101$ ) less than men at the beginning of transition and 23.6 percent less than men by the late 2000s.<sup>50</sup> Much of this increase occurred in the initial years of transformation, though the gender gap also rose steeply in the 2000s.

Comparing within-job, within-occupation, and within-establishment gender inequality to gender inequality at the population level, we find that within-occupation and within-establishment gender inequality were initially higher than gender inequality across the population as a whole. This indicates that in the initial years of transition, women typically worked in better-compensated occupations and establishments than men, which helped mitigate gender differences at the population level.<sup>51</sup> During these early years, we find that nearly all of the gender earnings gap was due to differences within occupation-establishment units (evinced by levels of within-job inequality that are nearly equal to the levels of inequality observed at the population level). If job-level inequality were becoming increasingly unacceptable and infeasible as Slovenia transitioned to a market society, we would expect occupation-establishment inequality to shrink over time

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<sup>50</sup> These differences are larger than those reported in official statistics for Slovenia, which do not account for human capital differences. This is consistent with previous findings showing that the earnings gap net of human capital is substantially larger in Slovenia (Plantenga and Remery 2006). According to UNICEF (1999), the gender earnings gap net of human capital variables is also larger than the unadjusted gap in Hungary, Kazakhstan, Latvia, Poland, Russia, and Slovakia, suggesting Slovenia is not the only postsocialist economy to exhibit this pattern of gender inequality.

<sup>51</sup> Interestingly, occupation-establishment differentials during this time were smaller than the overall population gap. Thus, while women tended to work in better-paid establishments and occupations, they were nevertheless employed in lower-paid jobs within these units. This could occur if, for example, women were more likely than men to work in better-compensated occupations such as law, more likely to work in better-compensated establishments like a law firm, but less likely to be a lawyer in a well-paying law firm.

relative to allocative inequality. Instead, we find that in absolute terms the level of occupation-establishment inequality has risen over time, and that it has remained a large and persistent component of the gender gap that we observe in the labor market more broadly. Hence, compared to Western countries like the United States, Sweden, and Norway where occupation and establishment sorting explain 70-90 percent of the gender gap (Meyersson et al. 2001; Petersen et al. 1997; Petersen and Morgan 1995), sorting in Slovenia remains relatively less important: by 2007 it comprised 29 percent of the total gender pay gap.<sup>52</sup> The majority of gender inequality in Slovenia therefore occurs between women and men performing the same work for the same employer, but who nevertheless receive different pay. These findings are congruent with Křížková et al. (2010), which shows that within-job inequality plays a significant role in Czech gender inequality.

Despite the comparably greater importance of within-job gender inequality vis-à-vis allocative inequality, we do see some evidence that marketization has altered the structure of gender inequality. Although within-job gender inequality grew over this period, gender inequality at the population level grew even faster, so that allocative inequality went from accounting for virtually none of the gender pay gap to accounting for 29 percent in 2007. The rising significance of sorting between occupations and establishments suggests that market transition in Slovenia has been accompanied by an increasing shift towards Western-style forms of inequality as in the U.S., Norway, and Sweden (Penner et al. 2012), even though within-job inequality remains the dominant source.

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<sup>52</sup> We obtain this number for the year 2007 by subtracting the occupation-establishment gap from the population gap divided by the population gender gap, i.e.:  $[(.269)-(.191)] / (.269) = .290$ . By contrast, sorting across occupations and establishments explained virtually none of the gender gap in the early 1990s (see Fig. 4.1).

### *Cohort Changes in Population Gender Earnings Inequality*

Figure 4.2 presents population-level gender differences separately by cohort, displaying how market transition differentially affected gender inequality by cohort. As this figure reveals, gender differences vary substantially by cohort.<sup>53</sup> Most notably, the gender gap remained fairly small and stable among the two oldest cohorts, but increased dramatically in the youngest cohorts.

Among the two youngest cohorts (i.e. those born between 1974-83 and 1964-73) we see marked changes in gender inequality. At the beginning of transition in 1991, individuals in these cohorts were aged 8-17 or 18-27, and were still attending school, had just begun working, or were in the early phases of their careers. Because many individuals in the very youngest cohort were still in school in the early 1990s, this cohort continued to add members to the labor force into the 2000s, so that its composition changed across the years. As a result, initially low and continually rising inequality among this cohort may partly reflect compositional changes. However, we also see steep increases in inequality during the early years of transition for the second youngest cohort (1964-73), the majority of which had already entered the labor force by 1993 when our data begin. Thus despite compositional effects influencing inequality among the 1974-83 cohort, the initial spurt in inequality among the 1964-73 cohort and later patterns among both cohorts provides strong evidence that individuals in younger cohorts were more strongly affected by the rapidly changing socioeconomic landscape of market transition.

Moreover, Figure 4.2 indicates that market transition appears to have stronger effects on younger compared to older cohorts.<sup>54</sup> Whereas the gender gap among the 1954-63 cohort increased

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<sup>53</sup> Although the results in Figure 4.2 were estimated separately by cohort, we conducted supplemental analyses to compare differences across cohorts. These analyses showed that the cohort-specific female earnings penalties were significantly different from each other, except for the 1974-1983 cohort in the early 1990s and for the 1934-43 cohort in the late 2000s.

<sup>54</sup> Retirement-related compositional changes may have affected the oldest cohort. While changes in the gender gap of this cohort may have partly been driven by labor force turnover, given the relative stability of inequality in this and the second oldest cohort, compositional effects are less of a concern in these cohorts.

from 10.1 to a 15.1 percent in the first three years of our data, the gap increased nearly *five times* from 5.2 to a 24.2 percent for the 1964-73 cohort during this same period. Among the youngest cohort the growth in inequality was even larger and continued to increase throughout the 2000s, though, as noted earlier, part of this rise may be compositional in nature. Furthermore, aggregate changes in inequality appear to be rooted in cohort-specific effects. Nearly all of the rise in aggregate population gender inequality in the early years of transition was concentrated among the 1964-73 cohort, and to a lesser degree, the 1954-63 cohort. Similarly, the rise in the aggregate population gender gap in the 2000s appears to have been driven primarily by growing inequality among the 1974-83 cohort. These results highlight important cohort-based differences in the gender gap, showing that the Slovenian transition appears to have more sharply affected individuals in younger cohorts. Our results are also important insofar as they portend a dramatic rise in population-level gender inequality as older cohorts (with lower levels of gender inequality) continue to retire and are replaced by younger cohorts (with substantially higher levels of gender inequality).

#### *Cohort Changes in Occupation-Establishment Gender Earnings Inequality*

While Figure 4.2 demonstrates that there were larger structural shifts that resulted in women receiving lower pay than men, particularly among the younger cohort, it is unclear whether these differences are the result of processes occurring within jobs or the result of differences in how men and women came to be sorted into different jobs. Figure 4.3 thus provides insight into how the opportunity structure for gender inequality in Slovenia changes by documenting the degree to which these different inequality-generating processes were responsible for the cohort patterns in Figure 4.2. Specifically, Figure 4.3 reports the occupation-establishment (i.e. job-level)

gender earnings gap by cohort; because cohort-specific gender gaps in Figure 4.3 are estimated net of yearly occupation-establishment fixed effects, comparing Figure 4.2 to Figure 4.3 tells us about the relative importance of allocative versus within-job inequality. To the degree that the gender differences in Figure 4.3 resemble those in Figure 4.2, we can attribute the rise in population gender inequality (in Fig. 4.2) to within-job inequality-generating processes as yearly pay differences between jobs do not account for the gender pay gap for that cohort in that year. To the extent that the differences in Figure 4.3 are smaller than those in Figure 4.2, we can attribute differences to allocative processes, as between-job differences account for this portion of the gender gap for that cohort in that year.

Overall, we see that although allocative processes become more important over time, the majority of the rise in gender inequality that we observe is due to the growth in within-job inequality. Similar to the cohort-specific changes in population-level gender inequality reported in Figure 4.2, Figure 4.3 reveals that within-job gender inequality spiked dramatically in the early years of transition for the 1964-73 cohort, rising from 5.4 to 23.3 percent between 1993 and 1996. We also observe similar though smaller rises in job-level inequality among the middle (1954-63) cohort during this same period, as gender inequality increased from 9.8 to 14.2 percent. Nearly all of the growth in population gender inequality in the initial years of marketization among the 1964-73 and the 1954-63 cohorts that we observe in Figure 4.2 is therefore the product of rising job-level inequality. Moreover, these results indicate that virtually the entire rise in aggregate population gender inequality in the early 1990s (see Fig. 4.1) resulted from increasing job-level inequality among these two cohorts. Within-job inequality also rose among the youngest (1974-83) cohort in the 2000s, suggesting that growth in their cohort-specific population gender differentials (see Fig. 4.2) were also largely driven by within-job inequality. Still, aside from the

youngest cohort, job-level gender differences have slowly declined from the mid-1990s, though cohort-specific differences in within-job inequality remain important even at the end of the period. Thus, with the exception of the most recent cohort where within-job inequality continues to increase, job-level inequality became substantially more common at the onset of marketization, but its prevalence has subsequently waned over time.<sup>55</sup>

#### *Differential Earnings Growth: A Cohort-Specific Mechanism of Inequality*

What could account for the particularly large growth in gender inequality among the two youngest cohorts? Figures 4.4a and 4.4b depicts one possible mechanism – differential growth in pay among men and women. Among the 1964-73 cohort, which experienced substantial increases in inequality in the early years of transition, men’s real earnings rose steadily across time while women’s earnings initially faltered before subsequently growing at a similar rate to men’s (see Figure 4.4a). Auxiliary analyses indicated that stagnation in women’s earnings in the early 1990s was due to a sharp and sustained increase in gender differences in starting pay within jobs (i.e. when years of tenure in occupation-establishment unit was zero). Conversely, while gender differences in the returns to years of tenure within jobs also increased briefly at this same time, these differences declined to non-significance across time (results available upon request). Because women’s returns to job tenure never outpaced men’s, this meant women were never able to close initial differences in job starting pay, leading to an enduring and stable gender pay gap in this cohort.

This figure also reveals a slightly different pattern of gender inequality among the 1974-1983 cohort. Although men and women in this cohort entered the labor market on roughly equal

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<sup>55</sup> Cohort-specific within-establishment and within-occupation gender differences, which also reveal enduring cohort-based differences in sorting patterns since transition, are depicted in Appendix A4.1 and A4.2.

footing, men's earnings growth outpaced women's by approximately 25% each year, leading to a widening gender earnings divide over time. Once again, supplementary analyses showed that rising inequality was driven by differential starting pay within jobs, with gender differences in job tenure playing a more minor role. However, in contrast to the 1964-73 cohort, gender differences in within-job starting pay among the 1974-83 cohort widened throughout the period of observation, contributing to an ever-expanding gender gap among these individuals. As a result, heightened gender inequality among the two youngest cohorts since the onset of marketization was attributable to gender differences in within-job starting pay, though patterns diverge somewhat between cohorts. Although we are unable to identify further mechanisms underlying the rise in differential starting in these cohorts due to a limited number of covariates in our data, this indicates that marketization may possibly have accompanied a rise in statistical discrimination among the two youngest cohorts since the beginning of transition, with employers "learning" about worker quality over time (Altonji and Pierret 2001). We see this insofar as the gender gap was largest when men and women started working in a new job and decreased with years of tenure in a given job, suggesting employers may be statistically discriminating based on ascriptive attributes such as gender most greatly at the beginning of a new employment arrangement, and decreasing their reliance on these signals as they gather additional information about a worker's true quality. Comparing these trends to Figure 4.4b, while we see slight indication of stagnation in women's pay growth in the early 1990s among the 1954-63 cohort, cohort-specific earnings growth among men and women in these older cohorts nevertheless remained approximately in step. As a result,

economic transition did not result in large gender earnings divergences among these cohorts, suggesting the changing opportunity structure affected these cohorts to a smaller degree.<sup>56, 57</sup>

## **Discussion**

Given that the transition to capitalism is accompanied by new structures and norms that alter both labor supply and demand, gender scholars have long been interested in the effects of market transition on gender equality. In this paper we draw on life course theory and take a cohort-based approach to shed new light on how transformation affects gender inequality, using Slovenia as a case study. We argue that the transition to a market-based economy should produce cohort-specific patterns of gender inequality, as workers in different cohorts are differentially susceptible to economic transformation processes (Zhou and Moen 2001). In doing so we not only further life course research among transition societies, but also extend Petersen and Saporta's (2004) notion of the opportunity structure for discrimination to the organization of markets more broadly.

We find substantial cohort-specific differences in how market transformation affected gender inequality. As predicted, the largest increases in population gender inequality among individuals were found in younger cohorts, whose careers were not well established when the transition began. By contrast, the gender gap remained relatively stable among workers in older

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<sup>56</sup> We find similar results for the oldest cohort (not shown), though retirement appears to have introduced noise, somewhat obscuring the general trend.

<sup>57</sup> As an additional robustness check we analyzed cohort-specific trends in within-gender earnings inequality, which revealed that earnings inequality remained essentially flat over time across cohorts (results available upon request). Similarly, the returns to education have been largely uniform among men and women (Stanovnik 1997). Consequently, cohort-specific trends in gender inequality appear to be driven largely by gender differences in starting pay within jobs, rather than rising within-gender earnings inequality or differing returns to education by gender.



cohorts since transition. The rising gender inequality we observe in the population thus appears to have been driven primarily by cohort-specific increases. Practically all of the growth in aggregate gender inequality in the early years of transition was confined to the then-youngest cohort. Later in the early 2000s, inequality began to rise sharply again and was likewise concentrated among a new cohort of young workers. The large gender differences concentrated in the youngest cohort suggest that inequality is likely to continue to increase over time as older cohorts – where there is less inequality – continue to retire.

Results also suggest that younger cohorts experienced a different form of gender inequality, and that the organization of gender inequality has changed since the beginning of marketization. Compared to relative stability or declines in job-level differences among the oldest cohorts, the younger cohorts experienced rises in job-level inequality, with the steepest rise in the youngest cohort. Market transition thus accompanied an increase in the degree to which women and men doing the same work for the same employer received different pay among more recent labor force entrants. Importantly however, the relative magnitude of the allocative processes that sort women and men into different jobs has also increased. This is due in part to changes in the older cohorts, where we see decreases in the absolute level of within-job inequality in the face of relatively stable overall gender pay differences. This means that in these cohorts the amount of gender inequality did not change, but became increasingly a function of women and men being sorted into different jobs, and less about within-job pay disparities. But even in the younger cohorts where within-job inequality has grown substantially – and is a much larger factor than the allocative processes sorting men and women into different jobs – allocative processes have also become more important than they were previously. Consequently, economic change in Slovenia has been accompanied by a slow but steady transition to Western-style forms of inequality, with sorting increasingly playing

a larger role in gender inequality (Petersen et al. 1997; Petersen and Morgan 1995), even though within-job differences are still more important in the younger cohorts.

We point to one potential explanation – differential earnings increases – as a cohort-specific mechanism of gender inequality. As we found, men in the cohort that entered the labor market immediately following the beginning of economic transition received steady pay increases over time while women’s pay initially faltered before growing. This brief stagnation in women’s earnings growth yielded an indelible gender gap for this cohort. For the youngest cohort, which entered the labor market in the late 1990s and early 2000s, men’s earnings grew at a consistently faster rate than women’s, contributing to a widening gap over time. Auxiliary analyses suggested that nearly all of the rise in within-job gender inequality among these cohorts was attributable to an increase in gender differences in starting pay within jobs, with differences in returns to job tenure playing a more minor role. Although we can only speculate as to the cause of increased gender differences in starting pay due to limited covariates, these results suggest that transition may have accompanied a rise in employer reliance on statistical discrimination against women in the youngest cohorts, with employers “learning” about worker quality over time (Altonji and Pierret 2001).

The markedly greater increase in gender inequality among younger cohorts suggests that economic restructuring altered the opportunity structure for inequality. While the data do not allow us to discern whether this rise in inequality resulted from actions on the part of employees, employers, or a combination of the two, the growth in job-level inequality nevertheless suggests that the transition to capitalism in Slovenia changed the structural feasibility as well as social norms regarding acceptable forms and levels of gender inequality. Although male-female earnings differences have been shown to vary across economic sectors in other CEE countries (Křížková et

al. 2010), in supplemental analyses we find that the cohort patterns in gender inequality in Slovenia were comparable in privately- and publicly-owned establishments (results available upon request). As a result, these findings support the idea that the transition to capitalism – and not simply privatization – reinforces gender differences in the realm of work, disproportionately rewarding men and reinforcing male dominance (Corrin 1992; Funk and Mueller 1993; Hartmann 1976). Likewise, the stability of these patterns over time indicates that changes in the cohort-specific opportunity structure were enduring across individuals' life course. The persistent, cohort-specific effects of market transition in Slovenia attest to the fundamental imprint that economic restructuring has on individuals' lives and the role of cohorts in shaping this experience. Consequently, like the large-scale societal changes detailed in Elder's (1974) classic study of the Great Depression, we suggest that the effects of market transition can be fruitfully viewed through a life course lens.

While it is not possible to make strong generalizations from an examination of one formerly socialist society, there is little reason to believe that Slovenia is an exceptional case (though the changes related to the transition in Slovenia may be smaller than in countries that attempted a shock therapy approach). More generally, these results speak to how the transition to capitalism and structural conditions influence the organization of gender inequality. If, as sociologists often suggest (e.g. Reskin 1998), employers discriminate whenever possible so that discrimination is common in the labor market, we can interpret these results as suggesting that the opportunity structure for discrimination changed, resulting in cohort-specific opportunities for within-job pay discrimination in Slovenia. At the same time, we also observe a rise in allocative inequality, suggesting that new forms of inequality (and potentially discrimination) are becoming increasingly important under growing capitalistic, Western influence. Thus, our results indicate that structural

factors yield decisive influences on social stratification processes by shaping the feasibility and acceptance of various forms of inequality, and that these changes appear to have had the largest effects among individuals whose careers were not yet established.

## **CHAPTER 5: Summary and Conclusions**

The concept of “market disruption” has become increasingly popular, though its consequences have remained restricted to a handful of outcomes thus far. This dissertation expands the purview of disruptions’ effects by investigating how two common types of disruptions, technology-induced and government-induced disruptions, influence inequality. Specifically, I examine how the spread of computers and the transition to capitalism are related to wage differentials and gender earnings differentials, respectively, as these represent two of the largest and most important disruptions in recent times. Compared to prior work, I focus particularly on the heterogeneous consequences of these disruptions by revealing their differential inequality impacts across birth cohorts as well as between and within work establishments. In doing so this dissertation furthers our understanding of how these phenomena contribute to social stratification.

Chapters 2 and 4 show how disruptions in the life course may yield uneven effects across cohorts. As described in Chapter 2, the spread of computers in Western Germany was most strongly related to wage inequality among older cohorts who came of age and entered the labor market significantly before the beginning of the computer revolution in the early-1980s. By contrast, individuals in younger cohorts that were born closer to the start of the computer revolution were less influenced by computerization. Moreover, cohorts importantly moderated the relationship between computers and inequality across the wage distribution. Although aggregate results suggest computers correlate with higher upper-tail inequality as predicted by skill-biased technological change (SBTC) in the mid-1980s and early-1990s, this is driven primarily by cohort differences in the wage returns to computer use. Cohorts also strongly moderated the computer earnings premium in the 2000s, especially among low-wage workers. The strong, direct link

between computers and inequality posited by SBTC is therefore not supported as computerization is more greatly related to inequality among particular cohorts.

Whereas Chapter 2 indicated computerization affected older cohorts more strongly, Chapter 4 demonstrates that market transformation impacted younger cohorts more greatly in Slovenia. In particular, marketization in Slovenia coincided with a rise in gender earnings inequality among the two youngest cohorts that either were in the early stages of their careers at the beginning of marketization or entered the labor market after the start of transformation. This disruption also changed the organization of gender inequality in the labor market, with younger cohorts experiencing a different form of inequality. While within-job gender differences in pay remained stable or declined among older cohorts, among younger cohorts within-job inequality grew, with the sharpest rise in the youngest cohort. Market transition thus accompanied an increase in the degree to which women and men doing the same work for the same employer received different pay among more recent labor force entrants. Importantly however, the relative magnitude of the allocative processes that sort women and men into different jobs has also increased. This was driven primarily by older cohorts, though allocative inequality also grew among younger cohorts. As a result, economic reforms in Slovenia have accompanied by a slow but steady transition to Western-style forms of inequality, with sorting increasingly playing a larger role in gender inequality (Petersen et al. 1997; Petersen and Morgan 1995), even though within-job differences are still more important in the younger cohorts.

In addition to differential effects across cohorts, Chapter 3 shows that disruptions may also have dissimilar impacts on earnings inequality between and within work establishments in Germany. In particular, this chapters shows that investments in information and communication technology (ICT) are related to skill-based (i.e. educational attainment and formal qualification)

inequality between and within establishments, and class-based (i.e. collective bargaining status) inequality within establishments according to cross-sectional estimates. However, net of establishment fixed effects, changes in ICT investments do not have a significant effect on changes in either between- or within-establishment inequality. As a result, this provides little evidence for either skill- or class-biased technological change at the establishment level. Instead, this suggests the well-known association between computerization and inequality appears to be driven by unobserved establishment heterogeneity. Still, this chapter finds a faint but nevertheless significant influence of lagged ICT investment on between-establishment inequality; thus computerization may have a minor influence on workplace inequality over a longer period.

These results reveal how disruptions may have heterogeneous consequences on social stratification. In the case of computerization, because this process disrupts the relative productivity of particular types of labor tasks (Autor et al. 2003; Goos and Manning 2007; Spitz-Oener 2006), this is linked to cohort differences in the relationship between computers and inequality, as shown in Chapter 2. Although Chapter 3 finds little evidence of a causal effect of computers on establishment-level inequality, computer investments tend to be higher in workplaces with greater heterogeneity in pay. ICT investments may also slightly contribute to between-establishment inequality in the long term. Thus while its causal effect remains unclear, computerization is nevertheless strongly associated with stratification across birth cohorts and establishments. In the case of market transformation, given that this disruption alters the existing gendered employment arrangement (Fodor 2002; Giddens 2002; van der Lippe and Fodor 1998), this is related to cohort-specific changes in gender inequality, as demonstrated in Chapter 4. More importantly, marketization coincided with changes in the organization of gender inequality across cohorts. As

a result, at least in the case of Slovenia, the transition to capitalism therefore differentially affected the life patterns of cohorts in two important ways.

Overall, these findings indicate disruptions have far-reaching and diverse social consequences. Although computerization and marketization represent disparate types of disruptions, they both fundamentally alter the life patterns of successive cohorts. Therefore like the large-scale societal changes detailed in Elder's (1974) classic study of the Great Depression, this dissertation suggests that the effects of technology-induced and governmental-induced disruptions can be usefully viewed through a life course lens. Furthermore, as sociologists have long asserted (Baron and Bielby 1980; Bielby and Baron 1986; Tomaskovic-Devey et al. 2006), this dissertation not only shows that establishments play a central role in the creation and maintenance of categorical social inequalities (see Chapter 4), but increasingly also gradational inequalities (see Chapter 3). Thus, this dissertation highlights how disruptions shape inequality in nuanced ways and that cohorts and workplaces represent important structural boundaries that determine this effect.



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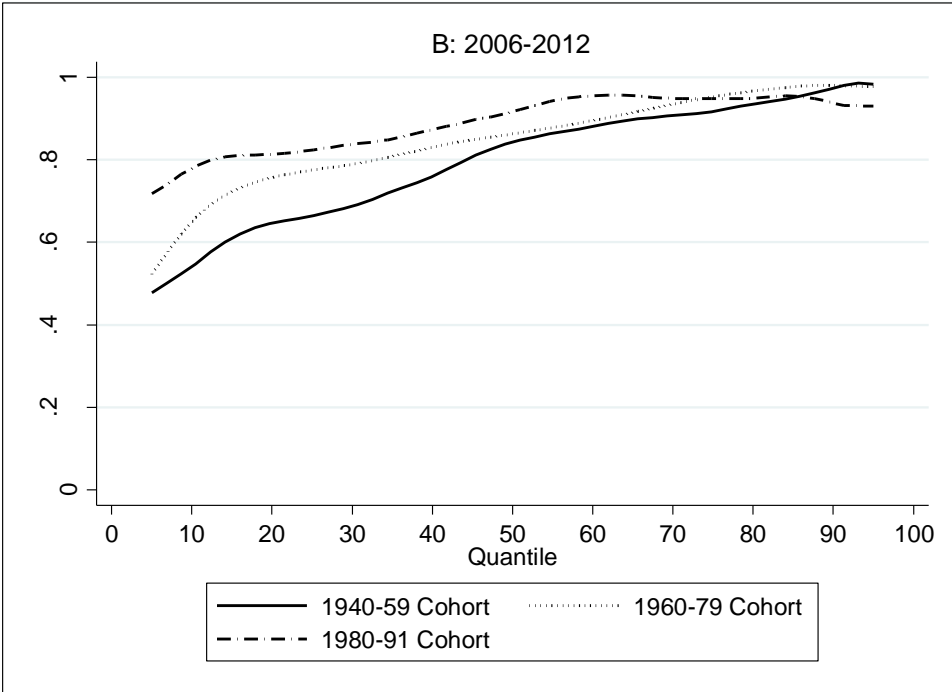
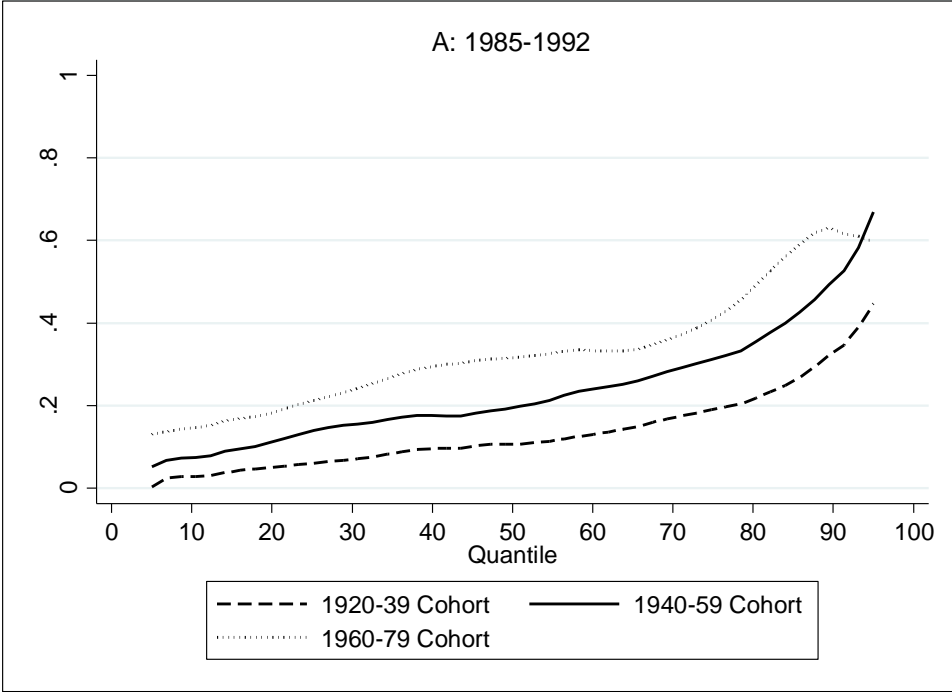
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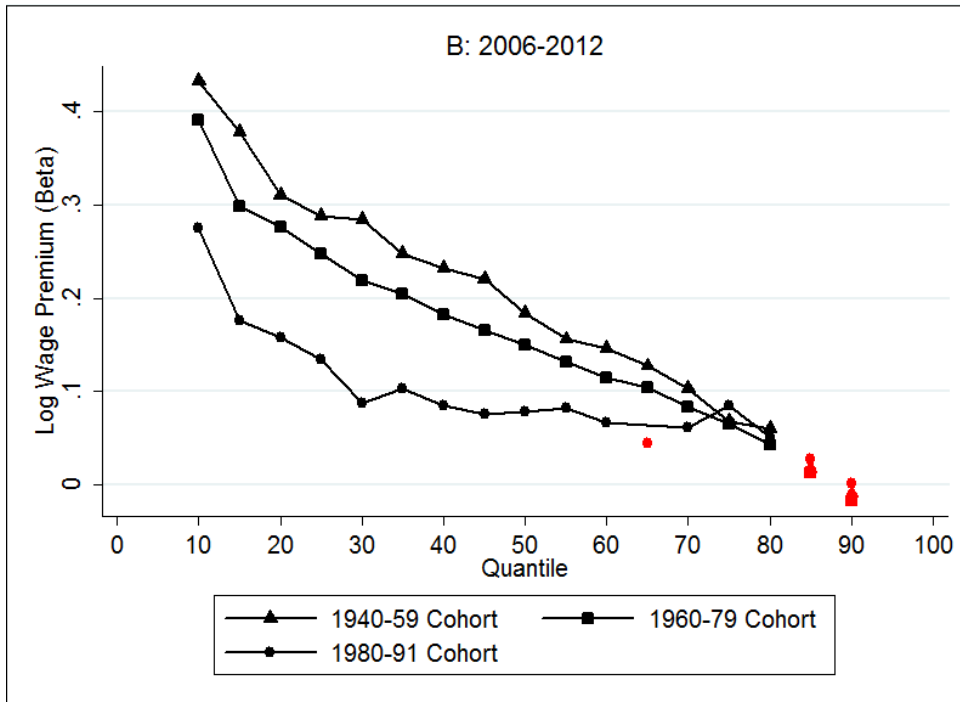
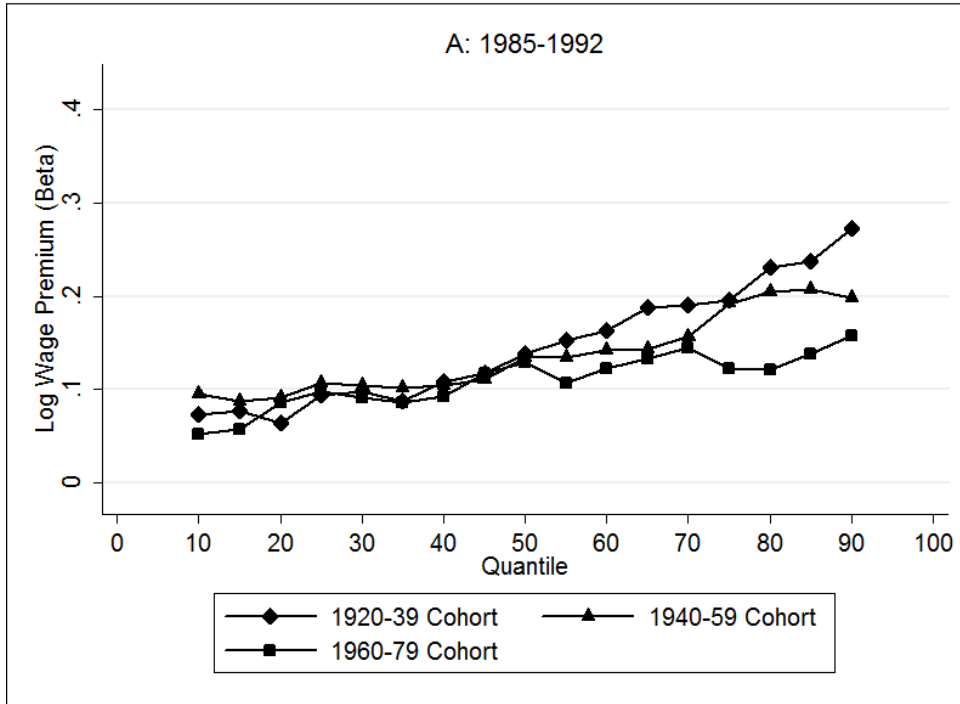
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**Figure 2.1** Cohort-Specific Computer Use across the Wage Distribution



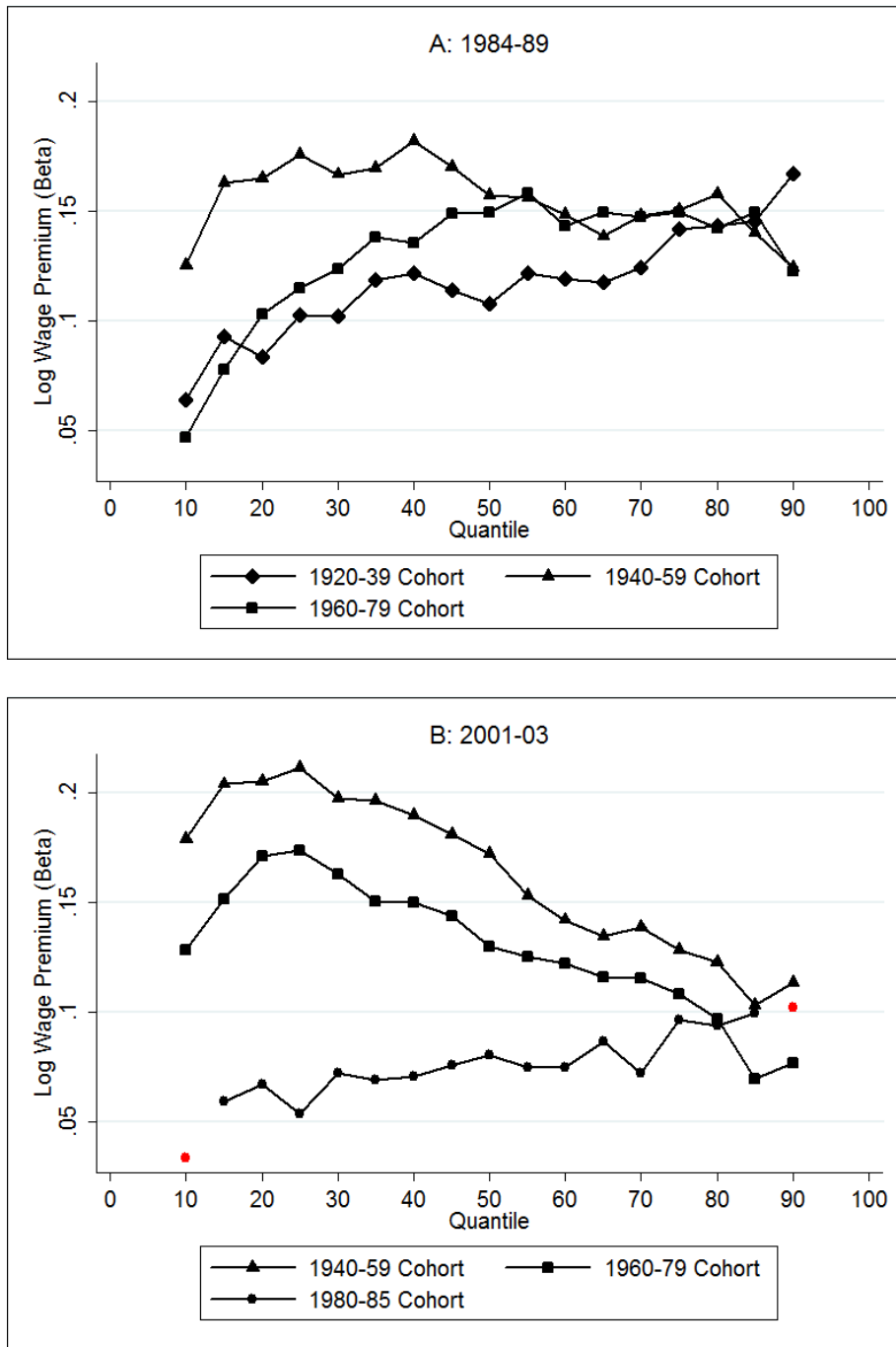
*Note:* Data from BIBB/BAuA. Results obtained via kernel-weighted local polynomial smoothing function (lpoly in Stata).

**Figure 2.2** Cohort-Specific Returns to Computer Use



*Note:* Data from BIBB/BAuA. Unconditional quantile regression estimates. Connected point estimates are all significantly different from zero (95% confidence, two-tailed test), while unconnected estimates are non-significant.

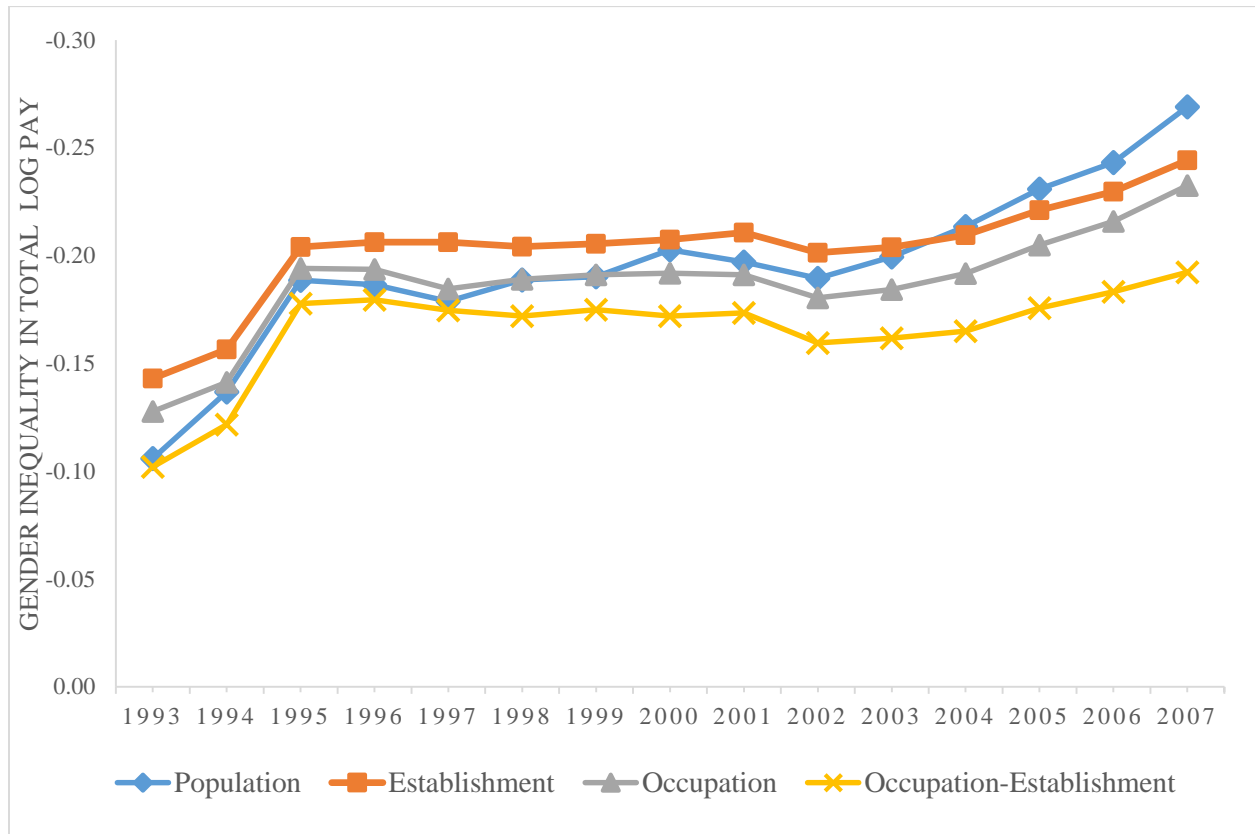
**Figure 2.3** Cohort-Specific Returns to Computer Use, CPS Data



*Note:* Data from October 1984, October 1989, September 2001, and October 2003 CPS. Unconditional quantile regression estimates, dependent variable is log hourly wage. Connected point estimates are all significantly different from zero (95% confidence, two-tailed test), while unconnected estimates are non-significant. Controls include gender, age, age squared, 4 education dummies, 3 race dummies, Hispanic ethnicity, public sector, part-time, union status, 51 state dummies, 11 industry dummies, and 9 occupation dummies. Sample restricted to workers aged 18-64 that earned less than 100 dollars (in constant prices) per hour.

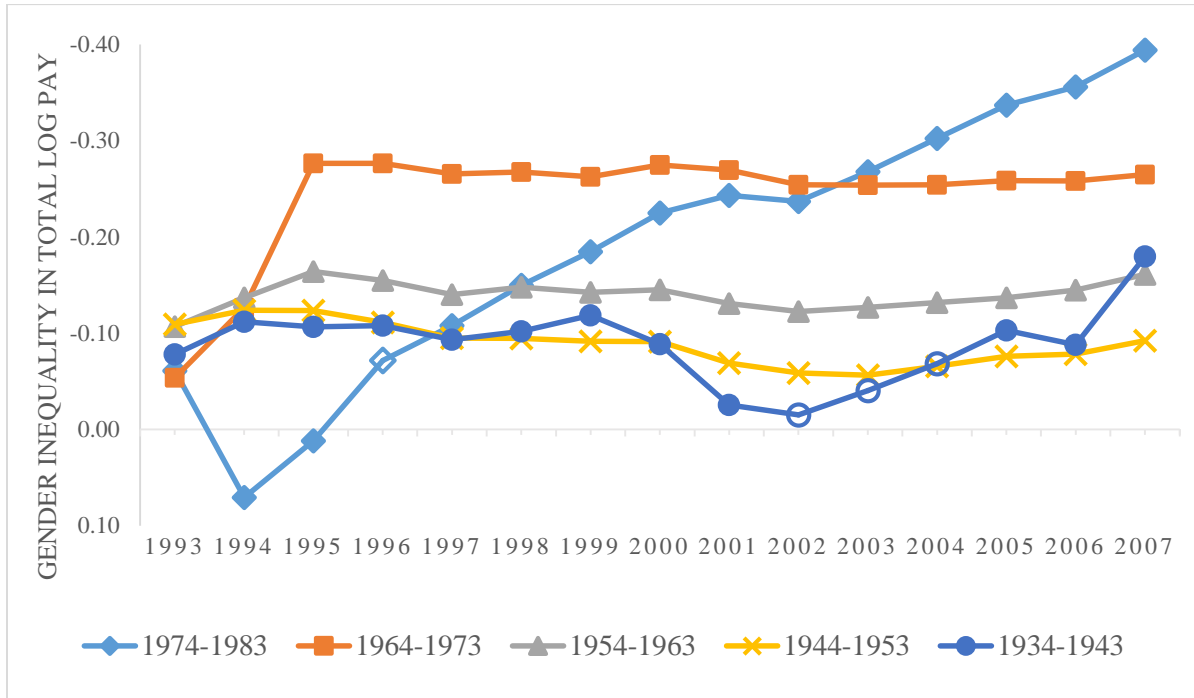


**Figure 4.1** Aggregate Trends in Gender Pay Inequality, 1993-2007



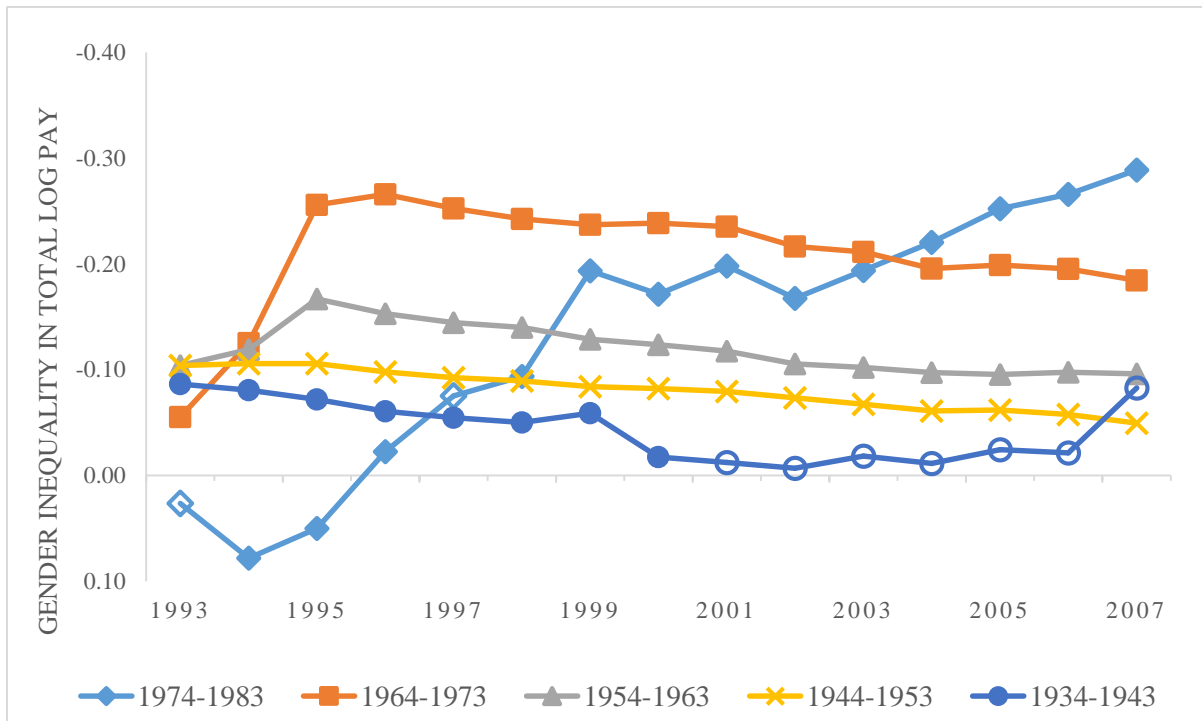
*Note:* Models estimated separately for each year, controlling for education and experience. Coefficients are all statistically significant with robust z-statistics ranging from 56 to 209.

**Figure 4.2** Population-Level Gender Earnings Inequality by Cohort



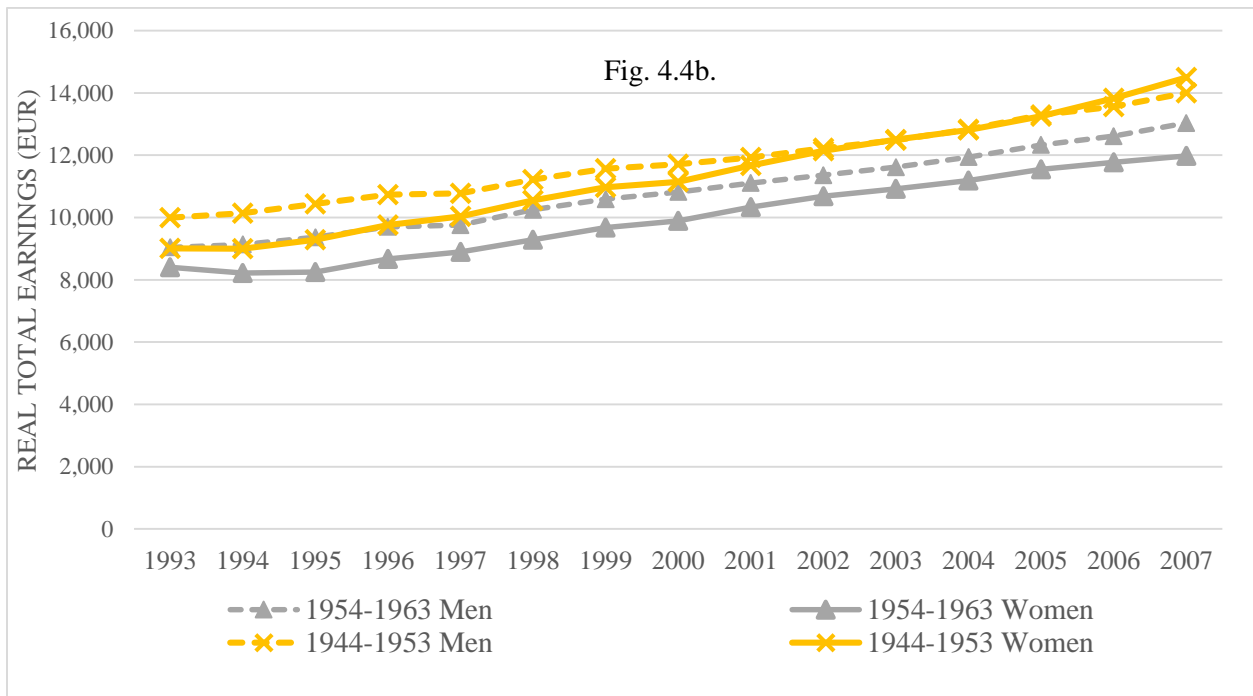
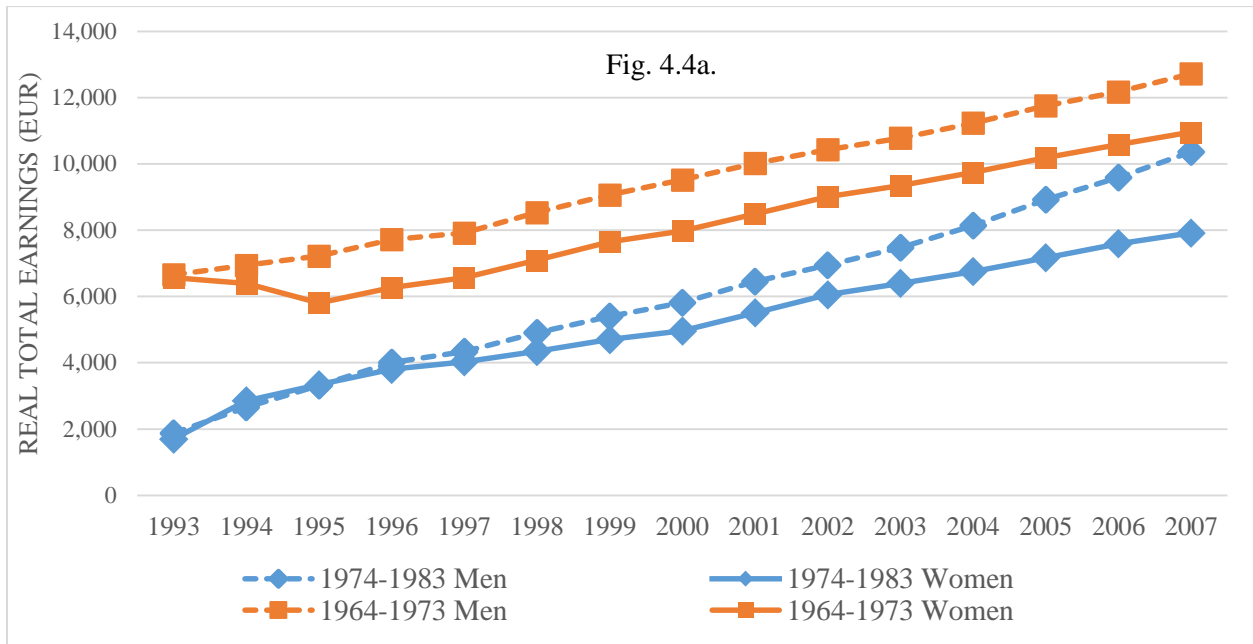
*Note:* Models estimated separately for each year, controlling for education and experience. Non-significant year estimates denoted with a hollow shape, otherwise all estimates are significant at <.05 level (two-tailed test) using robust SEs.

**Figure 4.3** Occupation-Establishment (Job-Level) Gender Earnings Inequality by Cohort



*Note:* Models estimated separately for each year, controlling for education and experience. Non-significant year estimates denoted with a hollow shape, otherwise all estimates are significant at <.05 level (two-tailed test) using robust SEs clustered at the occupation-establishment level.

**Figure 4.4** Trends in Yearly Real Total Earnings by Cohort and Gender



**Table 2.1** Descriptive Statistics

	<i>1985-86</i>	<i>1991-92</i>	<i>2006</i>	<i>2012</i>
Log hourly wage (EUR)	2.325	2.493	2.601	2.643
Standard Deviation	0.421	0.421	0.490	0.442
<i>Computerization (proportion)</i>				
Computer Use	0.159	0.336	0.813	0.863
<i>Cohorts (proportion)</i>				
1920-39	0.225	0.162	-	-
1940-59	0.575	0.511	0.285	0.248
1960-79	0.200	0.327	0.634	0.607
1980-91	-	-	0.081	0.145
<i>Educational Attainment (proportion)</i>				
No Degree	0.232	0.160	0.083	0.060
Vocational Graduate	0.688	0.780	0.720	0.746
Univ. of Applied Sciences	0.030	0.033	0.101	0.090
University Degree	0.050	0.047	0.103	0.108
<i>Control Variables</i>				
Female (proportion)	0.379	0.406	0.492	0.514
Experience (years)	18.042	19.652	19.750	24.668
Tenure (years)	9.635	10.651	10.910	13.800
Public Sector (proportion)	0.190	0.194	0.214	0.271
Part Time (proportion)	0.112	0.146	0.211	0.166
Observations per Wave	16,651	15,742	9,853	8,388

**Table 2.2** Cohort Differences in Average Returns to Computer Use

	(1) <b>Years 1985-1992</b>	(2) <b>Years 2006-2012</b>
Computer Use (main effect)	0.170** (0.012)	0.180** (0.015)
<i>Computer-Cohort Interactions</i>		
Computer × 1940-59 Cohort	-0.036** (0.013)	-
Computer × 1960-79 Cohort	-0.088** (0.014)	-0.005 (0.018)
Computer × 1980-91 Cohort	-	-0.067* (0.030)
<i>Cohort Main Effects</i>		
1940-59 Cohort	-0.024* (0.009)	-
1960-79 Cohort	-0.066** (0.012)	-0.046* (0.018)
1980-91 Cohort	-	-0.061* (0.031)
Constant	2.044** (0.025)	2.012** (0.043)
<i>N</i>	32,172	18,237
<i>R-sq</i>	0.376	0.424

*Note:* OLS regressions, robust standard errors in parentheses. \* $p < 0.05$ ; \*\* $p < 0.01$ , two-tailed test. Reference cohort in Model 1 is 1920-39 cohort. Reference cohort in Model 2 is 1940-59 cohort. Reference groups changed across models as members of the earlier cohort had reached retirement age and were excluded from the data in later waves. Models also control for the influence of education, experience, experience squared, tenure, public sector, part-time work, establishment size, federal state, industry, occupation, and year.

**Table 3.1** Descriptive Statistics for Linked Employer-Employee Data (LIAB) from 2001-2007

	Total		West		East	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Log earnings	4.059	0.375	4.127	0.350	3.854	0.373
ICT Investment (proportion)	0.164	0.237	0.166	0.231	0.161	0.255
Collective Bargaining						
Individual Agreement	0.136	0.343	0.106	0.308	0.227	0.419
Sectoral Agreement	0.709	0.454	0.750	0.433	0.585	0.493
Firm Agreement	0.155	0.362	0.144	0.351	0.188	0.391
Log establishment size	6.723	1.786	6.987	1.789	5.923	1.516
Educational attainment						
No degree	0.035	0.184	0.033	0.177	0.042	0.201
Hauptschule or Mittlere Reife	0.755	0.430	0.761	0.427	0.737	0.440
Abitur or Fachabitur	0.210	0.407	0.207	0.405	0.221	0.415
Formal qualification						
None	0.153	0.360	0.174	0.379	0.089	0.285
Vocational training	0.702	0.458	0.689	0.463	0.741	0.438
College degree	0.146	0.353	0.138	0.345	0.170	0.376
Tenure	10.244	7.953	11.062	8.507	7.767	5.242
Female	0.296	0.457	0.254	0.435	0.425	0.494
Age	41.497	9.579	41.054	9.557	42.838	9.520
Nationality						
German	0.933	0.251	0.915	0.279	0.986	0.119
Turkish	0.022	0.147	0.028	0.165	0.004	0.064
All other	0.045	0.208	0.057	0.232	0.010	0.101
East Germany	0.248	0.432	-	-	-	-
N person years	3,652,108		2,762,503		895,095	
N establishments	18,122		12,009		6,116	

**Table 3.2** Estimated effects of ICT investments on between-establishment inequality in Western Germany from 2001-2007

	<b>WEST</b>					
	Without FEs			With establishment FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>ICT Investment</b>	0.085*** (0.006)	0.055*** (0.005)	0.058*** (0.005)	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
<b>Collective Bargaining</b>						
Sectoral Agreement			0.043*** (0.005)			0.003 (0.002)
Firm Agreement			0.056*** (0.007)			-0.001 (0.002)
Constant	3.002*** (0.023)	3.203*** (0.020)	3.181*** (0.020)	3.565*** (0.021)	3.620*** (0.017)	3.619*** (0.017)
Human Capital		✓	✓		✓	✓
Other Controls	✓	✓	✓	✓	✓	✓
R-Squared	0.411	0.387	0.393	0.573	0.584	0.584
Observations				35,318		
Establishments				11,894		

*Note:* Robust standard errors in parentheses, \*\*\* p<0.001, \*\* p<0.01, \* p<0.05. Dependent variable: Establishment-year fixed effect. Controls include log establishment size, gender, age, age squared, tenure, nationality, schooling, and educational qualification. Cross-sectional models do not include establishment fixed effects, but additionally control for industry and federal state dummies. See methods section for further details.



**Table 3.3** Estimated effects of ICT investments on between-establishment inequality in Eastern Germany from 2001-2007

	<b>EAST</b>					
	Without FEs			With establishment FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>ICT Investment</b>	0.078*** (0.011)	0.052*** (0.009)	0.060*** (0.009)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
<b>Collective Bargaining</b>						
Sectoral Agreement			0.152*** (0.007)			0.003 (0.002)
Firm Agreement			0.084*** (0.010)			-0.000 (0.003)
Constant	2.845*** (0.023)	2.940*** (0.021)	2.946*** (0.020)	3.266*** (0.021)	3.257*** (0.017)	3.256*** (0.017)
Human Capital		✓	✓		✓	✓
Other Controls	✓	✓	✓	✓	✓	✓
R-Squared	0.372	0.348	0.394	0.316	0.199	0.199
Observations				21,461		
Establishments				6,104		

*Note:* Robust standard errors in parentheses, \*\*\* p<0.001, \*\* p<0.01, \* p<0.05. Dependent variable: Establishment-year fixed effect. Controls include log establishment size, gender, age, age squared, tenure, nationality, schooling, and educational qualification. Cross-sectional models do not include establishment fixed effects, but additionally control for industry and federal state dummies. See methods section for further details.

**Table 3.4** Estimated effects of ICT investments on within-establishment inequality in Western Germany from 2001-2007

	<b>WEST</b>					
	Without FEs			With establishment FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>ICT Investment</b>	0.176*** (0.036)	0.142*** (0.034)	0.112** (0.036)	0.001 (0.011)	0.006 (0.011)	0.006 (0.011)
<b>Collective Bargaining</b>						
Sectoral Agreement			-0.299*** (0.026)			-0.004 (0.013)
Firm Agreement			-0.151*** (0.038)			0.013 (0.014)
Constant	-4.500*** (0.152)	-3.248*** (0.138)	-3.334*** (0.158)	-5.926*** (0.904)	-4.041*** (0.771)	-3.648*** (0.722)
Human Capital		✓	✓		✓	✓
Other Controls	✓	✓	✓	✓	✓	✓
Observations			7,470,763			
Establishments			11,894			

*Note:* Robust standard errors in parentheses, \*\*\* p<0.001, \*\* p<0.01, \* p<0.05. Dependent variable: Within-establishment variance of wages. Controls include log establishment size, gender, age, age squared, tenure, nationality, schooling, and educational qualification. Cross-sectional models do not include establishment fixed effects, but additionally control for industry and federal state dummies. See methods section for further details.

**Table 3.5** Estimated effects of ICT investments on within-establishment inequality in Eastern Germany from 2001-2007

	<b>EAST</b>					
	Without FEs			With establishment FEs		
	(1)	(2)	(3)	(4)	(5)	(6)
<b>ICT Investment</b>	0.172** (0.053)	0.213*** (0.059)	0.163** (0.058)	0.004 (0.019)	0.010 (0.018)	0.009 (0.017)
<b>Collective Bargaining</b>						
Sectoral Agreement			-0.487*** (0.053)			-0.021 (0.024)
Firm Agreement			-0.224*** (0.063)			-0.021 (0.026)
Constant	- 2.353*** (0.191)	-1.862*** (0.192)	-1.736*** (0.187)	4.484*** (0.963)	4.224*** (0.952)	3.290*** (0.900)
Human Capital		✓	✓		✓	✓
Other Controls	✓	✓	✓	✓	✓	✓
Observations			2,467,181			
Establishments			6,104			

*Note:* Robust standard errors in parentheses, \*\*\* p<0.001, \*\* p<0.01, \* p<0.05. Dependent variable: Within-establishment variance of wages. Controls include log establishment size, gender, age, age squared, tenure, nationality, schooling, and educational qualification. Cross-sectional models do not include establishment fixed effects, but additionally control for industry and federal state dummies. See methods section for further details.

**Table 3.6** Lagged estimated effects of ICT investments on between-establishment inequality in Western and Eastern Germany

	WEST		EAST	
	$\beta$	<i>se</i>	$\beta$	<i>se</i>
<b>ICT Investment</b>				
Previous year	-0.000	(0.003)	-0.002	(0.004)
-2 year	-0.004	(0.003)	-0.003	(0.004)
-3 years	0.005	(0.003)	-0.000	(0.005)
-4 years	0.006*	(0.003)	0.007*	(0.004)
Constant	3.580***	(0.030)	3.293***	(0.032)
Controls		✓		✓
R-Squared	0.587		0.333	
Observations	9,309		6,960	
Establishments	3,726		2,524	

*Note:* Robust standard errors in parentheses, \*\*\* p<0.001, \*\* p<0.01, \* p<0.05. Dependent variable: Establishment-year fixed effect. Models estimated with establishment fixed effects. Controls include log establishment size, gender, age, age squared, tenure, nationality, schooling, and educational qualification. See methods section for details.

**Table 4.1 Descriptive Statistics**

	Women	Men	Overall
<b>Cohorts</b>			
1974-1983	826,987	668,595	1,495,582
1964-1973	1,526,368	1,545,307	3,071,675
1954-1963	1,600,026	1,655,271	3,255,297
1944-1953	1,086,526	823,224	1,909,750
1934-1943	210,744	65,497	276,241
<b>Education (%)</b>			
Basic education or less	22.61	23.42	23.03
Secondary education	54.50	60.68	57.74
Tertiary education	22.89	15.90	19.22
Mean experience (years)	20.47	21.52	21.07
Wage gap (mean female wage/mean male wage)	--	--	.88
N (observations)	4,757,894	5,250,651	10,008,545
N (persons)	489,216	574,422	1,063,638
N (mixed sex occupations)		3,044	
N (mixed sex establishments)		128,683	
N (mixed sex jobs)		869,380	

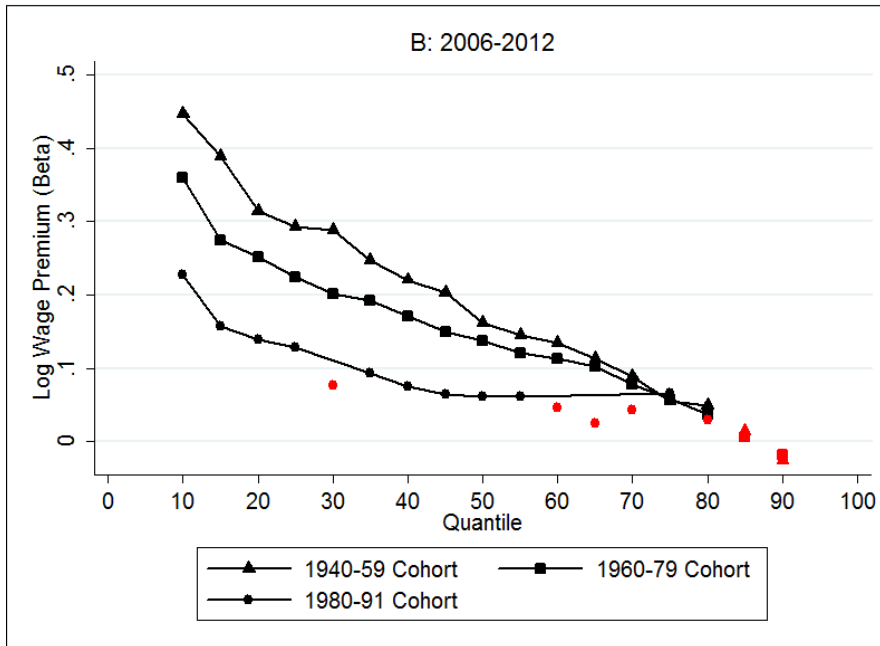
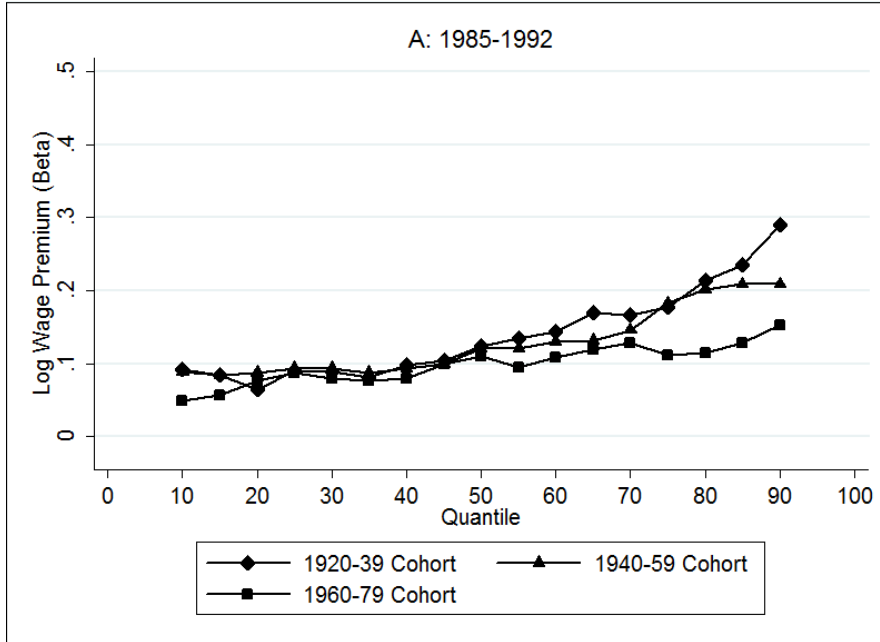
Note: Education levels measured according to ISCED classification system. Occupation measured according to 4-digit national classification system.

**Table 4.2** Cohort Ages during Slovenian Historical Milestones

	Formation of Republic of Yugoslavia (1945)	Tito- Stalin split (1948)	Beginning of workers' self- management (early 1950s)	Tito's Death (1980)	Slovenian independence and new constitution (1991)	Beginning of privatization (1992)	Slovenia joins EU and NATO (2004)	Slovenia assumes Euro currency (2007)
<b>Cohorts</b>								
1974-1983	-	-	-	0-6	8-17	9-18	21-30	24-33
1964-1973	-	-	-	7-16	18-27	19-28	31-40	34-43
1954-1963	-	-	0-1	17-26	28-37	29-38	41-50	44-53
1944-1953	0-1	0-4	1-10	27-37	38-47	39-48	51-60	54-63
1934-1943	2-11	5-14	11-20	37-46	48-57	49-58	61-70	64-73

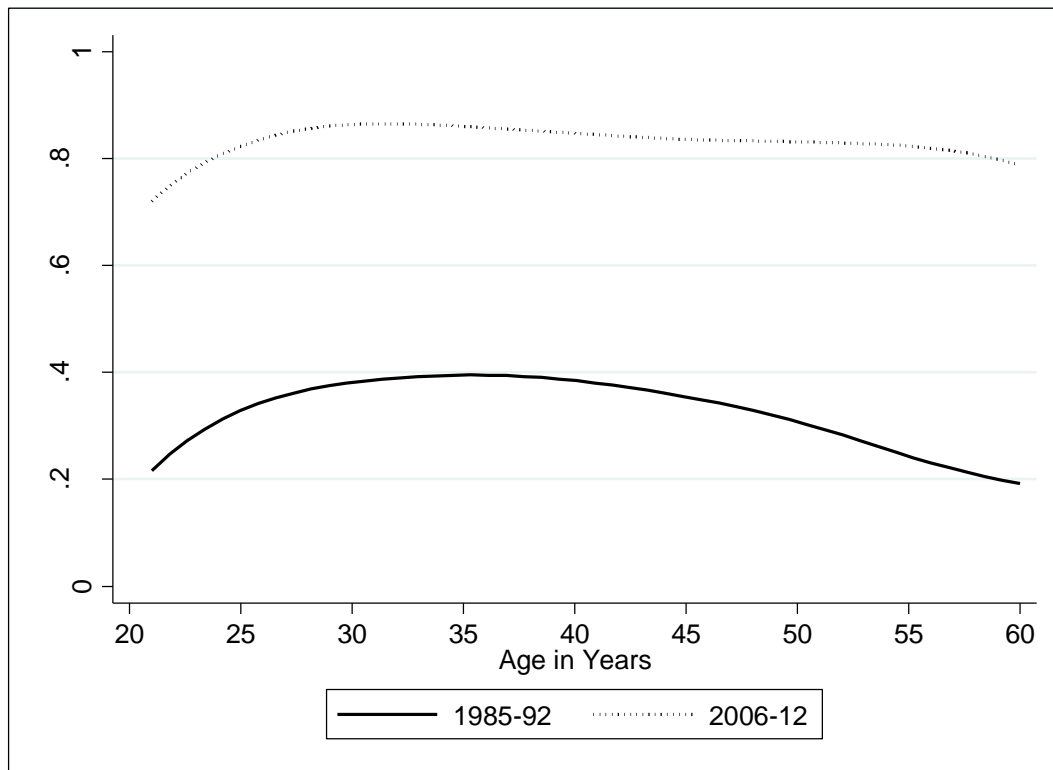
## APPENDIX A: Figures

**Figure A2.1** Cohort-Specific Returns to Computer Use with Task Controls



*Note:* Data from BIBB/BAuA. Unconditional quantile regression estimates. Connected point estimates are all significantly different from zero (95% confidence, two-tailed test), while unconnected estimates are non-significant.

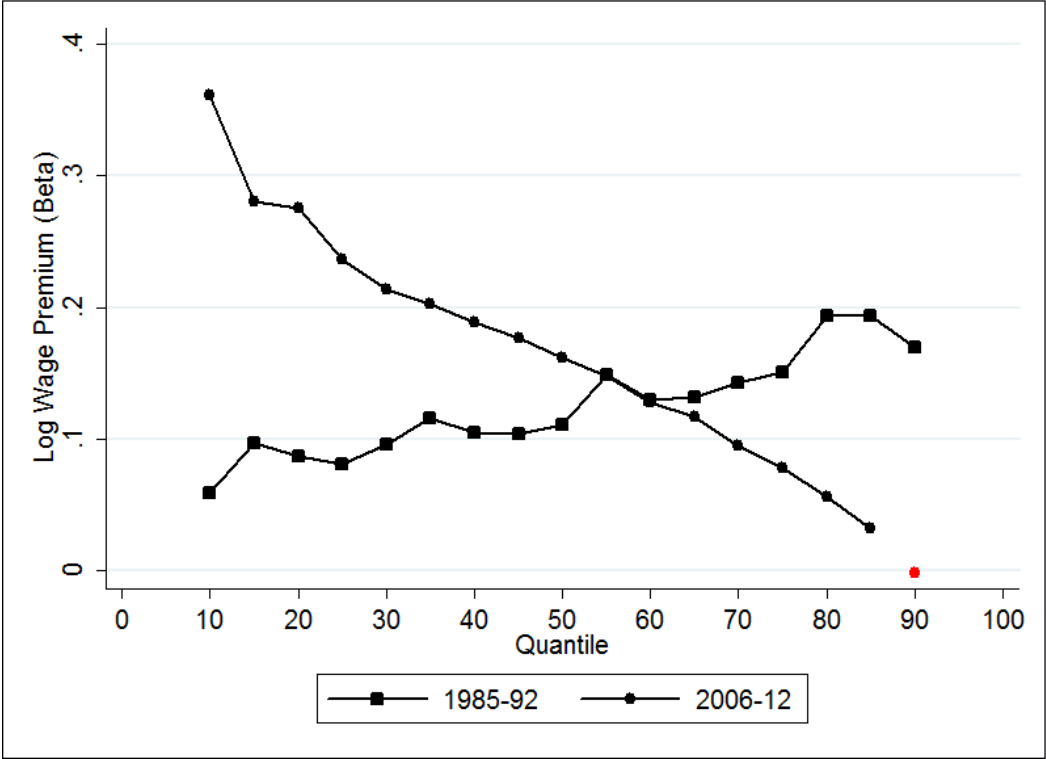
**Figure A2.2 Computer Use by Age in 1985-92 and 2006-12**



*Note:* Data from BIBB/BAuA. Results obtained via kernel-weighted local polynomial smoothing function (lpoly in Stata). Results are averaged across educational levels, though similar age-based trends are apparent within each educational level across time.

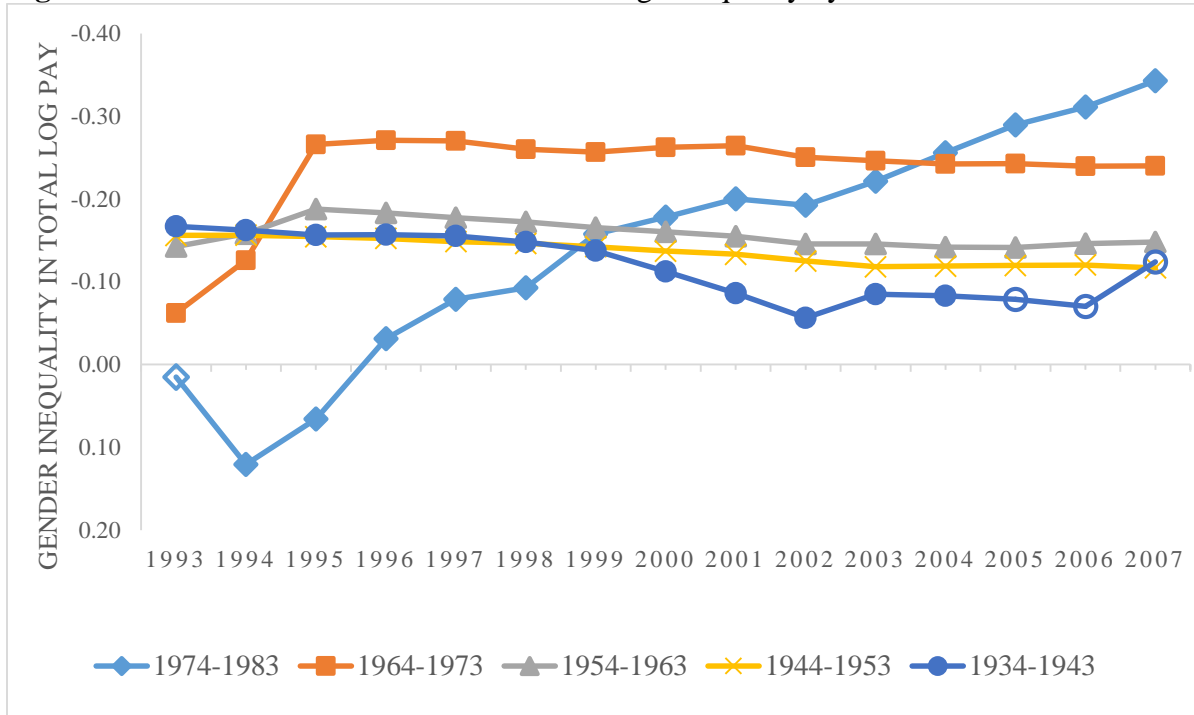


**Figure A2.3** Aggregate Computer Wage Premium: 1985-92 vs. 2006-12



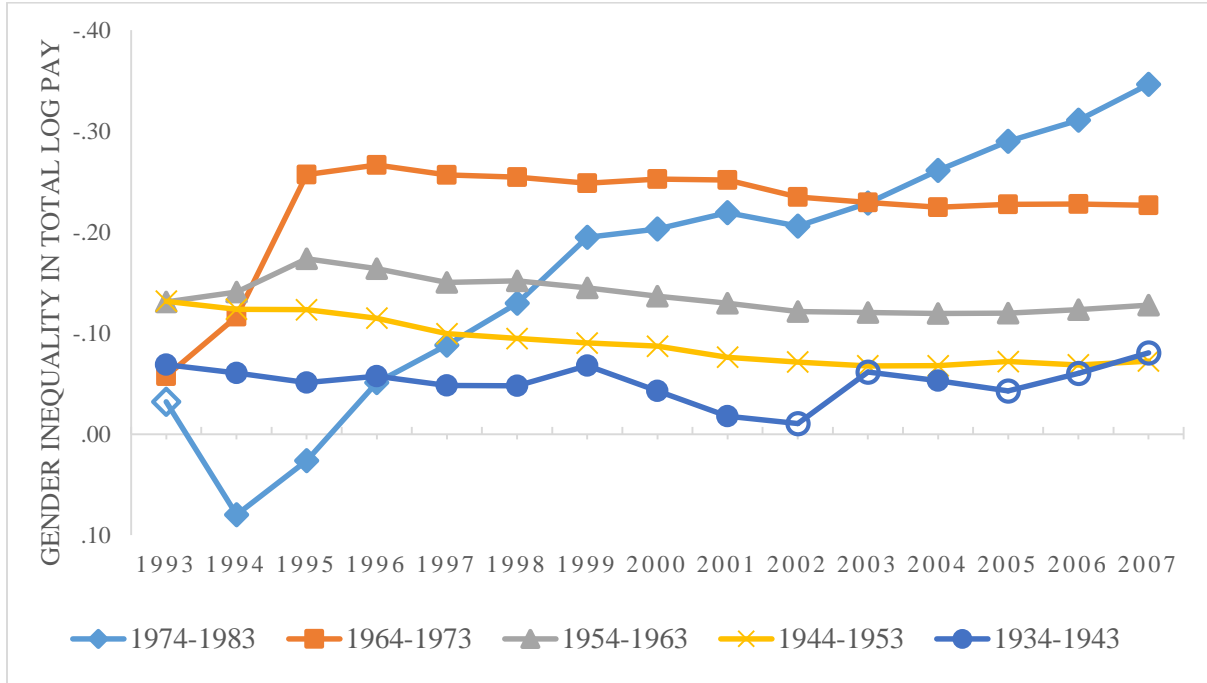
*Note:* Data from BIBB/BAuA. Unconditional quantile regression estimates. Connected point estimates are all significantly different from zero (95% confidence, two-tailed test), while unconnected estimates are non-significant.

**Figure A4.1** Establishment-Level Gender Earnings Inequality by Cohort



*Note:* Models estimated separately for each year, controlling for education and experience. Non-significant year estimates denoted with a hollow shape, otherwise all estimates are significant at <.05 level (two-tailed test) using robust SEs clustered at the firm level.

**Figure A4.2** Occupational Gender Earnings Inequality by Cohort



*Note:* Models estimated separately for each year, controlling for education and experience. Non-significant year estimates denoted with a hollow shape, otherwise all estimates are significant at <.05 level (two-tailed test) using robust SEs clustered at the occupation level.

## APPENDIX B: Tables

**Table B2.1** Cohort-Specific Estimates at the 10<sup>th</sup>, 50<sup>th</sup>, and 90<sup>th</sup> Quantiles, 1985-1992

	1920-39 Cohort			1940-59 Cohort			1960-79 Cohort		
	Quantile			Quantile			Quantile		
	10	50	90	10	50	90	10	50	90
Computer use	0.073** (0.018)	0.138** (0.015)	0.272** (0.042)	0.095** (0.012)	0.135** (0.010)	0.198** (0.018)	0.053** (0.020)	0.129** (0.012)	0.158** (0.022)
Female	-0.338** (0.033)	-0.216** (0.015)	-0.267** (0.029)	-0.293** (0.024)	-0.196** (0.009)	-0.216** (0.015)	-0.156** (0.028)	-0.149** (0.012)	-0.155** (0.016)
<i>Education (ref: vocational degree)</i>									
No Degree	-0.128** (0.030)	-0.120** (0.014)	-0.014 (0.019)	-0.205** (0.022)	-0.097** (0.009)	0.036** (0.009)	-0.118** (0.029)	-0.059** (0.013)	-0.001 (0.014)
University	-0.038 (0.044)	0.143** (0.023)	1.164** (0.121)	0.017 (0.021)	0.209** (0.014)	0.656** (0.042)	-0.110* (0.050)	0.133** (0.027)	0.552** (0.068)
Univ. of Appl. Sciences	-0.057 (0.037)	0.073* (0.030)	0.769** (0.129)	0.032 (0.020)	0.174** (0.017)	0.514** (0.042)	0.053 (0.042)	0.171** (0.034)	0.459** (0.078)
Experience	0.010 (0.010)	0.008 (0.004)	0.002 (0.006)	0.010** (0.004)	0.013** (0.002)	0.029** (0.003)	0.022* (0.010)	0.014 (0.010)	0.011 (0.009)
Experience squared	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000** (0.000)	-0.001** (0.000)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Tenure	0.004** (0.001)	0.004** (0.001)	0.004** (0.001)	0.006** (0.001)	0.005** (0.000)	0.004** (0.001)	0.008** (0.003)	0.009** (0.002)	0.010** (0.002)
Public sector	0.113** (0.042)	-0.006 (0.023)	-0.121** (0.045)	0.034 (0.024)	-0.005 (0.013)	-0.079** (0.020)	0.061 (0.033)	0.023 (0.022)	-0.059* (0.024)
Part-time	-0.252** (0.054)	0.094** (0.018)	0.120** (0.027)	-0.088* (0.035)	0.032** (0.010)	0.095** (0.016)	-0.042 (0.061)	0.052** (0.019)	0.205** (0.030)
Constant	1.554** (0.196)	2.136** (0.082)	2.638** (0.140)	1.652** (0.076)	2.116** (0.040)	2.320** (0.062)	1.434** (0.122)	2.044** (0.053)	2.364** (0.067)
N	6,260	6,260	6,260	17,494	17,494	17,494	8,418	8,418	8,418
R-sq	0.187	0.289	0.263	0.144	0.264	0.208	0.124	0.244	0.189

*Note:* BIBB/BAuA data. Unconditional quantile regression estimates, bootstrapped standard errors in parentheses. \*p<0.05; \*\*p<0.01, two-tailed test. Cohorts estimated separately. Additional controls include establishment size, federal state, industry, occupation, and year.

**Table B2.2** Cohort-Specific Estimates at the 10<sup>th</sup>, 50<sup>th</sup>, and 90<sup>th</sup> Quantiles, 2006-2012

	1940-59 Cohort			1960-79 Cohort			1980-91 Cohort		
	Quantile			Quantile			Quantile		
	10	50	90	10	50	90	10	50	90
Computer use	0.433** (0.051)	0.184** (0.018)	-0.009 (0.019)	0.391** (0.040)	0.150** (0.013)	-0.017 (0.013)	0.275** (0.085)	0.079** (0.026)	0.001 (0.033)
Female	-0.143** (0.029)	-0.142** (0.016)	-0.221** (0.027)	-0.169** (0.021)	-0.139** (0.011)	-0.151** (0.017)	-0.027 (0.041)	-0.065** (0.023)	-0.098* (0.038)
<i>Education (ref: vocational degree)</i>									
No Degree	-0.069 (0.062)	-0.050* (0.022)	-0.019 (0.032)	-0.292** (0.053)	-0.086** (0.015)	-0.025 (0.016)	-0.450** (0.095)	-0.194** (0.032)	-0.005 (0.044)
University	0.065 (0.038)	0.254** (0.023)	0.555** (0.063)	0.093** (0.022)	0.284** (0.015)	0.613** (0.039)	0.070 (0.055)	0.260** (0.045)	0.545** (0.088)
Univ. of Appl. Sciences	-0.017 (0.036)	0.203** (0.021)	0.349** (0.050)	0.116** (0.019)	0.244** (0.014)	0.356** (0.030)	0.056 (0.054)	0.262** (0.037)	0.393** (0.089)
Experience	0.013 (0.018)	0.013* (0.006)	0.001 (0.009)	0.007 (0.005)	0.022** (0.002)	0.036** (0.004)	0.020 (0.017)	0.037** (0.010)	0.019 (0.012)
Experience squared	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.001** (0.000)	-0.001** (0.000)	-0.001 (0.001)	-0.002** (0.001)	-0.001 (0.001)
Tenure	0.011** (0.001)	0.008** (0.001)	0.005** (0.001)	0.014** (0.001)	0.011** (0.001)	0.006** (0.001)	0.013** (0.004)	0.024** (0.003)	0.022** (0.005)
Public sector	0.151** (0.037)	0.006 (0.021)	-0.119** (0.030)	0.088** (0.024)	0.029* (0.013)	-0.122** (0.018)	-0.005 (0.048)	0.055 (0.031)	-0.106* (0.042)
Part-time	-0.162** (0.045)	-0.047** (0.017)	0.061* (0.027)	-0.211** (0.027)	-0.039** (0.011)	0.021 (0.014)	-0.077 (0.071)	0.028 (0.030)	0.121* (0.048)
Constant	1.556** (0.327)	2.123** (0.127)	2.735** (0.184)	1.613** (0.139)	1.993** (0.057)	2.371** (0.089)	1.469** (0.204)	1.696** (0.140)	2.337** (0.170)
N	4,888	4,888	4,888	11,334	11,334	11,334	2,015	2,015	2,015
R-sq	0.177	0.302	0.189	0.178	0.310	0.206	0.190	0.314	0.193

*Note:* BIBB/BAuA data. Unconditional quantile regression estimates, bootstrapped standard errors in parentheses. \*p<0.05; \*\*p<0.01, two-tailed test. Cohorts estimated separately. Additional controls include establishment size, federal state, industry, occupation, and year.

**Table B4.1** Point Estimates from Models for Figure 2.1

<b>YEAR</b>	<b>Population</b>	<b>Firm</b>	<b>Occupation</b>	<b>Occupation-Firm</b>
1993	-0.106	-0.143	-0.128	-0.102
1994	-0.137	-0.157	-0.141	-0.122
1995	-0.189	-0.204	-0.194	-0.178
1996	-0.187	-0.206	-0.194	-0.179
1997	-0.179	-0.206	-0.185	-0.175
1998	-0.189	-0.204	-0.189	-0.172
1999	-0.190	-0.206	-0.191	-0.175
2000	-0.203	-0.207	-0.192	-0.172
2001	-0.197	-0.211	-0.191	-0.173
2002	-0.189	-0.201	-0.180	-0.159
2003	-0.199	-0.204	-0.184	-0.162
2004	-0.214	-0.210	-0.192	-0.165
2005	-0.231	-0.221	-0.205	-0.176
2006	-0.243	-0.230	-0.216	-0.183
2007	-0.269	-0.244	-0.232	-0.192

**Table B4.2** Point Estimates from Models for Figure 2.2

<b>YEAR</b>	<b>Cohort 1: 1974-1983</b>	<b>Cohort 2: 1964-1973</b>	<b>Cohort 3: 1954-1963</b>	<b>Cohort 4: 1944-1953</b>	<b>Cohort 5: 1934-1943</b>
1993	-.061	-.054	-.107	-.109	-.078
1994	.071	-.126	-.137	-.124	-.112
1995	.012ns	-.277	-.164	-.123	-.107
1996	-.072	-.277	-.155	-.111	-.108
1997	-.108	-.266	-.140	-.095	-.093
1998	-.150	-.268	-.148	-.095	-.102
1999	-.185	-.262	-.142	-.092	-.118
2000	-.225	-.275	-.145	-.091	-.089
2001	-.243	-.270	-.131	-.069	-.025ns
2002	-.237	-.254	-.123	-.059	-.015ns
2003	-.268	-.254	-.127	-.056	-.040ns
2004	-.302	-.254	-.132	-.066	-.068
2005	-.337	-.258	-.137	-.076	-.103
2006	-.356	-.258	-.145	-.078	-.088
2007	-.394	-.265	-.161	-.092	-.180

**Table B4.3** Point Estimates from Models for Figure 2.3

<b>YEAR</b>	<b>Cohort 1: 1974-1983</b>	<b>Cohort 2: 1964-1973</b>	<b>Cohort 3: 1954-1963</b>	<b>Cohort 4: 1944-1953</b>	<b>Cohort 5: 1934-1943</b>
1993	.026ns	-.055	-.104	-.104	-.087
1994	.078	-.125	-.119	-.106	-.081
1995	.050	-.256	-.167	-.106	-.072
1996	-.023ns	-.266	-.153	-.098	-.061
1997	-.075	-.253	-.145	-.093	-.055
1998	-.094	-.243	-.140	-.090	-.050
1999	-.194	-.237	-.129	-.084	-.059
2000	-.172	-.239	-.124	-.082	-.018ns
2001	-.198	-.235	-.118	-.080	-.012ns
2002	-.167	-.217	-.106	-.074	-.007ns
2003	-.194	-.212	-.102	-.067	-.018ns
2004	-.221	-.196	-.097	-.061	-.011ns
2005	-.252	-.199	-.095	-.062	-.025ns
2006	-.266	-.195	-.098	-.058	-.021ns
2007	-.289	-.184	-.096	-.050	-.083ns

*Note:* Point estimates significant at  $p < 0.05$  with robust standard errors unless otherwise indicated

**Table B4.4** Observed Real Earnings (in EUR) from Figure 2.4

<b>YEAR</b>	<b>Cohort 1: 1974-1983</b>		<b>Cohort 2: 1964-1973</b>		<b>Cohort 3: 1954-1963</b>		<b>Cohort 4: 1944-1953</b>	
	<b>Men</b>	<b>Women</b>	<b>Men</b>	<b>Women</b>	<b>Men</b>	<b>Women</b>	<b>Men</b>	<b>Women</b>
1993	1877	1697	6657	6567	9043	8404	9992	9009
1994	2662	2853	6941	6390	9136	8221	10138	8999
1995	3312	3342	7220	5804	9365	8247	10432	9287
1996	4013	3806	7720	6269	9700	8672	10739	9755
1997	4333	4031	7915	6569	9754	8891	10778	10033
1998	4910	4344	8535	7095	10247	9283	11222	10546
1999	5398	4703	9064	7646	10589	9678	11564	10968
2000	5817	4964	9517	7981	10818	9890	11713	11142
2001	6455	5510	10014	8488	11105	10331	11931	11668
2002	6944	6055	10432	9012	11361	10688	12228	12143
2003	7471	6396	10779	9344	11618	10916	12478	12500
2004	8145	6755	11233	9746	11939	11187	12828	12811
2005	8919	7169	11752	10189	12329	11546	13292	13254
2006	9588	7594	12171	10585	12614	11769	13560	13823
2007	10364	7916	12720	10957	13032	11974	14006	14493