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DOCTORAL THESIS

Essays in Labour Economics

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Declaration of Authorship

I, Patryk BRONKA, declare that this thesis titled, "Essays in Labour Economics" and the work presented in it are my own. I confirm that:

- This work was done while in candidature for a research degree at this University.
- No part of this thesis has been submitted for another degree.
- Where I have consulted the published work of others, this is always clearly attributed.
- Chapter 4 has been co-authored with Diego Collado and Matteo Richiardi.

UNIVERSITY OF ESSEX

Abstract

Department of Economics

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Essays in Labour Economics

by Patryk BRONKA

This thesis contains three essays in Labour Economics.

The first chapter introduces the topic and the theoretical framework aiding interpretation of the empirical results.

In the second chapter, I investigate transitions through unemployment, which – in opposition to job-to-job transitions – have been shown to have a large and persistent negative effect on workers' earnings and wages. Using a matched employer-employee administrative dataset (SIAB) and the German Socio-Economic Panel survey, I document disparity between outcomes of workers of different level of education: lower-qualified workers have shorter job and employment spells and longer non-employment periods and are less likely to climb the job ladder than better-qualified workers. They also experience significantly larger losses due to unemployment, which persist up to 15 years after displacement. I also document gender differences in unemployment losses, proposing childbirth and part-time work as possible explanations.

Gender differences are further explored in the third chapter, where I estimate the cost of motherhood and quantify its magnitude and persistence. I quantify the longer-term effects of motherhood on the labour market outcomes, finding an up to 48% reduction in earnings and 34% reduction in wages that persist for up to 15 years and affect higher-skilled workers the most. I furthermore quantify the effects of maternity benefit reform introduced in year 2007, finding that while it has likely increased the number of births, it negatively affected earnings of the high-skilled mothers.

In the fourth chapter, we nowcast the economic effects of the Covid-19 pandemic and related lock-down measures in the UK. We then analyse the distributional and budgetary effects of the estimated individual income shocks, distinguishing between the effects of automatic stabilisers and those of the emergency policy responses. We predict the rescue package to cost £26 billion but have a progressive effect and contain the reduction in average household disposable income to 1 percentage point.

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Chapter 1

Introduction

This thesis is focused on the empirical evaluation of the consequences of career-interrupting shocks in the labour market: unemployment scarring in Chapter 2, motherhood in Chapter 3, and Covid-19 in Chapter 4. Thanks to the availability of detailed administrative data sources, the consequences of the former two shocks can be precisely estimated both in the short- and long-term; while the consequences of the Covid-19 policy response can only be assessed in the short-term, focusing on its impact across the income distribution. Understanding the drivers of the distributional effects brought about by the Covid-19 policy response is possible due to a detailed microsimulation model, UKMOD. In general, to fully assess consequences of labour market interruptions, it is important to understand the source of costs associated with them. A way to achieve that for unemployment scarring and motherhood costs, is to interpret the empirical findings in context of the structure that a theoretical model imposes. In this work, I refer to the model of Burdett et al., 2020.

Burdett et al., 2020 propose a theoretical framework of wage formation and quit turnover which reproduces the large and persistent wage and earnings loss following a job loss and provides insight into sources of the cost of job loss. They study a labour market with on-the-job search, in which workers accumulate human capital through learning by doing, and lose skills in unemployment. Foregone human capital accumulation is found to be the major source of the cost of losing a job.

Burdett and co-authors build upon existing models of equilibrium wage formation and labour turnover in frictional labour markets, in particular of Burdett and Coles, 2003 and Burdett and Mortensen, 1998. Burdett and Mortensen, 1998 offer a structural explanation of the evolution of wages during workers' careers and formalise a hypothesis that the observed wage dispersion stems from the frictions in the labour market. The model captures a significant part of the variation in outcomes across workers and, because it allows for heterogeneity in firms' productivities, provides a useful framework for the analysis of wage inequality and workers turnover and reallocation across firms. However, a limitation of the model lies in the fact that it is restricted to steady states. Burdett and Coles, 2003 extend Burdett and Mortensen, 1998 to equilibria in which firms post contracts such that the worker's wage depends on their tenure at the firm. Workers in the model are risk averse, and firms offer wage-tenure contracts smoothly increasing with tenure. Contracts offered by the firms can be described as different starting points on the baseline salary scale, which is defined as the equilibrium wage-tenure profile of a firm offering the lowest starting wage for new hires in the market. Even though firms offer different contracts, they obtain the same steady state profit, as firms with more generous offers have a higher number of employees and fewer quits than firms offering less. Workers' wages increase with tenure within the firm, and across firms through on-the-job search and transitions to firms offering higher wage-tenure contracts. Burdett et al., 2020 extend the model of Burdett and Coles, 2003 by incorporating learning-by-doing in employment, and skill loss in unemployment.

The equilibrium market structure of the Burdett et al., 2020 model is consistent with the approach of Jacobson et al., 1993 to estimating costs of job displacement, which allows the cost of job loss to be decomposed into three different channels:

- job ladder losses arising because in a framework with on-the-job search, employed workers gradually transition to better jobs through employment-to-employment transitions that are beneficial to them. A laid-off worker falls off the ladder and seeks re-employment at a new firm. Therefore, the job ladder loss depends on the probability of being laid-off and the probability of receiving an outside offer. If the probability of being laid-off exceeds the probability of receiving an outside offer, the job ladder effects should be relatively small. If the probability of receiving an outside offer is higher than the probability of being laid-off, the job ladder effects increase. The first scenario should apply to low-skilled workers, while the second to medium- and high-skilled, and Burdett et al., 2020 report a 6.2% temporary loss for the low-skilled, 10.02% for the medium-skilled, and 9.03% for the high-skilled. I discuss statistics describing the job ladders of different skill groups in the data section of Chapter 2.

- skill losses arising because unemployed workers do not accumulate new human capital and lose human capital due to skill atrophy. This process is not instantaneous and depends on time spent in unemployment – if a worker can find new job fast, forgone skill accumulation and skill decay should be small. Because the loss due to loss of skills is measured in comparison to the control group, it also depends on the job loss rates – if the job loss rate is high, workers in the control group are likely to become unemployed in the future as well. Burdett et al., 2020 observe that low-skilled and medium-skilled workers have similar long-term losses associated with skill loss, despite the decreasing rates of learning-by-doing, because the low-skilled exhibit slow re-employment rates but high lay-off rates.

- the employment gap effect arising because it takes time for a laid-off worker to find new employment and the laid-off worker is more likely to be unemployed at a future date t than the control group worker. This effect decays at the sum of the rate at which treated worker regains employment and rate at which control group worker becomes unemployed. Model parameterization suggests a fast decline in the importance of the employment gap effect as time since displacement goes by, particularly for the medium-skilled workers.

Burdett et al., 2020 show that as time since displacement increases, the cost of job loss converges to the cost of skill loss.[1] In the long-term, skill loss is the most significant source of the cost of losing a job, accounting for 70.7% of lifetime earnings losses of the low-skilled workers, and 80.7% of the medium-skilled. Falling off the job ladder has an approximately 67% greater immediate effect for the medium-skilled workers than for the low-skilled. Because it is more persistent, converging to zero after 5 years for the low skilled, but 12 years for the medium-skilled, the effect of falling off the job ladder is twice as important for the medium-skilled in terms of lifetime earnings losses (amounting to 11.3%), as it is for the low-skilled workers (5.5%). Job ladder losses are therefore the least important channel for the low skilled, and second in importance for the medium-skilled. The employment gap effect is important for the low-skilled workers due to the time spent in unemployment and contributes 23.8% of their lifetime earnings losses. For the medium-skilled, it is a dominating factor in the year immediately following the displacement, but its importance declines fast, converging to zero within 2 years post-displacement, and overall contributing only 8% of the total lifetime earnings losses. Overall, while job ladder shocks are driving the short-term losses, it is primarily the loss of human capital which explains very large and persistent loss of lifetime earnings.

Models closely related to Burdett et al., 2020 include Bagger et al., 2014; Jarosch, 2021; Krolikowski, 2017; Jung and Kuhn, 2019. However, Burdett et al., 2020 is chosen as the main framework aiding the interpretation of empirically estimated displacement and childbirth losses as it best aligns with estimation strategy used in this work, as it provides a decomposition of the cost of job loss consistent with the statistical framework of Jacobson et al., 1993, separately considers workers of three different skill levels, and allows workers in the control group to become unemployed at a future time. In context of this thesis, referring to the model helps to interpret significant displacement losses estimated in Chapter 2, and motherhood costs estimated in Chapter 3.

[1] Figure 4 of Burdett et al., 2020 provides a helpful illustration

Chapter 2

Unemployment scarring and worker heterogeneity

2.1 Introduction

Labour markets are characterised by large gross flows of workers. For example, according to the Current Population Survey (CPS)[1], close to seven million American workers go in or out of employment each month. The gross flows are lower in Germany than in the United States[2], but more closely related to the business cycle, and therefore more volatile (Jung and Kuhn, 2014). The underlying process of job reallocation, which the observed flows reflect, has the potential to benefit workers[3], through employment-to-employment transitions allowing for upward mobility on the job ladder by sorting workers into higher productivity, better paid jobs. Multiple studies examine worker flows from the aggregate point of view of unemployment dynamics. For example, Fallick and Fleischman, 2004; Elsby et al., 2009; Fujita and Ramey, 2009 and Shimer, 2012 study the US labour market, and Burda and Wyplosz, 1994; Petrongolo and Pissarides, 2008 and Elsby et al., 2013 evaluate European labour markets. Many researchers have also been interested in estimating the cost of such transitions to individuals, and a thorough review of this strand of work

[1]CPS is a monthly survey of about 60 thousand household, conducted in the USA since 1949

[2]However, the exact measurement methods vary - see for example Petrongolo and Pissarides, 2008; Shimer, 2012

[3]Bowlus and Neuman, 2006 suggest that job mobility might be *the most important* component in earnings growth.

is provided in Section 2.2. On the other hand, the effects of reallocations through unemployment on short- and long-term trajectory of earnings and wages of different subgroups of the population are less clear and not always comparable across different studies, due to different time periods, countries, datasets, control groups, and econometric techniques these studies rely on. However, different workers are likely to have very different experiences in the labour market in terms of the jobs they undertake, the process of searching for a job, returns to each additional year of experience and tenure, or job mobility (Haltiwanger et al., 2018). As the employment-to-unemployment flow rate is over twice as volatile in Germany as in the US, and accounts for between 60 and 70 percent of fluctuations in the German unemployment rate, it is particularly important to understand the consequences of such transitions, not only in aggregate, but across different sub-populations. This work focuses on empirical investigation of the short- to long-term costs of employment-to-unemployment transitions for low, medium, and high educated workers, men and women, mothers, and full-time and part-time workers. Previous studies rely on either survey or administrative data, each of which has its own benefits and disadvantages. To provide a complete picture, I apply unified methodology to two datasets, SIAB and SOEP. SIAB, the Sample of Integrated Labour Market Biographies, is a matched employer-employee administrative dataset from Germany. It is a 2% random sample of German population liable to the social security, observed between 1975 and 2014. SOEP, the German Socio-Economic Panel, is a yearly survey of around 30 thousand individuals living in Germany, which started in 1984. As outlined in Chapter 1, I evaluate my empirical findings in context of the structural model proposed by Burdett et al., 2020.

The paper progresses as follows: Section 2.2 reviews the literature, Section 2.3 provides a description of the data and descriptive statistics, Section 2.4 introduces the econometric framework, Section 2.5 presents the main results from the SIAB, Section 2.6 discusses the results from the SOEP data, Section 2.7 discusses the importance of gender, motherhood, and employment type on unemployment losses, and Section 2.8 concludes.

2.2 Literature review

The interest in quantifying workers' displacement costs can be traced back at least to Bale, 1976 who examines the cost, to workers and the society, arising from displacement of workers that occurs with trade liberalisation. While the displacement costs were often considered transitory at the time (Magee et al., 1972), Bale shows that job displacement reduces wages obtained upon re-employment and, if workers remain unemployed long enough, the cost of displacement both to individual workers and the society can exceed any gains from trade liberalisation. While the presence of losses and at least a degree of persistence are in line with the current literature, it is worth noting that the workers' cost in Bale's work is calculated as a sum of lost wages, less any benefits paid to the workers, and is hence lower than more recent estimates presented in the literature, which are based on counterfactual analysis and compare treated workers' earnings to the control group of workers who kept their jobs. Neumann, 1978 analyses a similar sample of trade-displaced workers and reports increased unemployment rates and decreased wages, with high-tenure workers affected more strongly. Blau and Kahn, 1981 focus directly on the effects of displacement on labour market outcomes of young workers, using NLS survey data. Their research focuses on race-sex differentials in displacement losses – finding that white men suffer larger losses than black and female workers – but overall adds to the early evidence that involuntary job transitions are costly to the workers. Until Ellwood, 1982, not much attention has been devoted to the temporal pattern of losses. Ellwood introduces a widely adopted terminology of *scars*, occurring when the displacement leads to a persistent loss of earnings, and *blemishes*, when the loss is transitory. Results from the analysis of teenage employment using the CPS data presented in the paper show that early experience has large effects on future employment rates and wages, suggesting a degree of persistence in employment patterns.

Methodological issues closely related to statistical methods used to analyse longitudinal data to measure displacement losses, such as the distributed lag models, received significant interest around the same time. Ashenfelter, 1978 presents a conceptual framework for the analysis of longitudinal, administrative data and its application to estimating the effects of training programs on earnings, comparing affected individuals to an appropriate control group. Heckman and Robb, 1985 and LaLonde, 1986 add to the topic of methodological issues arising when evaluations of outcomes of training programs are conducted, focusing primarily on questions of data quality: Heckman et al. consider whether longitudinal data is always required, while LaLonde assess the quality of observational data in comparison to experimental results. These developments are significant as they lead to econometric methods underpinning the displacement literature for many years, such as the work of Jacobson et al., 1993, who apply econometric techniques developed for program evaluation to detailed administrative data. Until then, survey data has often been used to estimate wage equations. For example, Podgursky and Swaim, 1987 analyse the Displaced Workers Survey, which covers respondents from the Current Population Survey who were displaced between 1979 and 1984, to measure the loss of earnings resulting from job loss. They report substantial and persistent earnings losses for workers who made large investments in specific human capital, and only moderate losses of 5 to 10 percent of pre-displacement earnings for all workers. It should be noted that this figure is based on earnings losses of workers re-employed full-time, in comparison to their pre-displacement earnings, and as such is not directly comparable with counterfactual estimates reported in more recent studies. Addison and Portugal, 1989 study displacement losses, with a particular focus on the effects of unemployment duration on post-displacement wages. Using the same dataset as Podgursky and Swaim, they show that post-displacement wages depend negatively on the duration of unemployment. Overall, Addison and Portugal report displacement losses to increase with tenure, and for industry or occupation switchers. This result appears to be contradicted by Kletzer, 1989, who uses the same dataset but finds tenure to be positively related to post-displacement earnings, which can arguably reflect heterogeneity in workers' ability and the degree to which specific skills are transferable – high skilled workers, whose specific human capital might be more transferable, experience a smaller reduction in returns to tenure than the low skilled. While the direction of the effect of tenure can be debated and likely depends on a specific subsample, there appears to be strong evidence for the importance of tenure for displacement losses, supported also by Shapiro and Sandell, 1985, whose work shows that 90 percent of the average wage loss can be attributed to the loss of firm-specific human capital associated with tenure. The importance of specific human capital is further highlighted by Topel, 1990, who argues that it is a central factor in determining the magnitude of earnings losses of displaced workers. Using PSID data, Topel estimates the effect of job loss on wages and earnings to be substantial – in the short term, equal to a 40 percent reduction in annual earnings for a typical manufacturing worker - and persistent. Reduction in labour supply is found to be responsible for two-thirds of the loss, while the remainder is attributed to a decline in wage rates. Ruhm, 1991 analyses 1969 – 1982 waves of the PSID and confirms that displaced workers are significantly more likely to be unemployed and experience a significant wage reduction, exceeding 25 percent. Ruhm finds that displacement leads to temporary blemishes in unemployment, but persistent scarring in earnings. However, the sample consisting of 800 displaced workers observed for four years after displacement is relatively small. Farber et al., 1993 reports that displaced workers are less likely to be in employment than equivalent non-displaced workers, those who are reemployed are less likely to work full time, and those who are reemployed full-time earn significantly less than their non-displaced counterparts. Carrington, 1993 also shows that displaced workers have substantial wage losses, but the magnitude of losses varies with the industry and local labour market conditions. Conditional on local labour market conditions, experience does not appear to have a major effect on the displacement losses, but strong tenure effects can be observed – suggesting that workers' specific human capital plays an important role, as has been suggested by Shapiro and Sandell, 1985 and Topel, 1990. Neal, 1995, on the other hand, argues that it is industry-specific, and not firm-specific human capital that is important for the returns to seniority and losses of displaced workers: displaced workers who stay in their pre-displacement industries have substantially higher returns to pre-displacement tenure, than those who switch industries. While some studies, such as Kletzer and Fairlie, 2003, find little persistence in displacement losses for selected subsamples, presence of large and persistent losses caused by displacement appears to be a recurring theme in the literature, with attention devoted to explaining the sources of such losses. For example, in addition to studies focused on the importance of different types of human capital reviewed above, Stevens, 1997 confirms that displacement has a persistent negative effect on wages and earnings using the PSID, but explains persistence by multiple job losses following the initial displacement – workers who have avoided additional displacements incur significantly smaller losses.

Following the literature estimating displacement losses on small-sample survey data and econometric advances building on the seminal work of Jacobson et al., 1993 (henceforth JLS), there has been a considerable interest in estimating short- and long-term displacement losses and trajectories of displaced workers' labour market outcomes using administrative data. One of the first examples is Jacobson et al., 2005, using administrative data on earnings histories of displaced workers and a framework similar to Jacobson et al., 1993 to estimate returns to schooling and retraining of the displaced workers. Carneiro and Portugal, 2006 use a longitudinal linked employer-employee data on Portuguese workers to assess the long-term earnings losses of displaced workers. Four years after displacement, earnings of affected workers are reported to be between 9 and 12% below the expected counterfactual level. Most of the loss can be attributed to loss of tenure and sector-specific human capital. Eliason and Storrie, 2006 use Swedish matched employer-employee data to estimate effects of displacement due to establishment closure in 12 years post-displacement time frame. Displaced workers are reported to experience earnings losses and worsened labour market position both immediately after the displacement and longer-term, in the whole observation period. An important difference between the work of Eliason and Storrie and majority of the literature lies in the use of an estimator combining exact covariate matching and propensity score matching (described in detail by Angrist and Krueger, 1999 and Heckman et al., 1999), instead of the fixed effect econometric specification like Jacobson et al., 1993. The choice of the econometric setup does not appear crucial for the main finding, of the presence of unemployment scarring. Eliason et al. show, however, that the persistence of scarring effects depends on the macroeconomic conditions of the labour market. Couch and Placzek, 2010 use administrative data on workers from Connecticut State in the US, for the period between 1993 and 2004, to estimate displacement losses using two different econometric approaches: the fixed-effects approach of JLS , and matching estimators, similar to Eliason et al. Using the JLS estimator, Couch et al. find immediate displacement loss to be about 8 percentage points smaller than reported by the JLS, which they attribute to better macroeconomic conditions in Connecticut in their sample. There appears to be no significant difference between the magnitude of estimates obtained from fixed-effects and matching estimators, mirroring the conclusions of Eliason et al. and suggesting that both approaches are appropriate for estimating long-term displacement losses. Hijzen et al., 2010 use uncommon, matched employer-employee, administrative dataset from the UK, which they create from different datasets provided by the Office for National Statistics. The reported magnitude of losses is in line with literature for other countries and is in the range of 14 – 35 percent per year during the first five years post-displacement. While authors report less heterogeneity than JLS for the United

States, they point out that substantial part of the cost of displacement is due to periods of non-employment, which contrasts the findings of JLS. Davis and Wachter, 2011 use administrative longitudinal data on US workers observed between 1974 and 2008. Analysing workers with at least 3 years of tenure who were displaced between 1980 and 2005, they document large and persistent earnings losses, equal to between 1.4 and 2.8 years of pre-displacement earnings of displaced workers. The magnitude of losses increases with tenure and, similarly as in the work of Eliason et al. and Couch et al., depends on the macroeconomic conditions – strong economic growth and low unemployment at the time of displacement strongly improve medium- and long-term outcomes of displaced workers. They furthermore compare estimated displacement losses with predictions of search models of unemployment, finding that models such as of Mortensen and Pissarides, 1994 significantly underestimate displacement losses in comparison to the data. Huttunen et al., 2011 use census data to analyse displacement losses of Norwegian, male, manufacturing-sector workers separating between 1991 and 1998 in consequence of either plant closure or downsizing. The study differs from most of the literature in that its authors focus on earnings losses for workers staying in the labour force and difference between plants and firms. In that aspect, they report only very moderate displacement effects, however, displacement is reported to increase the probability of exiting the labour force by 31 percent. Browning and Heinesen, 2012 observe health and employment of all individuals in Denmark between 1980 and 2006 using administrative, matched employer-employee data. The focus of the study lies in estimating effects of job displacement due to plant closures on health. Job displacement is shown to significantly increase the risk of mortality, by 79 percent in the displacement year. Increase in mortality risk appears to be persistent and present up to 20 years post-displacement, similarly to persistent earnings and wages losses typically reported in the literature. Garda, 2012 studies the long-term impact of losing a job in a mass-layoff on evolution of wages between 1996 and 2008, using an administrative dataset from Spain (MCVL). MCVL data contains information about the reason of separation from employer, allowing voluntary and involuntary separations to be distinguished, which is typically unavailable in administrative data. Garda focuses on the effect of permanent versus fixed term employment contract on employment losses, finding that workers on permanent contracts have larger and more persistent wage losses, which arise from the loss of pre-displacement firm-specific tenure. Leombruni et al., 2013 use Italian administrative data for 1989 to 2003 to investigate the effect of displacement on earnings and risk of injury in the workplace. They find a moderate earnings loss and a significant increase in the risk of injury, driven by reduction in working conditions due to displaced workers switching occupations – in comparison to the control group selected using propensity score matching. Displaced workers are reported to lose -21% of average annual earnings in the displacement year, and -15% in the three years afterwards. Authors attribute majority of these losses to a decline in time worked, and not reduced wage rates. Mossucca, 2016 use administrative data to study long-term earnings losses of Italian workers using a study design similar to JLS. The key contribution of the study is the differentiation between workers separating from distressed firms and all separators. Authors classify the former as involuntary separations and report earnings losses in this group to significantly exceed losses in the group of all separating workers, which are only moderate. This significant difference in estimates highlights the importance of voluntary and involuntary separations and their definition in the data. Bennett and Ouazad, 2020 use a matched employer-employee longitudinal dataset for all residents in Demark to estimate the impact of job loss on individual's criminal activity. They focus on high-tenure workers losing employment in a mass-layoff event occurring between 1990 and 1994. Displacement is reported to have a negative and long-lasting impact on earnings, which fall by up to 53.5 percent one year after displacement and remain 22.3 percent lower than pre-displacement earnings after seven years. Moore and Scott-Clayton, 2019 use administrative data from Ohio State to estimate earnings of workers displaced in mid-2000s. Large and persistent earnings losses are reported to exist, but only between

16 and 24 percent of the loss can be explained by firm-specific pay premiums. This result is close to findings of Lachowska et al., 2020. Similarly to Eliason and Storrie, 2006, Seim, 2019 provides evidence on the effects of displacement on earnings, wages, hours worked, and unemployment for Swedish workers, displaced between 2002 – 2004. Administrative data on all workers is used, and records are matched to military establishment records to obtain a measure of cognitive and non-cognitive skills. Younger and less cognitively and non-cognitively able workers are reported to be more likely to experience displacement, but there is no evidence of different displacement outcomes and recovery rates between high and low skilled workers. Halla et al., 2020 study married males from Austria who lose their job in a mass-layoff or due to a plant closure. They find that job displacement results in large and persistent decrease in earnings and employment of the husband. An increased labour market participation of the wife is observed, however, it covers only a small proportion of lost earnings of the husband. Gulyas, Pytka, et al., 2019 study labour market histories of Austrian workers using machine learning method called random forest for estimation of displacement losses. The majority of displaced workers are affected by significant and persistent loss of earnings; however, they also document heterogeneity in the cost of job loss across individuals, with 10 percent of workers gaining in terms of earnings. They identify the pre-displacement firm wage premium as the most important channel driving observed losses and conclude that mean reversion in firm rents and losses in match quality, and not the destruction of firm-specific human capital, are the most important channels behind the cost of losing a job. Lachowska et al., 2020 focus on evolution of earnings, wages, and hours of work of workers from Washington State in the US displaced during the Great Recession. They show that the main driver of displacement losses is the decrease in hourly wages and their slow recovery, and only about a fifth of the loss can be attributed to loss of employer-specific premium, measured by the firm fixed effect. Scarring is responsible for 26 percent of the loss, and lost employer-employee match accounts for 57 percent of the total effect. Schmieder et al., 2022 use administrative

data from Germany to document large, persistent, and highly cyclical losses in earnings caused by job displacement. While short-term losses appear to be driven by unemployment, in longer term it is the decline in wages, caused by displaced workers switching to smaller and lower paying firm, that drives the decline is earnings. Observed cyclicality in displacement losses is attributed to the labour market conditions at the time of job loss, as changes in the composition of displaced workers and firms cannot explain it. Fackler et al., 2021 study displacement losses using German administrative data on displacements from small and large employers. Like Schmieder et al., they attribute displacement losses to lost firm wage premiums, arising because workers displaced from larger firms move to smaller firms after displacement. However, Fackler et al. estimate losses to be significantly smaller than Schmieder et al. and other studies and argue that displacement losses have been overestimated in the studies focusing on large employers only. Raposo et al., 2021 decompose the displacement loss into firm, job title, and match quality parts. Similarly to Huckfeldt, 2022, sorting into lower-paying jobs is documented to be the most important cause of loss, accounting for 37 percent of the total loss in monthly earnings, and 46 percent in hourly wages. Bertheau et al., 2022 note that there is a considerable difference in the magnitude of estimated losses among existing studies of displacement losses and, due to varying specifications, direct comparisons are frequently not possible between studies. Using an econometric setup similar to JLS and a harmonized dataset, authors document displacement losses occurring in Denmark, Sweden, Austria, France, Spain, Italy, and Portugal. The harmonized framework allows comparative analysis across countries, and authors report Northern European workers to experience a significantly smaller reduction (10 percent five years post-displacement) in earnings than Southern European workers (30 percent). Within countries, a large part of the earnings loss - between 40 and 95 percent - can be attributed to the loss of employer-specific wage premiums, which appears to be higher than similar studies decomposing the source of losses, such as Lachowska et al., 2020 (about 20 percent), Moore and Scott-Clayton, 2019 (between 16 and 24 percent), but not Gulyas, Pytka, et al., 2019 or Schmieder et al., 2022 who report employer-specific wage premiums to be an important factor in explaining displacement losses. Brandily et al., 2022 contribute to the literature decomposing sources of displacement losses. They use French administrative data on workers and firms to show that involuntarily displaced workers experience large and persistent earnings losses, which they attribute to a decrease of workers' negotiation power and subsequent loss in firm wage premium driven by re-employment of workers in firms with, conditional on their productivity, unfavourable wage policies. Huckfeldt, 2022 contributes to the literature on occupation switching and shows that the typically reported large and persistent earnings losses arising from involuntary job displacement are concentrated among workers who switch occupations, especially during recessions.

In addition to empirical studies using survey and administrative data to document displacement losses and decompose their sources, another strand of literature can be identified in studies focused on using structural models of the labour market to obtain a measure of displacement losses. Recent examples include Davis and Wachter, 2011; Jarosch, 2021; Krolikowski, 2017; Burdett et al., 2020.

Davis and Wachter, 2011 are interested in cumulative earnings losses caused by worker's displacement and the effect of the labour market conditions on the losses. They note that in the existing literature, a displacement leads to large and persistent losses in terms of earnings, reduced stability of earnings and employment, and non-monetary effects such as worse health, increased mortality, and lower educational achievements of the children of displaced workers. Davis and Wachter, 2011 are primarily interested in explaining the cyclical variation in earnings losses and assessing the fit of the main theoretical models of unemployment fluctuations. They find that the standard models significantly underestimate the magnitude of the displacement losses observed in the data - the empirical losses are an order of magnitude larger than in the basic Mortensen-Pissarides model, and about 4 times larger than in richer models calibrated to the U.S. data (Burgess and Turon, 2010). In terms of the estimated displacement losses, Davis and Wachter, 2011 find that men lose on average 1.4 years of predisplacement earnings (in present-value terms, discounting at a 5% annual rate over a 20-year period) if the displacement took place when the unemployment rate was below 6%, to 2.8 years of predisplacement earnings in years when the unemployment rate exceeded 8%.

Jarosch, 2021 builds up on the analysis of Davis and Wachter, 2011. He proposes a model accounting for the consequences of losing a job and decomposing the cost into different economic mechanisms. The key component of the model is that jobs are allowed to differ in terms of stability - there is on-the-job-search, and workers on the bottom levels of a job ladder have a high risk of unemployment, while those on higher rungs get increasingly insulated from the risk of losing a job. Jobs are therefore heterogeneous in two dimensions: first of all, each job has a level of productivity determining the output from an employer-employee match. Second of all, each job comes with a level of security governing the rate at which the employment relationship ends (possible reasons for different job stability are industry and management practices, unionisation status etc.). Both features are observable to all parties and exogenous. Unemployed workers are willing to accept jobs with relatively little productivity and security, but as they climb the job ladder, they sort into increasingly more productive and secure jobs through job-to-job transitions (and for that reason the risk of becoming unemployed is higher for those who just recently left unemployment). That implies that a spell of unemployment is likely to have long-lasting effects on future labour market outcomes of a worker. Jarosch, 2021 estimates the model on the SIAB data (the same dataset as used in this work) for the period from 1974 to 2010. To obtain the empirical measure of the cost of losing a job, he follows the above-described Davis and Wachter, 2011; however, he considers not only displacements (separations occurring during a mass layoff) but separations defined more broadly as well. He finds that wages drop sharply after separation and never fully recover, with significant difference remaining 20 years after separation. On average, workers lose 21.2% of counterfactual present discounted value earnings over the period of 20 years following the separation. His model appears to fit the data well, being able to replicate such losses.

Krolikowski, 2017 develops a model with a substantial job ladder due to a fixed component within matches, capturing the idea that a worker is a better fit for some jobs than the others, and searching for such jobs takes time. Non-employed workers start with poor employment relationships and obtain better jobs through on-the-job-search. That prolongs the recovery of earnings after displacement, resulting in a better fit with the data, as most of the standard models fail to replicate the magnitude and persistence of displacement losses. Krolikowski, 2017 model, similarly to Jarosch, 2021, has higher separation hazard for newly hired workers, as their jobs may be terminated by even a slight productivity shock (because for the workers coming out of non-employment, the first job is not very good in terms of the match quality). This is also documented by Stevens, 1997, reporting higher hazard rates for workers transitioning through unemployment than those whose jobs originated from a job-to-job transition. Krolikowski, 2017 estimates are based on the PSID data for 1988 - 1997, which is a survey data of about 18 thousand individuals from the U.S. The procedure for the empirical estimation of displacement losses follows, similarly as in Jarosch, 2021, the work of Davis and Wachter, 2011. He finds the average losses to be at around 20%, in line with other research following this methodology.

The work of Burdett et al., 2020 has been discussed in Chapter 1.

This work contributes to the empirical literature estimating displacement losses in several ways. First, it provides a measure of the cost of displacement across several subgroups of the population, exploring the importance of education, contract type, gender, and motherhood. Second, it applies the same data preparation and econometric methods to administrative and survey data. This allows comparisons between the two, which cannot always be made between different studies due to different characteristics of the data, and data preparation and econometric techniques. Third, because the estimation framework is consistent with that of Burdett et al., 2020, the empirical results are interpreted in context of the theoretical model.

2.3 Data

The main source of data used for the analysis is the Sample of Integrated Labour Market Biographies (SIAB) (Antoni et al., 2016), a large-scale, matched employer-employee, administrative dataset from Germany. It is supplemented by the German Socio-Economic Panel (SOEP) survey (Goebel et al., 2019). The characteristics of each dataset and motivation for their choice as data sources are reviewed first. I then discuss the sample selection procedure and construction of variables in detail, and provide summary statistics describing each dataset.

SIAB is a 2 percent random sample drawn from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB) in Germany. The IEB tracks employment status of all individuals in Germany who fall into one of the following categories: employees subject to the social security system, employees in marginal employment, benefit recipients, officially registered jobseekers, or participants in active labour market programs. While SIAB is a *sample* drawn from the full IEB dataset, it is large and covers detailed employment histories of 1 million 760 thousand individuals between 1975 and 2014. The dataset has a modular structure, depicted in Figures 2.1 and 2.2, in which separate files containing individual and establishment-level information can be linked to form a matched employer-employee dataset. It is supplied in a spell format, with an exact daily start and end date of a spell provided, where individual spells cover all notifications to the social security system for the sampled individuals. The treatment of multiple sources of information and episode splitting is discussed in the sample construction section below. Main advantages of the SIAB lie in the representative sample of the labour force in Germany, detailed and long individual labour market histories recorded with daily precision, accurately recorded wage information, linkage with establishment information for each of the employment spells, and large size which allows for analysis of outcomes of different socioeconomic subgroups over time. Main disadvantages are related to complicated structure of the data, limited number of available variables as primarily administratively useful data is recorded, and top coding of wage information above the level of maximum social security contributions.

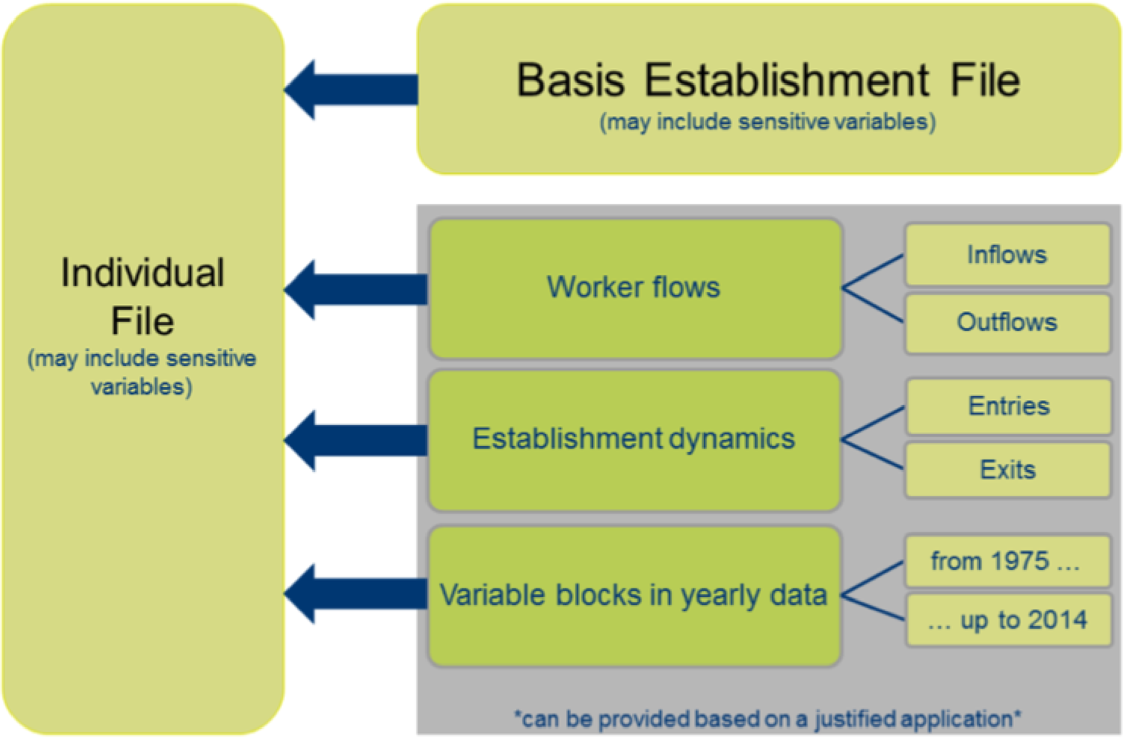
SOEP is a representative longitudinal survey of private households conducted by the German Institute for Economic Research in Berlin. The survey started in 1984 and provides information on all household members of a representative sample of approximately 19 thousand households and 35 thousand individuals, in aspects such as household composition, occupational biographies, employment, and earnings. The data is provided in a standard form of a longitudinal dataset. Advantages of SOEP data lie in the large number of detailed variables, as well as design oriented for research, which facilitates the use of the data. On the other hand, the sample size is significantly smaller than in administrative data, especially when attrition is considered (Kroh et al., 2018), and a researcher is interested mainly in the evolution of individual outcomes over time, as opposed to a cross-sectional analysis. Furthermore, sampling frequency is lower than in administrative data which is collected alongside compulsory reporting duties, and self-reported data can be less accurate, for example due to imperfect recall of information by surveyed individuals.

Due to a large number of individuals observed for a long time period, accurate employment and wage records, and establishment level information, SIAB is used as the primary source of data to estimate the job displacement costs for different subgroups of the population. SOEP is used as a secondary data source, providing information on aspects of employment histories not observed in SIAB, such as the reason for termination of an employment spell. Since this is often proxied by changes in the number of employees in the administrative data, survey data provides a robustness check on the validity of such approach. Furthermore, while top coding of wages affects a relatively small number of individuals in the SIAB, it is concentrated in certain socioeconomic subgroups and can reach almost 50 percent within them, for example among university educated males (Dauth and Eppelsheimer, 2020). SOEP data is exploited to compare the distribution of wages in the SIAB, and validity of the imputation procedure implemented to correct top coded values.

2.3.1 Data structure

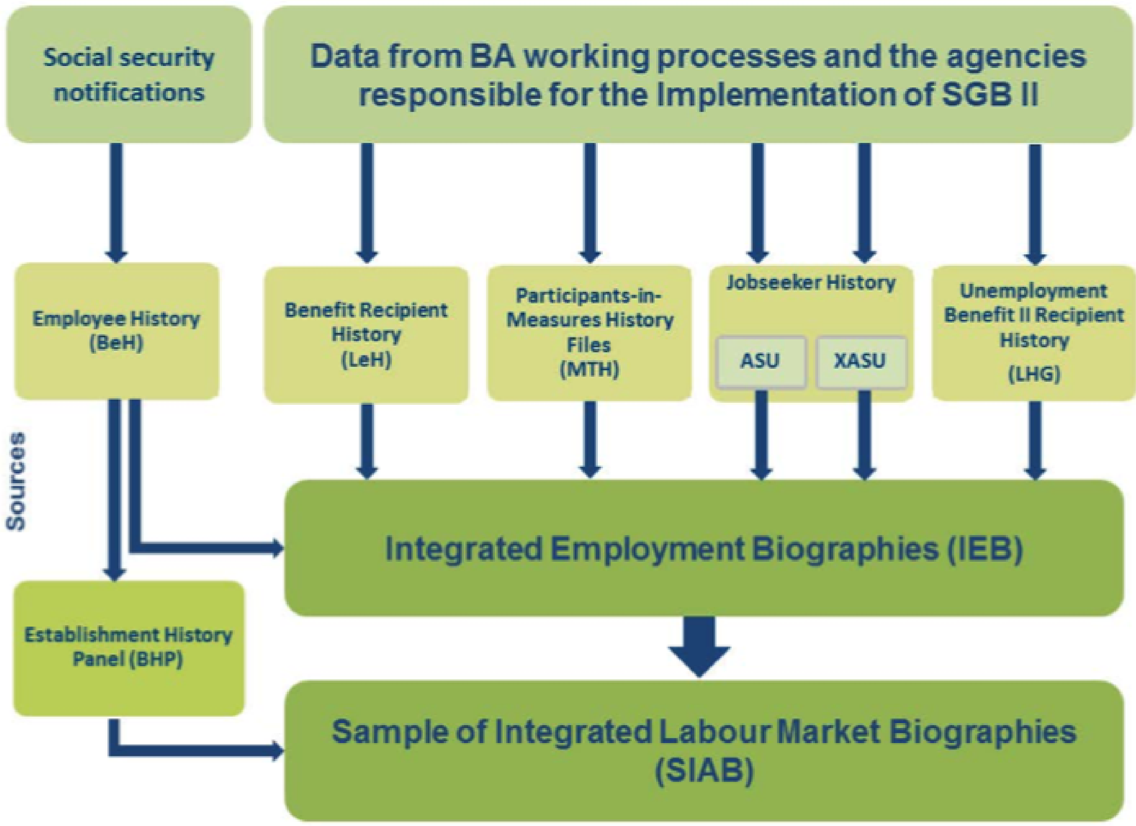
As outlined above, the 2 percent sample of the SIAB is drawn from the IEB dataset, which contains all individuals who were classified as employed subject to social security, or employed in marginal part-time jobs, or in receipt of benefits, or registered as jobseeker, or participating in employment or training programs at any point in the observation window. For each individual in the sample, employment history is obtained from the IAB. Employers are obligated to submit notifications about all their employees covered by social security to the responsible social security agencies at least once a year, for the purpose of health, pension, and unemployment insurance. The Federal Employment Agency collects and edits the data, and merges it with the History File of the IAB. Data on workers' individual employment histories is supplemented by data from establishments employing them. Establishment data reflects the characteristics of establishments on June 30th of each year, therefore providing information at lower frequency than the individual history file. The individual file is merged with establishment file using establishment identifier and year of observation to create a matched employer – employee dataset. Figures 2.1 and 2.2 provide a graphical overview of the structure of the dataset.

FIGURE 2.1: Structure of the SIAB data



Source: SIAB documentation (FDZ, 2016)

FIGURE 2.2: Structure of the SIAB data



Source: SIAB documentation (FDZ, 2016)

While the spell format of SIAB data provides great accuracy and detailed information about individual labour market biographies, it is complex, and multiple spells can overlap. Overlapping spells are split into episodes by the data provider, resulting in parallel spells having the same start and end dates. (See Dauth and Eppelsheimer, 2020 and Antoni et al., 2016 for a detailed explanation of the spell splitting procedure). Parallel episodes can arise when a worker is employed by two firms at the same time, for example. As I construct a monthly panel dataset for the analysis, single status is assigned to any given month. To achieve that I apply the following rules:

- if there are two spells starting on the same date and they have the same duration (measured as the number of days within a given month), the spell with a higher wage is kept

- if two spells still coexist in the same month, the longer spell is kept.

The above procedure removes all overlapping spells of employment and allows me to uniquely identify observations by worker's identifier and date.

SOEP provides a sample representative of Germany's resident population. Initial samples collected in 1984 included private households with German national as head of the household (sample A) and - oversampled – immigrant head of the household (sample B). In the following years, the sample has been enlarged to account for immigration and retain the cross-sectional representativeness of the survey. Additionally, refreshment samples taken from the general population and boost samples focused on specific subgroups of the population (e.g., affluent household, low-income households, families with young children) have been conducted to address the issue of attrition in the dataset. Households are selected using random sampling and individuals of the originally sampled households are followed longitudinally even if they move to a new household. As data is collected both at the household and individual level, it allows for analysis of household and individual dynamics. Survey participants are asked a set of core questions every year, with the household and individual questionnaires being central to the survey. These are extended by topical modules, such as wealth, neighbourhood, family, and networks. In contrast to administrative data, SOEP contains multiple generated variables and is provided in the long format by default, with data pooled and harmonized over all available years, which simplifies the analysis.

2.3.2 Sample selection

This section describes the sample selection procedure. In the SIAB, the sample covers years 1975 to 2014. Because the effect of a job loss can depend on gender, to maintain comparability with the job displacement literature, only male workers are selected for the initial analysis. However, the relationship between gender and unemployment is examined in Sections 2.7 and 3.6.1. Similarly, as migrants can have a significantly different labour market outcomes than the natives (see for example Clark and Drinkwater, 2008), there is evidence of them downgrading in their host country (Dustmann et al., 2013), and their labour market histories before arrival in Germany are unobserved, only German nationals are selected. Furthermore, as the observation window contains the time when Germany has undergone reunification in the 1990s, only individuals who work in West Germany are retained in the sample. There are two reasons for this: first, East Germany differed from the West in the years following reunification in terms of macroeconomic conditions and the labour market (Bryson, 1992 reviews literature on the topic). Second, the data for East Germany is available only from 1992 onwards, and constitutes 10 percent of the total number of observations. To track workers throughout their careers, workers are required to be between 22 and 36 years of age if they are university graduates, and 16 to 30 years old otherwise, at the time of the first observation. This accounts for differences in schooling time and ensures that workers have a comparable amount of labour market experience when they enter the dataset. Finally, only full-time job spells in jobs liable to social security are considered until Section 2.7, which excludes civil servants, self-employed, students, uniformed services (soldiers, border guard, police) and members of parliament and ministers from the sample.

The same restrictions are applied in the SOEP sample, apart from the available observation years, which span between 1984 and 2014.

2.3.3 Overview of existing and created variables

Table 2.1 describes main variables used from the SIAB dataset. A more detailed description of all variables available in the dataset can be found in Antoni et al., 2016.

Variable name	Description
persnr	Artificial numerical individual ID which identifies observations belonging to the same person.
betnr	Artificial numerical establishment ID which identifies observations belonging to the same establishment. If the company has several offices in a given municipality, they are merged into a single establishment if they belong to the same economic class. If the company has several offices of different economic class, or in different municipalities, each of these offices is considered to be a separate establishment. Establishment is therefore defined as "a regionally and economically delimited unit in which employees work" (\cite{antoni2016sample}).
spell	Numerical variable counting the number of episodes observed per person, beginning with 1 and incremented by 1 for each episode.
quelle	Indicated the data source for a given observation.
jahr	Year of observation. For establishments, obtained from the Basis Establishment File and indicated the year of validity of the establishment data. For individuals, generated from the begepi variable.
begepi	Start date of an episode.
endepi	End date of an episode.
frau	Gender dummy variable equal to 0 for a male and 1 for a female. Gender information is constant for each individual.
gebjahr	Individual year of birth. Constant for each individual.
german	Nationality dummy variable equal to 0 for non-German individuals and 1 for German individuals. Detailed nationality information (nation variable) is considered a sensitive variable and available on application only.
ausbildung	Individual vocational training qualification. See description of newly generated skill group variable below.
schule	Individual school leaving qualification. See description of newly generated skill group variable below.
tentgelt_gr	Individual's gross daily wage in euro.
teilzeit	Dummy variable distinguishing between full-time and part-time employees. The classification is based on the ratio between the contracted hours and the usual working hours in the establishment.
erwstat_gr	Individual's employment status. Erwstat_gr variable differentiates between employees liable to social security and other categories.
grund_gr	Reason for submitting a notification.
beruf_gr	Individual's occupation (coarsened to 120 categories).
grd_jahr	Year of the first appearance of the establishment in the dataset.
lzt_jahr	Year of the last appearance of the establishment in the dataset.
az_ges	Total number of employees reported by an establishment to the social security agencies on 30 June of a given year. (Grouped)
az_vz	Share of full-time employees reported by an establishment to the social security agencies on 30 June of a given year.
az_gf	Share of employees in marginal part-time employment reported by an establishment to the social security agencies on 30 June of a given year. Available from 1999 onwards.
te_imp_mw	Mean imputed gross daily wage of the full-time employees in an establishment.
ao_bula	Federal state in which establishment is located.

TABLE 2.1: Description of existing and newly created variables in the SIAB dataset

Additional variables generated in the SIAB

West and East Germany: a dummy variable indicating whether the establishment is located in West or East Germany is created on the basis of ao_bula variable. Distribution of observations by the establishment location is shown in Table 2.2. Regions 1 – 11 are classified as West Germany, constituting 88.42% of all observations, while Region 12 – 16 are East Germany. The last two columns compare the distribution of observations by establishment location with sample restrictions applied to the full, original sample shown in columns two and three.

	Federal state	% of observations	Cumulative %	% of observations with sample restrictions	Cumulative %
1	Schleswig-Holstein	3.22	3.22	3.35328	3.35328
2	Hamburg	3.01	6.23	3.11493	6.46821
3	Niedersachsen	9.33	15.57	10.64257	17.11078
4	Bremen	1.19	16.76	1.32875	18.43953
5	Nordrhein-Westfalen	22.68	39.43	26.33115	44.77068
6	Hessen	8.1	47.53	9.40792	54.1786
7	Rheinland-Pfalz	4.62	52.14	5.3572	59.5358
8	Baden-Wuerttemberg	14.31	66.45	16.32156	75.85736
9	Bayern	16.34	82.79	19.17444	95.0318
10	Saarland	1.36	84.15	1.78531	96.81711
11	Berlin	4.27	88.42	3.1829	100
12	Brandenburg	2.1	90.51	0	100
13	Mecklenburg-Vorpommern	1.5	92.01	0	100
14	Sachsen	3.88	95.9	0	100
15	Sachsen-Anhalt	2.08	97.98	0	100
16	Thueringen	2.02	100	0	100

TABLE 2.2: Distribution of observations by region of the establishment

Age: individual's age is calculated as the difference between the year at the beginning of an episode and the year of birth.

Skill groups: Germany has an extensive vocational education system which I consider in a way similar to Fitzenberger et al., 2006, classifying individuals as low-, medium-, or high-skilled on the basis of combined information about their formal school leaving and vocational qualifications. The two systems are combined into 8 categories as shown in Figure 2.3, which are further aggregated to the 3 skill groups. Group 1 indicates the least educated, with no recorded formal schooling or vocational training; 2 schooling up to and including intermediate school; 3 no formal schooling but vocational qualification; 4 schooling up to and including intermediate school and vocational qualification; 5 no vocational qualification but up to and including upper-secondary school; 6 formal education up to and including upper-secondary school and vocational qualifications; and 7 and 8 indicate higher education. Groups 1 and 3 are empty, and the remaining groups are pooled together on the basis of their job market characteristics (duration of spells, estimated returns to tenure and experience) into 2 and 5 together (low-skilled), who are low educated having at most upper-secondary schooling but no vocational training of any kind, 4 and 6 (medium-skilled) together who have some vocational training in addition to some schooling, and 7 and 8 (high-skilled) who have attained a level of tertiary education. It is worth noting that while firms are obliged to report workers' educational attainment to the social security agencies, the information they provide has no consequences for the social security obligations or claims for either the firm or the worker. It is therefore possible that there is a degree of inconsistency in the variables recording workers' level of education, which I attempt to limit by not allowing the level of education to decrease. Inconsistent education level, which might be due to employers under-reporting, affects 0.2% of all observations. While Fitzenberger et al. propose three imputation procedures to correct the under-reporting, they are not implemented in this work as the number of affected observations is low and evidence of Fitzenberger et al. suggest that it does not affect wage estimates.

Potential experience: calculated as the number of months individual has been observed for (up to the point of observation).

Actual experience: calculated as the number of months individual has been employed for (up to the point of observation).

Tenure: calculated as the number of months individual has been employed for in a given establishment (up to the point of observation).

Real daily wages: calculated by deflating the nominal gross daily wage in euro (tentgelt_gr) using the CPI.

SOEP provides a large number of variables for which excellent documentation is available as a website, see SOEP, 2022. The description of available variables is therefore omitted and only summary statistics are provided. Additional variables are generated in the way matching the above-described variables in the SIAB.

FIGURE 2.3: Definition of skill groups

School leaving qualification / School education and vocational training	1 Without vocational training	2 In-company voc. training/traineeship/External (on-school) voc. training	3 Technical school (voc. training)	4 Technical school (advanced voc. training)	5 University of applied sciences (FH)	6 University	7 Voc. training not accepted in Germany	8 University degree not accepted in Germany	11 University of applied sciences without further specifications	12 University without further specifications
1 No school leaving certificate	1	3	3	3	7	8	3	7	7	8
4 lower secondary school certificate/ grade school certificate	2	4	4	4	7	8	4	7	7	8
5 Grade-/lower school certificate, intermediate school or equivalent qualification	2	4	4	4	7	8	4	7	7	8
6 Intermediate school leaving certificate	2	4	4	4	7	8	4	7	7	8
7 Completion of education at a specialised upper secondary school/completion of higher education at a specialised college	5	6	6	6	7	8	6	7	7	8
8 Completion of education at a specialised upper secondary school/completion of higher education at a specialised college or upper secondary school leaving certificate, A-level equivalent, qualification for university; 13 years of schooling	5	6	6	6	7	8	6	7	7	8
9 Upper secondary school leaving certificate, A-level equivalent, qualification for university; 13 years of schooling	5	6	6	6	7	8	6	7	7	8

Source: Own classification

2.3.4 Wage imputation procedure

Wages are imputed for workers whose wages exceeded the level of maximum contribution to the social security system and have been recorded as top-coded in the data. Top-coding means that all values above a threshold for a given year are replaced with the threshold value. For some subgroups of the population, the extent of top-coding is high. Imputation is therefore necessary to make up for some of this missing information on wages. The values above which top-coding takes place are shown in Table 2.4. The overall share of top-coded spells by skill group is reported in Table 2.3.

Wages are imputed using an interval regression, which is a generalization of the tobit model that can account for any type of censoring or truncation (Reichelt, 2015), repeated multiple times (multiple imputation) as suggested by Little and Rubin, 1989 and – although with a more computationally demanding algorithm - by Gartner and Rässler, 2005. Variables used as independent variables in other parts of the analysis, where wages are used as the dependent variable, should be included in the imputation procedure (Dauth and Eppelsheimer, 2020). The imputation procedure hence controls for potential experience, tenure, and their quadratic terms.

To examine the extent of wage top-coding and therefore imputation in the treated group, the share of observations with imputed wages by skill group is reported in Table 2.5. The share of imputed wages, as well as average annual earnings and wages, are then compared to the control group (which is also affected by top-coding) and the overall distribution of imputed wages is compared to SOEP data (which is not affected by top-coding) in Figure 2.6 (distribution of average daily wages above the top-coding limit in the SOEP), Figure 2.7 (distribution of average daily wages above the top-coding limit in the SIAB), and Figure 2.8 (original distribution of top-coded wages in the SIAB, prior to wage imputation).

The overall share of imputed wages is similar in the treated and control group. Average earnings account for periods spent out of employment which results in the treated group having lower average earnings but similar average wages as the control group.

Figure 2.7 shows the distribution of imputed average daily wages in the SIAB data, for a population to which sample restrictions have been applied. Figure 2.6 shows the distribution of observed average daily wages for a comparable population in the SOEP, whose wages would have been top-coded in the SIAB as they were above the limit of social contributions shown in Table 2.4.

Figure 2.8 shows the original distribution of top-coded wages in the SIAB. The imputation procedure brings the distribution closer to the distribution observed in the SOEP, shown in Figure 2.6. However, further improvements to the imputation model are likely to improve the fit.

TABLE 2.3: Top-coded spells by skill group

% of top-coded wages by skill group	
Group	**%**
All	9.05
Low skilled average	1.22
Medium skilled average	5.75
High skilled average	41.84

Year	Limit	Year	Limit	Year	Limit	Year	Limit
1975	47.1	1986	94.1	1997	137.8	2008	173.8
1976	52.0	1987	95.8	1998	141.2	2009	177.5
1977	57.2	1988	100.6	1999	142.9	2010	180.8
1978	62.2	1989	102.5	2000	144.2	2011	180.8
1979	67.2	1990	105.9	2001	146.2	2012	183.6
1980	70.4	1991	109.3	2002	148.0	2013	190.7
1981	74.0	1992	114.0	2003	167.7	2014	195.6
1982	79.0	1993	121.0	2004	168.9	2015	198.9
1983	84.0	1994	127.8	2005	171.0	2016	203.3
1984	87.2	1995	131.1	2006	172.6	2017	208.8
1985	90.8	1996	134.1	2007	172.6		

TABLE 2.4: Limit of social contributions in each year, in euro

	Treated	**Control**
Share of imputed wages (%)		
All groups	7.8	11.3
Low skill	2.6	1.7
Medium skill	5.8	7
High skill	46.2	48.3
Average earnings (daily average, euro)		
All groups	66.7	100.3
Low skill	56.9	68
Medium skill	65.7	96.4
High skill	102.9	153
Average wages (daily average, euro)		
All groups	98.6	105.2
Low skill	84.1	77.7
Medium skill	97	101.3
High skill	156.1	157.1

TABLE 2.5: Comparison of treated and control groups

Daily wage				
Percentiles		Smallest	Obs	64208
1%	98.8274	84.09863		
5%	114.3123		Mean	207.4282
10%	131.1123		Std. dev.	99.14102
25%	158.0055			
50%	189.9616	Largest	Variance	9828.942
75%	230.137		Skewness	5.217601
90%	295.8904		Kurtosis	54.92295
95%	351.7808			
99%	624.6575	1857.534		

TABLE 2.6: Distribution of average daily wages above the top-coding (imputation) limit in the SOEP

	Daily wage			
Percentiles		Smallest	Obs	6,247,780
1%	78.65389	49.565		
5%	102.8916		Mean	156.6541
10%	116.8772		Std. dev.	29.09418
25%	136.5826			
50%	159.7206	Largest	Variance	846.4711
75%	183.4321		Skewness	-0.60364
90%	190.8952		Kurtosis	2.75246
95%	194.1976			
99%	199.7375	246.8731		

TABLE 2.7: Distribution of average daily wages above the top-coding (imputation) limit in the SIAB

	Daily wage			
Percentiles		Smallest	Obs	6,247,780
1%	51	47		
5%	73		Mean	135.9131
10%	90		Std. dev.	33.01656
25%	109			
50%	142	Largest	Variance	1090.093
75%	168		Skewness	-0.54299
90%	173		Kurtosis	2.487508
95%	177			
99%	180	180		

TABLE 2.8: Distribution of average daily wages at the top-coding limit before the imputation

2.3.5 Descriptive statistics

Table 2.9 reports selected statistics for the main SIAB and SOEP samples corresponding to the sample selection procedure described in Section 2.3.2.

Variable	**SIAB**				**SOEP**			
	Mean	Std. dev	Min	Max	Mean	Std. dev	Min	Max
Year of observation	1997	10.83	1975	2014	2000	8.64	1983	2014
Age	37.5	10.17	18	74	35.4	8.64	18	66
Sex	1	0	1	1	1	0	1	1
Education level low (share)	0.12	0.33	0	1	0.11	0.30	0	1
Education level medium (share)	0.76	0.42	0	1	0.68	0.47	0	1
Education level high (share)	0.12	0.32	0	1	0.21	0.41	0	1
Gross labour income in euro	2606	1203.2	0	5928	2701	1873.89	0	56500

TABLE 2.9: Descriptive statistics: SIAB and SOEP data

2.3.6 Mincer estimates of returns to tenure and experience

Table 2.10 presents the % returns to tenure and potential experience, based on parameter estimates from a Mincer-like earnings model (Mincer, 1974). Mincer equation is a standard framework to estimate returns to experience and tenure (Heckman et al., 2003). It models the logarithm of wages as a function of potential experience and tenure:

$$log(w_{it}) = \beta_0 + \beta X_{it} + \epsilon_{it} \tag{2.1}$$

where $log(w_{it})$ is the logarithm of real wage of person i at time t, β_0 is the constant, vector X_{it} contains the quadratic polynomial of potential experience and tenure of individual i at time t, and ϵ_{it} is the error term.

First part of Table 2.10 shows result with imputed wages, which has been introduced in Section 2.3.4. The number of top-coded spells clearly increases in skill, and for the highly skilled is equal to 41.8%. Wage imputation has an effect on the distribution of wages of high skilled workers, who are most affected by top-coding, but its magnitude is limited. This finding is in line with the results of Card et al., 2013, who find almost no effect of imputation on women and a 2.7%-point increase in mean log wages of men.

Without wage imputation, returns to potential experience reach approximately (cumulatively) 8% after 10 years for the low and medium skilled, and half of that for the highly skilled. Imputing wages results in increased returns to potential experience across all skill groups, but the returns for the highly skilled workers remain lower than for the lower-skilled workers. In terms of the returns to tenure, without wage imputation they are equal to about 8% after 10 years for the low skilled, and decrease significantly as skills increase: equating 4.3% for the medium skilled, and around 3% for the high skilled. With imputed wages the pattern between differently skilled workers remains the same, however the returns for the university graduates decrease slightly. The estimated returns to tenure are not much smaller than returns to experience, especially for the low skilled workers.

However, the finding that low skilled workers enjoy the highest returns to tenure mirrors Burdett et al., 2020 and its earlier version, Burdett et al., 2015 estimating the returns to tenure and experience on the British Household Panel Survey data. They attribute this to very different job ladders across the skill groups: as shown in Table 2.14, higher skilled workers have substantially longer average employment spells and higher rate of arrival of job offers. Job-to-job transitions are therefore more frequent than among the low skilled workers, who have short employment spells and are significantly more likely to be fired than to receive an outside offer. In their model, low skilled workers are employed at the low points of the baseline salary scale. On the other hand, high skilled workers experience more job-to-job transitions and are able to climb the job ladder. While their starting wages may be relatively low, they then enjoy steep returns to tenure - but, on average, high skilled workers have this phase behind them and enjoy higher wages and lower returns to tenure. (In the model they are employed at higher points of the *baseline salary scale*). Moreover, marginal returns to tenure decrease quickly. That means that for the high skilled workers average returns to tenure estimated by Mincer equation do not fully reflect the underlying structure of the job ladder.

Estimated % returns to potential experience and tenure

(Based on Mincer regression)

Time	Imputed wages						Without wage imputation					
	Skill group						Skill group					
	Low		Medium		High		Low		Medium		High	
	Exp	Tenure	Exp	Tenure	Exp	Tenure	Exp	Tenure	Exp	Tenure	Exp	Tenure
1	0.91	0.87	1.11	0.43	0.54	0.29	0.81	0.85	0.79	0.44	0.42	0.33
2	1.82	1.73	2.21	0.87	1.08	0.57	1.61	1.70	1.58	0.87	0.83	0.66
3	2.72	2.59	3.32	1.30	1.62	0.86	2.42	2.55	2.37	1.31	1.25	0.99
4	3.62	3.45	4.41	1.73	2.16	1.15	3.22	3.39	3.16	1.74	1.67	1.33
5	4.52	4.30	5.51	2.16	2.70	1.43	4.01	4.23	3.94	2.17	2.09	1.66
6	5.41	5.15	6.60	2.58	3.24	1.72	4.81	5.06	4.72	2.60	2.51	1.99
7	6.30	6.00	7.69	3.01	3.78	2.01	5.60	5.89	5.50	3.03	2.93	2.32
8	7.19	6.84	8.77	3.43	4.32	2.29	6.38	6.72	6.28	3.46	3.35	2.65
9	8.07	7.67	9.85	3.85	4.86	2.58	7.17	7.54	7.05	3.88	3.77	2.98
10	8.95	8.51	10.93	4.27	5.40	2.87	7.95	8.36	7.82	4.30	4.18	3.32

TABLE 2.10: Mincer returns to tenure and potential experience, by skill

2.3.7 Frictional wage dispersion among differently skilled workers: mean-min ratios

Mean-min ratios

Group	**Mm**	**Mm1**	**Mm5**	**Mm10**
All	1978.05	2.24	1.39	1.25
Low skilled	1370.85	2.16	1.38	1.24
Medium skilled	1897.72	2.00	1.36	1.23
High skilled	1839.96	1.98	1.30	1.18

TABLE 2.11: Mean-min ratios, by skill

Models incorporating search frictions in their representation of the labour market are naturally interested in wage inequality among observationally similar workers arising due to frictions in the process of searching for jobs, called frictional (Hornstein et al., 2011) or pure (Mortensen, 2003) wage dispersion. Because of references to the model of Burdett et al., 2020, I describe the data in terms of the observed frictional wage dispersion using a simple statistic proposed by Hornstein et al., 2011, the *mean-min ratio*. The mean-min ratio is calculated as the ratio of the average accepted wage to the lowest accepted wage observed in the data. Table 2.11 also displays average wage ratio to the 1st percentile, 5th percentile, and the 10th percentile, because the mean-min ratio is affected by some very small values of wages reported in the administrative data. On the other hand, focusing on the 1st, 5th, and 10th percentile ratios shows that the frictional wage dispersion decreases in skill, which indicates lower levels of inequality amongst the higher-skilled workers. The same pattern is reported by Burdett et al., 2020, as the model reproduces frictional wage dispersion observed in the data and is consistent with findings of Hornstein et al., 2011. According to Hornstein et al., 2011, this is rarely the case: even disregarding the small minimum values observed in the data, and focusing on the Mm5 ratio, the data implies a between 30 and 38% differential between the average and the lowest wage, which is tenfold of values typically used by standard search models.

2.3.8 High wage firms and workers: framework of Abowd, Kramarz, Margolis 1999

Abowd et al., 1999 introduce a framework with simultaneous heterogeneity in individuals and firms ,with respect to the determination of workers' compensation, to disentangle the effects of firms' and workers' decisions. Research conducted prior to Abowd et al. did not allow for separate identification of the worker and firm effects. Thanks to the use of matched employer-employee data from France, which covers over a million French workers employed at 500 thousand firms, observable and unobservable differences between workers and firms can be controlled for, workers and firms can be classified as high-wage. A high-wage firm offers compensation higher than expected on the basis of observable characteristics, and a high-wage worker is paid in excess of a prediction based on observable characteristics, such as labour force experience, level of education, region, or sex.

The main goal of Abowd et al., 1999 is to estimate the following equation:

$$log(w_{i,t}) = \beta X_{i,t} + \delta_t + \theta_i + \psi_j + \epsilon_{i,t} \tag{2.2}$$

with a following structure on the fixed effects:

$$\theta_i = \alpha_i + u_i \eta \tag{2.3}$$

$$\psi_j = \phi_j + \gamma_j s_{i,t} \tag{2.4}$$

where $w_{i,t}$ denotes wages of individual i at time t, $X_{i,t}$ is a vector of observable characteristics, which includes a quadratic polynomial of potential experience, and industry and region indicators, δ_t is the time effect, θ_i is the person effect, ψ_j is the firm effect, u_i are individual observable fixed characteristics; α_i and η are unobserved, ϕ_j is a pure firm effect; $\gamma_j s_{i,t}$ are firm-specific gains to tenure (heterogeneous tenure slopes).

Estimating the Abowd et al., 1999 model is not directly required in order to estimate displacement losses. However, the structure imposed by Abowd et al. on the firm fixed effect, which consists of the pure firm effect and a firm-specific tenure slope, would allow the correlation between firm effects and firm-specific tenure slopes to be calculated, providing a statistic directly relatable to the theoretical model of by Burdett et al., 2020.

However, while the model of Abowd et al. is frequently used in the literature (Card et al., 2013; Card et al., 2018; Song et al., 2019; Carrillo-Tudela et al., 2020; Bias et al., 2021), it is typically estimated on an unrestricted administrative dataset (the whole universe of workers and firms), available to selected researchers, in which case the largest connected set is of a sufficient size (Card et al., 2013 report that in the whole Integrated Employment Biographies (IEB) dataset the largest connected set contains more than 95% of all workers and 90% of establishments). A difficulty in estimating the specification of Abowd et al. arises in the SIAB sample, because identification relies on workers moving between firms – fixed effects are only separately identified in sets of firms connected by workers moving jobs; estimation can therefore be infeasible in samples which do not provide a large enough connected set of firms between which workers move (Abowd et al., 2002). Another issue concerns worker mobility in the largest connected set, which must be high enough to identify the parameters of the Abowd et al. model. Bias et al., 2021 notes that there is a discussion in the literature whether this assumption is satisfied.

Some researchers choose to use estimates obtained directly from the original studies instead of estimating the parameters themselves (Butschek, 2022). Recent versions of the SIAB provide a set of estimated fixed effects, based on the whole universe of workers and firms, and can be linked to individual observations included in the SIAB sample. (Antoni et al., 2019 describe the procedure of linking SIAB dataset with estimated fixed effects for the AKM equation). While it was not available for the version of the data used in this article, own estimates based on the SIAB are compared with the estimates included in that file and reported by Bellmann et al., 2020, to assess the feasibility of estimating AKM model in the SIAB sample.

Table 2.12 compares the person and firm fixed effects estimated on the SIAB with values estimated on the unrestricted dataset as reported in Bellmann et al.

Mean establishment effect averaged across all reported years is close to the value estimated in the SIAB data. However, mean person effect has a significantly different magnitude and opposite sign. While estimated establishment effects are close

Source	Time range	Effect	N	Mean	Sd	P25	P50	P75
SIAB (own calculation)	1975- 2014	Person	101,312	-.1110888	.4069448	-.2986156	-.0881031	.1331746
	1975 - 2014	Establishment	204,577	-.1095202	.429099	-.183084	-.00706	.087128
IAB (Bellmann et al. 2020)	1985 - 1992	Person	28,297,724	4.23985	0.36039	4.06029	4.25160	4.43068
	1993 - 1999	Person	32,645,910	4.27066	0.36898	4.07831	4.26679	4.46693
	1998 - 2004	Person	30,598,327	4.37484	0.39716	4.16841	4.36806	4.58898
	2003 - 2010	Person	29,865,417	4.73742	0.42029	4.51389	4.72881	4.96846
	2010 - 2017	Person	30,787,607	4.14973	0.43482	3.88705	4.12223	4.40707
	1985 - 1992	Establishment	1,898,388	-0.06271	0.36764	-0.20938	0.01428	0.16560
	1993 - 1999	Establishment	2,543,452	-0.05080	0.36083	-0.22096	0.00946	0.18410
	1998 - 2004	Establishment	2,537,182	-0.14612	0.38348	-0.32135	-0.08231	0.10138
	2003 - 2010	Establishment	2,476,096	-0.51582	0.43532	-0.70263	-0.43718	-0.23825
	2010 - 2017	Establishment	2,103,298	0.12236	0.37050	-0.02249	0.17988	0.34469

TABLE 2.12: AKM effects, SIAB and IAB datasets

to values reported by Bellmann et al., 2020, and correlations between establishment effects and establishment-specific tenure effects reported in Table 2.13 are close to those reported by Burdett et al., 2020 for medium and high skilled workers (who estimate the correlation to be equal to -0.1833 for the low skilled, -0.1881 for the medium skilled, and -0.1949 for the high skilled), sampling based on individuals, likelihood of observing only one worker per firm, and different estimated person effects make SIAB inappropriate for estimating the AKM effects.

TABLE 2.13: Firm effect and firm-specific tenure correlations in the SIAB sample

Correlation between firm effect and firm-specific tenure			
Whole sample	Low skilled	Medium skilled	High skilled
-0.2009	-0.0012	-0.2153	-0.1829

2.4 Methodology

2.4.1 Loss of employment

Transitions from employment to non-employment are a common occurrence in the labour market. Extensive empirical research on the large and persistent losses of workers displaced into unemployment and their sources, reviewed in the literature review section, has been conducted. As outlined in the introduction, Burdett et al., 2020 extend the set of frameworks used to analyse the cost of job displacement in a frictional labour market by providing one which considers learning-by-doing while employed to make wages exhibit both experience and tenure effects; allowing job displacement to result in a loss of human capital.

In the SIAB dataset I cannot fully differentiate between non-employment and unemployment due to the fact that only official unemployment is registered, i.e. periods when an individual was registered as unemployed with the Federal Agency for Employment, especially for the receipt of unemployment benefits. Since I cannot exclude a possibility that some workers were laid off but decided not to register (for example, because they expect to find a new job quickly, or the amount of unemployment benefits that they would be eligible to receive is relatively small in comparison to their earnings) I consider all periods in which an individual was not in full-time employment to be non-employment. A simple employment-to-non-employment (EU) transition is defined henceforth as a "separation", while a "displacement" is an EU transition which took place in a year when a mass lay-off occurred at worker's establishment.

To identify a mass lay-off I follow a set of criteria used by Jarosch, 2021. I consider employees of a company i at time t to be subject to a mass-layoff if the number of full-time employees at t is at most 70% of the number of full-time employees at t - 2, but not less than 1% of the number of full-time employees at t - 2, and the number of full-time employees at t - 2 is at most 130% of the number of full-time employees at t - 3, and the number of full-time employees at t + 1 is at most 90% of the number of full-time employees at t - 2. Additionally, I require that the number of full-time employees at t - 2 is larger than 50. Due to the data anonymization process I do not observe the exact number of full-time employees in an establishment. I do, however, know the range of the size of the establishment (1-5 workers, 6-20, 21-50, 51-100, 101-200, 201-500, more than 500) and the percentage of full-time employees. I use these variables to approximate the number of full-time employees at time t.

The distinction between separations and displacements is important because displacements can be thought of as a quasi-natural experiment - it is reasonable to assume that mass-layoffs arising from establishment closures are exogenous to the individual workers' characteristics. However, separations are often used either in addition to or instead of displacements. For example, Davis and Wachter, 2011 consider both mass lay-offs and displacements in the main part of their analysis, while Jarosch, 2021 relies on separations for the main part of his paper, using displacements as a robustness check. He finds no significant differences in the results, and notes that only up to 20% of workers transitioning through unemployment do so voluntarily, suggesting that separations are a good approximation for displacements. In this paper I primarily focus on separations as the larger sample size allows for a more detailed exploration of workers' heterogeneity. However, I compare the results with those obtained by using displacements as a robustness check.

2.4.2 Identification

In an ideal world, to understand the effect of losing a job on wages, earnings, and the future trajectory of labour market outcomes, and whether it differs by gender, and - if so - for what reason, a controlled randomised experiment would be ideal. Such setup is unfortunately rarely - if ever - possible in economics, and in this particular case would require some individuals to be made unemployed, and yet others to be forced to give birth to children, all while observed for a period of at least 15 years. Given the infeasibility of such a design, with a large-enough amount of data, a pseudo-natural approach - an event study - is the second best. The introduction of this methodology can be attributed to finance and accounting research investigating changes in the prices of stocks in response to unanticipated events (news) (Fama et al., 1969; Ball and Brown, 1968). Since then, similar techniques have been used widely in public and labour economics, where the event is, for example, a policy change. Such studies belong to the broadly defined family of differences-in-differences models, and have been gaining popularity since at least Angrist and Pischke, 2010. Schmidheiny and Siegloch, 2019 note that the use of event study approaches has exploded since 2010 (See Figure 1 of Schmidheiny and Siegloch, 2019) as they allow the coefficients to be easily graphed, provide an immediate visibility of the "no pre-event trends" identifying assumption, and have an intuitive underlying econometric model when applied to panel data. Importantly, they show that the event study model is a reparametrisation of a distributed-lag model and is equivalent to it - which is the model implemented in this study.

Let i denote an individual, who receives treatment at time e_i. The goal is to estimate the effect of this treatment on a dependent variable y, observed at different time periods $t = t_{min}, ..., t_{max}$. $[t_{min}, ..., t_{max}]$ is the observation window for the dependent variable, in this case annual earnings or wages. I also define the effect window as $[j_{min}, ..., j_{max}]$, which is the time from $j_{min} < 0$ time periods before the event to $j_{max} > 0$ time periods after the event, of which the dynamics of the treatment effect (which can vary over time) I am interested in. This gives rise to a specification as in Equation 2.6, where $D_{i,t}$ is an event dummy that takes the value of 1 in the treatment year. [4]

Following Schmidheiny and Siegloch, 2019, such a model is econometrically identified if each lag and lead j is observed in the outcome window $[t_{min}, ..., t_{max}]$ for at least one unit, and for at least one observed endpoint j_{min} or j_{max} in t there is at least one other unit which is treated after $t + j_{min}$ or before $t - j_{max}$. The second condition is automatically satisfied when at least one never-treated unit exists. Following Schmidheiny and Siegloch, 2019; Borusyak and Jaravel, 2017 if these conditions are met, the time fixed effects can be separated from the dynamic treatment effects and the model is identified.

[4]To recover the event study effects from the distributed lag model coefficients, distributed lag coefficients up to a time t have to be added up.

Selection concerns

Dustmann and Meghir, 2005 discuss a number of assumptions required to estimate the average returns to experience. Similar issues are relevant to estimation of unemployment scarring, and assumptions that have to be made are outlined below.

Selection into unemployment Selection into unemployment may occur if workers of lesser ability or willingness to work are more likely to become unemployed. It is also possible that workers voluntarily decide to leave employment. Three things limit this source of bias: i) workers are required to become re-employed within 3 years; ii) as is common in the literature, treated sample consists of male, German, high-tenure (36 months at least) workers who have a strong labour market attachment. If ability and productivity are positively correlated with tenure, this should limit the first source of bias as tenure increases. iii) As a robustness check, mass layoffs are used to estimate the cost of job loss and the results are reported in Section A.1. This specification yields similar results to the all-separations specification, and because high ability workers might foresee worsening conditions which culminate in a mass-layoff and resign, using mass-layoffs is likely to have only a limited effect on preventing the two sources of bias described above. Therefore, all separations are used throughout this study.

Therefore, with regard to losing a job it is assumed that:

- Workers losing a job in a mass-layoff event cannot reliably predict mass-layoffs and firm closures, to ensure that there is no self-selection in terms of unobserved characteristics.
- Workers separating from the employer (employment to non-employment transition) do so involuntarily. Workers who decide to leave the labour force are not kept in the sample.

Searching for work and accepting a job If workers of higher ability were more likely to receive offers of employment, estimates could be biased. However, displacement effects are estimated separately for each of the three skill groups, who search for work in different labour markets. Workers who leave the labour force are excluded from the sample, and estimates are only used in the aggregate form of per-group performance. The previously discussed sample selection procedure (which involves selecting workers with a strong labour market attachment) should also reduce this source of bias.

A second source of bias might arise if other characteristics are correlated with likelihood or speed of finding work, and they differ between skill groups. Again, because the effect is calculated at the skill group level, and the control group is composed of other workers in the same skill group who kept their jobs, this should not bias the results.

Therefore, with regard to searching for work and accepting a job it is assumed that:

- Workers of different skill operate in different labour markets and don't compete for the same jobs. Otherwise, a shock to e.g. high skilled workers, sending a large number of high-ability workers to compete with medium-skilled for the same set of jobs could bias the estimates.

2.4.3 Empirical setup

To empirically investigate displacement losses, I use a distributed lag model adapted from Jacobson et al., 1993 who develop a framework for estimating the magnitude and temporal pattern of workers' earnings following a separation or displacement into unemployment. The goal is to compare workers' earnings after separation from employer with earnings they would have received had they kept their jobs. To control for the possibility that the displacement or separation event might have been foreseen prior to it taking place, Jacobson et al., 1993 suggest tracking worker's earnings for several periods preceding the separation. In this work, I track earnings for three years prior to the displacement, which effectively imposes an assumption that there are no displacement effects earlier than three years before the event. This value has been chosen to optimize the number of available observations, since Jacobson et al., 1993 estimate the model with up to 10 years of pre-displacement periods and report not observing any evidence for an effect of displacement prior to three to four years preceding it. Workers can separate from the employer in any year in the treatment window between 1981 and 2005, which allows full 3 years prior to the separation and 15 years post separation to be observed for all treated workers.

Formally, following Jacobson et al., 1993, denoting earnings of worker i at time t as y_{it} and a displacement indicator $D_{is} = 1$ for a worker i displaced at time s (which takes value of zero otherwise), the loss of earnings is the change in expected earnings if p years prior to date s it was revealed that the worker would separate at date s. Therefore, the loss can be written as

$$E(y_{it}|D_{it} = 1, I_{is-p}) - E(y_{it}|D_{iv} = 0, \forall v, I_{is-p}) \tag{2.5}$$

where I is the information at date s-p, and p is large enough that the events leading to displacement have not begun. Such definition of earnings losses allows the events resulting in a separation to affect earnings prior to separation.

The information set I_{is-p} contains variables related to demographic characteristics that influence earnings. Jacobson et al., 1993 control for time-varying characteristics of the worker (interactions between sex, age, and age squared) and individual fixed effect. It would be possible to evaluate a specification controlling for the firm fixed effect as well. However, the danger of conditioning on worker's firm lies in the fact that those who retained their jobs may also experience earnings losses if there has been a mass-layoff. In that case, conditioning on worker's firm would not capture the full impact of the events leading to separation, but only the effects specifically associated with workers' job losses.

The above translates into a following statistical model:

$$e_{it}^{y} = \alpha_i^{y} + \gamma_t^{y} + \beta^{y} X_{it} + \sum_{k=-3}^{15} \delta_k^{y} D_{it}^{k} + \mu_{it}^{y} \tag{2.6}$$

where

y is the displacement year y,

e_{it}^{y} denotes earnings or wages of individual i in year t,

α_i^{y} is the individual i fixed-effect,

γ_t^{y} is the calendar year t fixed effect,

X_{it} is the cubic polynomial in potential experience of individual i at time t,

D_{it}^{k} denotes dummy variables equal to one in the individual i's k-th year before of after displacement, and zero otherwise,

δ_k^{y} denotes coefficients measuring the time path of e changes for job separators, relative to the baseline and change in e of the control group,

and μ_{it}^{y} is the error term

There is one other potential source of bias: firms might fire workers whose performance was poor in the years leading to separation. In that instance, there are two possible cases: if errors are covariance stationary and if the errors are nonstationary. The potential bias is less important in the first case, since then the spurious effects of displacement are symmetric about the date of displacement. In other words, if the estimated displacement effects are zero a number of years prior to separation, the spurious effects of displacement must also be zero the same number of years following the separation (Heckman and Robb, 1985; Jacobson et al., 1993). In the latter case, with the nonstationary error, there is no ground to assume that poor performers' earnings would recover; it is likely that earnings of those workers would be low even had they not separated from the firm. However, this bias can be significantly reduced by considering only workers who are displaced in a mass-layoff, as such workers are unlikely to be separating as a result of their own poor performance (implicitly assuming that the mass-layoff cannot be foreseen, as otherwise higher-ability workers could be more likely to leave the firm beforehand, leaving the lower-ability workers behind). Therefore, in the empirical part of this paper, displaced workers are considered as a robustness check for the main sample of separating workers.

Similar statistical specifications are also presented in Ashenfelter, 1978, Heckman and Robb, 1985, and LaLonde, 1986 who focus on program evaluations, but the methods of analysis of the longitudinal data create a base for the distributed lag model used to measure the displacement losses.

2.5 Results

2.5.1 Duration of spells

Table 2.14 shows the average duration (in months) of employment, job, and non-employment spells for each skill group.

An employment spell is defined as a consecutive number of months spent in employment, without an intervening spell of non-employment. Because workers' whole labour market history is observed in the data, all periods in which the establishment identifier is provided are classified as periods of employment. On average, workers spend 5 years and 4 months in employment. A clear pattern of employment length increasing with the skill level is visible: an average employment spells lasts 2 years and 8 months for the low skilled workers, 6 years and 1 month for the medium skilled, and 7 years and 7 months for the high skilled. While not shown in the table, it is interesting to note that workers with vocational training have, on average, longer uninterrupted periods of employment. However, the importance of vocational qualifications decreases with the level of education - for the university and technical university graduates, for instance, the difference is minimal.

Job spells are defined as uninterrupted periods, within an employment spell, spent working at a particular establishment. On average a job spell lasts for 2 years and 10 months, which implies that an average worker has approximately 2 jobs within an employment spell. Similarly as in case of employment spells, the length of a job spell increases with skill: from just 1 year and 8 months for the low educated, 3 years for the medium educated, to 4 years for the high educated. The ratio of job spell duration to an employment spell duration shows how many job-to-job transitions workers in each skill group experience, on average, and therefore the dynamics of job switching: medium and high skilled workers change jobs through employment-to-employment transitions 2 times within an employment spell on average, while the low skilled only 1.4 times. The job ladder theory implies that workers seek better wages through job-to-job transitions and climbing the job ladder - and since the low skilled appear to have significantly fewer such transitions, they will have fewer chances at climbing the job ladder and improving their situation in the labour market.

A non-employment spell is defined as an uninterrupted period in which the establishment identifier is missing. Because the data coming from BeH agency only contains information on employment, all remaining periods are considered to be non-employment. As discussed earlier, non-employment is considered instead of the official unemployment. This is because workers are only recorded as unemployed if they receive unemployment benefits or register with the appropriate agency, but the rate of unemployment benefit uptake is likely to differ for workers of different skill level. On average, workers remain in non-employment for a year and 8 months. However, the mean duration of non-employment is significantly larger than the median (11 months), and with the standard deviation of almost 30 months, the surprisingly long duration of non-employment appears to be driven by the individuals with very long spells of non-employment (up to 38 years in the analysed sample). While there is a considerable difference in the average length of non-employment spell between the low skilled (23.9 months) and higher-skilled workers (18.9 months), both medium and high educated workers spend about a year and a half in non-employment.

Considering the duration of different spells allows a pattern to be established. On average, low skilled workers have short employment spells, job spells that make up a significantly higher part of an employment spell than in case of their higher-skilled counterparts, and very long non-employment spells. Since low-skilled workers remain employed for a relatively short time, not having many opportunities to climb the job ladder through employment-to-employment transitions, and frequently transition into long spells of non-employment, they spend a significant part of their careers in low-paid jobs, or without a job at all. Lack of opportunities to climb the job ladder and develop human capital suggest that low skilled workers are likely to follow different trajectories in the labour market than the higher-skilled workers, and suffer different consequences of losing a job.

Education group	Observations	Mean	Median	SD
Employment spells				
Low	153,077	31.9	10.3	58.2
Medium	303,248	73.3	41.7	88
High	71,125	90.6	56	94.7
Job spells				
Low	474,704	19.7	5	43.1
Medium	1,393,006	36.2	12	61.3
High	182,914	48	24	63.5
Non-employment spells				
Low	108,899	23.9	12.3	32.6
Medium	224,878	17.9	9	28.1
High	32,598	18.9	8	33.7

TABLE 2.14: Summary statistics of employment, job, and non-employment spells, by education

2.5.2 Employment-to-employment transitions

Previous section establishes that low-skilled workers experience, on average, fewer employment-to-employment (EE) transitions than their higher-skilled counterparts. This by itself hinders their chances of climbing the job ladder and increasing their wages and earnings. Employment-to-employment transitions can be analysed in more detail however, by taking into account the fact that not all of them must occur voluntarily - taking a pay cut, but avoiding unemployment, is still likely to be a preferred option. To analyse weather there are significant differences in EE transition between skill groups, I define a ratio of involuntary-to-voluntary EE transitions as the number of people who received a wage cut upon an EE transition over the number of people who received a wage increase. Using such proxy is the only feasible way of identifying workers transitioning voluntarily and involuntarily in the SIAB data, and requires observing only the firm identifier and wages. Later analysis using SOEP data shows another way of calculating this ratio, if more accurate information is available.

Table 2.15 displays the ratios by skill group. Low skilled workers have the highest ratio of involuntary-to-voluntary transitions, suggesting they are more likely to take a pay cut moving between jobs than other skill groups. This further highlights the instability of their careers - not only the low skilled have shorter employment spells and longer non-employment spells than the other groups, changing jobs appears to more often be a way of maintaining employment, as opposed to advancing their labour market position.

TABLE 2.15: Ratio of involuntary to voluntary EE transitions, by skill

Ratio of involuntary/voluntary EE transitions				
Group	Low skilled	Medium skilled	High skilled	All
Ratio	0.71	0.60	0.65	0.62

2.5.3 Separation losses

This section describes the estimation results of the distributed lag model introduced in the methodology section.

The values reported are a percentage change in earnings (in levels), wages (recorded in levels and log-transformed), and wages at one point within a year (first available observation) in relation to the counter-factual: estimated effects of displacement are presented in the figures in this section as a percentage loss, in comparison to the value of earnings or wages of workers in the control group who were not displaced in a given year. The percentage loss shown in the figures is calculated using real values of average daily earnings or wages for the control group of workers not displaced in a given displacement year in the displacement window, standardised to the values of the first year in the observation window. The coefficients and control group earnings or wages are estimated separately for each year in the displacement window, resulting in displacement estimates and average earnings or wages for the control group for each year in the displacement window. All the values are then averaged across the years, and values shown in graphs are average losses in comparison to average earnings (or wages) of not displaced workers. Jacobson et al., 1993 use only workers who are never laid-off as the control group. Burdett et al., 2020 argue that this approach conditions on workers who are ex-post lucky, and instead adopt Sianesi, 2004 approach, using workers who were employed but not laid-off in a given year and remain at risk of a future layoff. The latter approach appears more appropriate, particularly when the sample of all separating workers is considered, as opposed to mass-layoffs only. Otherwise, the control group would be composed of workers who remained employed for the whole observation period, which is likely a group with different unobservable characteristics than the treated group, and hence not an appropriate control.

However, Section 2.6.4 considers the impact of using a control group composed of workers who were not displaced in years future to a given displacement year. Such a modification increases estimated losses in the first period, but overall has a limited effect on the trajectory of losses over time.

Earnings

Table 2.16 and Figures 2.4 and 2.5 show the change in earnings of separating workers, in comparison to a control group of similar workers who remained employed. In the three years preceding the separation the values for two groups are similar. When earnings are based on imputed wages, an average separating worker loses approximately a third of earnings in the year of separation. Earnings recover quickly in the first three years post-separation, but no full recovery is made even after 15 years.

As suspected when analysing the transition patterns of different groups, the largest earnings penalty, lasting for the longest time, applies to the low skilled workers and amounts to the immediate loss of -61.2%, decreasing to -10.9% after 15 years. While low-skilled workers do not have many opportunities to climb the job ladder, and therefore the immediate loss shouldn't reflect the fall from the job ladder, they spend long time in non-employment, with no earnings. For the same reason earnings of low-skilled workers recover slowly: to -35.5% in the first year, -21.5% in the second, and -17.9% in the third year.

High skilled workers also have a substantial immediate loss of up to -33.8% (with imputed wages; -39.9% without), but recover quickly, with any earnings penalty mitigated four years post-separation. 15 years post-separation there is no significant difference between workers who became unemployed and the counterfactual for the high-skilled group; but a visible gap remains for the low and medium skilled workers.

The overall pattern of losses is similar to the results reported by Jarosch, 2021, and results for different skill groups are similar to Burdett et al., 2020, who find the low-skilled workers to suffer a larger immediate loss than the medium-skilled workers. Using the model-based decomposition provided by Burdett et al., 2020, introduced in Chapter 1, the immediate loss of low-skilled workers is driven by the employment gap effect, reflecting the fact that the laid-off worker is more likely to be unemployed in the future. While the employment gap effect accounts for approximately a quarter of the total lifetime loss, it declines quickly, and the estimated profile of earnings losses approaches the profile of wage losses. The job ladder effect is shown to be relatively unimportant in the decomposition, accounting for about 5 percent of the lifetime loss. Loss of skill due to foregone accumulation of human capital is the main channel through which lifetime earnings are affected, accounting for approximately 70 percent of the lifetime earnings loss. This is consistent with the transition patterns observed for the low-skilled workers, who become unemployed more frequently and remain out of work for longer than the higher-skilled.

Due to a smaller employment gap effect, which disappears within two years post-separation, higher-skilled workers have a smaller immediate loss and a faster recovery. While the job ladder effects are more important than for the low-skilled workers, skill loss is still the most important explanation of the lifetime earnings loss.

% loss in earnings in comparison to non-separators, levels						
Time	Imputed			No imputation		
	Skill group			Skill group		
	Low	Medium	High	Low	Medium	High
t-3	1.27	-0.29	-3.32	1.36	1.07	-3.07
t-2	2.96	-0.63	-3.41	3.21	-0.48	-2.80
t-1	13.00	0.77	0.07	13.50	-0.24	1.20
t	-61.20	-30.20	-33.81	-61.59	-29.72	-39.89
t+1	-35.49	-14.84	-11.06	-35.40	-14.21	-12.63
t+2	-21.45	-8.57	-2.97	-21.11	-7.75	-3.04
t+3	-17.94	-7.03	-0.82	-17.49	-6.10	-0.50
t+4	-11.63	-5.51	2.15	-11.09	-4.58	2.69
t+5	-9.94	-5.15	3.12	-9.45	-4.23	3.68
t+6	-9.84	-4.99	2.97	-9.41	-4.13	3.37
t+7	-8.39	-4.83	2.68	-7.82	-4.05	3.09
t+8	-8.80	-4.80	2.42	-8.28	-4.06	2.65
t+9	-9.27	-4.84	1.81	-8.80	-4.15	2.11
t+10	-9.64	-5.03	1.80	-9.10	-4.39	1.94
t+11	-9.41	-5.12	0.85	-9.03	-4.56	0.79
t+12	-10.47	-5.25	0.56	-10.00	-4.71	0.73
t+13	-10.88	-5.35	0.31	-10.61	-4.82	0.39
t+14	-10.75	-5.41	0.17	-10.46	-4.91	0.35
t+15	-10.93	-5.44	-0.47	-10.67	-5.00	-0.36

TABLE 2.16: Separation losses, % earnings, by skill

FIGURE 2.4: % earnings losses in level, with imputation

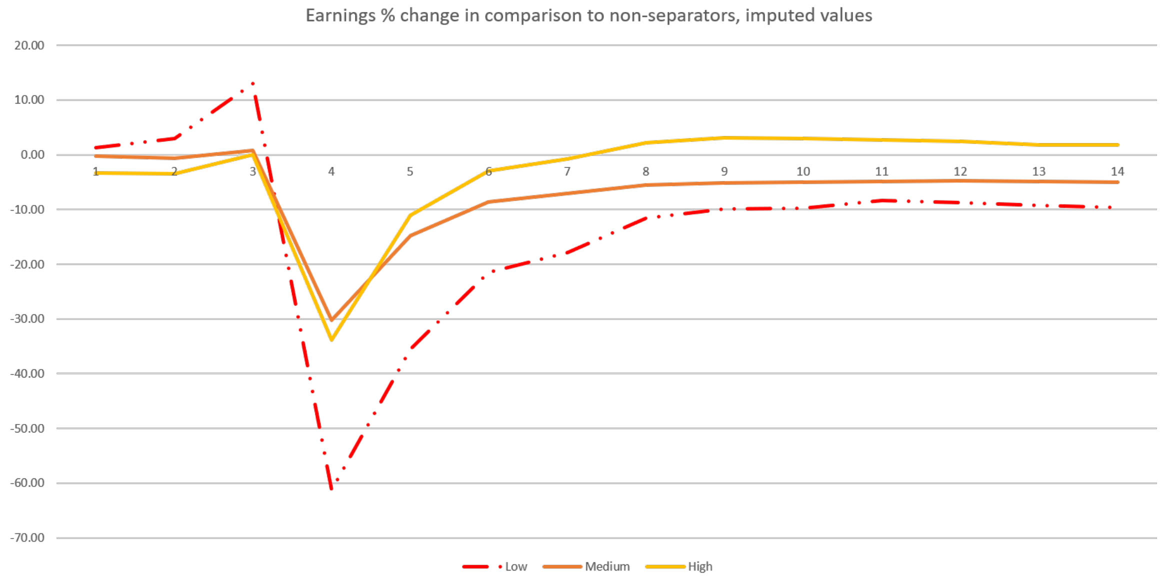
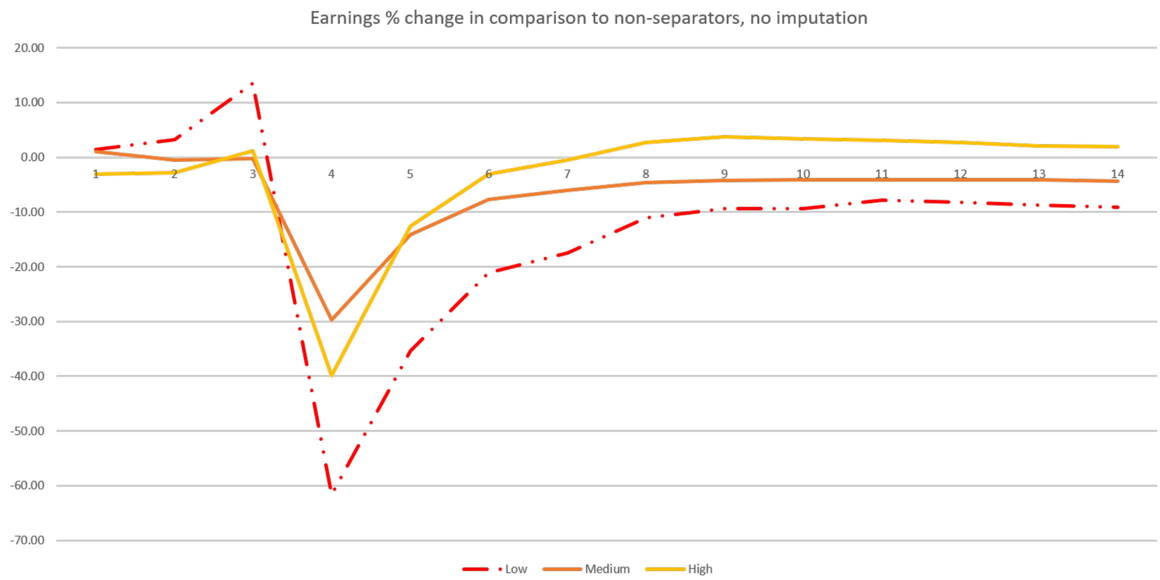


FIGURE 2.5: % earnings losses in level, without imputation



Wages

Secondly, the evolution of the level of wages after a separation is examined in Table 2.17 and Figures 2.6 and 2.7. Wages are defined as the mean of average daily earnings across the months of employment in a given year.

Without wage imputation, the immediate reduction in wages for all skill groups equals -1.6%, which deepens as time goes by, reaching -3.9% after 15 years. The immediate reduction in wages is smallest for the lowest skilled workers, at -1.7%, but it subsequently increases to -6% after 15 years (Table 2.17). A similar pattern is also visible for the medium skilled workers. The response of wages of the high skilled workers, showing a sharp increase after separation, is most likely an artefact of top-coding - I do not observe the true wage, but the (top-coded) maximum increases each year. Since the proportion of workers affected by the top-coding is very high in that groups (Table 2.3), a worker moving from one top-coded job to another will have an artificial increase in wages in the data - purely because the top-coded amount has increased. Attempting to resolve the issue of top-coding, the first three columns of Table 2.17 report estimates obtained from data with imputed wages; however, the overall pattern remains largely the same. Similar issues arising from top-coding are encountered by Burdett et al., 2020, who do not obtain statistically significant results for the evolution of wages of high-skilled workers.

Estimated profiles of wage losses are qualitatively similar to Burdett et al., 2020 for the low-skilled workers. Albeit the size of losses is smaller, there is no indication of recovery of wages over time. For the medium-skilled, results of Burdett et al., 2020 indicate a moderate recovery in wage losses, up to -5%, 15 years post-displacement. Estimates presented in Table 2.17 indicate a similar penalty after 15 years, but a different profile of wage losses over time, with no sign of recovery of wage losses over time, but a smaller initial loss. Referring back to the decomposition of earnings losses discussed in 1, each of the three channels can be considered in the context of observed wage losses, assuming that each channel contributes to the observed losses in the same way as in the model of Burdett et al., 2020. Since wages are calculated using only time spent in employment, the observed loss cannot be attributed to the employment gap effect. The observed loss is therefore a combination of job ladder effects and skill loss experienced in unemployment.

% loss in wages in comparison to non-separators, levels						
Time	Imputed			No imputation		
	Skill group			Skill group		
	Low	Medium	High	Low	Medium	High
t-3	0.31	0.44	-2.51	0.36	0.48	-2.26
t-2	0.54	-0.41	-3.31	0.67	-0.25	-2.79
t-1	0.87	-1.31	-3.16	1.07	-1.01	-2.88
t	-1.54	-2.48	-4.99	-1.67	-2.29	-4.24
t+1	-3.30	-3.26	-1.06	-3.02	-2.59	0.14
t+2	-3.76	-3.91	1.08	-3.40	-3.07	2.06
t+3	-4.01	-4.43	1.55	-3.64	-3.49	2.38
t+4	-4.08	-4.44	2.47	-3.67	-3.48	3.00
t+5	-3.69	-4.47	2.92	-3.32	-3.53	3.32
t+6	-4.17	-4.55	2.76	-3.83	-3.67	3.04
t+7	-4.18	-4.45	2.62	-3.77	-3.66	2.92
t+8	-4.51	-4.57	2.35	-4.12	-3.82	2.50
t+9	-4.91	-4.70	1.80	-4.56	-4.00	1.97
t+10	-5.14	-4.85	1.52	-4.74	-4.20	1.53
t+11	-5.30	-4.95	1.09	-5.00	-4.37	1.08
t+12	-5.54	-5.01	0.59	-5.20	-4.46	0.66
t+13	-5.88	-5.06	0.31	-5.67	-4.53	0.34
t+14	-6.22	-5.11	-0.08	-5.99	-4.61	0.00
t+15	-6.21	-5.13	-0.59	-5.96	-4.68	-0.56

TABLE 2.17: Separation losses, % wages, by skill

FIGURE 2.6: % wage losses in level

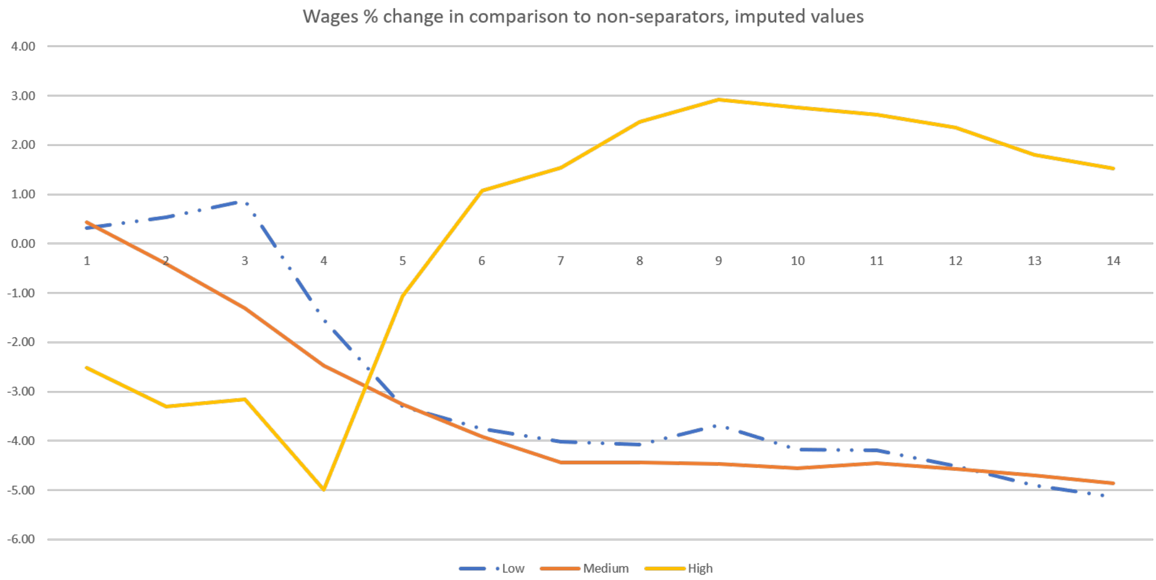
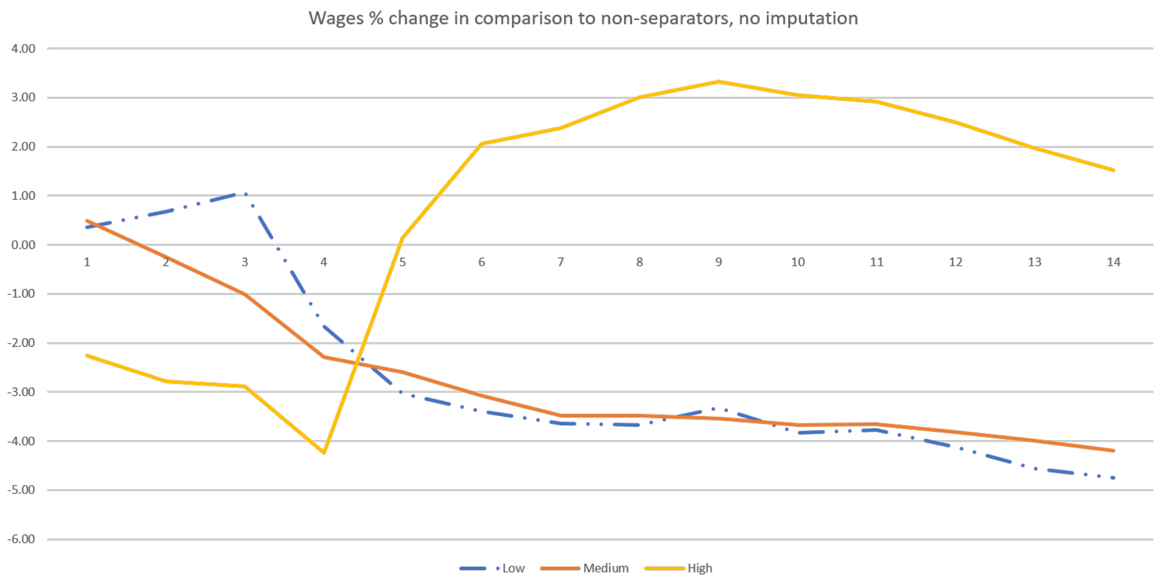


FIGURE 2.7: % wage losses in level



To check the robustness of estimated wage losses, two additional specifications are considered. The first one uses log-transformed wages, and the second uses wages observed at the first available point within a year. These specification yield results similar to wage losses discussed above.

Wages (log) The specification in logs confirms the pattern observed analysing the wages in levels. Losses are stronger with wage imputations. The immediate loss is higher for the highly skilled workers, but as time passes it deepens for the low and medium skilled workers. The results are shown in Table 2.18.

% loss in wages in comparison to non-separators, logs						
	Imputed			No imputation		
Time	Skill group			Skill group		
	Low	Medium	High	Low	Medium	High
t-3	-0.36	-0.68	-5.29	-0.35	-0.65	-4.40
t-2	0.19	-1.33	-4.92	0.22	-1.23	-3.86
t-1	0.84	-1.71	-3.73	0.90	-1.54	-3.02
t	0.19	-2.69	-5.75	0.22	-2.61	-4.40
t+1	-2.14	-2.70	-0.54	-2.05	-2.34	0.34
t+2	-1.81	-2.47	2.21	-1.71	-2.02	2.49
t+3	-1.97	-2.89	2.79	-1.85	-2.38	2.85
t+4	-1.99	-2.78	3.90	-1.87	-2.27	3.59
t+5	-1.81	-2.81	4.45	-1.72	-2.32	3.97
t+6	-2.16	-2.94	3.98	-2.06	-2.48	3.47
t+7	-1.97	-3.02	3.74	-1.84	-2.61	3.29
t+8	-2.12	-3.25	3.14	-2.00	-2.86	2.66
t+9	-2.46	-3.50	2.55	-2.36	-3.14	2.22
t+10	-2.53	-3.74	2.05	-2.42	-3.40	1.67
t+11	-2.43	-3.91	1.60	-2.34	-3.62	1.32
t+12	-2.59	-3.97	0.82	-2.49	-3.69	0.69
t+13	-2.87	-4.07	0.77	-2.81	-3.81	0.68
t+14	-3.32	-4.08	0.49	-3.26	-3.82	0.52
t+15	-3.21	-4.14	-0.26	-3.13	-3.90	-0.16

TABLE 2.18: Separation losses, % wages, by skill

FIGURE 2.8: % wage losses in level

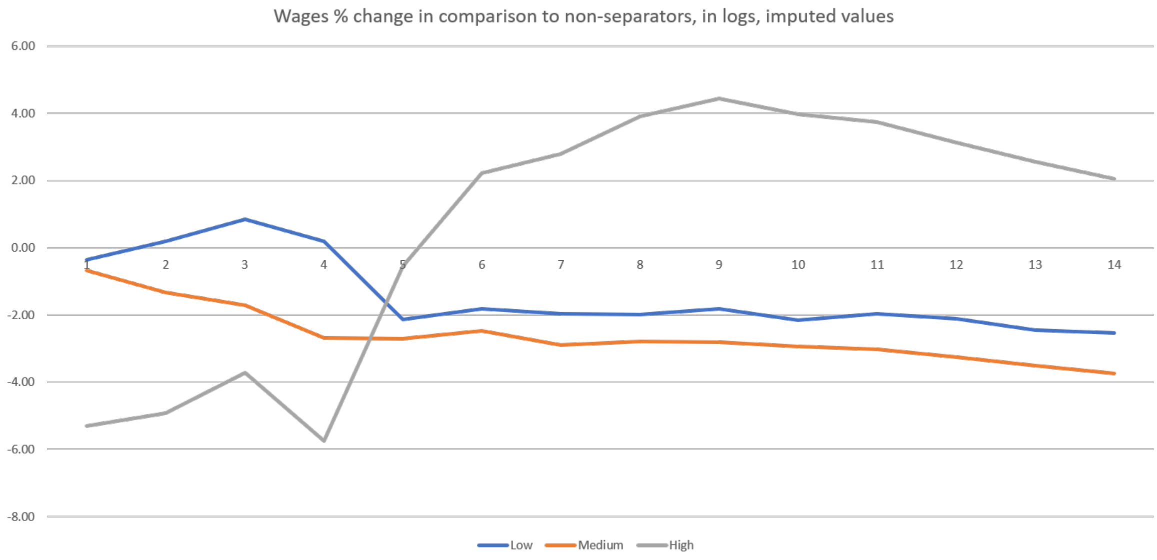
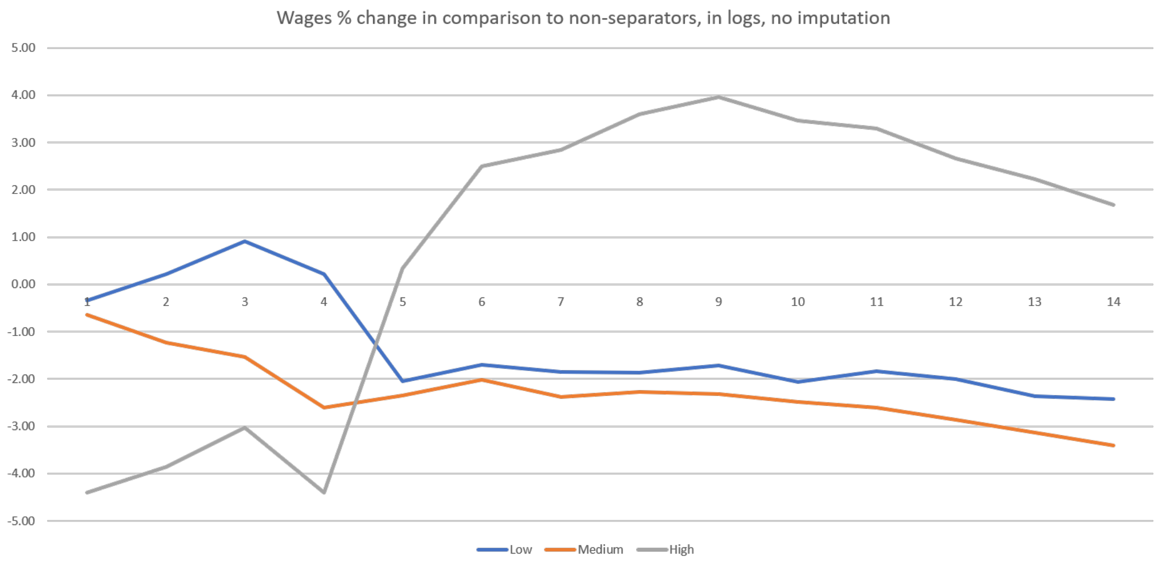


FIGURE 2.9: % wage losses in level



Wages at one point, in levels Selecting the first available wage observation within a year instead of the mean across all months of employment also does not affect the results in a significant way, with the estimated loss slightly increasing for all groups. The results are shown in Table 2.19.

% loss in wages in comparison to non-separators, levels at one point						
Time	Imputed			No imputation		
	Skill group			Skill group		
	Low	Medium	High	Low	Medium	High
t-3	0.03	-0.05	-3.22	0.04	-0.03	-3.03
t-2	0.04	-0.73	-3.47	0.12	-0.62	-3.07
t-1	0.59	-1.29	-2.53	0.73	-1.03	-2.22
t	-1.49	-3.08	-6.32	-1.57	-2.96	-5.72
t+1	-2.63	-3.57	-0.52	-2.43	-3.00	0.29
t+2	-1.90	-3.08	1.13	-1.63	-2.33	1.95
t+3	-1.96	-3.61	1.32	-1.72	-2.75	2.07
t+4	-1.81	-3.79	1.80	-1.56	-2.91	2.35
t+5	-1.67	-3.78	2.59	-1.43	-2.92	2.98
t+6	-2.05	-3.86	2.36	-1.82	-3.06	2.70
t+7	-2.34	-3.84	2.24	-2.07	-3.11	2.54
t+8	-2.64	-3.91	2.05	-2.38	-3.23	2.14
t+9	-2.76	-3.97	1.68	-2.53	-3.32	1.88
t+10	-2.68	-4.09	1.41	-2.41	-3.49	1.42
t+11	-2.89	-4.20	0.88	-2.71	-3.69	0.88
t+12	-3.29	-4.25	0.45	-3.06	-3.76	0.52
t+13	-3.39	-4.25	0.27	-3.25	-3.78	0.34
t+14	-3.47	-4.31	-0.11	-3.32	-3.87	0.00
t+15	-3.46	-4.28	-0.46	-3.31	-3.88	-0.47

TABLE 2.19: Separation losses, % wages, by skill

FIGURE 2.10: % wage losses in level

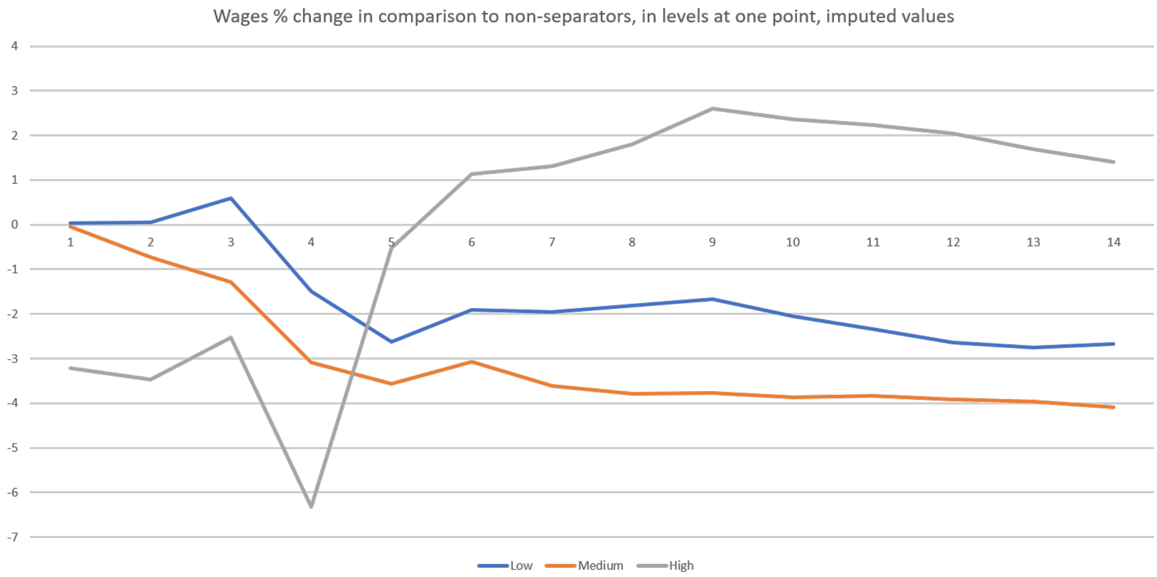
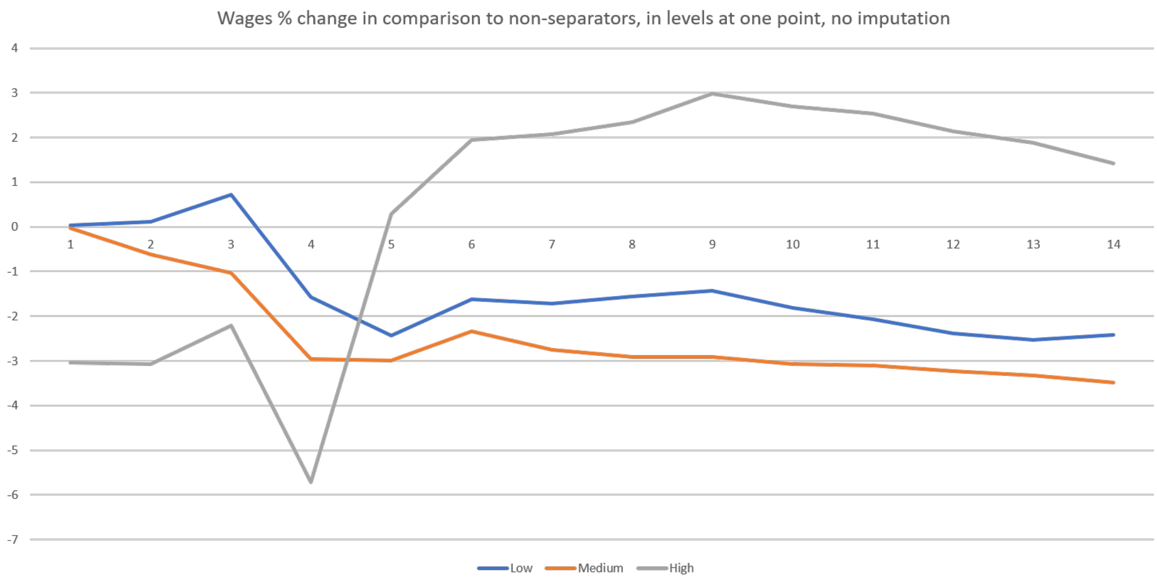


FIGURE 2.11: % wage losses in level



2.5.4 Results in light of Hartz reforms

A set of significant labour market reforms, collectively known as Hartz reforms, have been implemented in Germany between 2003 and 2005 to counteract high unemployment rates. The overall reform consists of four laws – Hartz I and II, implemented on 1st of January 2003, Hartz III, implemented on 1st of January 2004, and

Hartz IV, implemented on 1st of January 2005. Hartz reforms largely focused on increasing efficiency of labour market institutions, activating the unemployed, and stimulating labour demand through deregulation of the labour market (Jacobi and Kluve, 2006).

The benefit system existing in Germany before Hartz reforms has been described as generous and criticised for creating disincentives to work, leading to long-term unemployment and skill deterioration (Jacobi and Kluve, 2006). Active market policies conducted at the time were negatively evaluated in the literature, for example by Lechner, 1999 and Caliendo et al., 2008.

Features of Hartz reforms that are potentially particularly important in context of unemployment scarring include:

- re-design of active policy measures, to focus training programs on individuals benefiting most from training, and selection into public employment of individuals unlikely to find private employment
- integration subsidies, providing wage subsidies of up to 50% lasting between 6 and 24 months to firms hiring older and disabled workers
- start-up subsidies and other wage subsidies, which pay out amounts comparable with unemployment benefits to workers who start a company or take a lower-paid jobs, intended to integrate unemployed individuals with the labour market
- benefit reduction if unemployed individual does not accept offers of "suitable work", and introduction of *1-Euro jobs*
- expansion of exemptions to the regulations concerning fixed-term contracts dismissals (exemptions from dismissal protection regulation extended to firms with 10 or fewer employees).

Overall, studies examining the impact of the Hartz reforms point towards the effects of reduction in unemployment benefits (Krause and Uhlig, 2012), efficiency of the public employment agency (Launov and Wälde, 2013), and a limited effect of a decrease in reallocation costs (Bauer and King, 2018).

Since 2005, unemployment rate in Germany declined significantly, from about 12% in 2005 to 7% in 2009 and has not increased significantly during the 2008 financial crisis (Bauer and King, 2018). Boysen-Hogrefe and Groll, 2010 argue that a muted response of employment to the crisis was due to institutional changes introduced by the Hartz reforms. However, Burda and Hunt, 2011 and Möller, 2010 suggest low hiring levels pre-recession and flexibility in working hours as the explanation for only a small increase in the level of unemployment. The overlap between the Hartz reforms and the economic crisis makes disentangling of the effect on unemployment scarring challenging, especially as the Hartz reforms have been implemented over a number of years and have affected workers universally. (Labour market outcomes of workers displaced after 2005 will be affected by the crisis and the reforms, a pre-reform comparison group of workers displaced in 2002 will be affected by the reforms in terms of their labour market trajectories, and a group unaffected by either is arguably too far in the past and not comparable to those displaced after 2005). However, a number of assumptions made at the sample selection stage should limit the effect of the Hartz reforms on estimated scarring effects:

1. Only West Germany is considered in this article. Situation in East Germany was different, as outlined by Jacobi and Kluve, 2006.

2. Only full-time employees subject to social security are considered in this study. While Hartz reforms likely have an effect on wage formation, worker's and firms' search strategies, and human capital accumulation, this effect is likely largest for less typical employees

3. The role of the Hartz reforms was to decrease unemployment by increasing labour demand. If they were successful, workers should find jobs quicker –

which would decrease the average estimated loss for the whole period, providing an upper bound on the estimate of the scarring effect (in comparison to a hypothetical scenario in which the reforms have not been introduced).

2.6 Robustness check - SOEP

This section describes the results of the analysis on the German Socio-Economic Panel. It allows me to verify the results obtained from the SIAB, since the number of similar studies in the literature for Germany is limited, and to use additional variables - for example to identify involuntary and voluntary employment-to-employment transitions - since the SOEP is a rich survey and contains a large number of covariates. In this section, I present results of analysis of spell durations, measures of wage dispersion, Mincer estimates of returns to potential experience and tenure, and separation losses using the distributed lag model - however without disaggregating the sample by skill, due to the relatively small number of observations.

2.6.1 Duration of spells

Unemployment spell

Table 2.20 shows the average duration of officially registered unemployment by skill group. It can be seen that while the pattern is similar to the observed in non-employment spells in the SIAB (duration decreases in skill), which is expected, the length of time that workers report spending in unemployment is significantly shorter: around 6 months for the whole sample, 8 for the low skilled, 6 for the medium skilled, and under 5 for the high skilled. In the SIAB, however, mean values appear to be driven by the outliers, who had in excess of 30 years of non-employment - such individuals are unlikely to be observed in the survey - and the medians were lower. Non-employment in the SIAB is also defined as periods without full-time official employment, which does not necessarily have to match self-reported periods of employment and unemployment in SOEP.

TABLE 2.20: Average duration of unemployment spell, by skill

Unemployment spell						
Group						
Name	**Size**	**Mean**	**Mean std. error**	**Median**	**Std. dev.**
All	1802	6.32***	0.19	4	7.97
Low skilled	494	7.96***	0.47	5	10.5
Medium skilled	1099	6.21***	0.23	4	7.49
High skilled	299	4.79***	0.35	3.5	6.00

Employment spell

The average employment spell in SOEP, as shown in Table 2.21, is just slightly above 5 years. The low skilled workers have a significantly lower average spells of employment, at 39 months, while the medium and high skilled have employment spells of similar durations (65 and 68 months, respectively). Similarly as in the SIAB data, there is an increase in the employment spell duration as skill increases, and low skilled and medium skilled workers have similar durations. For the high skilled the duration in SOEP is visibly shorter than in the SIAB. This could, however, be caused by a degree of underreporting in the SIAB - some studies provide evidence of employers reporting the skill level required by the job, instead of actually possessed by the workers, which could result in a number of under-employed high-skilled workers not included in the high-skilled category in the SIAB.

TABLE 2.21: Average duration of employment spell, by skill

Employment spell					
Group					
Name	**Size**	**Mean**	**Mean std. error**	**Median**	**Std. dev.**
All	5259	60.95***	1.00	33	72.38
Low skilled	1039	39.10***	1.83	16	60.12
Medium skilled	3237	65.00***	1.33	36	75
High skilled	1447	68.30***	2.02	39	74.24

Job spell

The average job spell in SOEP equals 52.6 months, which is close in duration to the average length of an employment spell. While it increases in skill, for each skill level average job spell constitutes a large part of the average employment spell. This result is significantly different than in the SIAB, where job spells were on average a half of the employment spells, and clearly increasing in skill. The difference might arise from the fact that I do not observe a firm identifier in the SOEP and identification of job transitions is not as reliable as in the SIAB - I rely on the sub-sample for which the reason for a change of employer is provided.

TABLE 2.22: Average duration of job spell, by skill

Job spell					
Group					
Name	**Size**	**Mean**	**Mean std. error**	**Median**	**Std. dev.**
All	5259	52.62***	0.87	29	62.95
Low skilled	1039	35.38***	1.74	14.5	56.49
Medium skilled	3237	57.10***	1.19	32	66.82
High skilled	1447	58.00***	1.67	36	64.42

2.6.2 Measures of wage dispersion

Mean-min ratios

Table 2.23 shows the Mean-Min ratios by skill, for wages without trimming, trimmed by 1% on each side of the distribution, and trimmed by 5%. The reason for trimming the distribution of wages is measurement error in the data. Overall, the mean-min ratio resembles the value reported by Hornstein for the U.S. (1.7) (Hornstein et al., 2011). However, results suggest a slight increase in the frictional wage dispersion as skills increase, which is opposite to the findings from the SIAB.

TABLE 2.23: Mean-min ratios for different levels of trimming, by skill

Mean-min ratios						
Group	**No trim**		**1% trim**		**5% trim**	
	Mm1	**Coeff var**	**Mm1**	**Coeff var**	**Mm1**	**Coeff var**
All	2.02	0.21	1.82	0.19	1.55	0.15
Low skilled	1.96	0.21	1.70	0.18	1.50	0.15
Medium skilled	1.86	0.20	1.73	0.18	1.52	0.16
High skilled	2.09	0.20	1.94	0.18	1.59	0.14

Re-employment wage to average wage ratio

Another measure of wage dispersion is the ratio of the re-employment wage to average wage, as shown in Table 2.24. I find that it takes a similar value for all skill groups, indicating that re-employed workers obtain, on average, approximately 70% of the mean wage of a given skill group. This is significantly lower than, for example, estimates of Burdett et al., 2015 at 0.91 for the low-skilled and 0.85 for the high-skilled in the UK and can suggest a larger cost of non-employment in Germany in terms of the re-employment pay that workers can obtain.

TABLE 2.24: Ratio of re-employment to average wages, by skill

Re-employment to average wage ratio		
Group	**Ratio**	**Std. error**
Low skilled	0.72***	0.14
Medium skilled	0.77***	0.008
High skilled	0.73***	0.018

Ratio of involuntary to voluntary employment-to-employment (EE) transitions

To calculate the ratio of involuntary to voluntary employment-to-employment transitions, I use two ways, depending on the data available in each dataset. Due to insufficient data, it is necessary to use a proxy in the SIAB data: the ratio of involuntary to voluntary EE transitions is therefore calculated as a ratio of EE transitions with a wage cut (i.e., the wage reported in the new job is smaller than the wage reported in the old job) to EE transitions with a wage increase. In the SOEP, respondents are explicitly asked about the reason for termination of their previous job, such as: company shut down, dismissal, temporary contract expired (which I classify as involuntary) or own resignation, mutual agreement, leave of absence (which I classify as voluntary). The variable stating the reason for termination is available for 56% of the sample. The results are shown in Table 2.25: involuntary transitions appear to be more common among low skilled workers, and the ratio decreases significantly as skill level goes up. The ratio for the low skilled is similar to the one obtained in the SIAB (0.65 and 0.69); the high skilled however have a significantly lower number of involuntary transitions in the SOEP than in the SIAB - this difference can likely be explained by top-coding and the necessity to proxy for the reason of termination with the observed change in wages: if a worker transitions between two top-coded wages, it is not possible to observe a change in wages; hence the need for additional variables from the survey dataset.

TABLE 2.25: Ratio of involuntary to voluntary EE transitions, by skill

Ratio of involuntary/voluntary EE transitions			
Group	Low skilled	Medium skilled	High skilled
Ratio	0.65	0.46	0.36

Mincer estimates

Table 2.26 shows estimated % returns to tenure and potential experience. In terms of returns to potential experience, they equal 6.4% after 10 years for the whole sample, 8.7% for the low skilled, 4.4% for the medium skilled, and 6.4% for the high skilled. The potential experience in SOEP is calculated as the time since the first observation, which does not have to cover the whole labour market history of a worker. Identifying tenure spells is also difficult, due to the lack of a firm identifier. Overall, however, the returns to potential experience are similar to the SIAB - higher for the low skilled workers than the high skilled workers. The same pattern is observed in the returns to tenure, and low skilled workers are estimated to have significantly higher returns than the high-skilled workers, even if the overall magnitude appears to be very large.

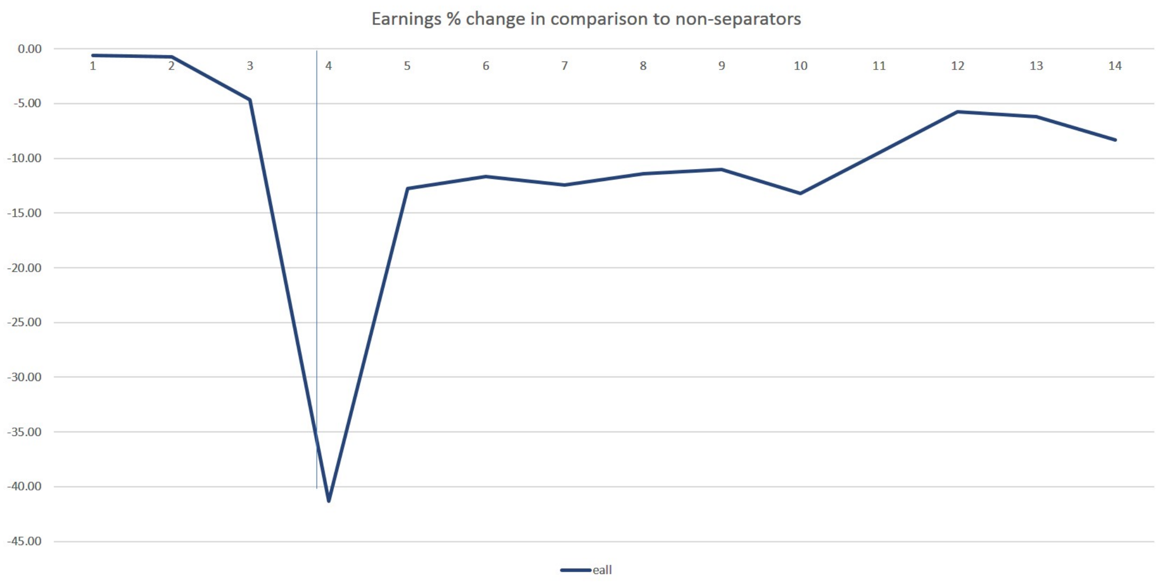
TABLE 2.26: Mincer estimated % returns to tenure and experience

Year	Group			
	All	**Low skilled**	**Medium skilled**	**High skilled**
Mincer estimated % return to potential experience				
1	0.662	0.905	0.451	0.668
2	1.319	1.803	0.899	1.330
3	1.970	2.694	1.344	1.988
4	2.615	3.577	1.786	2.639
5	3.254	4.453	2.226	3.286
6	3.888	5.322	2.663	3.927
7	4.516	6.184	3.096	4.563
8	5.139	7.038	3.527	5.194
9	5.756	7.886	3.956	5.819
10	6.367	8.726	4.381	6.439
Mincer estimated % return to tenure				
1	3.182	5.669	2.581	3.761
2	6.060	10.658	4.992	7.057
3	8.644	14.993	7.238	9.911
4	10.946	18.700	9.322	12.342
5	12.977	21.805	11.248	14.372
6	14.750	24.335	13.022	16.023
7	16.274	26.315	14.647	17.314
8	17.563	27.772	16.128	18.268
9	18.627	28.731	17.468	18.906
10	19.477	29.219	18.671	19.248

2.6.3 Unemployment losses

Table 2.27 presents the average % change in earnings and wages (in levels and logs) in comparison to the workers who have not separated, for the whole sample. (Due to a small number of observations and therefore small number of separations, disaggregating by skill level is not possible in the SOEP with a good degree of accuracy). The loss in earnings, shown in Figure 2.12, follows a pattern very similar to the SIAB - a significant immediate drop of -41%, followed by a rapid recovery within the first year, and a gap visible 10 years after the separation (-8%).

FIGURE 2.12: % earnings losses in level



In terms of wages, displayed in Figures 2.13 and 2.14, both the immediate loss and the loss observed after 10 years, are stronger than in the SIAB. On average, workers' wages decrease by 8.5% - 10% in the year of separation and remain at about -5 to -8% 10 years after the separation. While the losses do not appear to deepen as in the SIAB, there is also no sign of recovery in wages.

Overall, there is clear evidence of separation losses, both in earnings and wages, found in the SOEP, confirming the validity of the findings from the SIAB.

TABLE 2.27: % unemployment losses, all skill levels

	% change in		
Time (year)	**Earnings (level)**	**Wages (level)**	**Wages (log)**
t - 3	-0.59	-0.84	0.14
t - 2	-0.76	-0.35	0.31
t - 1	-4.64	-1.92	-1.11
t 0	-41.33	-9.66	-8.45
t + 1	-12.77	-8.76	-6.94
t + 2	-11.66	-9.29	-7.68
t + 3	-12.45	-11.00	-8.61
t + 4	-11.39	-9.57	-7.00
t + 5	-11.00	-9.28	-6.64
t + 6	-13.21	-11.41	-8.58
t + 7	-9.48	-9.01	-6.89
t + 8	-5.77	-5.41	-3.85
t + 9	-6.22	-6.72	-4.56
t + 10	-8.33	-8.22	-5.35

FIGURE 2.13: % wage losses in level

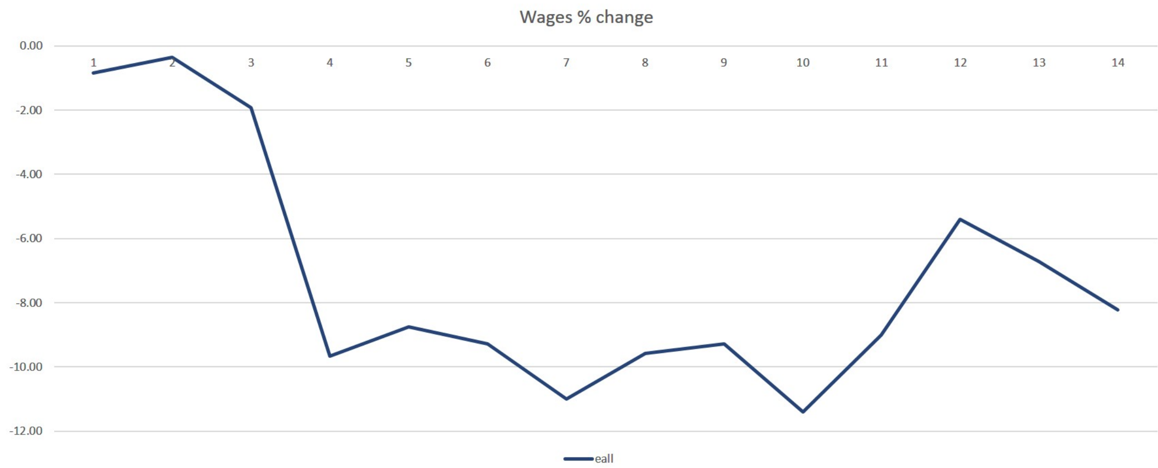
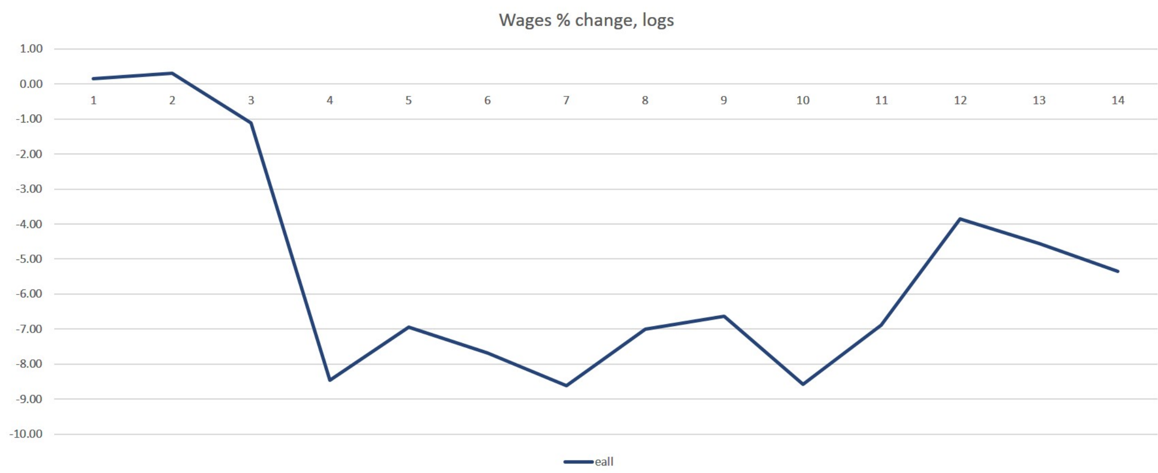


FIGURE 2.14: % wage losses in log



2.6.4 Choice of the control group

To check the robustness of the control group selection procedure, described in Section 2.5.3, I consider the possibility that workers being part of the control group lose their jobs in years following the displacement year, which would result in lower wages observed in the control group and a faster convergence between the treated and the control group.

To evaluate the effect of workers in the control group possibly losing their jobs after the displacement year, I estimate an alternative specification using the SOEP sample and contrast the results with the original estimates of earnings and wages losses for individual of all skill levels. For every displacement year y, I identify individuals who were displaced in any year $y + 1, 2, ..., j$, where j is the end year of the observation window, and exclude such individuals from the sample. Therefore, they are not a part of the control group for individuals displaced in the displacement year y.

Introducing this restriction on the control group reduces the number of individuals used in regressions by between 8.7% and 0%, depending on how many years of data are available after a given displacement year y. The average reduction in the number of individuals across all years is equal to 5.1%.

In terms of the impact on estimated displacement losses, the results are compared with the main approach in Figures 2.15 and 2.16 and indicate that using a control group of workers who were not displaced in future years results in larger immediate loss of earnings and wages. However, there appears to be no significant difference in the pattern of earnings and wages losses over time.

FIGURE 2.15: % earnings losses for different control groups

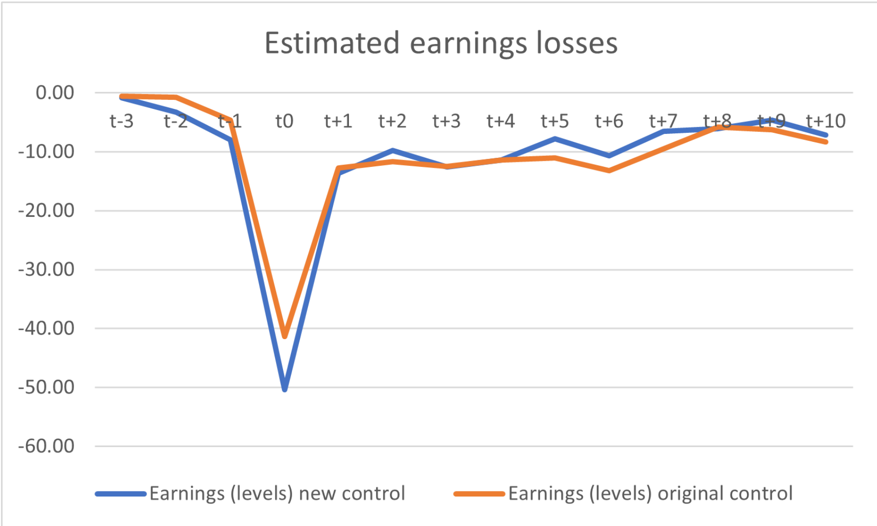
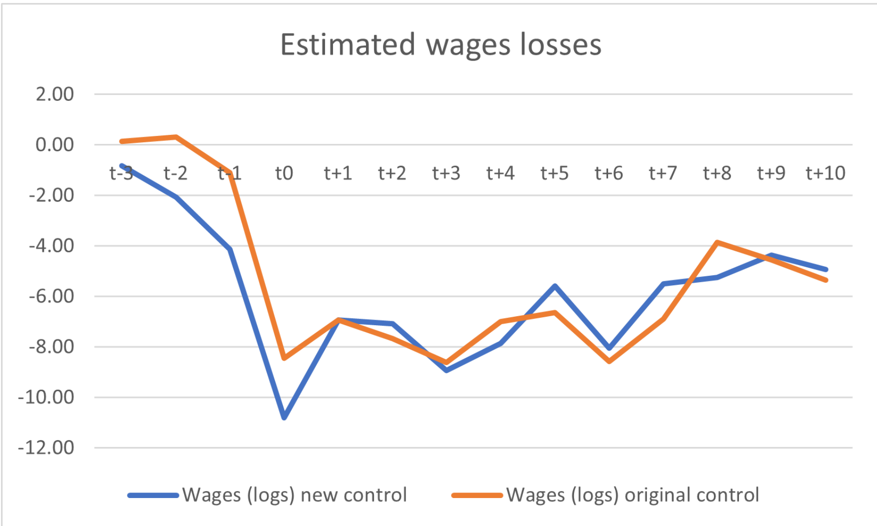


FIGURE 2.16: % wages losses for different control groups



2.7 Unemployment and gender

2.7.1 Unemployment losses and fertility

Women's role in the labour market has changed from secondary workers with a limited planning horizon to independent decision makers with a life-time planning perspective. Jobs that provide opportunities for advancement have become more desirable for women, and labour market conditions that impede establishment of stable careers, such as unemployment, may be reasons for a delay or a permanent reduction in fertility, according to Del Bono et al., 2012 who argue that the relationship between career shocks and fertility received little attention in the literature. Del Bono et al., 2012 investigate the effect of job displacement on the probability of having a child, using matched employer-employee administrative micro-data from Austria to identify firm closures. They compare births to women affected by firm closure with a control group of non-displaced women using an event study approach. They find that job displacement reduced the number of children born by 5 - 10% in the short and medium term and the effect persists even after 9 years, which suggests it's permanent. They demonstrate this is driven by women in high-income occupations, with steep wage growth profiles. A worker experiencing a spell of unemployment typically experiences a loss of some human capital. In standard frameworks, job loss is expected to have a substitution effect and increase fertility, as the opportunity cost of women's time is lower during a period of unemployment, and income effect, as the reduction of income during unemployment lowers the incentive to have a child. I would expect, however, a significant inter-temporal effect of fertility decisions - putting the earning and career progression path on a different trajectory. The substitution effect suggests births should occur in periods with lower opportunity costs, i.e. after the job loss. Del Bono et al., 2012 do not find evidence of a strong substitution effect. They report the career effect as the strongest, which means that women with steeper wage profiles adjust their fertility behaviour after job displacement to a larger extent than those with flatter wage profiles. Overall, they conclude that one of the main factors causing a reduction of fertility after job loss is the difficulty women face in re-establishing their careers. This effect is strongest for women with the steepest wage profiles.

The remaining sections of this chapter investigate the importance of gender for unemployment losses. The effects of motherhood itself on the trajectory of earnings and wages are considered separately in Chapter 3. In particular, section 3.3 investigates the effects of changing the incentive to return to the labour market, in the form of a maternity benefit policy reform, for different skill groups, to quantify the effect of motherhood on women's careers in short-medium term.

2.7.2 Separation losses

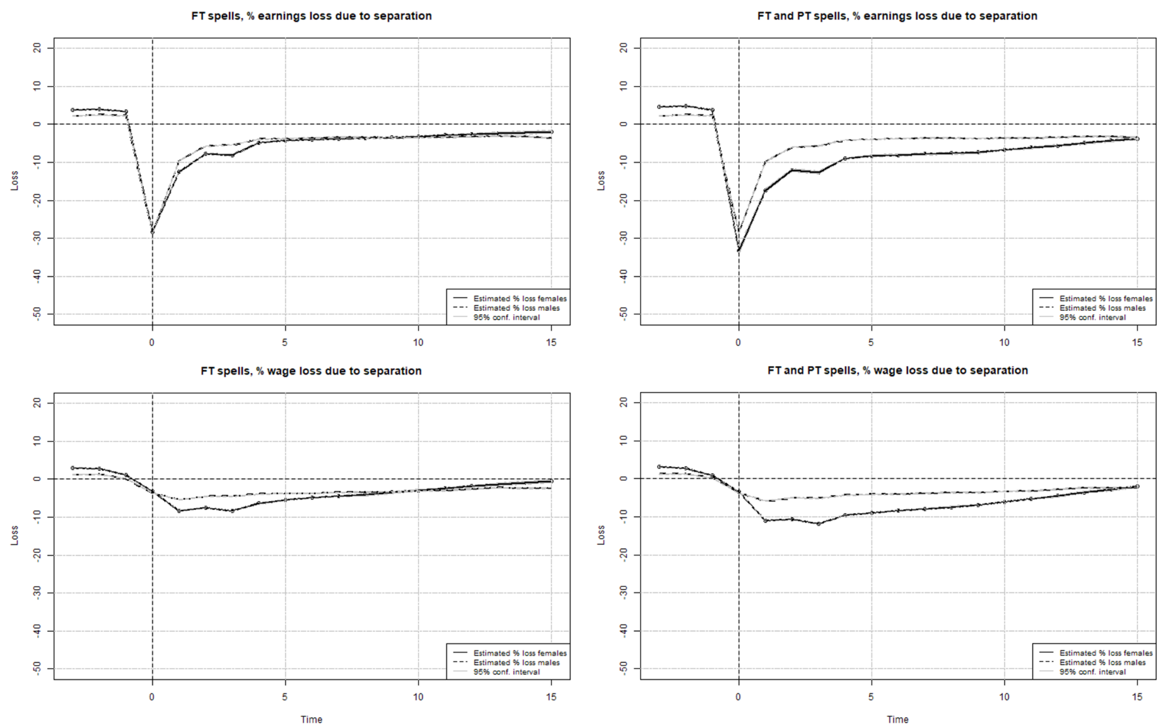


FIGURE 2.17: Losses in earnings (top row) and wages (bottom row) of men (dashed lines) and women (solid lines) working full-time only (left column) and full-time or part-time (right column) upon separation from employment. The areas shaded in grey show a 95% confidence interval on the point estimates.

First, in this section I consider only situations where a separation occurred from a full-time job, and the worker became re-employed in a full-time job as well, which corresponds to the left panel of Figure 2.17.[5] In this setting, spells of part-time employment are treated as periods of non-employment. A separation is defined as a transition from full-time employment, which lasted for a minimum of 3 years, to non-employment.[6] Figure 2.17 graphs the percentage loss of earnings and wages for men and women (the exact values corresponding to all the figures shown are included in Appendix A.1 Section B.1). Starting with full-time spells, losses of both genders are in line with the literature in terms of the magnitude and speed of recovery, and while the difference between males and females is statistically significant within the first few years, it's small in magnitude. In terms of earnings, for both genders I observe flat pre-trends in the 3-year period leading to separation, suggesting that there is no selection into the treatment group ex-ante, and an approximately 30% loss of earnings in the year of separation, which reduces to approximately a 5% loss within the first 5 years, and recovers almost entirely within 15 years for females. There appears to be only a small difference in losses of males and females. Since the observed loss can be attributed either to lower wages or a decrease in the hours of work, or a combination of the two, analysis of full-time spells of employment only provides a partial picture. I therefore investigate the consequences of adding the part-time spells, shown in the right-hand side panel of Figure 2.17, in Section 2.7.3. It is worth noting that these results are relative to each gender's baseline - therefore the loss of males is expressed in terms of the loss in comparison to males who remained employed, and the loss of females in comparison to females who remained employed.

A similar pattern of losses emerges when wages are the focus of the analysis. Overall, both in terms of earnings and wages, I do not find large differences between males and females when only full-time spells of employment are considered: as

[5]See Section A.1 in the Appendix A for a discussion of separations resulting from a mass-layoff, which is frequently used in the literature as exogenous source of variation in the employment status, as a proxy for involuntary unemployment. However, the assumption that workers do not expect a mass-layoff and *"jump ship"* in advance - especially those of high ability - is sometimes questioned. For that reason I also use data from SOEP to separate involuntary and voluntary unemployment in Section 3.6.1

[6]As noted in Section 3.4, I also tried using shorter tenure durations with similar results.

the left column of Figure 2.17 shows, the losses of both genders converge within 10 years.

As is standard in the literature (Jacobson et al., 1993; Jarosch, 2021) the high-tenure restriction along with the individual and time fixed effects used in the regressions aim to address selection on unobservable characteristics into the treatment group. This is also the reason for using mass lay-off event as a robustness check in the Appendix A.1. As a further robustness check, however, I repeat the analysis for workers with a minimum of 24 and 12 months of tenure and find the results to be almost identical. Furthermore, I considered a specification with a richer set of controls such as occupational tenure, which also did not affect the results.

2.7.3 Full-time and part-time

I now include part-time spells of employment and focus on all separations from employment. Right column of Figure 2.17 shows that there is a gender gap in earnings and wage losses that can be observed for up to 15 years following the separation. In the year of separation (year 0), men and women experience a similar reduction in earnings in percentage terms, however men recover faster (especially in the first 3 years following the separation). Bottom-right panel of Figure 2.17 shows that men's wages reduce considerably less than women's. Right column of Figure 2.18 also shows losses of women who separated from employers for reasons different than maternity. The pattern remains very similar, but shifted upwards, narrowing the gap between genders. In terms of earnings, the gap fully closes in approximately 12 years. In terms of wages, men's and women's losses converge within 10 years as well. Interestingly, after the gap closes, females' earnings and wages appear to increase at a higher rate than males', which is the pattern observed when considering only full-time spells of employment as shown in Figure 2.17. This suggests that voluntary separations of females becoming mothers can contribute to the observed gender gap.

As a robustness check, I also estimated losses of those individuals who separate from full-time employment and get re-employed part-time and found that the gap between genders existed. Similarly as in the previous section, I also used 12 and 24 months of pre-separation tenure restriction, which did not affect the results.

2.7.4 Effect of children on separation losses

Figure 2.18 decomposes the overall separation losses of women into those who separated and had a child and those who separated but did not have a child. There is a significant gap between these two groups. For women who did not have a child - when I consider only full-time spells of employment - the difference between males and females is minimal. This suggests that giving birth to a child can account for a significant part of the difference in non-employment losses observed between genders.

Until now I have evaluated the medium to long-term trajectory of earnings and wages following a separation from employment and documented: i) a small difference between losses of the two genders when only full-time spells of employment are considered; ii) a larger gap in separation losses when both full-time and part-time spells of employment are considered; iii) a very large gap between women separating due to having a child, and women separating for other reasons as well as men.

One possible channel is that women who have children are more likely to stay out of employment for longer and transition into part-time employment upon their return to the labour force than those who do not. To evaluate this, I use the SOEP dataset which contains a richer set of individual characteristics, allowing me to differentiate between voluntary and involuntary transitions into non-employment. There are 27,438 females aged between 18 and 54 in the SOEP, and 2,192,988 monthly observations. 4.11% of the observations are classified as Maternity Leave. Details of

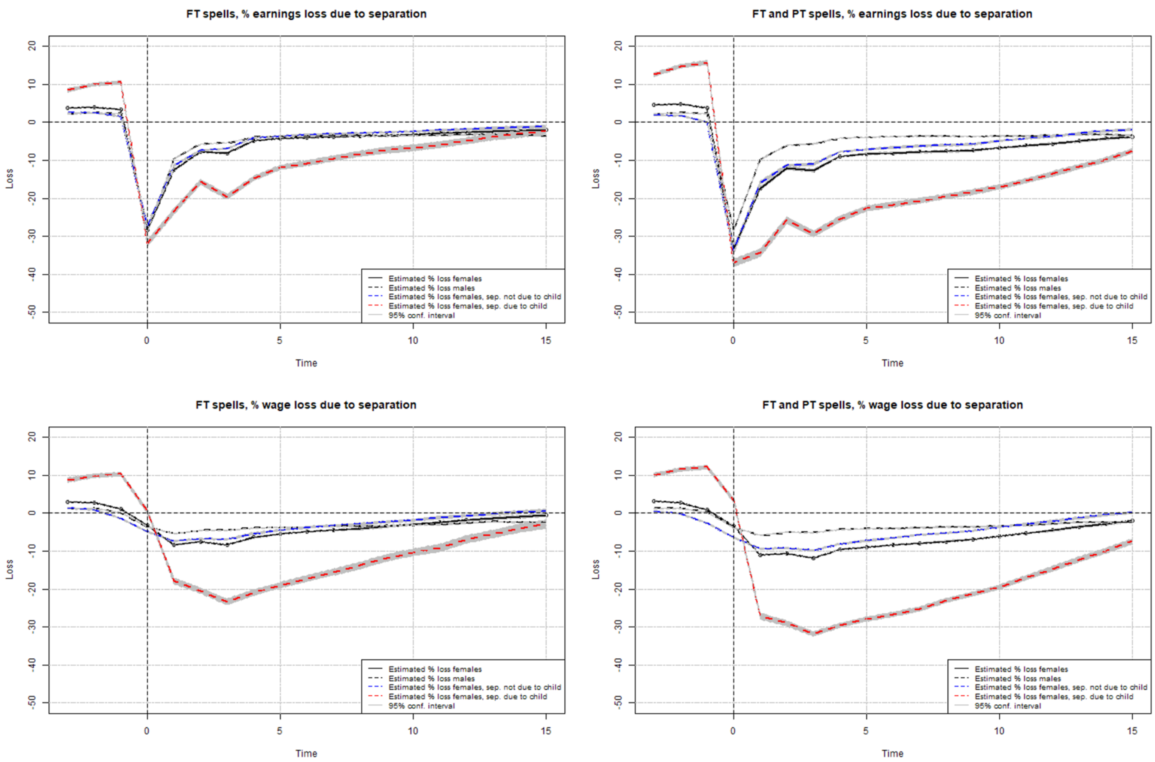


FIGURE 2.18: Losses in earnings (top row) and wages (bottom row). Red lines show losses of women who separated and had a child in the same year; blue show losses of women who separated but did not have a child. The areas shaded in grey show a 95% confidence interval on the point estimates.

the identification and definition of mothers in both the SIAB and SOEP data are described in Appendix 3.4.1.

2.7.5 Non-employment and number of children

As shown in Figure 2.18, there is a difference in unemployment losses between women separating at a time when a childbirth occurs and those separating when childbirth does not occur. In this section I consider whether the difference is related to labour market choices, that is, whether a voluntary transition to non-employment is positively associated with the probability of giving birth to a child.

I estimate the following equation:

$$ChildDiffMax_{i,t} = \beta_0 + \beta_1 ENVol_{i,t} + \beta Z_{i,t} + \epsilon_{i,t} \tag{2.7}$$

On a sample of women who transitioned to non-employment from a full-time or a part-time job, and for whom the reason for the transition is known. $ChildDiffMax_{i,t}$ is defined as a dummy variable which takes the value of 1 if individual i gave birth to a child in any month of year t. $ENVol_{i,t}$ is a dummy variable which takes the value of 1 if individual i has transitioned from full-time or part-time employment to non-employment in any month of year t and the reason for the transition is known and voluntary, and the value of 0 if individual i has transitioned from full-time or part-time employment to non-employment in any month of year t and the reason for transition is known and involuntary. $Z_{i,t}$ is a vector of observable characteristics and contains college degree, marital status, years of education, tenure, and full-time experience.

Therefore, the average marginal effect calculated for the coefficient β_1 should be interpreted as the average difference in probability of childbirth between women who transitioned to non-employment voluntarily vs women who transitioned to non-employment involuntarily, conditional on college degree, marital status, years of education, tenure, and full-time experience. On average, women voluntarily transitioning to non-employment have a 35.6%-points higher probability of giving birth to a child. (Full set of estimates on the basis of which average marginal effect is calculated is shown in Table A.2 in Appendix A). There is a positive association between a (contemporaneous) voluntary transition to non-employment and having a child. Part of the difference in non-employment losses shown in Figure 2.18 might possibly be explained by women transitioning to non-employment to give birth to a child, however since the variables are contemporaneous, voluntary transition to non-employment cannot be interpreted as predictive of childbirth, but illustrating a positive association between the two events. Chapter 3 further explores the relationship between childbirth and labour market outcomes, looking at the cost of motherhood and potential switch to a part-time job.

2.8 Conclusions

This paper set out to document unemployment experience of workers using two German datasets: SIAB, a large administrative dataset, and as a robustness check, SOEP, smaller but more in-depth survey. Workers in both datasets were split into various skill groups, determined by combining the formal education and vocational qualifications obtained, due to the nature of the German educational system. To determine transition patterns in different skill groups, I first analysed the average duration of employment, job, and non-employment (in SIAB) or unemployment (in SOEP) spells. I find that low skilled workers spend significantly less time in continuous employment (32 months) than the high skilled (91 months) and medium skilled workers (73 months). While they also hold any single job within an employment spell for shorter (20 months, versus 36 and 48 for the higher skilled), their average job spell makes up a higher proportion of their average employment spell. That means that low skilled workers have, on average, few job-to-job transitions, and since such transitions are normally beneficial for the worker, they are less likely to climb the job ladder and move to better jobs. I also find that low skilled workers spend a long time in non-employment - on average at least 33% (6 months) more than the medium and high skilled workers. Taken together, these statistics show stark contrast between the low skilled workers, and the higher skilled ones: the low skilled spend significantly more time in their career not being employed, forfeiting not only earnings, but also chances to accumulate human capital and climb the job ladder. Estimated returns to potential experience and tenure show that low skilled workers have returns two-three times higher than the high skilled. This might be a confirmation that low skilled workers tend to be employed at lower rungs of the job ladder, enjoying steeper returns for each additional year, while high-skilled workers managed to climb the job ladder through job-to-job transitions. Low skilled workers also appear to have a slightly higher measure of frictional wage dispersion (the mean-min ratio) and more often than high skilled workers transition directly between jobs in an involuntary way, which is usually associated with a pay-cut. Overall, I find that low skilled workers experience significantly larger losses when they become unemployed, that persist even after 15 years. This finding is robust to using different specifications and datasets. In conclusion, the data shows that there exist large differences in the consequences of unemployment for differently skilled groups, with largest losses affecting the least-skilled group with smallest average earnings. Understanding the mechanism causing such differences could be potentially important for designing future labour market policies. Furthermore, gender differences in unemployment losses are documented, which are significantly larger when full-time and part-time jobs are considered together, as opposed to full-time jobs only. A large part of the difference might arise due to childbirth, and hence the cost of motherhood is further examined in Chapter 3.

Chapter 3

The cost of motherhood

3.1 Introduction

OECD's *Closing the Gender Gap* report (Economic Co-operation and Development, 2012):

> *Gender gaps are pervasive in all walks of economic life and imply large losses in terms of foregone productivity and living standards to the individuals concerned and the economy*

In terms of the gender pay gap - defined as the difference between median earnings of men and women - there has been convergence between countries in the last few decades (see Figure B.1 for selected countries). However, despite the convergence, gender inequality still persists in all countries and women earn less than men, are less likely to get promoted to positions of leadership, and their careers develop at a slower pace. Analysis conducted in Chapter 2 shows that the impact of unemployment varies by gender and, for women, is likely linked to childbearing. The cost of motherhood-related career interruptions has a large impact on labour market outcomes of women and is one of the main drivers of inequality. Moreover, it becomes more important as other sources of inequality reduce: Kleven et al., 2019 show that the fraction of gender inequality caused by child penalties has increased sharply, from 40% in 1980 to 80% in 2013.

In this chapter, I use a large administrative dataset (Sample of Integrated Labour

Market Biographies) and a representative longitudinal survey (Socio-Economic Panel) from Germany, to conduct an event-study evaluating the effects of motherhood on labour market outcomes. I find that women who give birth to a child experience an up to 48% reduction in earnings and an up to 34% reduction in wages which don't disappear within 15 years. These losses can potentially be partially attributed to part-time work. Combined results of Chapter 2 and Chapter 3 suggest that a voluntary switch to part-time work can explain some of the observed gender gap in earnings and wages. Finally, I investigate the relationship between policy, fertility, and labour market outcomes by estimating short- and medium-term effects of a reform of the maternity benefit policy implemented in Germany in 2007, disaggregating the results by skill level.

3.2 Literature review

In an early example of research estimating the wage penalty associated with the motherhood, Waldfogel, 1997 estimates a fixed-effects model on a panel dataset to show that mothers of single children suffer a 6 percent wage penalty, while mothers of two or more children suffer a 13 percent wage penalty. Subsequently, Waldfogel observes that while the pay gap between men and childless women has decreased over time, this has not been the case for women with children. The pay gap between women with and without children appears to widen and equal pay and opportunity policies do not appear to sufficiently compensate the costs of motherhood. Waldfogel argues that policies related to maternity leave, childcare, and flexibility in working hours are required as they help to increase the likelihood of mothers returning to the workforce soon after childbirth, which helps to maintain work experience, tenure, and match effects if returning to the same employer, therefore having a positive effect on wages. Budig and England, 2001 build upon the work of Waldfogel to investigate the causes of earnings penalty observed amongst American women of childbearing age. Using 1982 – 1993 waves of the National Longitudinal Survey of Youth (NLSY) to estimate a fixed-effects model, they find a motherhood wage penalty of 7 percent per child. A third of the total penalty can be attributed to diminished accumulation of experience and tenure due to employment breaks and part-time employment, but a major part of the penalty remains unexplained. Observable characteristics such as marital status, job characteristics, and level of education are reported to have small or no statistically significant association with the cost of motherhood. Anderson et al., 2002 also explore possible causes of motherhood penalties. They note that many mothers exit the labour force, which is likely to result in depreciation of human capital and loss of match effects. As low skilled workers have less human capital, they should be less prone to the motherhood wage penalty than the high skilled. Results from NLSYW survey appear to confirm this hypothesis, however, the wage penalty for having the first child is small (4 percent) and a larger, 15 percent, wage penalty is attributed to having more than one child. Avellar and Smock, 2003 also find a negative effect of each additional child on wages using the National Longitudinal Survey of Young Women (NLSYW) and the NLSY data. Kunze and Ejrnaes, 2004 estimate the effects of giving birth to a first child on female wages using a longitudinal dataset from Germany. They find a 10 to 20 percent drop in wages on return to the labour market after the maternity leave. Molina and Montuenga, 2009 report that in Spain, one child in the household is associated with 6 percent reduction in wages, two children a 14 percent loss, and three or more children an over 15 percent loss. Bertrand et al., 2010 find that motherhood is associated with increased career interruptions, decreased hours of work, and reduced accumulation of job experience, and results in a large and persistent reduction in earnings of high-skilled female graduates. Authors suggest that more flexible work options may provide economic benefits and reduce the productivity cost of motherhood. A similar recommendation is made by Goldin, 2014, arguing that changes in the labour market, which increase the flexibility in working hours and working patterns, are required in order to further reduce the economic disparity between men and women in labour force participation, in hours of work, occupation and education choices, and earnings. Goldin notes that despite increases in the human capital of women a gender gap – increasing with age and differing by occupation - is still visible in earnings. Analysing data from the O*Net, Goldin shows that, consistently with a compensating differentials model, gender gap exists because flexibility in working hours is costly, especially in high-paid professions such as corporate, financial, and legal careers. It is argued that to reduce the gender gap further, flexibility needs to extend to all sectors in which it is possible. This is in contrast to some of the earlier findings. For example, Blair-Loy, 2009 suggest that increased flexibility can increase the work-family conflict in some professions, because the rigid schedule helps to prevent out-of-hours client demands. Briscoe, 2007 reports similar findings regarding a higher level of bureaucracy increasing flexibility. This effect can potentially depend on the skill level and be less applicable to low-skilled workers, but it is important to consider for the high-skilled. On the other hand, a positive relationship is reported between the number of hours worked and wages by Gicheva, 2013, suggesting that if increased flexibility leads to a smaller reduction of working hours of mothers, it should have a positive effect on earnings. Blau and Kahn, 2017 examine the gender wage gap between 1980 and 2010 using PSID data, noting that while the aggregate gender gap has considerably narrowed over this period, convergence in pay between gender has been significantly slower at the top of the wage distribution. They examine competing explanations, concluding that while factors such as noncognitive skills play a role, the largest effect is due to time spent out of the labour force, shorter working hours, and occupation and industry effects. Angelov et al., 2016 analyse the within-couple gap in income and wage trajectories of men and women and estimate the effects of parenthood both in the short and in the long-term. They find a significant and persistent effect: 15 years after the first child has been born, the gender gap enlarges by 32% points in earnings and 10% points in wages. This is consistent with other research highlighting the importance of hours of work and female participation in the labour market. They focus on the case of Sweden, where generous parental leave, in which the replacement rate is proportional to lost earnings, is claimed to result in a glass-ceiling with women not reaching best-paid positions but choosing less-demanding jobs. They attribute the estimated effect of parenthood to parental leave and switch to part-time work in the longer-term, however, they are unable to distinguish between the effects of the two. In Section 3.3 and 3.6.6 I analyse the effects of a 2007 reform of maternity benefit in Germany, which increased its generosity for certain groups. Being able to differentiate between full-time and part-time employment, the results can potentially contribute to Angelov et al., 2016 findings, suggesting that the effect is shared between the two channels. Adda et al., 2017 also investigate the persisting gender pay gap and point towards the substantial costs of having children for women's careers and lifetime earnings as one of the possible reasons for women's disadvantage. To investigate it, they estimate a dynamic model of female labour supply and fertility, incorporating occupational choices, skill atrophy, and intertemporal budget constraints. They use administrative and survey data from Germany, and find that about 75% of the career costs of children are due to intermittent or reduced labour supply, with the remainder due to lost investments and skill depreciation. They conclude that fertility and career choices are connected, and women anticipate having children and make career choices in advance, sorting into different jobs. Lundborg et al., 2017 estimate the causal effect of having children on careers of women using administrative data on in vitro fertilization-treated women in Denmark. Childbearing at the extensive margin (first child) is reported to have a large, negative, and persistent effect on earnings, which is driven by a reduction in the hourly wages more than a reduction in labour supply. At the intensive margin (having a second or subsequent child) the effects are negative but less persistent. While the article provides estimates only for Denmark, it argues that the adverse labour market consequences of childbirth would be stronger in other developed countries. Kuziemko et al., 2018 analyse data from multiple longitudinal studies (NLSW, NLSY, PSID, BHPS) and find a large and persistent negative effect of motherhood on women's careers. They then consider whether the perfect foresight assumption made in the literature (Attanasio et al., 2008; Blundell et al., 2016; Adda et al., 2017), which implies that women know how children will affect their labour supply and can plan accordingly, is warranted. They find that women underestimate the effect of motherhood on employment, both in the years before the first child is born, and in the long-term, when making decisions about education and human capital accumulation; possibly because of an increase in the cost of motherhood. Cools et al., 2017 focus on mothers with several children and note that according to theories of household specialization and conflict between home production and work (Becker, 1985; Becker, 1991), women with more children will be less productive than women with fewer children who work the same number of hours, and therefore less successful in the labour market. Cools et al. implement an instrumental variable study on administrative data from Norway and find that the number of children negatively affect labour supply and earnings, especially for college-educated women in demanding careers. The effect is persistent, with labour supply restored to its original level only after 20 years. These results confirm earlier findings of Anderson et al., 2002. Costa Dias et al., 2020 examine the long-term evolution of the gender pay gap in the UK and its association with fertility using Understanding Society data. The effect of working experience and working hours is evaluated by estimating an empirical wage model to obtain the causal effect of working experience on the wages of women, which is used to construct counterfactual scenarios. Differences in working experience and hours after childbirth are found to explain up to two thirds of the gender pay gap for college graduates, and up to one third for individuals without college education. Full-time experience appears to be the most important, as both working part-time and staying out of work are reported to result in lower hourly wages. The effect is persistent and can be observed up to 20 years after first childbirth. The importance of human capital and productivity is also highlighted by Gallen, 2018 who focuses on productivity gap between men and women, and finds that while there exists a pay gap for childless women whose productivity is comparable to men's productivity, mothers are less productive than men, which is reflected in their pay, concluding that lower pay of mothers is fully explained by differences in productivity. Kleven et al., 2019 conduct an event study on administrative data from Denmark between 1980 and 2013 and find that a large part of gender inequality in pay can be attributed to childbirth. Negative effect of motherhood is driven by a reduction in labour force participation, working hours, and wages. The effect is persistent in the long run and, as the overall gender gap has narrowed over time, became more important in explaining the total gender pay gap over time: the fraction of gender inequality caused by child penalties increased from 40% in 1980 to 80% in 2013. Echoing the findings of Kleven et al., Cortés and Pan, 2020 document that two thirds of the gender earnings gap is attributable to motherhood and that this share has been increasing over the last forty years. They argue that the gender pay gap arising due to motherhood could only be explained by comparative advantage if women had a lower earnings potential than men. However, the data suggests that all groups of women, including those with higher market wages than their husbands, suffer child-induced earnings losses. An alternative explanation can lie in career, occupation, and employment choices that women make in response to childbirth. Policies subsidising women's time out of the labour force, such as extended maternity leave, appear to have negative effect on their long-term employment prospects and earnings. In terms of policies that can address the motherhood gender gap, this is in line with findings of Costa Dias et al., 2020, explaining a large proportion of the gap by a reduction in working hours after childbirth.

The occupational and sector choice argument made by Cortés and Pan, 2020 has been explored by several studies. For example, Polachek, 1981 investigates why women tend to work in different occupations than men. Embedding the occupational choice decision in a human capital framework leads to an argument that for women occupation choice is related to the duration of time in and out of labour force. Polachek shows that differences in labour force participation account for a large share of differences in occupations – if women had the same level of labour force participation as men, the number of women in professional and managerial occupations would be significantly higher. However, different occupational choices between men and women might also arise due to preferences for a competitive environment. For example, Niederle and Vesterlund, 2007 conduct a laboratory experiment which shows that over twice as many men as women select a competitive remuneration scheme, despite there being no gender differences in performance. The result is driven by gender differences in preferences for participating in a competition and might therefore affect difference in occupation choice between men and women. As Altonji and Blank, 1999 points out, it is not clear whether differences in job characteristics of men and women are due to constraints in the labour market, or different preferences. For example, the true (negative) effect of part-time work on women's wages might be smaller than estimated if selection into part-time employment is not controlled for (Blank, 1990).

Time spent out of work and subsequent loss of productivity caused by depreciation of experience and tenure effects can also provide an explanation of wage reduction associated with motherhood. Number of articles study sources of wage growth. One of the seminal papers, Topel and Ward, 1992, explores career trajectories of young men over the first ten years of their labour force participation. In this early stage, workers are reported to experience high wage growth but also high turnover, holding on average seven jobs in that period. The decline in mobility as workers accumulate experience can be attributed to finding a higher-value match, through job-to-job transitions, as time goes by. Therefore, Topel et al. show that high turnover and wage growth are related, as over a third of observed wage growth can be attributed to changing jobs, and wage is a key element of job durability. Dustmann and Meghir, 2005 ask a similar question to Topel et al., studying the growth of wages of young workers using administrative data from Germany. They find concave wage-experience and wage-tenure profiles, with the fastest growth observed within the first 4 years of labour market experience for the skilled workers, and 2 to 3 years for the unskilled. In terms of tenure, returns decline after 5 years for the skilled workers both in terms of sector-specific and firm-specific tenure. Unskilled workers appear to gain more from stronger attachment to a particular firm than general experience and sector-tenure effects. This finding potentially has implications in terms of costs of motherhood – while time spent out of the labour force might be more costly for the skilled mothers, loss of match effects might have stronger and more immediate effect on unskilled mothers. It seems plausible that leaving employment at this prime stage of wage growth can lead to lower wages. Ruhm, 1998 analyses consequences of parental leave in European countries between 1969 and 1993 and finds that a period of leave of nine months or more is associated with an approximately 3 percent decrease in wages. Gruber, 1994 reports a similar, 5 percent, reduction in wages.

This work contributes to the literature in several ways. First of all, motherhood losses are estimated for a representative sample of the population in the medium-long term, which allows the trajectory of earnings and wages to be examined in more detail than if survey data has been used. Secondly, administrative data allows for a detailed measurement of wage information, which is not always available, for example, in census-based data (Raute, 2019; Kluve and Schmitz, 2018). Thirdly, different types of contracts are considered. Finally, three skills groups are considered separately, which allows for a detailed analysis of policy effects (the 2007 reform of maternity benefits), and the dynamics of earnings and wage changes within each group to be explored.

3.3 The 2007 reform of maternity benefits

In 2007, Germany implemented a fundamental reform to the maternity benefit system which compensates women for forgone earnings, creating a new parental leave benefit (Elterngeld). The reform, inspired by the model implemented by the Nordic countries, aimed to reverse low fertility rates and low employment rates of mothers with young children which have been observed in Germany in decades prior to the reform (Spiess and Wrohlich, 2008), and changed the amount of money provided to parents, the proportion of parents considered eligible for the benefits, and the maximum duration of the benefit recipiency.

The reform was designed to reduce income loss in the first year after childbirth due to child-related maternal employment interruptions (Kottwitz et al., 2016), as the key part of the reform was the replacement of the previous means-tested parental leave benefit by a wage-dependent benefit for the period of one year.

Overall, the reform aimed to: (Spiess and Wrohlich, 2008; Kluve and Tamm, 2013)

1. increase the employment rate of mothers with young children
2. increase the fertility rate
3. provide compensation to middle- and high-income parents, who experience a relatively high income loss due to birth-related employment break, to increase bonding between new parents and child
4. increase the percentage of fathers who assume care responsibility

Prior to the reform, Germany relied on the *breadwinner model* in which one parent (typically the mother) stayed at home or worked part-time and provided childcare, while the other continued full-time employment (Spiess and Wrohlich, 2008; Familie, 2006). Under the old scheme, payments (*Erziehungsgeld*) were targeted at low-income families and paid out flat transfers, under one of two options: i) a maximum of 300 Euro a month for up to 24 months, or ii) a monthly payment of 450 Euro for 12 months, for mothers who wanted to return to work in the second year after childbirth. Transfers were means tested (based on family income) during the receipt of the benefit. Only families earning below 30 thousand Euro after tax were eligible for the benefit. Average benefits paid to mothers in 2006, just before the reform, were between 3850 and 4440 Euro in total (per mother) (Raute, 2019).

On the 1st of January 2007, the old system has been replaced by a new leave benefit (*Elterngeld*), for which all mothers with children born on or after the 1st of January 2007 were eligible. In addition to being universal (instead of means-tested, like the previous system), the new benefit has also been significantly more generous, replacing approximately 67% of pre-birth net earnings, with a minimum of 300 Euro and a maximum of 1800 Euro per month, for up to 12 months. The maximum benefit in the new system was therefore equal to 21600 Euro. The system covered almost 100% of mothers, with the average amount paid in the first year of its operation equal to 7080 Euro (and over 10 thousand Euro for the sample of only employed individuals) (Raute, 2019; Kluve and Tamm, 2013).

The reform has had a different impact on mothers in different socioeconomic groups, with the post-reform system replacing a significantly higher proportion of high-earners' income than the pre-reform system, but having no effect or a negative effect on the replacement rate for the low-income individuals. It is interesting to establish what effect does a reform increasing fertility have on differently educated mothers with different types of contracts, in terms of long-term evolution of earnings and wages, and the cost of motherhood. For example, it is possible that while the reform has been successful at increasing fertility, it has prolonged the time spent out of employment, leading to larger losses (in comparison to the control group) in the medium-long term (for example, through slower accumulation of human capital reflected in lower wages, arising from the time spent out of employment). Such a possibility would be in line with consequences envisaged in the literature - for example, Raute, 2019 observes that *"Mothers who wish to spend more time at home with their children (and pre-reform were potentially finally constrained in doing so) may decrease their labor supply and reduce their labor earnings"*. Furthermore, while there has been research on short-term (Bergemann and Riphahn, 2010; Kluve and Tamm, 2013; Kluve and Schmitz, 2018) and medium-term (Kluve and Schmitz, 2018) effects, it is interesting to evaluate the medium-long term effects. In particular, this paper focuses on the cost of the period of motherhood for those who returned to work in terms of earnings and wages, which is different than studies looking at changes in the post-tax-and-benefit income of households.

Ideally, the reform could be used as an exogenous policy variation in a difference-in-difference approach to provide evidence on the effects of the reform (that is, on the effect of introducing changes covered by the reform) on the labour supply behaviour and labour market outcomes. A treated group of mothers who were affected by the reform could be compared to a control group of mothers who were not, but are otherwise the same. However, the choice of the control group in that setting is not straightforward, as there are no untreated mothers after the reform has been implemented. It is further discussed in Section 3.5.3.

To evaluate the effect of the reform on the medium-long-term profile of earnings and wages of women giving birth, by contract type and level of education, I compare two sets of estimates: i) where the treatment group consists of women giving birth between 2000-2006 and (separately) 2003-2006 (pre-reform); ii) where the treatment group consists of women giving birth between 2007-2014 and (separately) 2007-2010. This allows me to investigate whether the effect of the reform has been instantaneous and constant, or it has changed over time. (Ideally, the time window would be as small as possible. I have chosen a 3-year window to obtain a sufficiently large sample for each education level and contract type. It should be short enough not to have significant changes to maternity decisions, although it has to be acknowledged that the post-reform period covers the time of the financial crisis. Analysing a 6-year window should help overcome any transitory effects of the crisis. It is worth noting that a similar time period has been used in the literature to examine the effects of this reform on fertility, e.g. Raute, 2019. On the other hand, the new transfer payments provide universal coverage, which simplifies the analysis (as in the means tested system, the uptake of the benefit was likely different depending on the pre-maternity earnings, education level, and contract type)).

I start by describing the results using the 3-year window, i.e. to analyse the effects of the 2007 reform, I compare the (relative to the control group of those who did not have a child) earnings and losses trajectory of employed mothers who had a child in the pre-reform period of 2003 – 2006 and in the post-reform 2007-2010 period. I evaluate the effects by education group (low, medium, high) and type of contract: employed full-time pre- and post-child, employed either full-time or part-time pre- and post-child, or employed full-time pre-child and full-time or part-time post-child. These are depicted in Figure 3.8. Results using a 6-year window are shown in Figure 3.7. Summary statistics for treatment and control groups, pre- and post-reform, for full-time (FT), full-time and part-time (FTPT), and full-time to full-time or part-time (FTtoFTPT) groups are shown in Table 3.3.

3.4 Data

Chapter 3 uses the same datasets, SIAB and SOEP, as Chapter 2. As these have been introduced and described in detail in Section 2.3, this section focuses on data characteristics specific to 3.

Sample restrictions

I focus on German workers from West Germany aged 18 to 54. Only workers liable to social security are kept in the sample (which excludes groups such as civil servants, self-employed, and students from the analysis), and in the SIAB sample only information originating from the Employee History File (*BeH*) is used.

The SIAB sample consists of women of any nationality employed in West Germany, working full-time or part-time in jobs subject to social security contributions. Therefore, as before, trainees, interns, marginal part-time workers, and partially retired individuals are excluded. I restrict the sample to women aged 18 to 54 and select the time window in which women in the sample could have had a child to be between years 1975 and 2014, to allow for a maximum possible number of observations. I only consider individuals who return to employment within 3 years of giving birth, which provides a conservative estimate of the true effect, as including individuals who become inactive as having zero earnings and wages would strengthen the effect. I can identify 205 thousand first-time mothers, out of which 146 thousand can be matched to a dataset used to estimate the losses, to which sample restrictions described above have been applied. The total number of individuals in the above regressions is approximately 400 thousand, with approximately 5.1 million individual-year observations.

A matching set of restrictions is applied to the SOEP dataset, except for the observation window covering years 1984 to 2014.

Descriptive statistics

Table 3.1 reports selected statistics for the main SIAB and SOEP samples corresponding to the sample selection procedure described in Section 3.4.

Variable	**SIAB**				**SOEP**			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
Year of observation	1995	11.4	1975	2014	2000	8.8	1984	2014
Age	39.4	11.4	18	54	36.6	10.4	18	54
Sex	0.0	0.0	0	0	0.0	0.0	0	0
Education level low (share)	0.2	0.4	0	1	0.2	0.4	0	1
Education level medium (share)	0.7	0.4	0	1	0.6	0.5	0	1
Education level high (share)	0.1	0.2	0	1	0.2	0.4	0	1
Gross labour income in euro	1654.8	1002.1	0	5928	1621.5	1337.7	0	54000

TABLE 3.1: Summary statistics for the SIAB and SOEP samples

3.4.1 Procedure to identify mothers in the SIAB dataset

To identify mothers in the SIAB data I follow a procedure introduced by Müller, Strauch, et al., 2017. A detailed description and supplementary files (Stata code, comparison with official statistics on the number of births) can be found in the cited paper, but the procedure is summarised here for convenience.

The need for a procedure to identify mothers in the SIAB data arises from the fact that the kind of information recorded in the administrative data collected by the Federal Employment Agency is strictly defined, and some information that would be useful for research purposes is not collected - one of them being the information on childbirth.

The procedure is as follows:

- Keep only women in the sample
- Define a new variable for income (tentgelt_neu) which takes the value of income (tentgelt), except when single payments such as Christmas bonuses occur, in which case tentgelt_neu is set to zero
- Identify the beginning of paid maternity leave. This information is recorded in the variable *grund* taking value of 51[1] from BeH data, or 2016, 3002, 6010 from other data sources
- Impose the age restriction setting the maximum childbearing age to 40, based on a comparison with the data from the Federal Statistics Office on the number of births by age
- Calculate the employment interruptions - an interruption due to maternity leave must be longer than the duration of the maternity leave, which is 97 days. Based on that, calculate the expected date of delivery. (For siblings, a gap of at least 32 weeks is imposed).
- Generate the dummy variable for mother status, age of the mother at childbirth, the number of children, and the expected date of delivery.

The procedure applied and the availability of the data lead to several caveats:

[1]Due to the coarsening of the data to preserve its anonymity, this has been grouped to 1051 in my version of the data

- Expected childbirths can be identified only if women have a record in the administrative data sources. However, the analysis focuses on the employment trajectories of employees, so the lack of self-employed and public servants in the data is not an issue
- It is not possible to differentiate between live birth and stillbirths. Given the low level of stillbirths in Germany, according to the WHO data (WHO, 2020), I do not consider this a problem for the analysis
- The number of children per woman can be underestimated since twin births are not possible to identify and births following the first child can be hard to identify. However, I focus on the effect of the first-born child.

3.5 Methodology

3.5.1 Motherhood losses

To estimate the effect of giving birth to a child (Section 3.6) on workers' future earnings and wages, I use a distributed lag model similar to Jacobson et al., 1993 and Davis and Wachter, 2011.

$$e^y_{it} = \alpha^y_i + \gamma^y_t + \beta^y X_{it} + \sum_{k=-3}^{7or15} \delta^y_k D^k_{it} + \mu^y_{it} \tag{3.1}$$

where

y is the childbirth year y,

e^y_{it} denotes earnings or wages of individual i in year t,

α^y_i is the individual i fixed-effect,

γ^y_t is the calendar year t fixed effect,

X_{it} is the cubic polynomial in potential experience of individual i at time t,

D_{it}^{k} denotes dummy variables equal to one in the individual i's k-th year before of after childbirth, and zero otherwise,

δ_{k}^{y} denotes coefficients measuring the time path of e changes for mothers, relative to the baseline and change in e of the control group,

and μ_{it}^{y} is the error term

I use spell data which includes information about the individual's average daily level of income throughout employment spells in Euro called I, and construct a monthly panel; in each month the worker is either employed or not. If the worker is employed and only one spell is observed in a given month, I is the average daily income in that spell of employment. If there are multiple spells in a given month, the spell with the highest I is kept, and if two spells still co-exist, the longer one. If the worker is not employed, $I = 0$. I then aggregate the data to a yearly panel used in the estimation, where $Earnings_{i,t}$ is the average of I across all months (including non-employment), while $Wages_{i,t}$ is the average across the months of employment in a given year t.

The above distributed lag model is then estimated on the SIAB data, and a binary response model is used in Section 3.6.1 with SOEP data to evaluate the impact of having a child on the probability of re-employment in a part-time job. The impact of voluntary and involuntary transitions to non-employment on the probability of having a child has been discussed in Chapter 2.

3.5.2 Impact of the Hartz reforms on motherhood losses by type of employment

Section 3.6.5 estimates the profile of women's earnings and wage losses following a childbirth over time, differentiating between types of employment contracts. The distributed lag model defined by Equation 3.1 is estimated for three subsamples of individuals.

- The first group (A) consists of women who had a full-time job before childbirth, and are employed in a full-time job after the childbirth. Treatment is defined as giving birth to the first child in year y, between 1975 and 2014. Since only women in full-time work are considered, the control group consists of women employed full-time who did not give birth to a child in year y.

- Women in the second group (B) had a full-time job before childbirth, but are employed in a part-time job after the childbirth. Treatment is defined as giving birth to the first child in year y, between 1975 and 2014 and working full-time immediately before the childbirth. The control group consists of women employed full-time in year y, who did not give birth to a child in year y and were employed full-time or part-time in years future to y.

- In the third group (C), women who had either a full-time or a part-time job before the childbirth, and are employed in a full-time or part-time job after the childbirth are considered. Treatment is defined as giving birth to the first child in year y, between 1975 and 2014. The control group consists of women employed full-time or part-time who did not give birth to a child in year y.

Estimated childbirth losses shown in Figure 3.2 are expressed in percentage terms, relative to earnings of each control group and should be interpreted in that context. Fertility decisions and labour market decisions are both connected choices. This exercise cannot identify the causal effect of childbirth-induced change in the type of employment contract on earnings and wages. However, the results described in Section 3.6.5 suggest that – when compared to workers with the same contract type - women in full-time jobs lose a comparatively smaller proportion of earnings and wages than women working part-time. The loss of earnings appears to be driven by a reduction in wages, which is consistent with the results of Costa Dias et al., 2020 reported for part-time workers. On the other hand, the magnitude of wage losses of full-time workers appears surprisingly large. This could potentially be explained by, for example, individuals switching to jobs with more desirable non-pecuniary characteristics. Unfortunately, more detailed data would be required to investigate this further.

At the same time, the Hartz reforms previously introduced in Section 2.5.4 of Chapter 1, potentially affect these estimates, as they took place in the middle of the 1975 – 2014 observation window. Because Hartz reforms were universal and different policy changes were introduced simultaneously, it is difficult to devise a set-up allowing estimation of their causal effects in context of childbirth losses. For the reasons outlined in Section 2.5.4, excluding the post-Hartz reform period from the observation window is not practical either. Instead, the way in which the introduction of the reforms potentially biases the estimated coefficients needs to be considered.

Specific measures introduced in the Hartz reforms which are most relevant to part-time employment include (Immel, 2021):

- Deregulation of the non-standard work (Hartz I and II)
- Introduction of "Mini-jobs" with 400 euro per month threshold, exempt from social security contributions (Hartz II)
- Introduction of "Midi-jobs", reducing social security contributions between 400 and 800 euro per month (Hartz II)
- Reduction in the maximum duration of earnings-based unemployment benefits (Hartz IV)

Above changes introduced by Hartz reforms have overall deregulated non-standard forms of employment, increasing incentives to temporary, marginal, and part-time work, and reducing unemployment benefits. The potential effect on the estimates depends on the impact on each of the treatment and control groups described above. However, the fact that trainees and marginal part-time workers are not included in the sample possibly limits the influence of the Hartz reforms.

The first category (A), where both treated and control workers are employed full-time, is unlikely to be affected, except through the reduction in the maximum duration of unemployment benefits, if it increases employment rate and observed earnings in the control group. In that situation, the increase in average earnings in the control group would result in estimated losses of the treated group, relative to the control group, to have been higher in absence of the Hartz reform.

The second (B), where individuals are employed full-time before year y and either full-time or part-time afterwards, treatment and control groups are potentially affected because of the reduction in the maximum duration of unemployment benefits, deregulation of part-time work, and introduction of mini- and midi-jobs. The employment rate and observed earnings of treated and control workers would likely have been lower in absence of the Hartz reform. The direction of bias in estimated childbirth losses then depends on the ratio of increases in earnings between the groups. If earnings increased more (less) in the control group than in the treated group, estimated losses would have been higher (lower) in absence of the Hartz reform.

In the third category (C), individuals in the treatment and control groups can be employed either full-time or part-time. In this case, as for the second category, the direction of bias would depend on the ratio of increases in earnings between the groups. If earnings increase, due to Hartz reforms, was higher (lower) in the control group than in the treated group, estimated losses would have been higher (lower) in absence of the Hartz reform.

3.5.3 Effects of the 2007 maternity benefits reform

As outlined in Section 3.3 the reform introduces exogeneous variation to fertility decisions by affecting the incentives to give birth to a child. To estimate the cost of motherhood, and how it changed with the reform, trajectory of earnings and wages of treated individuals (those who gave birth to a child) is compared to an appropriate control group. The pre-reform and post-reform costs are then compared.

Since the reform is universal, no cross-sectional control group can be defined as there are no untreated units (where treatment is understood as being subject to the reform) after 2007. Kluve and Schmitz, 2018 consider longitudinal control group infeasible as well, as the reform incentivizes sociodemographic groups in different ways to become parents. Given these obstacles, the sample is divided in 3 different skill groups and comparisons of the treated vs control units are made by sociodemographic subgroups, pre- and post-reform. The evolution of earnings of women in the treated group who had a child pre-reform, in comparison to control group of women who did not have a child in that period, is contrasted with the evolution of earnings of treated women who had a child post-reform, in comparison to the control group of women who did not have a child in that period.

In the 3-year observation window specification (Figure 3.8) the comparison is made, separately for each skill group, between the A (solid line in the figure) and B (dashed line in the figure), where:

- A is defined as the difference in earnings or wages of the treated group composed of women who had their first child between 2003 and 2006, and the control group composed of women who did not give birth between 2003 and 2006.

- B is defined as the difference in earnings or wages between the treated group composed of women who had their first child between 2007 and 2010, and the control group composed of women who did not give birth between 2007 and 2010.

In the 6-year observation window specification (Figure 3.7) the following comparisons are made:

- A between the treated group composed of women who had their first child between 2000 and 2006, and the control group composed of women who did not give birth between 2000 and 2006
- B between the treated group composed of women who had their first child between 2007 and 2014, and the control group composed of women who did not give birth between 2007 and 2014.

The pre-reform and post-reform control groups are compared in Table 3.3 in terms of age, earnings, experience, and tenure. Pre- and post-reform control groups are similar, which ensures a like-with-like comparison is made when the effects of childbirth are compared in Figure 3.7 and 3.8.

The contribution of this approach lies in the fact that while Kluve and Schmitz, 2018 can implement more precise RDD-DID design, they cannot provide estimates of the effect of the reform on maternal earnings due to limitation of their data. Raute, 2019 is able to estimate effect on earnings for two years after the childbirth, but information on earnings is limited. I focus on longer-term evolution of earnings and consider the period of 6 years post-childbirth, using data with detailed and reliable information on earnings.

Parameters of interest in the econometric model of motherhood losses

Parameters of the model specified in equation 3.1 are estimated pre-reform and post-reform, separately for each of the three skill groups and results are shown as a percentage difference in comparison to the control group as specified in the section above.

I am interested in estimating δ_k^y. To interpret these estimates as the causal effect of motherhood on earnings requires that, conditional on the fixed effects and control variables, the counterfactual earnings of mothers in the absence of childbirth are captured by workers in the control group. To obtain the counterfactual earnings path of mothers, absent the childbirth, equation 3.1 is evaluated at $D_{it}^{k} = 0$ for all k (Davis and Wachter, 2011).

This assumption would not hold, if women self-selected into the treated group on the basis of some characteristics. However, giving birth to a first child is a common event and mothers are unlikely to be systematically different than the whole population. For that reason, the control group consisting only of women who never give birth in the entire observation window would not be appropriate, as they would likely be significantly different than the *treated* group. Therefore, it is important to note that the control group is composed of women who did not have a child in a given year, or a relatively short, 3 or 6 year *treatment* window, but might have one in the future.

3.6 Results

3.6.1 Childbirth and the probability of part-time re-employment

Section 2.7.4 of Chapter 2 examines the difference in unemployment losses of women who gave birth to a child and those who did not, and between women and men when part-time work is considered. Results show:

- a small difference between losses of the two genders when only full-time spells of employment are considered
- a larger gap in separation losses when both full-time and part-time spells of employment are considered
- a very large gap between women separating due to having a child, and women separating for other reasons, or men

A possible explanation for these findings is that women who give birth to a child are more likely to return to the labour force in part-time employment. To examine if that might be the case, I consider a sample of women who transitioned from non-employment to a full-time or part-time employment, and assess the relationship between childbirth and the likelihood transitioning from non-employment to part-time employment.

The following equation is estimated:

$$ReEmpPt_{i,t} = \beta_0 + \beta_1 Childbirth_{i,t} + \beta Z_{i,t} + \epsilon_{i,t} \tag{3.2}$$

On a sample of women who transitioned from non-employment to a full-time or part-time employment. $ReEmpPt_{i,t}$ is defined as a dummy variable which takes the value of 1 if individual i transitioned from non-employment to part-time employment in any month of year t, and the value of 0 if individual i transitioned from non-employment to full-time employment in any month of year t. $Childbirth_{i,t}$ is defined as a dummy variable which takes the value of 1 if the number of children in the household of individual i is higher at the time of non-employment to employment transition than it was at the time of employment to non-employment transition.

On average, women giving birth to a child in non-employment are 6.9%-points more likely to be re-employed part-time. (Full set of estimates on the basis of which average marginal effect is calculated is shown in Table A.3 in Appendix A). Long-term consequences of motherhood by type of employment are further investigated in Section 3.6.5.

3.6.2 Motherhood losses

I now move on to the analysis of earnings and wage losses of women becoming mothers, who can be identified in the SIAB data. The sample is divided in a treatment and control group, where treatment is defined as giving birth to the first child in a given year (I do not consider the effect of having subsequent children, due to not always precise method of identifying mothers in such cases, further discussed in the Data Section), and control as women who did not give birth in a given year.

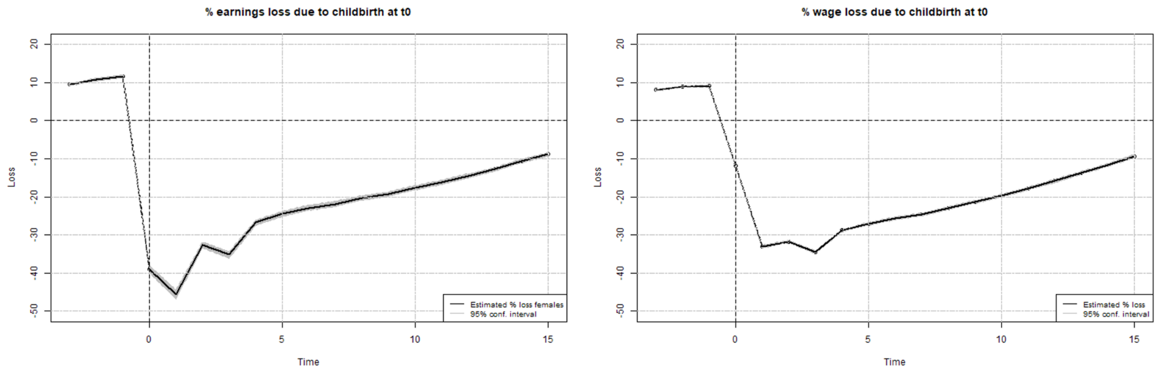


FIGURE 3.1: Percentage loss in earnings (left) and wages (right) of women having their first child at time 0, in comparison to those who do not.

First, I compare the women who have their first child at time 0 to those who do not, in terms of changes to their earnings and wages. Figure 3.1 shows that there is a significant penalty to having the child – as much as -46% in earnings and -33% in wages in the first year. This effect is also long lasting, as 15 years after having the first child mothers' earnings and wages were about 9% lower than of women's in the control group. A larger loss in earnings than in wages can be observed immediately after childbirth, at time zero and one, and a convergence of earnings losses to wage losses can be observed afterwards. In context of the decomposition of Burdett et al., 2020, this suggests a similar source of motherhood losses as for unemployment losses examined in Chapter 2; a combination of job ladder and employment gap effects, followed by skill loss or non-accumulation.

Table 3.2 presents selected statistics over the period of 2 years before and after the childbirth. The sharp reduction at time of childbirth is expected, however in the two years following it, the recovery of earnings, wages, and employment rates is slow, and the number of women working part-time increases. This might provide support for the hypothesis that a switch to part-time work occurs around the time of birth, and it results in diminished labour market outcomes in comparison to the

TABLE 3.2: Selected statistics from -24 months to +24 months of child-birth

	t-24	t-12	t	t+12	t+24	Control
Average daily earnings (annual)	65.7	67.4	33.8	16	21.8	51.9
Average daily wages (annual)	72.6	72.9	63.9	43.4	51.5	66.7
% Employed	89.1	91.7	19.3	36.1	40.7	76.3
% Employed Part-time	10.6	12.5	15.8	29.6	39.8	31.1
Number of employees	5.1	5.1	5.2	5.2	5.2	5.1
Share of FT employees	0.7	0.7	0.7	0.7	0.7	0.7
Tenure (months)	34.2	37.8	8.4	17.8	21.3	54.9

control group. The pattern of diminished unit wages related to reduced working time would be consistent with skill loss or non-accumulation being the major source of costs of motherhood over the whole 15-year period, and findings of Costa Dias et al., 2020, indicating that part-time work shuts down wage progression.

3.6.3 Motherhood losses by type of employment

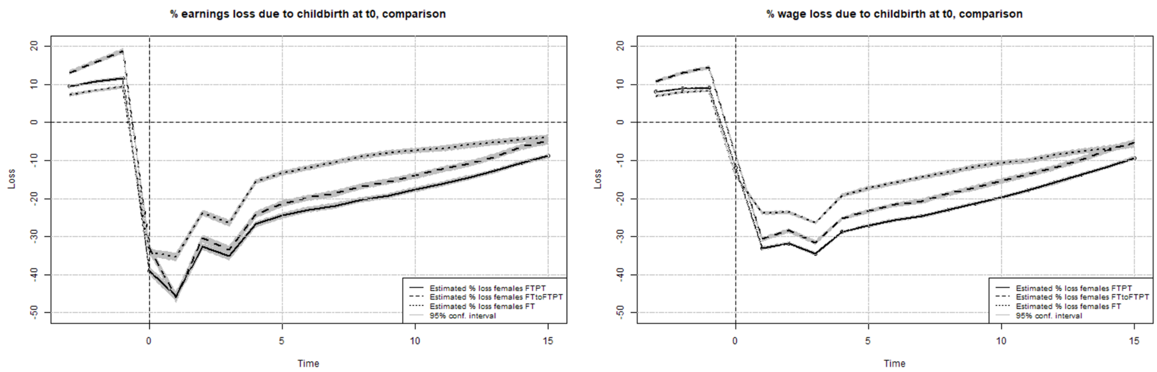


FIGURE 3.2: Percentage loss in earnings (left) and wages (right) of women having their first child at time 0, in comparison to those who do not, for three groups: those only ever working full-time (long-dashed line), those working either full-time or part-time at any time (solid line), and those who switch from full-time to part-time after having the child (short-dashed line).

Building upon Section 3.5.2, earnings and wage losses of women giving birth to a child are analysed by type of employment in Figure 3.2.

In terms of earnings, all groups have similar immediate losses of between 33-39%. Women who are observed working full-time only, however, start to recover immediately. This is in stark contrast to the sample of women also including those who work part-time – their earnings decrease even further in year 1, to almost -50%, and recover slower. Even after 10 years the gap of 7-10%-points remains. The difference between those who work full or part-time at any point, and those who switch to part-time after having the child, is small. This suggests that the result is not driven by women who only work part-time (who could be innately different than the full-time workers), but by those having the child in full-time employment, and switching to part-time afterwards. A similar pattern can be seen in wage losses (right column). Women working full-time both before giving birth and after suffer the smallest - although still significant - loss of wages.

3.6.4 Decomposition of motherhood losses by education

Previous sections show data on significant and persistent losses related to childbirth, which differ depending on the form of employment. However, I am also interested in understanding whether there exist differences conditional on the skill level of women becoming mothers. If the reduction of earnings and wages observed upon re-employment primarily reflects loss of firm-specific human capital and job tenure, differently skilled workers are likely to experience different losses. That would typically occur, in context of displacement losses, because workers who have invested more in specific human capital forfeit returns to the job-specific human capital upon re-employment (Madden, 1987). The speed of recovery might also depend on whether workers can re-invest in lost human capital, or if there are barriers to that and other factors behind the observed losses (Stevens, 1997). The second chapter of this thesis shows that displacement losses depend on the skill level, but it is important to evaluate whether the same holds true in context of women and maternity losses. If that was the case, it could have important implications for public policy and support systems, such as maternal benefits - I further investigate the effects of changes to the benefit system in in Section 3.6.6, using the 2007 reform implemented in Germany.

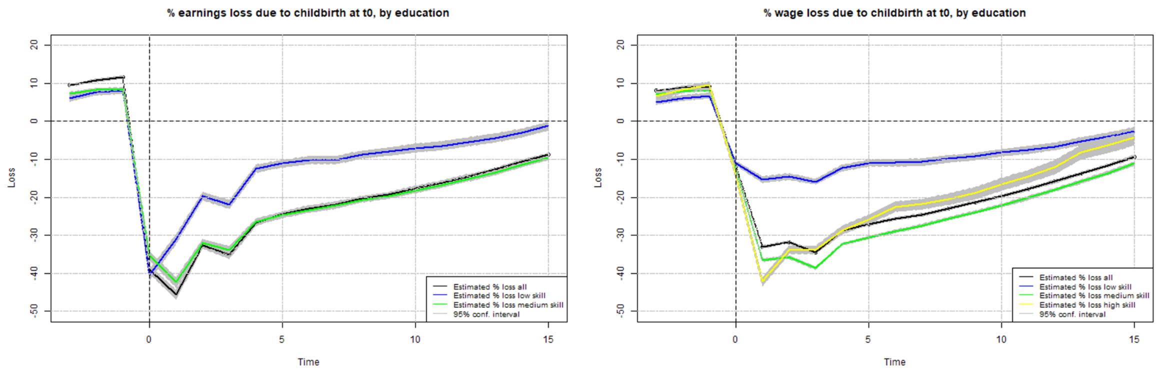


FIGURE 3.3: Earnings (left) and wages (right) percentage losses of women having their first child at time 0, in comparison to those who do not, for three sub-samples: low-educated (blue line), medium-educated (green line), and high-educated (yellow line).

Figure 3.3 decomposes the overall losses previously shown in Figure 3.1 by education group, for women working either full-time or part-time. In terms of earnings, all groups have similar immediate loss of about 40%, but low-educated women have the quickest initial recovery. The difference between the low-educated and those with higher levels of education is even more pronounced in wages – wages of low-educated women do not decrease as much as other groups, which could justify the limited reduction of earnings. However, the fact that the decrease in earnings for low educated women is sharper than the corresponding decrease in wages, suggests that wages are already close to the minimum and there occurs a reduction either along the intensive margin of labour supply (the move to part-time employment) or a temporary reduction on the extensive margin (temporary because individuals who do not return to employment are excluded from the sample). In context of the decomposition of Burdett et al., 2020, the pattern of similar earnings losses, but different wage losses, of the low-educated and medium- or high-educated women would also suggest that the employment gap effects are most significant for the low-educated group.

3.6.5 Decomposition of motherhood losses by education and type of employment

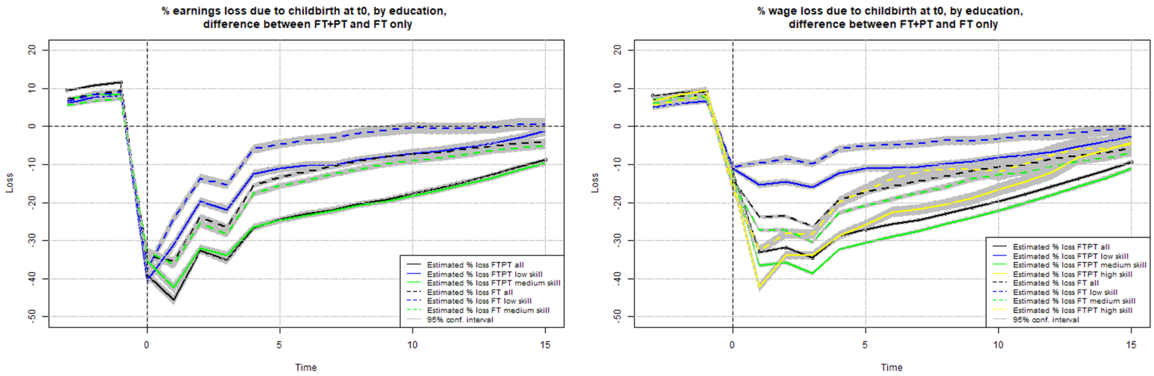


FIGURE 3.4: Earnings (left) and wages (right) percentage losses of women having their first child at time 0, in comparison to those who do not, for three sub-samples: low-educated (blue line), medium-educated (green line), and high-educated (yellow line). Dashed lines indicate estimates obtained using only full-time spells of employment, while solid lines include full-time and part-time.

In this subsection, I investigate the differences conditional on both the type of employment - full-time or part-time - and the level of education. The overall pattern remains the same as seen in Figure 3.3 but now I also show the losses of workers using only full-time employment spells. As in Figure 3.2, losses when both full-time and part-time spells of employment are considered are larger, suggesting that a switch to part-time employment after giving birth increases the losses. The gap between the two appears to increase for the higher-educated (yellow and green lines in Figure 3.4): the difference in earnings / wage losses of low-educated workers in full-time and full-time / part-time spells of employment is smaller. This could indicate that low-educated workers are less likely to switch to part-time employment upon childbirth. It could be that the wages of low-skilled workers are already close to the minimum and switching to part-time has smaller impact on them; or that low-educated workers are less likely to switch to part-time – for example due to insufficient savings and binding borrowing constraints, household characteristics, or similar reasons.

To explore the possibility that low-educated workers are less likely to switch to part-time after childbirth, I also estimate the losses using only women who were employed full-time before having a child and are observed employed either in full-time or part-time employment afterwards - this is shown in Figure 3.5. The losses of low-educated workers (blue line) remain virtually unchanged. The gap between lower and higher educated workers, however, narrows, due to the higher educated workers having slightly smaller initial losses and recovering faster than when considering full-time / part-time employment at any time.

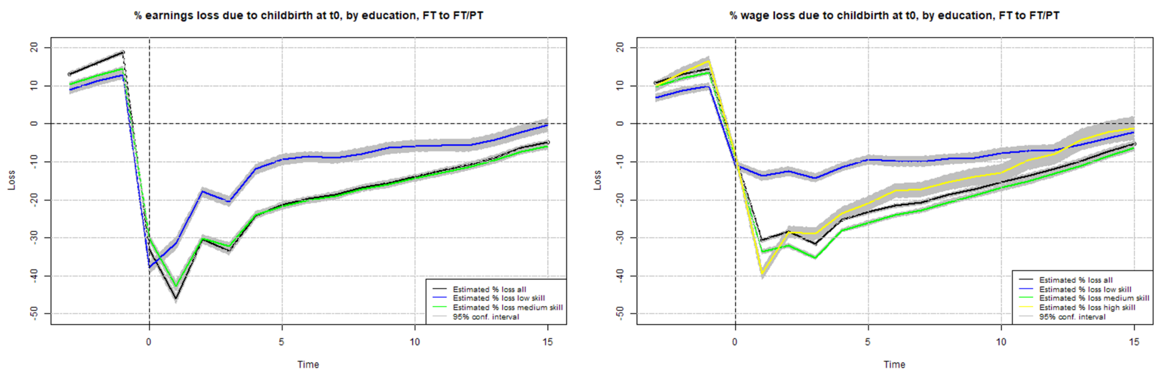


FIGURE 3.5: Earnings (left) and wages (right) percentage losses of women having their first child at time 0, in comparison to those who do not, for three sub-samples: low-educated (blue line), medium-educated (green line), and high-educated (yellow line).

Decomposition of motherhood losses by education, including zero-earnings years

The specification for motherhood losses disregards years with zero earnings and, as for separations, requires women to be in employment within 3 years after giving birth. On one hand this means my estimates of losses are somewhat conservative, on the other, if low-educated women are more likely to transition to long-term non-employment than higher-educated women, the estimates might suffer from bias. I include full zero-earnings years in Figure 3.6. The results suggest a similar pattern to the one observed before: losses of low-educated mothers, both in terms of wages and earnings, appear to be smaller than of higher-educated ones.

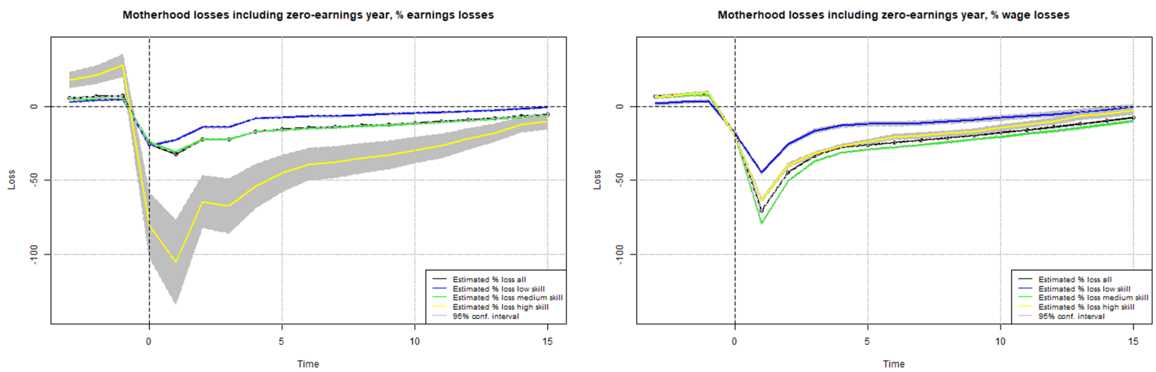


FIGURE 3.6: Earnings (left) and wages (right) percentage losses of women having their first child at time 0, in comparison to those who do not, for three sub-samples: low-educated (blue line), medium-educated (green line), and high-educated (yellow line).

3.6.6 Results: the 2007 maternity benefit reform

Next, I evaluate the effect of the 2007 maternity benefit reform on the medium-long-term profile of earnings and wages of women giving birth, by contract type and level of education. Treated individuals are on average younger (by 8 - 10 years), with correspondingly lower average daily earnings and shorter actual experience and tenure. This is to be expected, as the treatment is defined as those who had a child, in comparison to the control group of those who did not. However, what is important to analyse the effects of the reform, is that the pre-reform treatment and control groups are similar to the post-reform treatment and control groups. Table 3.3 shows that in terms of age, share of part-time workers, average daily earnings, actual experience and tenure, the pre-reform and post-reform treatment and control groups, compared within each working time subgroup, are remarkably similar, for both the 3-year and the 6-year treatment window. Therefore, analysing the effects of the policy change by comparing the pre-reform effect to the post-reform effect should be a good approach.

	6-year window											
	Pre-reform						**Post-reform**					
	Treatment (child born)			**Control**			**Treatment (child born)**			**Control**		
	FT	**FTPT**	**FTtoFTPT**	**FT**	**FTPT**	**FTtoFTPT**	**FT**	**FTPT**	**FTtoFTPT**	**FT**	**FTPT**	**FTtoFTPT**
Age	30.4	30.8	30.8	38.9	40.4	40.2	30.5	30.4	30.5	38.8	40.5	41.2
Share part-time	na	0.2	na	na	0.3	na	na	0.21	na	na	0.36	na
Average daily earnings	53.6	48.2	54.3	80.7	72.1	69.1	55	48	55	82.4	71.6	68.4
Actual experience (months)	85.8	88.7	92.6	130.2	146.2	144.1	79.5	79.2	83	138.2	156.9	159.4
Tenure (months)	39	36.7	41.3	74	81.2	77.6	36.6	32.9	37.1	75	82.3	81.1
Number of observations	6742	7989	4664	626186	899640	1052108	13408	18181	10540	694021	1106337	1296976
	3-year window											
	Pre-reform						**Post-reform**					
	Treatment (child born)			**Control**			**Treatment (child born)**			**Control**		
	FT	**FTPT**	**FTtoFTPT**	**FT**	**FTPT**	**FTtoFTPT**	**FT**	**FTPT**	**FTtoFTPT**	**FT**	**FTPT**	**FTtoFTPT**
Age	30.5	30.8	30.8	38.9	40.4	40.4	30.5	30.4	30.4	38.9	40.4	40.8
Share part-time	na	0.2	na	na	0.3	na	na	0.19	na	na	0.32	na
Average daily earnings	53.8	48.8	54.8	81.1	72.4	69.2	52.7	45.7	51.5	79.7	70.9	67.6
Actual experience (months)	86.5	89.6	93	134.8	151	149.8	82.6	82.2	85.4	138.3	155.8	157.1
Tenure (months)	40.1	38.1	42.8	75.9	82.8	79.8	37.1	32.8	36.6	75.4	82.5	80.7
Number of observations	4080	4905	2891	346071	503562	589062	5719	7435	4322	352302	529413	620076

TABLE 3.3: Summary statistics for treatment and control groups, pre- and post-reform.

Secondly, I compare the treatment groups (within each time window and pre- and post-reform group) as divided by the working time. In terms of age there does not seem to be a significant difference between the groups. In terms of average daily earnings, inclusion of the part-time workers results in a slightly lower average, as would be expected. The opposite holds true for the actual experience, which is slightly longer in the group including part-time workers. In terms of tenure, it is slightly longer among the full-time-only workers.

Thirdly, comparing the number of observations in each of the treatments pre- and post-reform suggests that the policy reform has been successful at increasing fertility in all groups: the number of women giving birth to a child post-reform has at least doubled, in comparison to the pre-reform value. While this does not speak to the causality, it is consistent with findings of the literature (Raute, 2019).

I now describe the medium-term effects of giving birth on labour market outcomes measured in terms of earnings and wages, up to 7 years post childbirth. Figure 3.7 shows changes in earnings (left column) and wages (right column) for three groups of workers, by education: those working full-time before the childbirth and either full-time or part-time post childbirth in the first row; those working full-time or part-time before and after the childbirth in the second row; those working full-time before and after childbirth in the third row. The solid lines show the evolution of earnings or wages before the reform, and the dashed lines after the reform. For all subfigures I can observe very similar and mostly flat pre-trends (denoted by the negative values on the horizontal axis), with the pre- and post-reform values not statistically significantly different, which suggests there are no selection effects that could confound the results.

Beginning with the evolution of earnings, it can be seen that the pattern of losses by education is consistent with findings reported in earlier sections, with the high skilled workers experiencing the largest losses in all three subgroups. The reform appears to deepen the earnings losses experienced by the highly educated workers in all three subgroups. Two things are noteworthy: i) the effect of the reform is the largest for the full-time and part-time group of workers, where convergence does not occur within 7 years, and smaller for the full-time workers either staying in full-time employment or moving to part-time employment; ii) the reform does not appear to have a significant effect on the trajectory of wages for the high skilled group. These suggest that the increase in earnings losses of the high skilled workers arises from more time spent outside of employment. Interestingly, both the wages and earnings of medium skilled workers seem to benefit from the reform, which suggests that substitution effects between the high skilled workers spending more time outside of employment and medium skilled workers employed in their place might occur. This would be in line with the literature analysing the effects of the reform described in section 3.3, reporting that while the reform increased the replacement rate of high earners, it had no effect or a negative effect on lower-income individuals.

Finally, I use a 3-year childbirth window in Figure 3.8 to check that the results are not driven by the financial crisis of 2008. In Figure 3.8, I compare the evolution of earnings and wages for those who gave birth between 2003 - 2006 and, post-reform, 2007 - 2010. If the results were driven by the crisis, I should see the difference between pre-reform and post-reform groups enlarging when the 3-year window is used, in comparison to the 6-year window. However, the opposite can be seen in Figure 3.8, suggesting that the original comparison is valid and that either i) there was some delay between the introduction of the reform and its full adoption into workers behaviour, visible also in the relative change in number of mothers reported in Table 3.3 being smaller than in case of the 6-year window; or ii) the financial crisis negatively affected individuals' expectations about the future and willingness to give birth to a child. However, this hypothesis is put in doubt due to a 52% increase in the number of births (for the full-time or part-time category) between the 3-year pre- and post-reform period visible in Table 3.3.

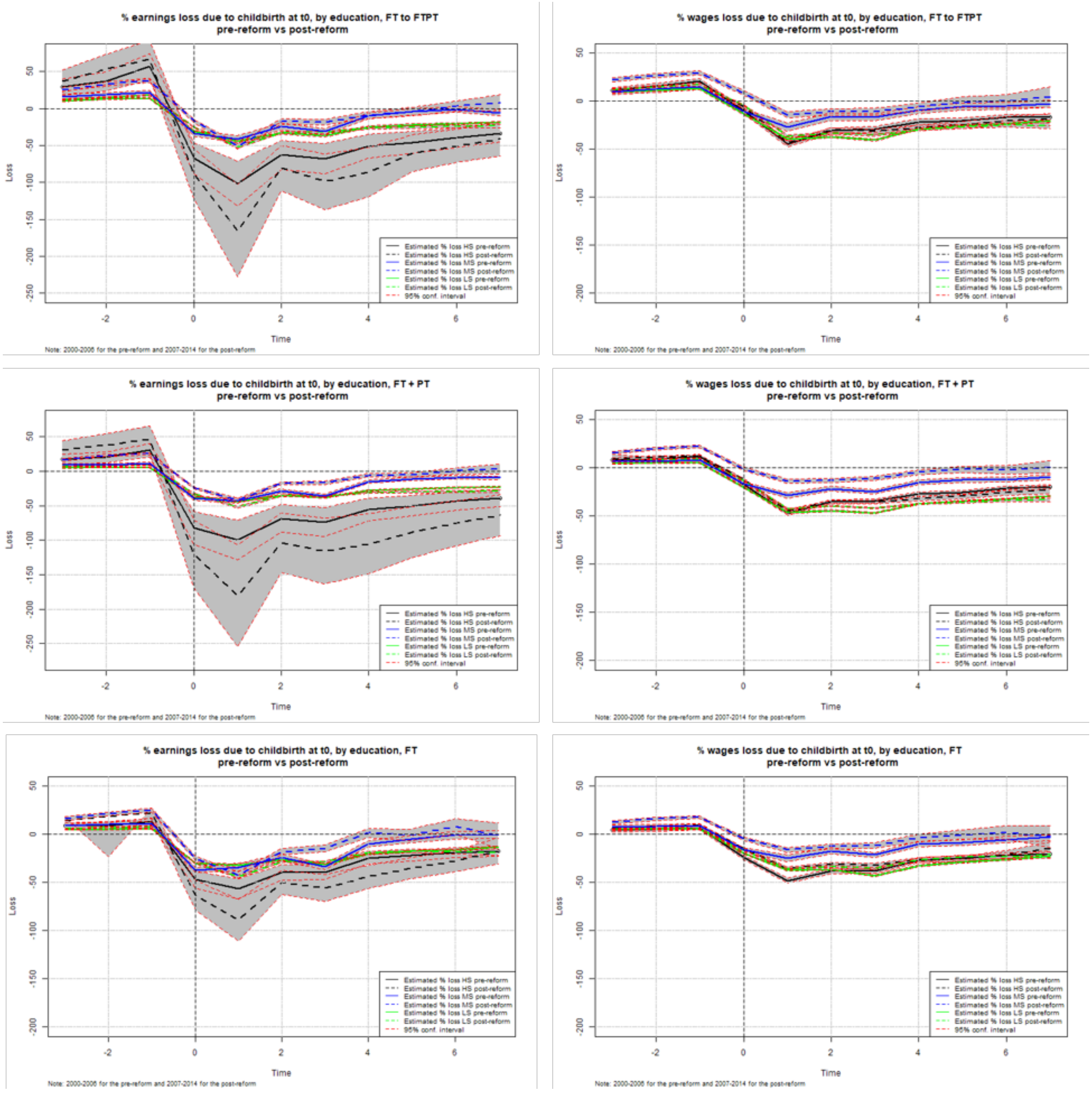


FIGURE 3.7: Childbirths in the 6 year window before and after the reform. Earnings (left) and wages (right) losses of women having their first child at time 0, pre and post-reform, in comparison to those who do not, for three sub-samples: low-educated (green line), medium-educated (blue line), and high-educated (black line). Pre-reform includes childbirths in years 2000 - 2006, while post-reform includes years 2007-2014.

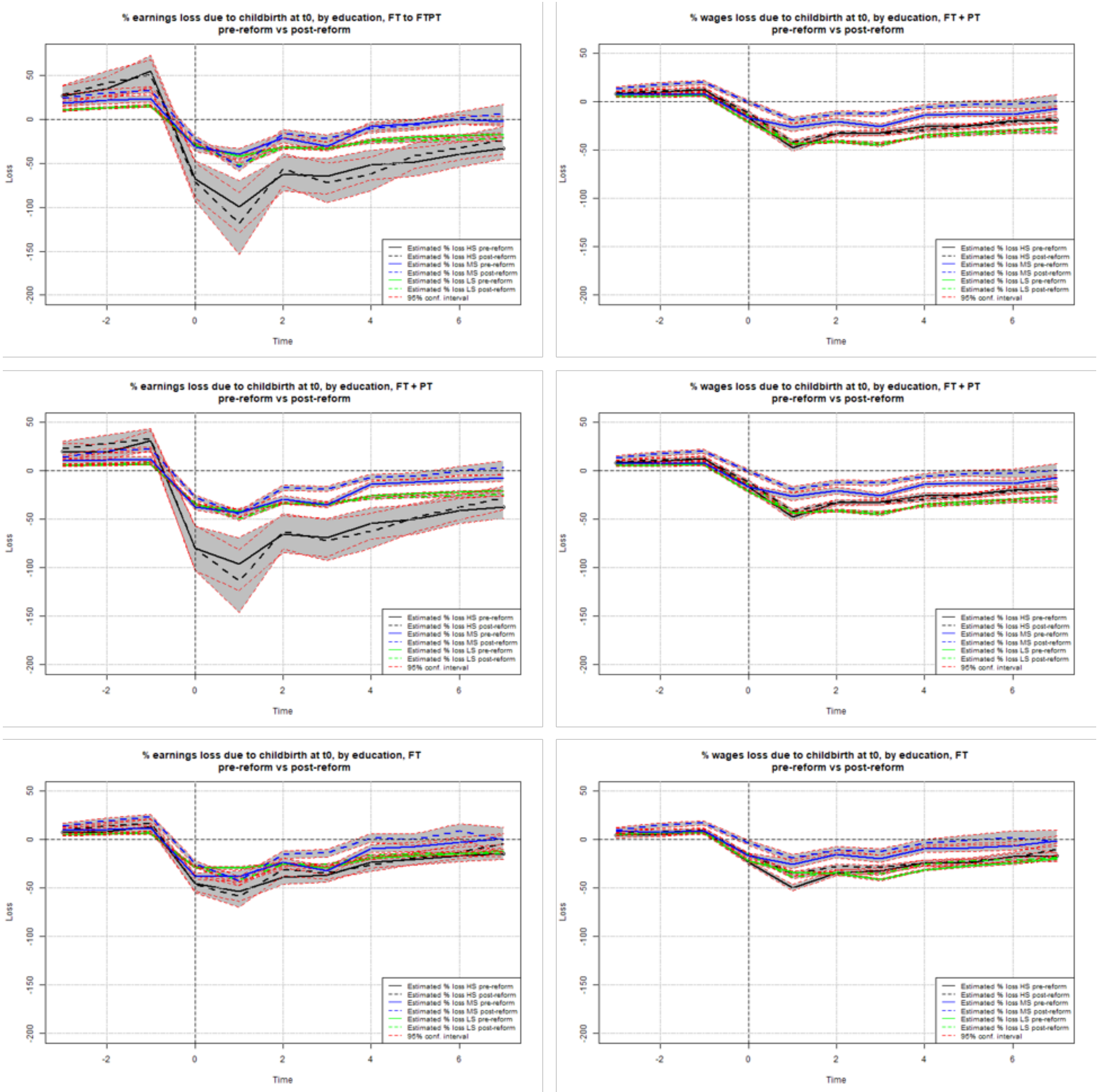


FIGURE 3.8: Childbirths in the 3 year window before and after the reform. Earnings (left) and wages (right) losses of women having their first child at time 0, pre and post-reform, in comparison to those who do not, for three sub-samples: low-educated (green line), medium-educated (blue line), and high-educated (black line). Pre-reform includes childbirths in years 2003 - 2006, while post-reform includes years 2007-2010.

3.7 Conclusions

In Chapter 2 I examine the difference between men and women in the loss of earnings and wages following a transition into non-employment. Section 2.7.2 analyses the effect of separations on full-time and part-time workers. The results show that women experience greater losses in terms of both earnings and wages than men, and the gap only starts to close 15 years after the loss of a job. However, when I take out separations due to childbirth, the gap narrows, and the recovery of losses between genders converges faster – with women recovering faster than men in years 11-15. In Appendix A.1, I estimate – separately for each gender and using full-time jobs only - the impact of a separation or displacement in a mass lay-off on the path of earnings and wages over a 15-year period and find no statistically significant difference between men and women losing a job in a mass lay-off, and a small difference when all separations are considered. This suggests that women might transition into non-employment or switch to part-time work to bring children up (Section 3.6.1 shows that childbirth is correlated with a higher probability of part-time re-employment). Following that observation, I focus on estimation of the motherhood costs in this chapter.

In Section 3.6.2, I use the birth of the first child as a treatment. I find that, in comparison to women who do not give birth, mothers suffer almost a 50% reduction in earnings and over a 30% reduction in wages, and neither makes a full recovery within the 15-years time frame. However, I also find that those who only work full-time suffer smaller losses and recover quicker – pointing towards part-time work as the reason for the losses.

Finally, in Section 3.6.6 I investigate the consequences of the 2007 reform to the maternity benefits system in Germany and evaluate its consequences for the longer-term dynamics of earnings and losses of women giving birth to a child, by different types of employment and levels of education. I find that while the policy has likely been successful at increasing the number of births, it appears to increase earnings losses of the highly educated workers by reducing their labour supply. The reform seems to be beneficial for the medium skilled workers - and while it would require further research, substitution effects between the medium and high skilled workers could be a plausible explanation.

Overall, I show that earnings and wages of men and women working full-time behave similarly when affected by an exogenous event such as mass lay-off. Women, however, experience a significantly larger reduction in earnings and wages when all separations and part-time work are included – a large proportion of which can be attributed to fertility decisions. One possible explanation for the observed gender gap in earnings and wages is that women may voluntarily separate from the employer to have children, and return to work in a part-time position, which results in a penalty in terms of their outcomes in the labour market.

Chapter 4

The Covid-19 crisis response helps the poor: the distributional and budgetary consequences of the UK lockdown

Patryk Bronka, Diego Collado, Matteo Richiardi. Published as: Bronka, P., Collado, D., Richiardi, M. (2020). "The Covid-19 Crisis Response Helps the Poor: the Distributional and Budgetary Consequences of the UK lock-down". Covid Economics, Issue 26

Abstract: We nowcast the economic effects of the Covid-19 pandemic and related lock-down measures in the UK and then analyse the distributional and budgetary effects of the estimated individual income shocks, distinguishing between the effects of automatic stabilisers and those of the emergency policy responses. Under conservative assumptions about the exit strategy and recovery phase, we predict that the rescue package will increase the cost of the crisis for the public budget by an additional £26 billion, totalling over £60 billion. However, it will allow to contain the reduction in the average household disposable income to 1 percentage point, and will reduce poverty rate by 1.1 percentage points (at a constant poverty line), with respect to the pre-Covid situation. We also show that this progressive effect is due to the increased generosity of Universal Credit, which accounts for only 20% of the cost of the rescue package.

4.1 Introduction

The objective of this paper is to nowcast the effects of the Covid-19 lock-down on the UK economy, in terms of lost income, budgetary impact, and distributional consequences. On Monday March 23, 2020, the UK Government followed a long list of countries and enforced drastic lock-down measures to limit and delay the spread of Covid-19. These included home confinement but for a limited list of exceptions, bans of public gatherings of more than two people, and closure of all retailers selling non-essential goods (essential shops include food retailers, pharmacies, hardware stores, corner shops, petrol stations, shops in hospital, post offices, banks, newsagents, laundrettes and pet shops). Schools were ordered to close a few days before, taking effect on that same Monday. The first phase of strict lock-down continued until May 13, when the Government allowed workers unable to work from home to return to their workplace provided social distancing was ensured at work, among other measures (Government, 2020).

There are no doubts that the effects of this forced breaks imposed on the economy, for the UK as well for the other countries following similar trajectories will be massive. Expert forecasts – reviewed in Hughes et al. (2020) – vary around a central estimate of around 2% GDP loss for each month of strict lock-down (see also OECD (2020)). The Office for Budget Responsibility's own forecasts lie on the pessimistic side, with a projected drop in the second quarter GDP of 35%, for a three-month lock-down (Budget Responsibility, 2020).

In order to cushion the effects of the lock-down, the Government has introduced emergency income-support measures. These include a Coronavirus Job Retention Scheme, covering 80% of the wage costs of furloughed employees up to a maximum of £2,500 a month, a Self-Employment Income Support Scheme, allowing to claim a taxable grant worth 80% of trading profits up to a maximum of £2,500 a month, plus modified conditions for Universal Credit and Local Housing Allowance, among other auxiliary measures. The furlough scheme was extended at the end of the first phase of the lock-down until the end of October, with part-time working allowed from August.

The OBR forecasts that the impact of reduced economic activity and increased spending on the public budget will amount to around £220 billion (Budget Responsibility, 2020), or 12% of GDP, split between £130 billion of lower receipts (a reduction of 15% with respect to the Budget), and almost £90 billion of increased spending (+9%

with respect to the budget).

In this paper we go beyond these aggregate estimates, characterise the groups most affected by the lock-down, identify who benefits from the emergency support measures and by how much, and the consequences in terms of poverty and the government budget. We do this by using UKMOD, the EUROMOD-based tax-benefit model for the four UK nations developed at ISER, University of Essex[1]. Tax-benefit microsimulation models apply the fiscal legislation to an observed input population, typically coming from survey data (the Family Resource Survey for UKMOD). The most recent input data for UKMOD is for the financial year 2017/18. To model the effects of the lockdown, these data need to be updated. Lacking timely data on sectoral activity and employment, we employ an input-output (IO) model based on the supply-use tables published by the Office for National Statistics and referring to 2016, parameterised with the results of a consensus analysis of the opinions of a large number of UK-based economists. We allow the lock-down measures to impact final demand by sector, and also model supply-side constraints originating from the government guidelines. An important result from our IO model is that 75% of the effect originates from demand-side constraints originating from restrictions preventing final consumers from physically visiting sellers in lock-down, reduction in the demand from importers, or difficulties to get the goods and services through the border. Supply-side constraints, due to social distancing and smart working measures reducing the output of intermediate goods and services, which producers sell to other producers, account for only 25% of the overall macro effect of the crisis according to our estimates.

Overall, our baseline scenario predicts a loss of 7.3 million jobs (22.3% of the total), once the economy is in the lock-down equilibrium. This is in line with other forecasts indicating a contraction of 25% of GDP approximately after a two-month lock-down (e.g. Pichler et al., 2020). In our analysis we assume that the economy

[1]See https://www.iser.essex.ac.uk/research/projects/ukmod

rapidly adjusts downwards to the Covid-19 shock, consistently with the preliminary evidence available. We also assume that the first phase of the crisis lasts for 2 months, followed by a further two months where the shock is reduced to 50%, and another four months where the shock is reduced to 25%. After that, we make the conservative assumption –in terms of the estimated impact of the crisis– that the economy goes back to the previous equilibrium.

The IO model allows us to differentiate the employment effects of the lock-down by industry. To distribute the income shock to workers within industries, we estimate individual relative probabilities of transitioning from employment to non-employment, on LFS data. We then analyse the effects of the estimated individual income shocks with UKMOD.

We show that the rescue package will add a net £26 billion bill to the £35 billion cost that the crisis would have entailed for the public budget, totalling £61 billion. However, it will allow to contain the reduction in the average household disposable income to 1 percentage point, and will reduce poverty rate by 1.1 percentage points (at a constant poverty line), with respect to the pre-Covid situation. We also show that this progressive effect is due to the increased generosity of Universal Credit, which accounts for around one fifth of the cost of the rescue package.

In our analysis we assume that there are no behavioural responses to the income shocks, with respect to labour supply behaviour. This is of course a simplification, which however is probably less dramatic than one would expect given the size of the shocks. This is because the crisis unfolded very rapidly and the emergency measures caught the economy entirely by surprise, being unconceivable just a few weeks before they were implemented. Moreover, they are coercive in nature and left very limited room for individual adjustment. Finally, they are generally understood to be limited in time. Hence, we argue that behavioural responses can be largely ignored, at least during the acute phase of the crisis.

Our paper belongs to a growing number of exercises trying to understand the distributional consequences of Covid-19[2]. Other contributions include Figari and Fiorio (2020), who perform the analysis on Italy, Beirne et al. (2020) for Ireland, O'Donoghue et al. (2020) also for Ireland, and we are aware of ongoing work in other countries. Figari and Fiorio use a legislation-based approach to identify what occupations should be affected by the regulation. Beirne and co-authors consider arbitrary employment scenarios. O'Donoghue et al. also start from a scenario analysis for sectoral shocks, and then distribute these shocks based on an income generation model.

The rest of the paper is structured as follows. Section 2 describes our dynamic IO model. Section 3 presents our parameterisation and quantification of the macroeconomic shock for the UK. Section 4 discusses the estimation of the employment transition model. Section 5 applies UKMOD and derives our main results. Section 6 summarises and concludes.

4.2 The macro model

Attempts to predict the macro-effects of the lockdown are more numerous than those looking at distributional consequences. Most exercises rely on aggregate macro models (e.g. Eichenbaum et al. (2020)), with fewer making use of input-output (IO) models, often also fairly aggregated (e.g. to two sectors as in Bodenstein et al. (2020)). IO models are typically of the Leontief (Leontief, 1936) or Ghosh (Ghosh, 1958) type. In the Leontief model, output depends on final demand, and a shock to demand for one sector reverberates its effects upwards in the production process through sectoral interdependencies. In the Gosh model, output depends on value added, and a shock to productivity in one sector reverberates its effects downwards

[2]Gender issues of the Covid-19 epidemics are discussed, but not estimated, in Alon et al. (2020)

in the production process through sectoral interdependencies[3].

In both cases, standard applications assume that no substitution among inputs is possible in the production of any good or service (Christ, 1955): production is then scaled up or down to meet final demand or supply constraints using the same optimal production plan, with a fixed mix of inputs in nominal terms.

Applications of the Leontief model to disaster impact assessment have led to the so-called Inoperability IO model, which follows a very similar logic (Dietzenbacher and Miller, 2015). The Inoperability model assumes that, when an entire sector or sub-sector is shut down or drastically impacted, the demand for that sector is picked up by imports. As such, the assumption that there is only one process used for the production of each output is maintained[4]. An alternative to assuming perfect substitutability between domestic intermediate inputs and imports is to consider a Cobb-Douglas specification with constant returns to scale both for production functions (supply side) and utility functions (demand side), as in Acemoglu et al. (2016) [5]. This assumption ensures that income and substitution effects exactly offset each other, and the optimal mixes of intermediate inputs and final demand depend only on technological and utility parameters respectively, and not on prices nor quantities. Acemoglu et al. show that, under those assumptions, demand shocks are only propagated upwards and supply shocks only propagated downwards.

Both approaches allow in principle for contemporaneous demand and supply shocks,

[3]The dual nature of the demand-driven Leontief model and the supply-driven Gosh model and their mathematical equivalence between the Leontief and Gosh model has been proposed (Dietzenbacher, 1997) and, while debated (De Mesnard, 2009), is generally accepted in the literature (see also Manresa and Sancho (2020).

[4]Again, the implicit assumption that prices do not change or that they are perfectly offset by changes in quantity is made.

[5]To be noted, Acemoglu et al. do not estimate production function and utility parameters, but rather use their theoretical framework to inform a reduced form econometric specification, estimated using past shocks (variation from the exogenous components of imports from China, changes in federal government spending, total factor productivity shocks and variation in foreign-industry patents).

but are not particularly well suited for analysing the disruptions caused by Covid-19. Starting from the Inoperability model, the assumption that imports can compensate for shortfalls of intermediate inputs looks unsatisfactory, given that imports are also affected, either by lock-down measures in the producing countries or by trade restrictions. The Cobb-Douglas assumption is also problematic in the Covid context, as it implies constant expenditure shares. This means, for instance, that if a company routinely uses low fare airlines to allow its managers to visit production facilities, and airlines cease to operate, it will hire a private plane to allow at least some managers to visit some plants, some of the time, so that the proportion of the budget that goes to travelling remains unchanged. This seems implausible in the current circumstances.

Most contributions trying to predict the effects of Covid-19 on the economy follow the standard IO literature without optimisation. They typically deal with the problem of reconciling demand and supply shocks by computing the effects of the two shocks separately, and then considering the biggest of the two. This is for instance the approach of Rio-Chanona et al. (2020), who construct their own measure of supply shocks for the US based on detailed occupation-specific considerations, while taking the Congressional Budget Office scenarios for the demand shocks[6]. Dorn et al. (2020) supposedly follow a similar approach in providing growth estimates for Germany, although they do not fully describe their methods. On the other hand, Pichler et al. (2020) allow for a reorganisation of production plans by adopting a hybrid Leontief + linear production function, where they distinguish between essential and non-essential inputs in production based on ad-hoc survey of market analysts. They also allow substitutability in household final demand by estimating consumption functions. Here we develop an IO model that – although less sophisticated than Pichler et al. (2020), also considers the joint effects of demand side and supply side

[6]The OECD (2020) works out its scenarios in an even simpler manner, by either looking at supply shocks (i.e. reductions in production) or demand shocks (i.e. reductions in sales), without working out their effects throughout the IO matrix.

shocks. Interestingly, we get to similar results in terms of the macroeconomic effects of the crisis.

Let $y = [y_i]$ be the total output of each industry, $Z = [z_(i,j)]$ the matrix of intermediary inputs supplied by industry i to industry j, $k = [k_i] = \sum_{j=1}^{J} z_{i,j}$ the total of intermediary inputs supplied by each industry to all other industries, and $f = [f_i]$ the final demand for each industry. We have

$$y = k + f \tag{4.1}$$

where y is supply (production), and $k + f$ is demand (sales). Inventories (included in the final demand) guarantee that the accounting identity production = sales holds, from which we obtain the familiar expression

$$Z = Ay \tag{4.2}$$

where A is a matrix of technical coefficients, assumed to remain constant. In a standard IO approach, a change in the final demand Δf is transmitted upwards and leads to a change in total production equal to

$$\Delta y = (1 - A)^{-1} \Delta f \tag{4.3}$$

while a change in production of Δy is transmitted downwards and leads to a change in final demand equal to

$$\Delta f = (1 - A) \Delta y \tag{4.4}$$

There is however no way to allow contemporaneous demand and supply shocks to all industries. The fundamental problem is that if the equation demand = supply is to hold, one of the three terms A, y or f needs to be endogenously determined. We solve this problem by allowing A to change endogenously. Ideally, this could be rationalised under the assumption of constant elasticity of substitution (CES) production functions, to be separately estimated by sectors. CES production functions nest the three cases of Leontief (no substitutability), Cobb-Douglas (constant shares) and linear production functions (full substitutability). However, CES production functions are not simple to estimate on UK data, and estimates for many sectors do not converge (Richiardi and Valenzuela, 2020). We therefore proceed by making the extreme assumption of full substitutability. While this assumption might work for some inputs, that are dependable at least in the short term (think of air travels), it is clearly inadequate for others, which are essential in the production process (for instance, iron ore for metalwork). We defend it with two arguments: first, Covid-19 restrictions mostly involve the production and consumption of non-essential goods and services; second, our approach puts us on the safe side, by providing a lower bound of the estimated effect of the lock-down on the UK economy.

Our modelling assumptions are best described in dynamic terms. We assume a linear production function in intermediate inputs z, imports m and labour l:

$$y_i^S = \sum_{j=1}^{J} z_{j,i} + m_i + l_i \tag{4.5}$$

Production is sold to other industries and final customers (including households, government, foreign markets and inventories):

$$y_i^D = \sum_{j=1}^{J} z_{i,j} + f_i \tag{4.6}$$

Because of the disruptions caused by Covid-19, final demand is reduced to $\hat{f}_i = \alpha_i f_i$[7] We assume that in a first period production plans are potentially affected by disruptions in supply, but otherwise continue unchanged even in the face of reduced final demand. Disruptions in supply, due to either an inability of firms to buy all the

[7] We assume that in a first period intermediate demand remains unchanged. Relaxing this assumption poses no problems (but also makes very little difference to our empirical results).

intermediate inputs originally planned, or to a diminished productivity of labour, reduce production to $\hat{y}_i^S = \beta_i y_i^S$. In absence of supply-side constraints, a reduction in final demand leads to over-production, which goes to inventories[8]. On the other hand, in absence of demand effects, a reduction in supply leads to under-production. We make the assumption that intermediate customers are served first, so that under-production leads to a reduction in sales to final customers.

Now, the subsequent dynamics is very different depending on whether there is over- or under-production in any given industry. In the first case, production is reduced to bring it in line with sales, meaning that the demand of all intermediate inputs is proportionally and uniformly reduced. This triggers further effects, as it worsen supply constraints in industries that are net buyers from industry i, and worsen demand constraints in industries that are net sellers to industry i.

Note that the symmetry between demand and supply shocks is broken because production is not allowed to expand in presence of supply-side constraints. Note also that supply-side constraints interact with final demand constraints by making the adjustment faster: if supply is reduced at the same time when demand is reduced, the economy remains closer to an equilibrium, although at a lower level of activity. Finally, our model maintains the original input mix as far as demand shocks are considered. It's only supply shocks that affect the composition of intermediary inputs.

4.3 Scenario assumptions and the size of the employment shocks

Equipped with our dynamic IO model, we need scenario parameters for the supply and demand shocks. We get these from a consensus analysis of an ad-hoc survey of

[8]So, technically, final demand remains unchanged, and only its composition is affected.

2,644 economists with UK affiliations and complete personal profiles in RePEc, realised between April 24 and May 1, 2020. The questionnaire asked for the expected change, at the industry level, in (i) household demand (which we assumed representative of all final demand with the exclusion for the demand for exports), (ii) supply of intermediate goods and services, and (iii) exports. Final demand is affected because consumers face limitations to buy certain goods or services. For instance, in strict lock-down beers can be ordered take-away from the local pub, and cars can be bought online without visiting a dealer, but fewer people are doing this. Supply is constrained due to the social distancing measures that producers have to put in place, or because productivity goes down due to working from home arrangements. In some sectors, distinguishing between reduction in demand and reduction in supply is difficult. This is particularly true for services requiring a personal contact: for instance, consumers can't buy a haircut in lock-down, while hairdressers cannot sell it. The distinction is more meaningful in manufacturing, wherever social distancing can be achieved in factories. Our approach is more sophisticated than some other early attempts to model the macro effects of the Covid-19 lockdown, but still disregards to a large extent substitution effects by households and producers. As discussed above for labour supply, we motivate this simplifying assumption with the consideration that the shock was large, exogenous, unexpected, and likely of short duration (a few months), hence limiting the opportunities for reorganizing production and consumption plans.

Filling in scenario assumptions on all the three dimensions cited above for the 64 industries used by the IO tables provided by the Office for National Statistics would have required asking for 192 different values. We have therefore opted for selecting key industries only: 23 industries most relevant for household demand, and 11 industries most relevant for exports and intermediate inputs (Appendix 1, Table A1). This brought down the number of industries on which the respondents were asked to focus to 34, and the single values on which they were asked for an opinion to 45. We obtained a 378 valid responses, for a response rate of 14.3%. Removing surveys in which no questions were answered and surveys in which respondents did not consent to the study, we obtain a sample of 257 responses with 81% of complete responses (208 completed surveys and 49 partially completed surveys)[9]. The distribution of the responses are reported in Appendix 1, Figures A1-A3.

We then created a mapping between the 192 parameters required, and the 45 obtained (Table C.2). On the basis of this mapping, we identify a baseline scenario with median values of the responses: feeding the IO model with these parameters leads to reduction in GDP of 22.6%, in the lock-down equilibrium. Our baseline is consistent with preliminary estimates showing that the UK economy contracted by 6% in March 2020. Given that lock-down was in place only in the last week of March, this points to a total effect close to one quarter of GDP, in equilibrium, not far away from our 22% figure. The combination of demand and supply side constraints, as discussed in Section 2, also helps to produce a rapid adjustment. The effects of such a dramatic contraction in production on employment however depend crucially on how firms respond – their specific HR policies at a time of a national emergency. The presence of quite generous government schemes, in this respect, undoubtedly takes some pressure to cushion employment responses away from companies. As a first approximation, we assume a decrease in employment proportional to the decrease in production. This leads to an equivalent of 7.3 million jobs (-22.3%), in the lock-down equilibrium[10]. Our estimated job losses are slightly more conservative than the figure of almost 8 million workers released by HM Treasury on May 20, 2020 – the advantage of the macro model of course being that our estimates are disaggregated by sector.

[9] More information on the study is available at www.euromod.ac.uk/covid-19/consensus.

[10] The results of a low-impact scenario with the p25 values, and a high-impact scenario with the p75 values are available on request, together with their distributional and budgetary consequences. In the aggregate, the employment losses go down to just above 3 million jobs (-9%) in the low-impact scenario, and shoot up to almost 13.5 million jobs (-41%) in the high-impact scenario.

Figure 4.1 reports the predicted employment losses by macro-sectors. Sector I - Accommodation & food services is the most badly hit, with an estimated reduction in lock-down of more than 80%, followed by H - Transport & storage with -40% and C - Manufacturing (almost -30%). The least affected sectors are L - Real estate activities, A - Agriculture, forestry & fishing, Q - Human health & social work and K - Finance and insurance, all around -10%.

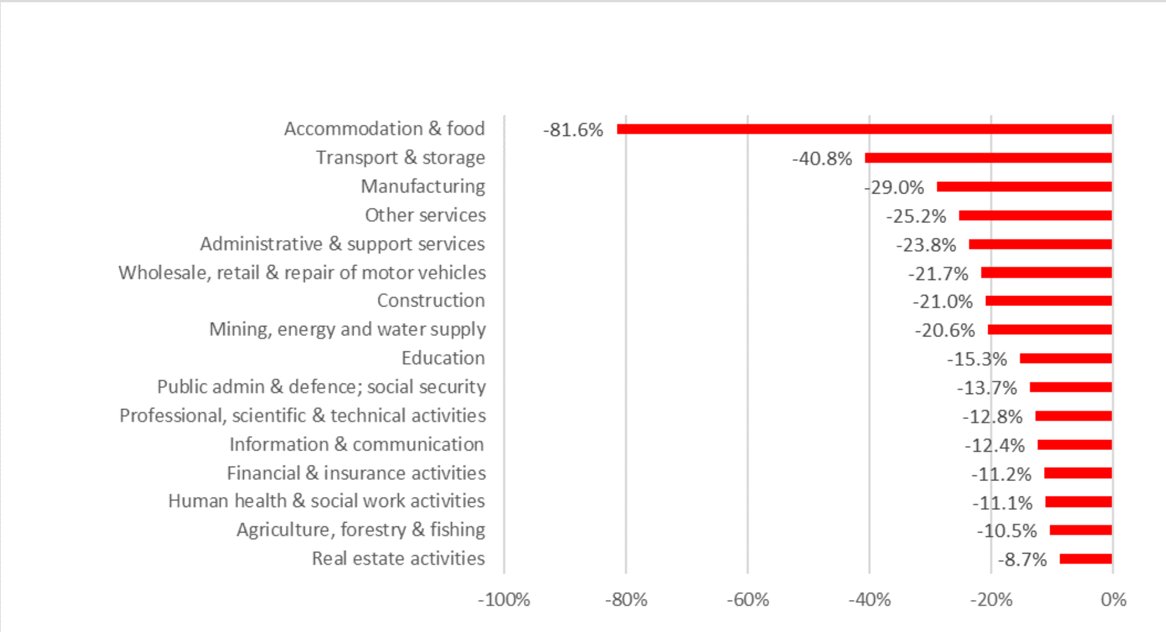


FIGURE 4.1: Employment effects by macro-sectors, baseline scenario.
Source: Our computation

The detailed employment effects predicted by our IO model by industry, which we use to adjust the input data of UKMOD, are reported in Figure 4.2. Note that the estimated effects differ sometimes significantly from the input values obtained from the scenario analysis. For instance, final household demand for industry 39 - Telecommunication services was projected to go up 20% in the consensus analysis, but overall output and employment is estimated to go down 9% from our IO model. This is because of inter-industry linkages in the supply and demand of intermediate inputs.

Interestingly, if we shut down supply constraints we obtain a modified Baseline scenario where the contraction in employment is reduced to 5.5 million jobs, or 16.9%

			Change in Employment (%)		
			Baseline	High-impact	Low-impact
	Industry		median	p25	p75
1	A	Products of agriculture, hunting and related services	-9	-24	-2
2	A	Products of forestry, logging and related services	-43	-65	-19
3	A	Fish and other fishing products; aquaculture products; support services to fishing	-13	-26	-2
4	BDE	Mining and quarrying	-37	-57	-19
5	C	Food products, beverages and tobacco products	-17	-30	-5
6	C	Textiles, wearing apparel and leather products	-34	-50	-17
7	C	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	-28	-46	-8
8	C	Paper and paper products	-23	-44	-2
9	C	Printing and recording services	-41	-58	-25
10	C	Coke and refined petroleum products	-27	-45	-11
11	C	Chemicals and chemical products	-22	-37	-4
12	C	Basic pharmaceutical products and pharmaceutical preparations	-12	-30	-2
13	C	Rubber and plastics products	-32	-51	-14
14	C	Other non-metallic mineral products	-26	-47	-3
15	C	Basic metals	-41	-61	-20
16	C	Fabricated metal products, except machinery and equipment	-33	-52	-15
17	C	Computer, electronic and optical products	-15	-35	-1
18	C	Electrical equipment	-27	-45	-8
19	C	Machinery and equipment n.e.c.	-41	-56	-28
20	C	Motor vehicles, trailers and semi-trailers	-53	-79	-31
21	C	Other transport equipment	-30	-48	-12
22	C	Furniture; other manufactured goods	-40	-65	-16
23	C	Repair and installation services of machinery and equipment	-17	-37	0
24	BDE	Electricity, gas, steam and air-conditioning	-18	-39	0
25	BDE	Natural water; water treatment and supply services	-16	-34	-1
26	BDE	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	-16	-35	-2
27	F	Constructions and construction works	-21	-42	0
28	G	Wholesale and retail trade and repair services of motor vehicles and motorcycles	-44	-72	-23
29	G	Wholesale trade services, except of motor vehicles and motorcycles	-13	-34	-1
30	G	Retail trade services, except of motor vehicles and motorcycles	-22	-43	-9
31	H	Land transport services and transport services via pipelines	-34	-59	-12
32	H	Water transport services	-49	-64	-30
33	H	Air transport services	-89	-96	-74
34	H	Warehousing and support services for transportation	-39	-60	-23
35	H	Postal and courier services	-10	-22	-4
36	I	Accommodation and food services	-82	-94	-51
37	J	Publishing services	-15	-41	0
38	J	Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services	-26	-40	-21
39	J	Telecommunications services	-9	-27	-1
40	J	Computer programming, consultancy and related services; information services	-8	-25	-1
41	K	Financial services, except insurance and pension funding	-11	-26	-8
42	K	Insurance, reinsurance and pension funding services, except compulsory social security	-12	-26	-9
43	K	Services auxiliary to financial services and insurance services	-9	-22	-4
44	L	Real estate services excluding imputed rents	-10	-27	0
45	L	Imputed rents of owner-occupied dwellings	-8	-25	0
46	M	Legal and accounting services; services of head offices; management consulting services	-13	-28	-6
47	M	Architectural and engineering services; technical testing and analysis services	-24	-40	-18
48	M	Scientific research and development services	-3	-18	0
49	M	Advertising and market research services	-14	-30	-6
50	M	Other professional, scientific and technical services; veterinary services	-10	-27	-2
51	N	Rental and leasing services	-12	-31	0
52	N	Employment services	-12	-31	-3
53	N	Travel agency, tour operator and other reservation services and related services	-92	-92	-92
54	N	Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services	-12	-29	-3
55	O	Public administration and defence services; compulsory social security services	-14	-32	-2
56	P	Education services	-15	-35	-7
57	Q	Human health services	-11	-29	-2
58	Q	Social work services	-11	-32	-3
59	RST	Creative, arts and entertainment services; library, archive, museum and other cultural services; gambling and betting services	-23	-54	-2
60	RST	Sporting services and amusement and recreation services	-63	-86	-34
61	RST	Services furnished by membership organisations	-10	-33	-4
62	RST	Repair services of computers and personal and household goods	-20	-42	-16
63	RST	Other personal services	-11	-34	-6
64	RST	Services of households as employers; undifferentiated goods and services produced by households for own use	-20	-50	0
		Total	**-22.3**	**-41.0**	**-9.2**

FIGURE 4.2: Estimated employment effects in the Baseline, High-impact and Low-impact scenarios.

of total employment. Supply side constraints therefore amount to one quarter only of the total macroeconomic effect, in our model[11].

4.4 The employment transition model

Having obtained from the IO model the expected contraction in employment in each of the 64 industries (as % change from the original level of employment), we need to assign the employment shocks at the individual level. Our assumptions distinguish between self-employment and dependent employment. For the self-employed, we simply assume that income is homogenously reduced proportionally to the industry-level shock. For employees, we assume that some workers remain unscathed, while others go down to 0 hours (whether because they are dismissed or furloughed, see Section 5 below). To identify the employees that make the transition to 0 hours, we model the probability of transitioning from dependent employment to non-employment between two consecutive quarters as a function of a set of individual observable characteristics X, the change in the industry-level aggregate employment ΔE_j, and a full set of industry dummies. We use the two-quarter longitudinal version of the Labour Force Survey (LFS). Due to a relatively small number of observations making the transition in any single file, we pool 11 two-quarter longitudinal datasets to cover the period from April 2014 to September 2019. Removing observations with missing values in any of the variables included in X we obtain a sample of 175,475 observations on 128,702 unique individuals, all dependent employees in the first quarter observations, for a total of 4,160 transitions from employment to non-employment. Table 4.1 reports the estimated coefficients from a logistic regression.

[11] Pichler et al. (2020) show that the role of supply side vis-a'-vis demand side constraints is sensitive to the assumptions about the production function used. In particular, assuming some degree of substitutability between inputs as we do lowers, *ceteris paribus*, the overall economic effects of the initial shock, and also the role of supply side constraints. As already noted however, the aggregate results we get from our model are quite in line with those of Pichler et al. (and also other independent estimates – see the review in Hughes et al. (2020), already cited).

	Coef.	St.Err.	
Sex of respondent (1= male)	0.011	0.039	
Age in years	-0.205	0.008	***
Age in years squared	0.003	0.000	***
% change in employment in sector	-0.096	0.008	***
2014 (omitted)	0.000	.	
2015.year	-0.010	0.060	
2016.year	-0.045	0.062	
2017.year	-0.142	0.063	**
2018.year	-0.131	0.063	**
2019.year	-0.135	0.065	**
Hours worked weekly			
	-0.028	0.002	***
Occupation:			
Managers (omitted)	0.000	.	
Professionals	0.000	0.070	
Technicians	-0.059	0.069	
Clerks	0.133	0.068	*
Sales	-0.003	0.068	
Trade and crafts	-0.169	0.092	*
Plant operators	0.189	0.088	**
Elementary	0.139	0.072	*
Public sector	-0.087	0.055	
Marital status:			
Single (omitted)	0.000	.	
Married	-0.317	0.048	***
Separated	-0.481	0.128	***
Divorced	-0.250	0.073	***
Widowed	-0.308	0.123	**
Education level:			
Low (omitted)	0.000	.	
Medium	-0.011	0.049	
High	0.089	0.062	
Tenure in months	-0.002	0.000	***
Industry dummies	Yes		
Constant	1.558	0.248	***
Mean dependent var 0.024		SD dependent var	0.152
Pseudo r-squared 0.082		Number of obs	175,475
Chi-square 3644.319		Prob >chi2	0.000
Akaike crit. (AIC) 36261.174		Bayesian crit. (BIC)	37137.721

TABLE 4.1: Employment transition model: Estimated coefficient (logistic regression) Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors reported are clustered at individual level. Source: Our computation on LFS two-quarter longitudinal data, April 2014 to September 2019.

4.5 Distributional and budgetary consequences

We finally analyse the distributional and budgetary consequences of the employment shocks estimated above, and of the associated policy responses. We utilise the tax-benefit microsimulation model UKMOD, the UK component of EUROMOD (Sutherland and Figari, 2013; Sutherland, 2018). We use UKMOD version A1.5+, released in April 2020 to calculate disposable (net) household incomes, given individual (gross) market incomes and personal/household characteristics. UKMOD runs on the Family Resources Survey (FRS), the latest data available being the 2017/18 wave with the different income components uprated to 2020 values.

UKMOD A1.5+ includes the changes announced in the Scottish and UK budgets of this year as well as Covid-19 policy measures, except for the Job Retention Scheme (JRS) and the Self-employment Income Support Scheme (SEISS), which we jointly label Market Income Support Schemes (MISS) and simulate directly. Besides MISS, the main policy changes in response to the Covid-19 crisis are:

- an increase in the yearly basic element of the Working Tax Credit (WTC) of £1,045;
- an increase in the weekly housing benefit disregard of £20;
- an increase in the monthly standard Universal Credit (UC) allowance of £86.67;
- the removal of the minimum income floor for self-employed within the UC calculation;
- an increase in the weekly local housing allowance of £14.86 (on average across regions and accommodation types).

We modify the input data to simulate the effects of the Covid-19 income shock (see Appendix C). With respect to the *size* of the income shock, we distinguish, as described in Section 4.4, between self-employed and dependent employees. For self-employed, we consider a homogenous reduction in earnings proportional to the projected reduction in output of their respective industry; for employees, we randomly put workers to 0 hours on the basis of the estimated probabilities coming out of the employment transition model. With respect to the duration of the income shock, we assume 2 months of strict lock-down at 100% of the estimated effects, 2 months of partial lock-down at 50% of the estimated effect, and a further 4 months of recovery phase at 25% of the estimated effect. In the recovery phase, self-employed see a reduction in their income loss, while a proportion of the dependent employees that were sent to 0 hours are allowed to get back to their previous employment status.

Our analysis is based on a comparison between three counterfactuals:

1. A "pre-Covid" scenario (referred to as 'Scenario 1'), corresponding to the income distribution and fiscal position that would have occurred in the absence of the Covid-19 crisis and related policy changes;
2. A "post-Covid employment, pre-Covid policies" scenario (referred to as 'Scenario 2'), corresponding to the impact of the Covid-19 crisis in the absence of policy changes, where only the automatic stabilisers already embedded in the tax-benefit system operate. In this scenario, the employed individuals who would stop working in lock-down receive contribution-based Job's Seekers Allowance (Cb-JSA) and other pre-Covid benefits, if they become eligible.
3. A "post-Covid employment, post-Covid policies" scenario (referred to as 'Scenario 3'), corresponding to the combined impact of the Covid-19 crisis and all policy changes.

Comparing Scenario 2 with Scenario 1 gives the un-mitigated socio-economic impact of Covid-19, and the cost that this would have entailed for the public budget due to lower tax revenues and increased benefit payments. Comparing Scenario 3 with Scenario 1 gives the mitigated socio-economic impact of Covid-19, and its overall effect on the public budget. Comparing scenario 3 with scenario 2 gives the additional costs and benefits of the emergency measures.

A crucial assumption in Scenario 3 concerns the take-up rate of MISS. We calibrate this using the latest data released by ONS on the number of people claiming benefits primarily for the reason of being unemployed (19 May 2020). These show an increase from 1.2 million in March 2020 to 2.1 million in April. Considering that the adjustment to the lock-down equilibrium – although fast – could have been still incomplete at the end of April[12], we assume that 1 million dependent employees become unemployed, rather than being furloughed, and are then checked for eligibility for the less generous contribution-based and income-based JSA and Universal Credit[13] [14]. On the other hand, we assume that all self-employed have access to the Self-Employment Income Support Scheme for their lost profits.

Comparing Scenarios 1 and 2, we see that in the absence of any policy change the Covid-19 crisis would have increased the number of claimants of unemployment benefits by 4.8 million, increased the poverty rate – at a constant poverty line – by 1.2 percentage points (pp), and decreased mean equivalised disposable income by 3%, with a more pronounced effect at the top half of the income distribution (Figure 4.3).

To understand the specific income components driving the changes, we decompose the percentage change in mean equivalised income for each decile looking at the contribution of different income sources (Figure 4.4). We find that the drop in market incomes (MI) hits proportionally harder at the top half of the income distribution: this is due to (i) many people not having market incomes in the first place, in the lowest deciles, (ii) the distribution of income by industries, and (iii) the distribution

[12] The ONS Claimant Count (series K02000001 UK) is a combination of claimants of Jobseeker's Allowance (JSA) and claimants of Universal Credit (UC) who fall within the UC 'searching for work' conditionality.

[13] This is more conservative than the 2 million unemployment figure considered by the Office for Budget Responsibility, which also considers a bigger contraction in GDP. Robustness analysis to this assumption is available upon request.

[14] Brewer and Handscomb (2020) show that the median effective replacement rate for the Job Retention Scheme is over 90%, compared to 53% for those who do not qualify (the reason why the replacement rate is over the 80% threshold is that many people will pay lower taxes after a 20 per cent fall in earnings, and might also qualify for other benefits – these effects are also included in our simulations).

	Scenario 1	Scenario 2	Δ[2-1]	Scenario 3	Δ[3-1]
Poverty					
Rate	17.4%	18.6%	1.2pp	16.3%	-1.1pp
Fixed Poverty Line	£ 982.10				
Mean equivalised income					
Decile 1	£ 613.02	£ 603.33	-2%	£ 630.20	3%
Decile 2	£ 935.34	£ 913.46	-2%	£ 955.82	2%
Decile 3	£1,129.70	£1,106.59	-2%	£1,146.46	1%
Decile 4	£1,322.55	£1,288.74	-3%	£1,328.06	0%
Decile 5	£1,529.15	£1,486.79	-3%	£1,524.97	0%
Decile 6	£1,757.29	£1,694.99	-4%	£1,739.52	-1%
Decile 7	£2,025.91	£1,955.69	-3%	£2,000.07	-1%
Decile 8	£2,359.14	£2,273.16	-4%	£2,327.18	-1%
Decile 9	£2,859.04	£2,752.04	-4%	£2,807.83	-2%
Decile 10	£4,554.44	£4,394.29	-4%	£4,451.20	-2%
All	£1,908.28	£1,846.64	-3%	£1,890.86	-1%

FIGURE 4.3: Distributional consequences of Covid-19.
Notes: Income figures are monthly averages over the year. Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 2 is a counterfactual exercise that considers "post-Covid employment, pre-Covid policies". Scenario 3 is our estimate of the real effect of the Covid-19 crisis, with "post-Covid employment, post-Covid policies".
Source: Our computation based on UKMOD A1.5+.

of the individual employment transition probabilities within industries[15]. We also confirm that JSA tends to be somewhat progressive due to its flat nature.

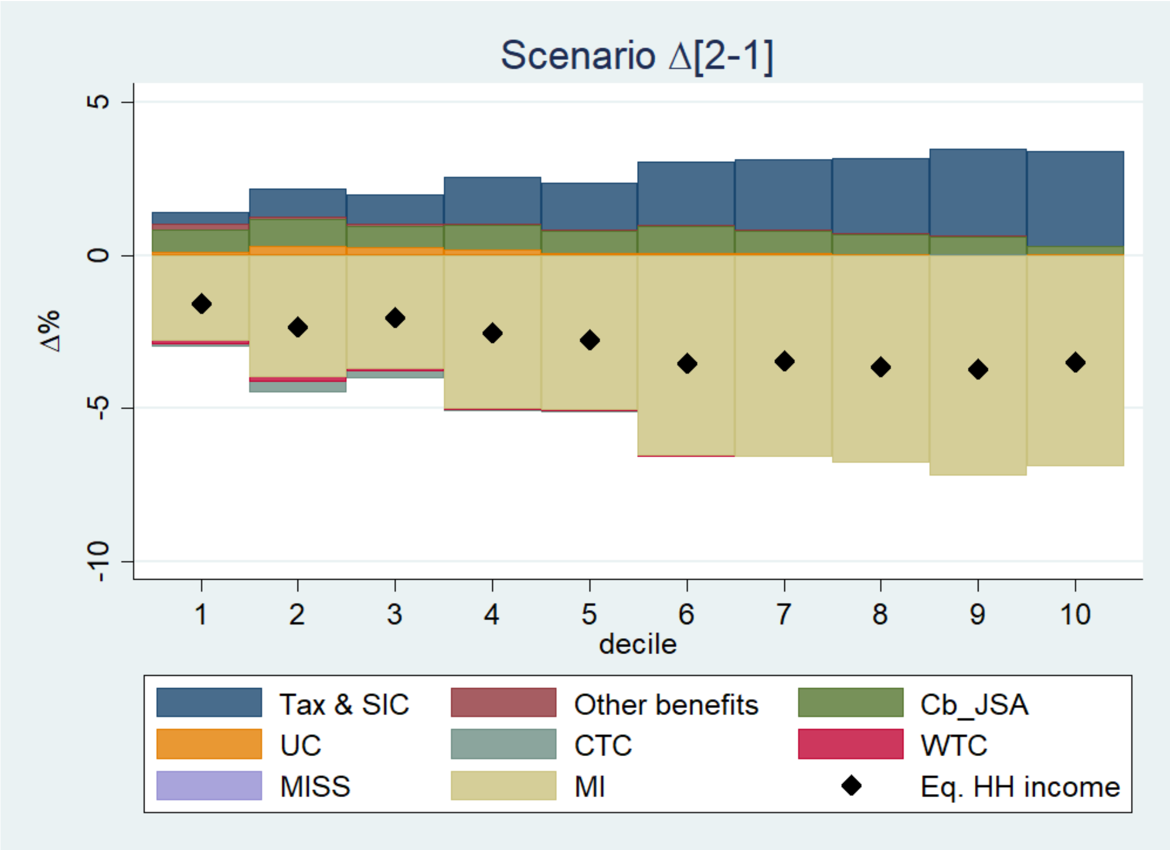


FIGURE 4.4: Decomposition of percentage change in mean equivalised income by income component, effects of income shock only (difference between Scenario 2 and Scenario 1).
Notes: Cb_JSA = contribution-based Job Seekers Allowance, UC = Universal Credit, CTC = Child Tax Credit, WTC = Working Tax Credit, MI = Market Income, MISS = MI Support Schemes. Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 2 is a counterfactual exercise that considers "post-Covid employment, pre-Covid policies". The figure reports a decomposition of the percentage change between Scenario 2 and Scenario 1.
Source: Our computation based on UKMOD A1.5+.

From the perspective of public finances (Table 4.5), this counterfactual scenario would have resulted in a drop in government revenues (taxes and social insurance contributions) of more than 28 billion pounds or 7.5% with respect to the baseline, and

[15]There is also a fourth, mechanical effect, as any given percentage drop in market income reduces household disposable income differently in different part of the income distribution, due to the rules of the tax-benefit system. The direction of this effect depends on the effective marginal tax rate, with losses for high incomes reducing taxes proportionally more than for low incomes, but triggering lower increases in benefits.

an increase in government expenditure on social transfers of more than 6 billion pounds. Due to the way eligibility conditions for contribution-based JSA are modelled in UKMOD (see footnote 17), this increase in social transfers is mostly concentrated in contribution-based JSA – as also visible in Figure 4.4 – while in reality we would expect more people falling into means-tested benefits such as Universal Credit, income-based Job Seekers Allowance and Income Support.

Overall, the increase in expenditures and the decrease in revenues would have caused a 20% deterioration in the total net revenues, or 35 billion pounds.

	Scenario 1	Scenario 2	Δ[2-1]	Scenario 3	Δ[3-1]	Δ[3-2]
Total market incomes	£ 1,104,502	£ 1,044,386	-£ 60,116	£ 1,044,386	-£ 60,116	£ -
... income from (self) employment	£ 954,334	£ 894,218	-£ 60,116	£ 894,218	-£ 60,116	£ -
... other sources	£ 150,168	£ 150,168	£ 0	£ 150,168	£ 0	£ -
Government expenditure supporting market incomes	£ -	£ -	£ -	£ 32,939	£ 32,939	£ 32,939
Government expenditure on social transfers	£ 205,315	£ 211,747	£ 6,433	£ 212,964	£ 7,649	£ 1,216
... contribution-based Job Seekers Allowance	£ 164	£ 6,188	£ 6,024	£ 1,265	£ 1,101	-£ 4,923
... WorkingTax Credit	£ 1,101	£ 861	-£ 240	£ 1,469	£ 367	£ 608
... Family Tax Credit	£ 4,511	£ 4,184	-£ 327	£ 4,674	£ 163	£ 489
... Universal Credit	£ 32,362	£ 32,958	£ 596	£ 38,123	£ 5,762	£ 5,165
... other benefits	£ 75,807	£ 76,293	£ 486	£ 76,424	£ 617	£ 131
Government revenue through taxes and social insurance contributions	£ 381,473	£ 352,832	-£ 28,641	£ 360,960	-£ 20,513	£ 8,128
... Direct taxes and (self) employee social insurance contributions	£ 301,749	£ 279,721	-£ 22,027	£ 291,198	-£ 10,551	£ 11,477
... employer social insurance contributions (not part of disposable income)	£ 79,725	£ 73,111	-£ 6,614	£ 73,111	-£ 6,614	£ -
... employer social insurance contributions paid by Job Retention Scheme	£ -	£ -	£ -	-£ 3,349	-£ 3,349	-£ 3,349
Total net revenue (revenue - expenditure)	£ 176,158	£ 141,085	-£ 35,074	£ 115,057	-£ 61,102	-£ 26,028

FIGURE 4.5: Budgetary consequences of Covid-19 (yearly, million £)
Notes: Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 2 is a counterfactual exercise that considers "post-Covid employment, pre-Covid policies". Scenario 3 is our estimate of the real effect of the Covid-19 crisis, with "post-Covid employment, post-Covid policies". Contribution-based Job Seekers Allowance is over-simulated due to lack of data in UKMOD. Claimants must have paid a minimum amount of National Insurance contributions in the two previous tax years. UKMOD does not have this information and approximates it using the number of years in work. Improving on this approximation would result in fewer unemployed individuals being entitled to this benefit and more households receiving other means-tested benefits such as Universal Credit, income-based Job Seekers Allowance and Income Support.
Source: Our computation based on UKMOD A1.5+.

Once we consider the policy changes in Scenario 3, we see that the effects of the Covid-19 crisis become progressive, with positive changes in equivalised household incomes up to the fifth decile, and negative changes in the deciles above (Table 4.3)[16].

[16]While inequality is reduced, changes in the Gini coefficients are too small to be noticeable.

The poverty rate consequently goes down from 17.4% in the baseline (Scenario 1) to 16.3%, travelling practically the same distance than in Scenario 2 (a change of 1.1 pp) but in the opposite direction. The result that the policy response to the crisis reduces poverty is mainly driven by the increase in the means-tested Universal Credit (UC) in the lowest part of the distribution (Figure 4.6). Note that MISS, with their 80% baseline replacement rate, mirror the distribution of losses in market incomes (which are the same as in Scenario 2), but for the cap at £2,500 per month which introduces some progressivity (this can be seen looking at the ratio between MISS and MI which goes down in absolute terms in the highest deciles). Because (i) MISS only covers 80% of the lost salaries and profits, (ii) some employees go into unemployment rather than being furloughed, and (iii) the rules for Universal Credit have become more generous, more people are now covered by the latter scheme. Moreover, people without labour income already on UC are net gainers from the Covid-19 crisis, as they benefit from the increased generosity of the scheme without suffering from market losses.

Finally, Figures 4.7 and 4.8 show the socio-economic groups most affected by the Covid-19 crisis in terms of both lost market incomes, and changes to household disposable income (lost market incomes are the same in Scenarios 2 and 3, while the change in equivalised household disposable income showed refer to Scenario 3, which includes the Government rescue package).

The figures show that the most affected groups in terms of lost market income are low-skilled people and people in elementary occupations. In particular, the losses for professionals and clerks are half the size, in percentage terms, than the losses for elementary occupations, craft and trade workers. This is the combined result of (i) the distribution of earnings by industries, and (ii) the distribution of the individual employment transition probabilities within industries. The working of the tax-benefit system reduces the losses, and eliminates most differences between groups. The gender, age, household type and country of origin gradients are less

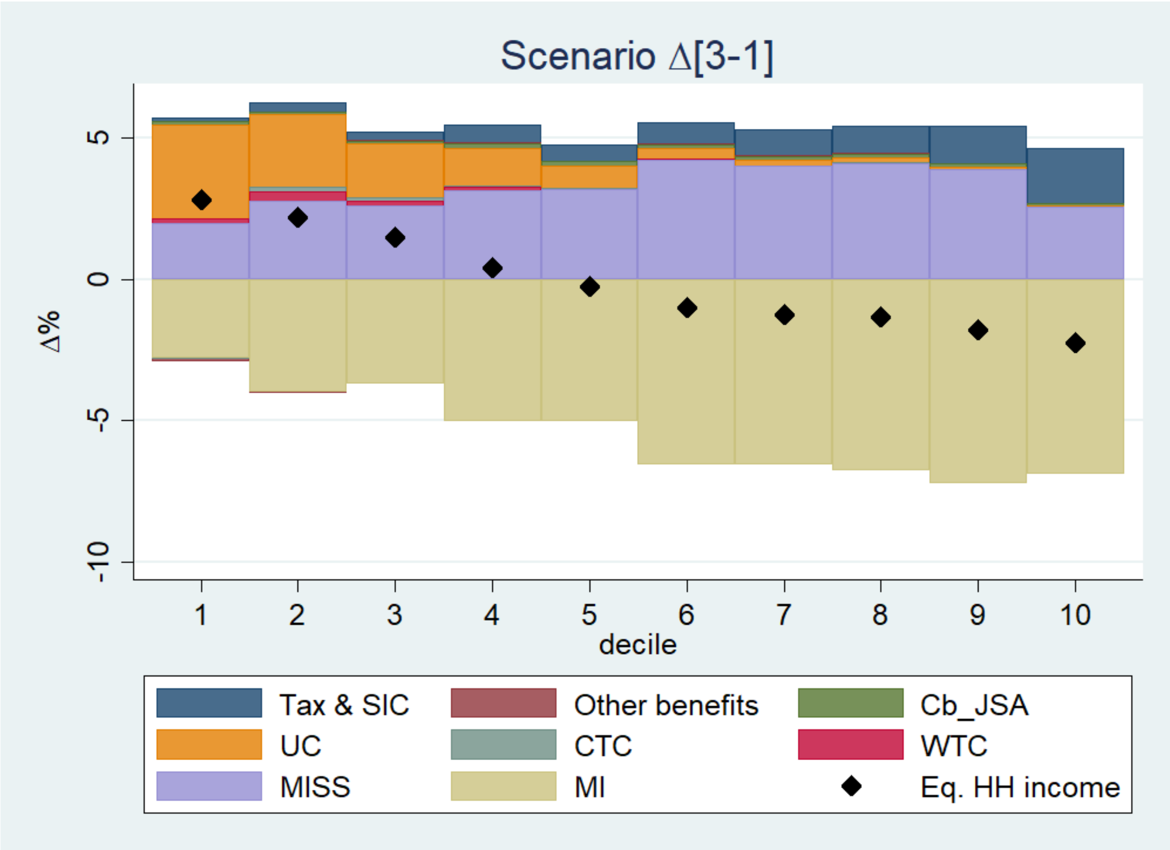


FIGURE 4.6: Decomposition of percentage change in mean equivalised income by income component, effects of income shock and policy responses (difference between Scenario 3 and Scenario 1).
Notes: Cb_JSA = contribution-based Job Seekers Allowance, UC = Universal Credit, CTC = Child Tax Credit, WTC = Working Tax Credit, MI = Market Income, MISS = MI Support Schemes. Employer National Insurance contributions paid by the government under the JRS are included as negative contributions (or credits) in the employer social insurance contributions category. Scenario 1 is our baseline and considers "pre-Covid" employment and policies. Scenario 3 is our estimate of the real effect of the Covid-19 crisis, with "post-Covid employment, post-Covid policies". The figure reports a decomposition of the percentage change between Scenario 3 and Scenario 1.
Source: Our computation based on UKMOD A1.5+.

pronounced, while with the exception of Northern Ireland (marginally less affected) there are no regional differences. Changes in after tax and benefits equivalised incomes are positive for inactive people of working age, and for single with children. These groups include many individuals with no market incomes and already on Universal Credit, who as noted above are net beneficiaries from the increased generosity of the system.

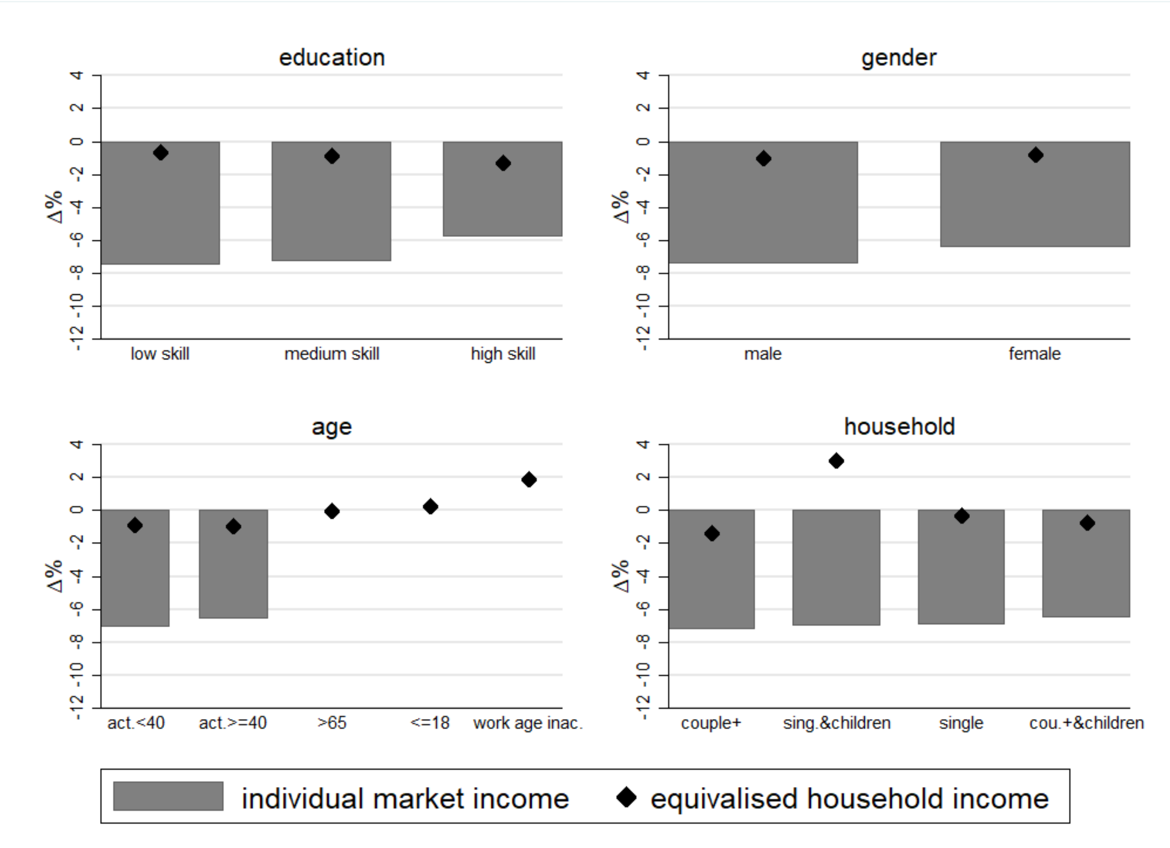


FIGURE 4.7: Mean income lost by education, gender, age and household composition.
Note: To make market and household incomes more comparable, the means only include people with positive market incomes, except for inactive people in the chart by age (there are few under-18 and elderly people with market incomes, and they are excluded from the graph). low skill = not completed primary, primary & lower secondary education, medium skill= upper secondary & post-secondary, high skill = tertiary. act. = working age with positive market income. couple+ = couple or more adults.
Source: Our computation based on UKMOD A1.5+.

The lifeline that the Government has given to the economy obviously comes at a high cost for the budget, with the rescue package expected to cause an extra deficit

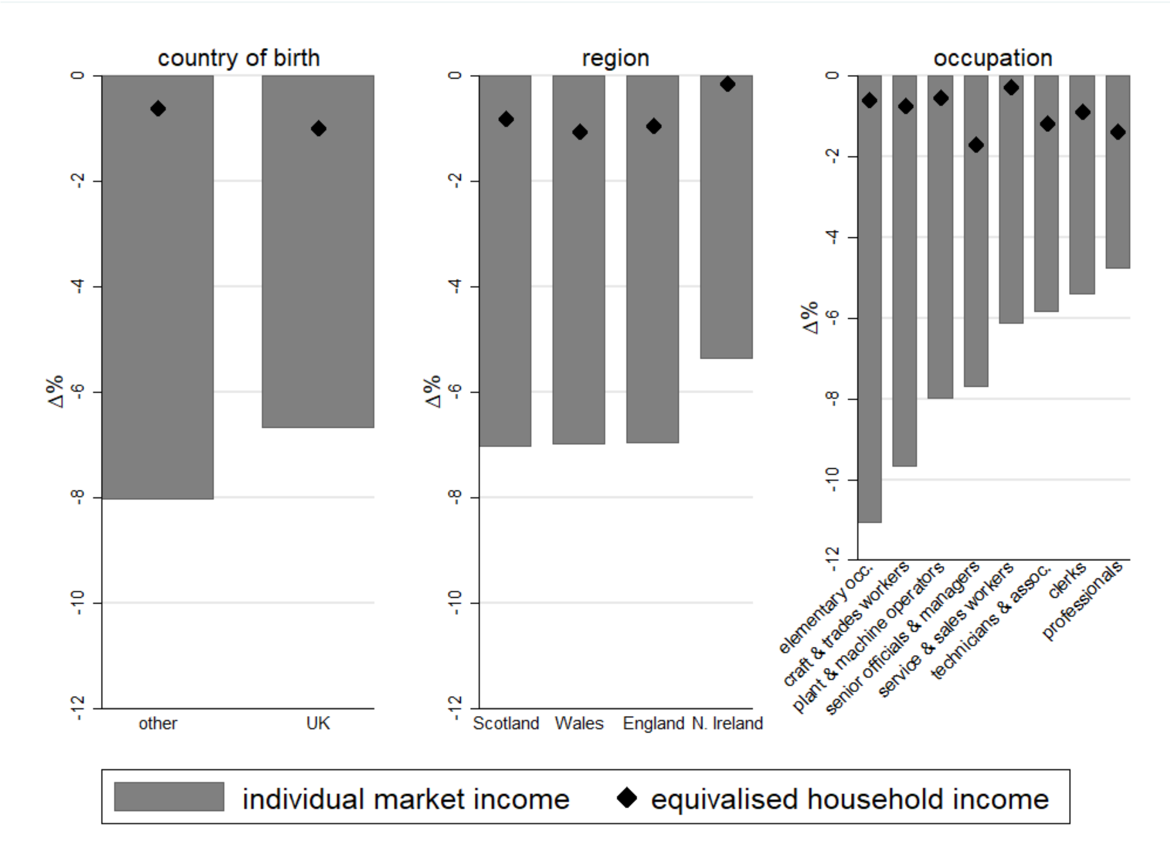


FIGURE 4.8: Mean income lost by country of origin, region and occupation.
Note: To make market and household incomes more comparable, the means only include people with positive market incomes. The regions of England are put together.
Source: Our computation based on UKMOD A1.5+.

of 26 billion pounds in 2020 with respect to Scenario 2 (Table 4, last column), bringing the overall reduction in total net revenues for the government due to the pandemic to over £60 billion (-35%). This is mostly due to MISS, with an expected direct cost of 36 billion pounds (£33 billion in income support plus £3 billion in employer social insurance contributions paid by the Government), partly offset by an increase in taxes and employee social insurance contributions (+11 billions). In Scenario 3 fewer people go on unemployment benefits with respect to Scenario 2, with a consequent reduction in expenditure from 6 billion to just over 1 billion. This expenditure however is replaced by an increased expenditure for Universal Credits, which are now more generous (+£5 billion). To be noted, this relatively minor component of the rescue package (£5 billion out of £25 billion, or 20%) does the bulk of the work in reverting the distributional consequences of the crisis. This is not surprising, as Universal Credits are a highly targeted measure[17].

4.6 Conclusions

In this paper we have provided an assessment of the distributional and budgetary impact of the Covid-19 crisis and associated policy responses, in the UK. Due to lack of timely data on the employment effects of the crisis, we have nowcasted the market income shocks by means of a dynamic IO model calibrated to the 2016 IO tables and parameterised with the results of a consensus analysis of over 250 UK-based economists to predict macro effects by industry, and a probabilistic model estimated on LFS data to predict employment-to-non-employment transitions within industry. Our macro results point to a reduction in GDP/employment of almost 25% in the lock-down equilibrium, with demand-side constraints accounting for 75% of this effect and supply-side constraints for the remaining 25%. These macro effects are in line with most of the expectations and preliminary estimates available for advanced economies, which roughly point to a 2% yearly GDP loss per month

[17]The positive role of Universal Credit in the crisis is also noted in Brewer and Handscomb (2020).

of full lock-down. Having distributed this macro shock between industries, and within industries to each individual worker, we have used the UKMOD tax-benefit model to analyse the distributional and budgetary impact of the crisis, distinguishing between the impact of the shock per se, as cushioned by the tax-benefit system in its pre-Covid configuration, and the impact of the emergency measures put in place during the crisis. We have shown that the extra intervention has contained the reduction in the average household disposable income from -3% to -1%. More importantly, we predict that the rescue package has reverted the distributional impact of the pandemic, reducing poverty by more than 1 percentage point with respect to the pre-Covid situation. This is mostly due the increased role of Universal Credit, which however accounts only for 20% of the total cost of the emergency rescue package (£26 billion). A few considerations need to be made here.

First, in this study we examine the income effects of the crisis, and we do not say anything with respect to the increased health inequalities that have been documented elsewhere (e.g. Bibby et al. (2020); Coronini-Cronberg et al. (2020)) – nor with respect to how health inequalities interact with income inequality (Baker, 2019).

Second, it is perhaps not surprising that at a time of a national emergency the country comes together and implements steps that reduce inequality, especially given that those more at risk from a health perspective come from more disadvantaged socio-economic group[18]. This is often seen in wars, for instance (Obinger et al., 2018).

Third, 80% of the emergency package goes to policy measures – the Job Retention Scheme and the Self-Employment Income Support Scheme – that are regressive for the lowest deciles and only mildly progressive at the top of the income distribution, while the bulk of the redistribution is operated by the increased generosity of Universal Credit, that accounts only for 20% of the rescue package. This does not

[18]Between March and April 2020, the age-standardised mortality rate of deaths involving COVID-19 in the most deprived areas of England was 55.1 deaths per 100,000 population compared with 25.3 deaths per 100,000 population in the least deprived areas, according to the ONS.

mean that these Market Income Support Schemes are a bad use of public money, as they are explicitly motivated by a desire to maintain as much as possible the pre-Covid status quo. Indeed, in their absence the shock to disposable incomes would have caused significant distributional consequences, with workers in some sectors affected much more than in others, and an overall increase in poverty. Moreover, the Market Income Support Schemes might serve other purposes, for instance help the economy bounce back to the previous equilibrium quicker.

Forth, and related, the issue of whether the Job Retention Scheme and the Self-employment Income Support Scheme will be maintained in place throughout the crisis is crucial. This is particularly true for some sectors, (e.g. hospitality and the travel industry) where the shock has been greater.

Finally, the overall cost of the crisis for the public deficit is massive – with a 35% projected decrease in total net revenues for the Government (£61 billion pounds). This raises the issue of how the increased debt will be managed in the years ahead, and in particular if the advances that have been achieved, most notably with an expansion in Universal Credit, will be maintained.

Appendix A

Additional Figures and Tables for Chapter 2

A.1 Comparison of losses resulting from mass-layoffs and all separations

I follow the literature as closely as possible to define a mass-layoff (Jacobson et al., 1993; Jarosch, 2015). An establishment is considered to have experienced a mass-layoff if the number of full-time employees is smaller than 70% but larger than 1% of the number of full-time employees two years earlier, and the number of full-time employees is smaller than 130% of the number of full-time employees 3 years earlier, and the number of full-time employees in the next year is smaller than 90% of the number of full-time employees 2 years ago, and the number of full-time employees 2 years ago was larger than 50. However, due to data protection regulations, the exact number of full-time employees was not available in our version of the SIAB data. I therefore approximate it by using the minimum number of employees corresponding to each coarsened category (1, 5, 10, 20, 50, 100, 200, 500) multiplied by the share of full-time employees in a given establishment in a given year.

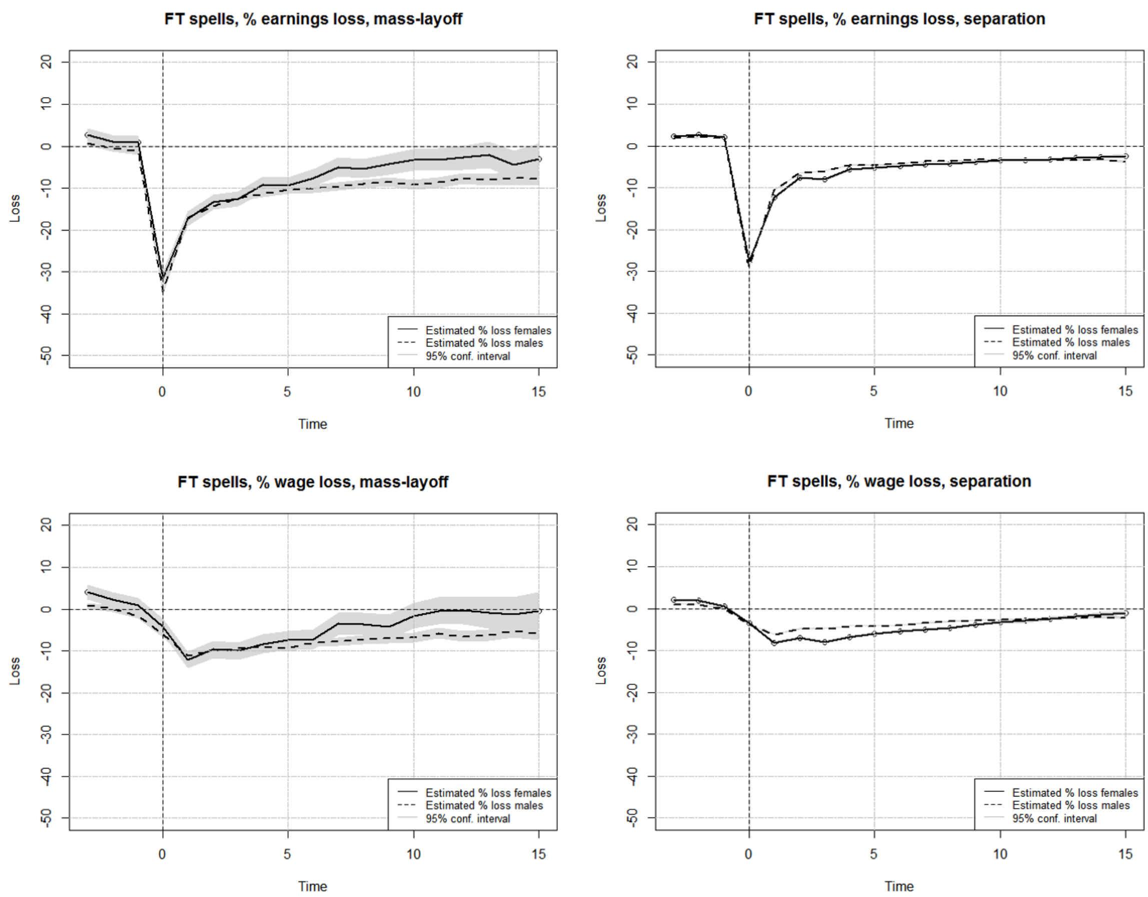


FIGURE A.1: Losses in earnings (top row) and wages (bottom row) of men (dashed lines) and women (solid lines) working full-time only upon separation in any circumstances (right column) and at a time of a plant closure resulting in a mass-layoff. The areas shaded in grey show a 95% confidence interval on the point estimates.

A.2 Voluntary transition to non-employment and childbirth

Random-effects probit regression				Number of obs = 3,185		
Group variable: pid				Number of groups = 2,624		
				Obs per group:		
				min = 1		
				avg = 1.2		
				max = 5		
				Wald chi2(17) = 181.54		
				Prob >chi2 = 0.0000		
Log pseudolikelihood = -1907.5207						
				(Std. err. adjusted for 2,624 clusters in pid)		
ChildDiffMax	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
ENVol	1.371171	0.113349	12.1	0	1.149012	1.59333
pgpbbil02						
2	-0.16843	0.164634	-1.02	0.306	-0.4911	0.15425
3	0.706173	0.424253	1.66	0.096	-0.12535	1.537694
4	-0.52279	0.362088	-1.44	0.149	-1.23247	0.186886
5	-1.29596	0.765187	-1.69	0.09	-2.7957	0.203781
6	1.285929	0.622062	2.07	0.039	0.066711	2.505147
7	0	(empty)				
9	0.173462	1.301106	0.13	0.894	-2.37666	2.723583
10	0	(empty)				
11	-0.55454	0.146804	-3.78	0	-0.84227	-0.26681
pgfamstd						
2	-0.34708	0.22233	-1.56	0.119	-0.78284	0.088681
3	0.121368	0.079824	1.52	0.128	-0.03508	0.27782
4	-0.27939	0.152804	-1.83	0.067	-0.57888	0.020103
5	-0.35735	0.565536	-0.63	0.527	-1.46578	0.75108
6	0	(empty)				
7	0.614148	0.795092	0.77	0.44	-0.9442	2.172499
11	0.255059	0.5556	0.46	0.646	-0.8339	1.344015
pgbilzeit	0.024051	0.011333	2.12	0.034	0.001839	0.046263
pgerwzeit	-0.14917	0.025556	-5.84	0	-0.19925	-0.09908
pgexpft	-0.00162	0.005984	-0.27	0.787	-0.01335	0.010109
_cons	-0.91996	0.233932	-3.93	0	-1.37846	-0.46146
/lnsig2u	-0.22283	0.263478			-0.73924	0.293577
sigma_u	0.894567	0.11785			0.690997	1.158109
rho	0.444522	0.065059			0.323171	0.572872

TABLE A.1: Voluntary transition to non-employment and childbirth

A.3 Childbirth and re-employment part-time

Random-effects probit regression				Number of obs = 5,580		
Group variable: pid				Number of groups = 3,572		
				Obs per group:		
				min = 1		
				avg = 1.6		
				max = 15		
				Wald chi2(17) = 303.72		
				Prob >chi2 = 0.0000		
Log pseudolikelihood = -1907.5207						
				(Std. err. adjusted for 3,572 clusters in pid)		
ReEmpPt	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
Childbirth	0.308916	0.09894	3.12	0.002	0.114997	0.502836
pgpbbil02						
2	-0.37188	0.168095	-2.21	0.027	-0.70134	-0.04242
3	-0.61239	0.349809	-1.75	0.08	-1.29801	0.07322
4	-0.37904	0.300023	-1.26	0.206	-0.96707	0.209
5	-1.09559	0.471734	-2.32	0.02	-2.02017	-0.17101
6	-0.06018	0.702899	-0.09	0.932	-1.43784	1.317473
9	0	(empty)				
10	0	(empty)				
11	0.065621	0.150019	0.44	0.662	-0.22841	0.359653
pgfamstd						
2	-0.45585	0.164449	-2.77	0.006	-0.77816	-0.13354
3	-1.23992	0.092554	-13.4	0	-1.42132	-1.05852
4	-0.67627	0.12522	-5.4	0	-0.92169	-0.43084
5	0.106771	0.313937	0.34	0.734	-0.50853	0.722076
6	0	(empty)				
7	-0.8469	0.824765	-1.03	0.304	-2.46341	0.769611
11	-0.59124	0.339732	-1.74	0.082	-1.2571	0.074626
pgbilzeit	0.055496	0.011375	4.88	0	0.033201	0.077791
pgerwzeit	0.006033	0.004903	1.23	0.218	-0.00358	0.015642
pgexpft	-0.07689	0.005698	-13.49	0	-0.08805	-0.06572
_cons	0.770872	0.217964	3.54	0	0.34367	1.198075
/lnsig2u	0.108798	0.141102			-0.16776	0.385353
sigma_u	1.055906	0.074495			0.919543	1.21249
rho	0.527173	0.035171			0.458159	0.595163

TABLE A.2: Part-time reemployment and childbirth

A.4 Exact values corresponding to figures presented in Chapter 2

A.4.1 Figure 2.17

Group / Year	-3	-2	-1	0	1	2	3
FT_sep_earn_loss_female	0.0372448	0.0405495	0.0339698	-0.2823736	-0.1252402	-0.0770363	-0.0807334
FT_sep_earn_loss_female_LC	0.0353981	0.0386751	0.0321579	-0.2885162	-0.1284754	-0.0795298	-0.083277
FT_sep_earn_loss_female_UC	0.0390915	0.0424239	0.0357817	-0.276231	-0.122005	-0.0745427	-0.0781899
FT_sep_earn_loss_male	0.0223611	0.0252624	0.0232054	-0.2847302	-0.0960526	-0.0575645	-0.0537487
FT_sep_earn_loss_male_LC	0.0211716	0.0240637	0.0220201	-0.2893072	-0.0979782	-0.0590828	-0.0552484
FT_sep_earn_loss_male_UC	0.0235505	0.0264612	0.0243907	-0.2801532	-0.094127	-0.0560462	-0.052249
FT_sep_wage_loss_female	0.0297858	0.0271882	0.010765	-0.0325259	-0.0829355	-0.0753616	-0.0832342
FT_sep_wage_loss_female_LC	0.0277879	0.0251962	0.0087795	-0.0346466	-0.085186	-0.0776303	-0.085504
FT_sep_wage_loss_female_UC	0.0317838	0.0291801	0.0127506	-0.0304052	-0.080685	-0.073093	-0.0809643
FT_sep_wage_loss_male	0.0118512	0.012226	0.0017593	-0.0357712	-0.054019	-0.0453809	-0.0454196
FT_sep_wage_loss_male_LC	0.0106375	0.0110183	0.0005559	-0.0370296	-0.0553046	-0.0466864	-0.046746
FT_sep_wage_loss_male_UC	0.0130649	0.0134338	0.0029628	-0.0345128	-0.0527334	-0.0440755	-0.0440932

	4	5	6	7	8	9	10
FT_sep_earn_loss_female	-0.0481865	-0.0423591	-0.0404826	-0.0377924	-0.0357076	-0.0342918	-0.0321352
FT_sep_earn_loss_female_LC	-0.0504171	-0.0446179	-0.0428142	-0.0401888	-0.0381823	-0.0368452	-0.0348257
FT_sep_earn_loss_female_UC	-0.045956	-0.0401003	-0.0381511	-0.0353959	-0.0332329	-0.0317384	-0.0294446
FT_sep_earn_loss_male	-0.0390096	-0.0378201	-0.0361263	-0.0342727	-0.0346303	-0.0359496	-0.0348258
FT_sep_earn_loss_male_LC	-0.0404269	-0.0392625	-0.0375921	-0.0357614	-0.0361564	-0.0375172	-0.0364592
FT_sep_earn_loss_male_UC	-0.0375923	-0.0363778	-0.0346605	-0.0327839	-0.0331043	-0.034382	-0.0331925
FT_sep_wage_loss_female	-0.0637209	-0.0545269	-0.048916	-0.044728	-0.0408793	-0.0346889	-0.0298098
FT_sep_wage_loss_female_LC	-0.0660994	-0.0570137	-0.0515157	-0.0474373	-0.043704	-0.0376242	-0.0329306
FT_sep_wage_loss_female_UC	-0.0613425	-0.0520401	-0.0463163	-0.0420187	-0.0380545	-0.0317536	-0.026689
FT_sep_wage_loss_male	-0.0386631	-0.0376346	-0.0374012	-0.0347399	-0.0339176	-0.0334634	-0.0310831
FT_sep_wage_loss_male_LC	-0.04003	-0.0390402	-0.0388466	-0.0362246	-0.0354425	-0.035028	-0.0327295
FT_sep_wage_loss_male_UC	-0.0372962	-0.0362289	-0.0359559	-0.0332553	-0.0323927	-0.0318989	-0.0294367

	11	12	13	14	15
FT_sep_earn_loss_female	-0.0287752	-0.0260135	-0.0239567	-0.0217012	-0.0199463
FT_sep_earn_loss_female_LC	-0.0316053	-0.0289975	-0.0271159	-0.0250454	-0.0234984
FT_sep_earn_loss_female_UC	-0.0259451	-0.0230296	-0.0207975	-0.0183569	-0.0163943
FT_sep_earn_loss_male	-0.0346012	-0.0327332	-0.0311148	-0.0320513	-0.035511
FT_sep_earn_loss_male_LC	-0.0363087	-0.0345168	-0.0329836	-0.0340162	-0.0375864
FT_sep_earn_loss_male_UC	-0.0328937	-0.0309497	-0.0292459	-0.0300864	-0.0334356
FT_sep_wage_loss_female	-0.0247794	-0.0183588	-0.0135424	-0.0088292	-0.0044929
FT_sep_wage_loss_female_LC	-0.0280916	-0.0218726	-0.0172779	-0.0127968	-0.0087163
FT_sep_wage_loss_female_UC	-0.0214673	-0.014845	-0.0098069	-0.0048616	-0.0002695
FT_sep_wage_loss_male	-0.0297806	-0.0262265	-0.0227757	-0.0232428	-0.0247354
FT_sep_wage_loss_male_LC	-0.0315117	-0.0280528	-0.0247042	-0.0252732	-0.0268729
FT_sep_wage_loss_male_UC	-0.0280494	-0.0244003	-0.0208472	-0.0212125	-0.0225978

TABLE A.3: Exact values corresponding to Figure 2.17 The table shows values for FT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3
FTPT_sep_earn_loss_female	0.0450971	0.048036	0.0383586	-0.3332308	-0.1731433	-0.1203243	-0.1263739
FTPT_sep_earn_loss_female_LC	0.04298	0.0458748	0.0363285	-0.3419228	-0.1779971	-0.1239659	-0.1301234
FTPT_sep_earn_loss_female_UC	0.0472142	0.0501973	0.0403887	-0.3245388	-0.1682894	-0.1166827	-0.1226245
FTPT_sep_earn_loss_male	0.0221422	0.024935	0.0230848	-0.2843807	-0.0982077	-0.0599808	-0.056581
FTPT_sep_earn_loss_male_LC	0.0209237	0.023707	0.0218697	-0.289158	-0.100233	-0.06157	-0.0581515
FTPT_sep_earn_loss_male_UC	0.0233606	0.026163	0.0242999	-0.2796034	-0.0961824	-0.0583916	-0.0550105
FTPT_sep_wage_loss_female	0.0321183	0.0276841	0.0087842	-0.0331619	-0.1096686	-0.1068954	-0.1184314
FTPT_sep_wage_loss_female_LC	0.030252	0.0258176	0.0069192	-0.0351138	-0.1117488	-0.1089425	-0.1204395
FTPT_sep_wage_loss_female_UC	0.0339846	0.0295507	0.0106493	-0.0312101	-0.1075885	-0.1048483	-0.1164232
FTPT_sep_wage_loss_male	0.0122174	0.0127654	0.0023111	-0.0369713	-0.0579807	-0.0499724	-0.0511221
FTPT_sep_wage_loss_male_LC	0.01087	0.0114246	0.0009749	-0.0383634	-0.0594079	-0.0514206	-0.0525917
FTPT_sep_wage_loss_male_UC	0.0135647	0.0141062	0.0036473	-0.0355793	-0.0565534	-0.0485242	-0.0496524

	4	5	6	7	8	9	10
FTPT_sep_earn_loss_female	-0.0897357	-0.0829575	-0.0809319	-0.0778205	-0.0760188	-0.0742735	-0.0671152
FTPT_sep_earn_loss_female_LC	-0.0927452	-0.0858694	-0.0838347	-0.0806955	-0.0788923	-0.0771466	-0.0699697
FTPT_sep_earn_loss_female_UC	-0.0867261	-0.0800456	-0.0780291	-0.0749455	-0.0731454	-0.0714003	-0.0642607
FTPT_sep_earn_loss_male	-0.0414618	-0.0398366	-0.0377677	-0.0357866	-0.0364406	-0.0375567	-0.0362084
FTPT_sep_earn_loss_male_LC	-0.0429335	-0.0413286	-0.0392781	-0.0373172	-0.0380088	-0.0391649	-0.0378805
FTPT_sep_earn_loss_male_UC	-0.0399902	-0.0383446	-0.0362572	-0.034256	-0.0348724	-0.0359485	-0.0345363
FTPT_sep_wage_loss_female	-0.0960902	-0.0888341	-0.0838463	-0.0790241	-0.0743619	-0.0688576	-0.0605626
FTPT_sep_wage_loss_female_LC	-0.0981461	-0.0909414	-0.0859969	-0.0812179	-0.0766004	-0.0711401	-0.0629743
FTPT_sep_wage_loss_female_UC	-0.0940344	-0.0867268	-0.0816958	-0.0768304	-0.0721234	-0.0665752	-0.0581509
FTPT_sep_wage_loss_male	-0.0429983	-0.0410554	-0.0403421	-0.0377562	-0.0363701	-0.0360038	-0.0333377
FTPT_sep_wage_loss_male_LC	-0.0445121	-0.0426111	-0.0419401	-0.0393959	-0.0380519	-0.0377277	-0.0351515
FTPT_sep_wage_loss_male_UC	-0.0414845	-0.0394996	-0.038744	-0.0361165	-0.0346883	-0.0342798	-0.0315239

	11	12	13	14	15
FTPT_sep_earn_loss_female	-0.0616279	-0.0559945	-0.0492161	-0.0431438	-0.0381081
FTPT_sep_earn_loss_female_LC	-0.0644877	-0.0588796	-0.052135	-0.0461255	-0.0411882
FTPT_sep_earn_loss_female_UC	-0.0587681	-0.0531093	-0.0462972	-0.0401621	-0.035028
FTPT_sep_earn_loss_male	-0.0355783	-0.0337327	-0.0319697	-0.0325381	-0.0351766
FTPT_sep_earn_loss_male_LC	-0.0373232	-0.0355528	-0.0338736	-0.0345375	-0.0372839
FTPT_sep_earn_loss_male_UC	-0.0338334	-0.0319126	-0.0300657	-0.0305387	-0.0330692
FTPT_sep_wage_loss_female	-0.0530898	-0.0451587	-0.0358507	-0.0285307	-0.0198643
FTPT_sep_wage_loss_female_LC	-0.0556114	-0.0478057	-0.0386325	-0.0314548	-0.0229482
FTPT_sep_wage_loss_female_UC	-0.0505683	-0.0425117	-0.0330688	-0.0256066	-0.0167804
FTPT_sep_wage_loss_male	-0.0319372	-0.0275644	-0.023804	-0.0233131	-0.0238089
FTPT_sep_wage_loss_male_LC	-0.033845	-0.0295754	-0.0259267	-0.0255474	-0.02616
FTPT_sep_wage_loss_male_UC	-0.0300295	-0.0255534	-0.0216814	-0.0210788	-0.0214578

TABLE A.4: Exact values corresponding to Figure 2.17 The table shows values for FT and PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

A.4.2 Figure 2.18

Year	-3	-2	-1	0	1	2	3
FT_sep_earn_loss_female	0.0372448	0.0405495	0.0339698	-0.2823736	-0.1252402	-0.0770363	-0.0807334
FT_sep_earn_loss_female_LC	0.0353981	0.0386751	0.0321579	-0.2885162	-0.1284754	-0.0795298	-0.083277
FT_sep_earn_loss_female_UC	0.0390915	0.0424239	0.0357817	-0.276231	-0.122005	-0.0745427	-0.0781899
FT_sep_earn_loss_male	0.0223611	0.0252624	0.0232054	-0.2847302	-0.0960526	-0.0575645	-0.0537487
FT_sep_earn_loss_male_LC	0.0211716	0.0240637	0.0220201	-0.2893072	-0.0979782	-0.0590828	-0.0552484
FT_sep_earn_loss_male_UC	0.0235505	0.0264612	0.0243907	-0.2801532	-0.094127	-0.0560462	-0.052249
FT_sep_wage_loss_female	0.0297858	0.0271882	0.010765	-0.0325259	-0.0829355	-0.0753616	-0.0832342
FT_sep_wage_loss_female_LC	0.0277879	0.0251962	0.0087795	-0.0346466	-0.085186	-0.0776303	-0.085504
FT_sep_wage_loss_female_UC	0.0317838	0.0291801	0.0127506	-0.0304052	-0.080685	-0.073093	-0.0809643
FT_sep_wage_loss_male	0.0118512	0.012226	0.0017593	-0.0357712	-0.054019	-0.0453809	-0.0454196
FT_sep_wage_loss_male_LC	0.0106375	0.0110183	0.0005559	-0.0370296	-0.0553046	-0.0466864	-0.046746
FT_sep_wage_loss_male_UC	0.0130649	0.0134338	0.0029628	-0.0345128	-0.0527334	-0.0440755	-0.0440932
FT_sep_earn_loss_nochild	0.0245887	0.0252655	0.0148026	-0.273215	-0.1140145	-0.0727777	-0.0687474
FT_sep_earn_loss_nochild_LC	0.0227401	0.0234151	0.0130011	-0.2790939	-0.1170619	-0.075247	-0.0711792
FT_sep_earn_loss_nochild_UC	0.0264373	0.0271159	0.0166042	-0.267336	-0.110967	-0.0703084	-0.0663156
FT_sep_earn_loss_child	0.084315	0.0993736	0.1053875	-0.3181135	-0.2332519	-0.1564226	-0.1962823
FT_sep_earn_loss_child_LC	0.0794985	0.094458	0.1004174	-0.3256784	-0.241078	-0.1634731	-0.2032972
FT_sep_earn_loss_child_UC	0.0891314	0.1042892	0.1103576	-0.3105486	-0.2254257	-0.1493721	-0.1892675
FT_sep_wage_loss_nochild	0.0130969	0.0088452	-0.0131515	-0.0487671	-0.0738433	-0.0675676	-0.0685608
FT_sep_wage_loss_nochild_LC	0.0109246	0.0066767	-0.0153203	-0.0510793	-0.0762234	-0.0699675	-0.0709814
FT_sep_wage_loss_nochild_UC	0.0152692	0.0110137	-0.0109826	-0.0464548	-0.0714631	-0.0651677	-0.0661401
FT_sep_wage_loss_child	0.0873915	0.0984607	0.1028635	0.0053314	-0.1780542	-0.2039974	-0.2337134
FT_sep_wage_loss_child_LC	0.0816576	0.0927338	0.0971259	-0.0004817	-0.1861834	-0.212072	-0.2412103
FT_sep_wage_loss_child_UC	0.0931254	0.1041876	0.108601	0.0111445	-0.169925	-0.1959228	-0.2262164

	4	5	6	7	8	9	10
FT_sep_earn_loss_female	-0.0481865	-0.0423591	-0.0404826	-0.0377924	-0.0357076	-0.0342918	-0.0321352
FT_sep_earn_loss_female_LC	-0.0504171	-0.0446179	-0.0428142	-0.0401888	-0.0381823	-0.0368452	-0.0348257
FT_sep_earn_loss_female_UC	-0.045956	-0.0401003	-0.0381511	-0.0353959	-0.0332329	-0.0317384	-0.0294446
FT_sep_earn_loss_male	-0.0390096	-0.0378201	-0.0361263	-0.0342727	-0.0346303	-0.0359496	-0.0348258
FT_sep_earn_loss_male_LC	-0.0404269	-0.0392625	-0.0375921	-0.0357614	-0.0361564	-0.0375172	-0.0364592
FT_sep_earn_loss_male_UC	-0.0375923	-0.0363778	-0.0346605	-0.0327839	-0.0331043	-0.034382	-0.0331925
FT_sep_wage_loss_female	-0.0637209	-0.0545269	-0.048916	-0.044728	-0.0408793	-0.0346889	-0.0298098
FT_sep_wage_loss_female_LC	-0.0660994	-0.0570137	-0.0515157	-0.0474373	-0.043704	-0.0376242	-0.0329306
FT_sep_wage_loss_female_UC	-0.0613425	-0.0520401	-0.0463163	-0.0420187	-0.0380545	-0.0317536	-0.026689
FT_sep_wage_loss_male	-0.0386631	-0.0376346	-0.0374012	-0.0347399	-0.0339176	-0.0334634	-0.0310831
FT_sep_wage_loss_male_LC	-0.04003	-0.0390402	-0.0388466	-0.0362246	-0.0354425	-0.035028	-0.0327295
FT_sep_wage_loss_male_UC	-0.0372962	-0.0362289	-0.0359559	-0.0332553	-0.0323927	-0.0318989	-0.0294367
FT_sep_earn_loss_nochild	-0.0408223	-0.0360691	-0.0323527	-0.0298554	-0.027721	-0.0264059	-0.0241573
FT_sep_earn_loss_nochild_LC	-0.0430615	-0.0383621	-0.0347199	-0.0323031	-0.030258	-0.0290351	-0.0269456
FT_sep_earn_loss_nochild_UC	-0.0385832	-0.0337762	-0.0299855	-0.0274077	-0.0251839	-0.0237768	-0.021369
FT_sep_earn_loss_child	-0.1476608	-0.1189541	-0.1074036	-0.0956594	-0.0833451	-0.073471	-0.066834
FT_sep_earn_loss_child_LC	-0.1542818	-0.1255696	-0.1142515	-0.1027181	-0.0906274	-0.0809437	-0.0745754
FT_sep_earn_loss_child_UC	-0.1410398	-0.1123386	-0.1005557	-0.0886006	-0.0760628	-0.0659983	-0.0590926
FT_sep_wage_loss_nochild	-0.054033	-0.0448972	-0.0375312	-0.0319912	-0.0283474	-0.0225758	-0.0181168
FT_sep_wage_loss_nochild_LC	-0.0565707	-0.0475518	-0.0403105	-0.0348906	-0.0313725	-0.0257243	-0.0214748
FT_sep_wage_loss_nochild_UC	-0.0514953	-0.0422426	-0.0347518	-0.0290917	-0.0253223	-0.0194273	-0.0147588
FT_sep_wage_loss_child	-0.2090108	-0.1898277	-0.1725438	-0.1561663	-0.1379036	-0.1178161	-0.1031542
FT_sep_wage_loss_child_LC	-0.2165883	-0.1976853	-0.1808043	-0.1647888	-0.1468857	-0.1270936	-0.1128054
FT_sep_wage_loss_child_UC	-0.2014334	-0.1819702	-0.1642834	-0.1475439	-0.1289214	-0.1085385	-0.093503

	11	12	13	14	15
FT_sep_earn_loss_female	-0.0287752	-0.0260135	-0.0239567	-0.0217012	-0.0199463
FT_sep_earn_loss_female_LC	-0.0316053	-0.0289975	-0.0271159	-0.0250454	-0.0234984
FT_sep_earn_loss_female_UC	-0.0259451	-0.0230296	-0.0207975	-0.0183569	-0.0163943
FT_sep_earn_loss_male	-0.0346012	-0.0327332	-0.0311148	-0.0320513	-0.035511
FT_sep_earn_loss_male_LC	-0.0363087	-0.0345168	-0.0329836	-0.0340162	-0.0375864
FT_sep_earn_loss_male_UC	-0.0328937	-0.0309497	-0.0292459	-0.0300864	-0.0334356
FT_sep_wage_loss_female	-0.0247794	-0.0183588	-0.0135424	-0.0088292	-0.0044929
FT_sep_wage_loss_female_LC	-0.0280916	-0.0218726	-0.0172779	-0.0127968	-0.0087163
FT_sep_wage_loss_female_UC	-0.0214673	-0.014845	-0.0098069	-0.0048616	-0.0002695
FT_sep_wage_loss_male	-0.0297806	-0.0262265	-0.0227757	-0.0232428	-0.0247354
FT_sep_wage_loss_male_LC	-0.0315117	-0.0280528	-0.0247042	-0.0252732	-0.0268729
FT_sep_wage_loss_male_UC	-0.0280494	-0.0244003	-0.0208472	-0.0212125	-0.0225978
FT_sep_earn_loss_nochild	-0.0202421	-0.0182498	-0.0156532	-0.0131414	-0.0119273
FT_sep_earn_loss_nochild_LC	-0.0231925	-0.0213802	-0.018985	-0.0166896	-0.0157165
FT_sep_earn_loss_nochild_UC	-0.0172917	-0.0151194	-0.0123214	-0.0095931	-0.0081381
FT_sep_earn_loss_child	-0.0592377	-0.0480414	-0.0387686	-0.0306571	-0.0213437
FT_sep_earn_loss_child_LC	-0.0672741	-0.0564146	-0.0474418	-0.0397064	-0.0307577
FT_sep_earn_loss_child_UC	-0.0512014	-0.0396683	-0.0300954	-0.0216077	-0.0119297
FT_sep_wage_loss_nochild	-0.0119137	-0.0067012	-0.0017724	0.0026656	0.0058344
FT_sep_wage_loss_nochild_LC	-0.015488	-0.0105042	-0.00583	-0.0016632	0.0012082
FT_sep_wage_loss_nochild_UC	-0.0083394	-0.0028982	0.0022852	0.0069943	0.0104606
FT_sep_wage_loss_child	-0.0918666	-0.0695028	-0.0546872	-0.0394801	-0.0289536
FT_sep_wage_loss_child_LC	-0.1019222	-0.0800202	-0.0656067	-0.0508899	-0.040836
FT_sep_wage_loss_child_UC	-0.0818109	-0.0589854	-0.0437676	-0.0280703	-0.0170713

TABLE A.5: Exact values corresponding to Figure 2.18 The table shows values for FT spells of employment, for females, males, females separating due to a child, females separating not due to a child. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3
FTPT_sep_earn_loss_female	0.0450971	0.048036	0.0383586	-0.3332308	-0.1731433	-0.1203243	-0.1263739
FTPT_sep_earn_loss_female_LC	0.04298	0.0458748	0.0363285	-0.3419228	-0.1779971	-0.1239659	-0.1301234
FTPT_sep_earn_loss_female_UC	0.0472142	0.0501973	0.0403887	-0.3245388	-0.1682894	-0.1166827	-0.1226245
FTPT_sep_earn_loss_male	0.0221422	0.024935	0.0230848	-0.2843807	-0.0982077	-0.0599808	-0.056581
FTPT_sep_earn_loss_male_LC	0.0209237	0.023707	0.0218697	-0.289158	-0.100233	-0.06157	-0.0581515
FTPT_sep_earn_loss_male_UC	0.0233606	0.026163	0.0242999	-0.2796034	-0.0961824	-0.0583916	-0.0550105
FTPT_sep_wage_loss_female	0.0321183	0.0276841	0.0087842	-0.0331619	-0.1096686	-0.1068954	-0.1184314
FTPT_sep_wage_loss_female_LC	0.030252	0.0258176	0.0069192	-0.0351138	-0.1117488	-0.1089425	-0.1204395
FTPT_sep_wage_loss_female_UC	0.0339846	0.0295507	0.0106493	-0.0312101	-0.1075885	-0.1048483	-0.1164232
FTPT_sep_wage_loss_male	0.0122174	0.0127654	0.0023111	-0.0369713	-0.0579807	-0.0499724	-0.0511221
FTPT_sep_wage_loss_male_LC	0.01087	0.0114246	0.0009749	-0.0383634	-0.0594079	-0.0514206	-0.0525917
FTPT_sep_wage_loss_male_UC	0.0135647	0.0141062	0.0036473	-0.0355793	-0.0565534	-0.0485242	-0.0496524
FTPT_sep_earn_loss_nochild	0.0196274	0.0179225	0.000957	-0.336922	-0.1586473	-0.1130916	-0.1102988
FTPT_sep_earn_loss_nochild_LC	0.0176106	0.0159137	-0.0009998	-0.3458295	-0.1632642	-0.1166874	-0.1138201
FTPT_sep_earn_loss_nochild_UC	0.0216442	0.0199313	0.0029139	-0.3280146	-0.1540304	-0.1094959	-0.1067776
FTPT_sep_earn_loss_child	0.1255246	0.1477773	0.157357	-0.3695102	-0.3431188	-0.2572754	-0.2938602
FTPT_sep_earn_loss_child_LC	0.119982	0.141972	0.1514218	-0.3790223	-0.3532231	-0.2656515	-0.3023744
FTPT_sep_earn_loss_child_UC	0.1310672	0.1535826	0.1632923	-0.3599981	-0.3330145	-0.2488992	-0.285346
FTPT_sep_wage_loss_nochild	0.0054452	-0.0007422	-0.0269151	-0.062318	-0.0937684	-0.0926763	-0.0974709
FTPT_sep_wage_loss_nochild_LC	0.0034029	-0.0027868	-0.0289655	-0.0644454	-0.0959801	-0.094864	-0.099639
FTPT_sep_wage_loss_nochild_UC	0.0074876	0.0013025	-0.0248646	-0.0601907	-0.0915568	-0.0904886	-0.0953029
FTPT_sep_wage_loss_child	0.1001289	0.1150695	0.1213482	0.0333779	-0.2707311	-0.2898734	-0.3174988
FTPT_sep_wage_loss_child_LC	0.0945953	0.1095393	0.1158101	0.0277443	-0.2784021	-0.2969676	-0.3238422
FTPT_sep_wage_loss_child_UC	0.1056624	0.1205997	0.1268863	0.0390114	-0.26306	-0.2827793	-0.3111555

	4	5	6	7	8	9	10
FTPT_sep_earn_loss_female	-0.0897357	-0.0829575	-0.0809319	-0.0778205	-0.0760188	-0.0742735	-0.0671152
FTPT_sep_earn_loss_female_LC	-0.0927452	-0.0858694	-0.0838347	-0.0806955	-0.0788923	-0.0771466	-0.0699697
FTPT_sep_earn_loss_female_UC	-0.0867261	-0.0800456	-0.0780291	-0.0749455	-0.0731454	-0.0714003	-0.0642607
FTPT_sep_earn_loss_male	-0.0414618	-0.0398366	-0.0377677	-0.0357866	-0.0364406	-0.0375567	-0.0362084
FTPT_sep_earn_loss_male_LC	-0.0429335	-0.0413286	-0.0392781	-0.0373172	-0.0380088	-0.0391649	-0.0378805
FTPT_sep_earn_loss_male_UC	-0.0399902	-0.0383446	-0.0362572	-0.034256	-0.0348724	-0.0359485	-0.0345363
FTPT_sep_wage_loss_female	-0.0960902	-0.0888341	-0.0838463	-0.0790241	-0.0743619	-0.0688576	-0.0605626
FTPT_sep_wage_loss_female_LC	-0.0981461	-0.0909414	-0.0859969	-0.0812179	-0.0766004	-0.0711401	-0.0629743
FTPT_sep_wage_loss_female_UC	-0.0940344	-0.0867268	-0.0816958	-0.0768304	-0.0721234	-0.0665752	-0.0581509
FTPT_sep_wage_loss_male	-0.0429983	-0.0410554	-0.0403421	-0.0377562	-0.0363701	-0.0360038	-0.0333377
FTPT_sep_wage_loss_male_LC	-0.0445121	-0.0426111	-0.0419401	-0.0393959	-0.0380519	-0.0377277	-0.0351515
FTPT_sep_wage_loss_male_UC	-0.0414845	-0.0394996	-0.038744	-0.0361165	-0.0346883	-0.0342798	-0.0315239
FTPT_sep_earn_loss_nochild	-0.0772532	-0.0710261	-0.066798	-0.062145	-0.0593733	-0.0574333	-0.0487849
FTPT_sep_earn_loss_nochild_LC	-0.0801681	-0.0738759	-0.0696204	-0.0649397	-0.0621719	-0.0602482	-0.0516278
FTPT_sep_earn_loss_nochild_UC	-0.0743382	-0.0681762	-0.0639757	-0.0593503	-0.0565748	-0.0546184	-0.045942
FTPT_sep_earn_loss_child	-0.254037	-0.2263077	-0.2165722	-0.2062384	-0.1943684	-0.1828928	-0.1698453
FTPT_sep_earn_loss_child_LC	-0.2617206	-0.2335434	-0.2236748	-0.2132116	-0.2011951	-0.1895813	-0.1764913
FTPT_sep_earn_loss_child_UC	-0.2463534	-0.219072	-0.2094697	-0.1992651	-0.1875417	-0.1762044	-0.1631994
FTPT_sep_wage_loss_nochild	-0.0808505	-0.0720783	-0.0648341	-0.057466	-0.0524462	-0.0463167	-0.0364948
FTPT_sep_wage_loss_nochild_LC	-0.0830763	-0.0743643	-0.0671758	-0.0598646	-0.0549019	-0.0488279	-0.0391677
FTPT_sep_wage_loss_nochild_UC	-0.0786247	-0.0697924	-0.0624925	-0.0550674	-0.0499904	-0.0438055	-0.033822
FTPT_sep_wage_loss_child	-0.2960027	-0.2784292	-0.2671897	-0.2512792	-0.2305863	-0.2127252	-0.1938031
FTPT_sep_wage_loss_child_LC	-0.3020562	-0.2844672	-0.2732519	-0.2573821	-0.2367212	-0.2188903	-0.2001465
FTPT_sep_wage_loss_child_UC	-0.2899492	-0.2723912	-0.2611274	-0.2451763	-0.2244513	-0.2065601	-0.1874597

	11	12	13	14	15
FTPT_sep_earn_loss_female	-0.0616279	-0.0559945	-0.0492161	-0.0431438	-0.0381081
FTPT_sep_earn_loss_female_LC	-0.0644877	-0.0588796	-0.052135	-0.0461255	-0.0411882
FTPT_sep_earn_loss_female_UC	-0.0587681	-0.0531093	-0.0462972	-0.0401621	-0.035028
FTPT_sep_earn_loss_male	-0.0355783	-0.0337327	-0.0319697	-0.0325381	-0.0351766
FTPT_sep_earn_loss_male_LC	-0.0373232	-0.0355528	-0.0338736	-0.0345375	-0.0372839
FTPT_sep_earn_loss_male_UC	-0.0338334	-0.0319126	-0.0300657	-0.0305387	-0.0330692
FTPT_sep_wage_loss_female	-0.0530898	-0.0451587	-0.0358507	-0.0285307	-0.0198643
FTPT_sep_wage_loss_female_LC	-0.0556114	-0.0478057	-0.0386325	-0.0314548	-0.0229482
FTPT_sep_wage_loss_female_UC	-0.0505683	-0.0425117	-0.0330688	-0.0256066	-0.0167804
FTPT_sep_wage_loss_male	-0.0319372	-0.0275644	-0.023804	-0.0233131	-0.0238089
FTPT_sep_wage_loss_male_LC	-0.033845	-0.0295754	-0.0259267	-0.0255474	-0.02616
FTPT_sep_wage_loss_male_UC	-0.0300295	-0.0255534	-0.0216814	-0.0210788	-0.0214578
FTPT_sep_earn_loss_nochild	-0.042272	-0.0370763	-0.0286076	-0.0224093	-0.0190501
FTPT_sep_earn_loss_nochild_LC	-0.0451661	-0.0400612	-0.0316852	-0.0256219	-0.0224389
FTPT_sep_earn_loss_nochild_UC	-0.0393778	-0.0340914	-0.0255301	-0.0191968	-0.0156614
FTPT_sep_earn_loss_child	-0.153107	-0.1360032	-0.116721	-0.0987089	-0.0757659
FTPT_sep_earn_loss_child_LC	-0.1596596	-0.1425305	-0.1232329	-0.105269	-0.0823841
FTPT_sep_earn_loss_child_UC	-0.1465544	-0.129476	-0.1102092	-0.0921489	-0.0691477
FTPT_sep_wage_loss_nochild	-0.0285172	-0.0216845	-0.0117656	-0.0042721	0.0021428
FTPT_sep_wage_loss_nochild_LC	-0.0313269	-0.0246489	-0.0148973	-0.0075838	-0.0013711
FTPT_sep_wage_loss_nochild_UC	-0.0257074	-0.0187202	-0.0086339	-0.0009604	0.0056567
FTPT_sep_wage_loss_child	-0.1695774	-0.1463645	-0.1222922	-0.0993353	-0.0740279
FTPT_sep_wage_loss_child_LC	-0.1760674	-0.1530644	-0.1292056	-0.1064859	-0.0814256
FTPT_sep_wage_loss_child_UC	-0.1630875	-0.1396645	-0.1153789	-0.0921846	-0.0666303

TABLE A.6: Exact values corresponding to 2.18 The table shows values for FT and PT spells of employment, for females, males, females separating due to a child, females separating not due to a child. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Appendix B

Additional Figures and Tables for Chapter 3

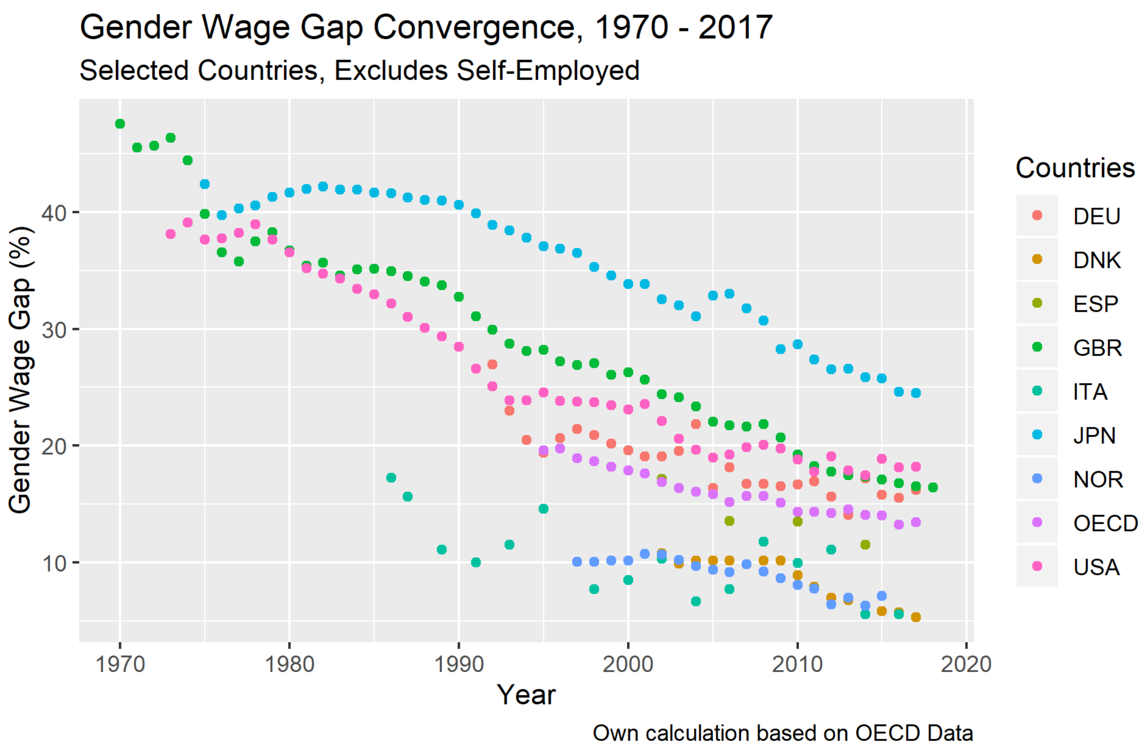


FIGURE B.1: Evolution of the Gender Gap in selected countries

B.1 Exact values corresponding to figures presented in Chapter 3

B.1.1 Figure 3.1

Year	-3	-2	-1	0	1	2	3
FTPT_mother_earn_loss	0.0944391	0.1076637	0.1151026	-0.3894929	-0.4561693	-0.3264739	-0.35159
FTPT_mother_earn_loss_LC	0.0905491	0.1036528	0.1110228	-0.3997187	-0.4681847	-0.3353739	-0.361
FTPT_mother_earn_loss_UC	0.0983291	0.1116746	0.1191824	-0.3792672	-0.4441539	-0.3175739	-0.34217
FTPT_mother_wage_loss	0.0801452	0.0893559	0.0902799	-0.1192413	-0.3307258	-0.3174412	-0.34491
FTPT_mother_wage_loss_LC	0.077111	0.0864503	0.0874697	-0.1221186	-0.3343375	-0.3208876	-0.34816
FTPT_mother_wage_loss_UC	0.0831794	0.0922616	0.0930901	-0.116364	-0.3271141	-0.3139948	-0.34166
	4	5	6	7	8	9	10
FTPT_mother_earn_loss	-0.2675775	-0.2449385	-0.2288689	-0.2186243	-0.203352	-0.1919245	-0.17698
FTPT_mother_earn_loss_LC	-0.2751313	-0.2520637	-0.235723	-0.2253436	-0.2098398	-0.1982627	-0.18312
FTPT_mother_earn_loss_UC	-0.2600236	-0.2378133	-0.2220149	-0.211905	-0.1968642	-0.1855864	-0.17083
FTPT_mother_wage_loss	-0.2881525	-0.2709904	-0.2562268	-0.2453803	-0.229779	-0.2139917	-0.1965
FTPT_mother_wage_loss_LC	-0.291574	-0.2745677	-0.2599445	-0.2492356	-0.2337637	-0.2180882	-0.20072
FTPT_mother_wage_loss_UC	-0.284731	-0.2674132	-0.252509	-0.241525	-0.2257942	-0.2098952	-0.19228
	11	12	13	14	15		
FTPT_mother_earn_loss	-0.1623434	-0.1456896	-0.1277108	-0.1057913	-0.087942		
FTPT_mother_earn_loss_LC	-0.168329	-0.1515052	-0.1333659	-0.1112728	-0.09335		
FTPT_mother_earn_loss_UC	-0.1563579	-0.139874	-0.1220558	-0.1003098	-0.0825339		
FTPT_mother_wage_loss	-0.1785758	-0.1583349	-0.1373302	-0.1166712	-0.0935105		
FTPT_mother_wage_loss_LC	-0.1829307	-0.1628247	-0.1419523	-0.1214253	-0.0984016		
FTPT_mother_wage_loss_UC	-0.1742209	-0.1538452	-0.1327081	-0.1119171	-0.0886193		

TABLE B.1: Exact values corresponding to Figure 3.3. The table shows values of motherhood losses, for FT and PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.2 Figure 3.2

Year	-3	-2	-1	0	1	2	3
FTPT_mother_earn_loss	0.0944391	0.1076637	0.1151026	-0.3894929	-0.4561693	-0.3264739	-0.3515861
FTPT_mother_earn_loss_LC	0.0905491	0.1036528	0.1110228	-0.3997187	-0.4681847	-0.3353739	-0.3610019
FTPT_mother_earn_loss_UC	0.0983291	0.1116746	0.1191824	-0.3792672	-0.4441539	-0.3175739	-0.3421702
FTPT_mother_wage_loss	0.0801452	0.0893559	0.0902799	-0.1192413	-0.3307258	-0.3174412	-0.3449128
FTPT_mother_wage_loss_LC	0.077111	0.0864503	0.0874697	-0.1221186	-0.3343375	-0.3208876	-0.348161
FTPT_mother_wage_loss_UC	0.0831794	0.0922616	0.0930901	-0.116364	-0.3271141	-0.3139948	-0.3416647

	4	5	6	7	8	9	10
FTPT_mother_earn_loss	-0.2675775	-0.2449385	-0.2288689	-0.2186243	-0.203352	-0.1919245	-0.176976
FTPT_mother_earn_loss_LC	-0.2751313	-0.2520637	-0.235723	-0.2253436	-0.2098398	-0.1982627	-0.183121
FTPT_mother_earn_loss_UC	-0.2600236	-0.2378133	-0.2220149	-0.211905	-0.1968642	-0.1855864	-0.170831
FTPT_mother_wage_loss	-0.2881525	-0.2709904	-0.2562268	-0.2453803	-0.229779	-0.2139917	-0.1965034
FTPT_mother_wage_loss_LC	-0.291574	-0.2745677	-0.2599445	-0.2492356	-0.2337637	-0.2180882	-0.2007244
FTPT_mother_wage_loss_UC	-0.284731	-0.2674132	-0.252509	-0.241525	-0.2257942	-0.2098952	-0.1922823

	11	12	13	14	15
FTPT_mother_earn_loss	-0.1623434	-0.1456896	-0.1277108	-0.1057913	-0.087942
FTPT_mother_earn_loss_LC	-0.168329	-0.1515052	-0.1333659	-0.1112728	-0.09335
FTPT_mother_earn_loss_UC	-0.1563579	-0.139874	-0.1220558	-0.1003098	-0.0825339
FTPT_mother_wage_loss	-0.1785758	-0.1583349	-0.1373302	-0.1166712	-0.0935105
FTPT_mother_wage_loss_LC	-0.1829307	-0.1628247	-0.1419523	-0.1214253	-0.0984016
FTPT_mother_wage_loss_UC	-0.1742209	-0.1538452	-0.1327081	-0.1119171	-0.0886193

TABLE B.2: Exact values corresponding to Figure 3.4. The table shows values of motherhood losses, for FT and PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3
FTtoFTPT_mother_earn_loss	0.1310498	0.1601842	0.1873555	-0.3313079	-0.459548	-0.3039747	-0.3340394
FTtoFTPT_mother_earn_loss_LC	0.1255671	0.1543306	0.181067	-0.3407744	-0.4724579	-0.3132504	-0.3438342
FTtoFTPT_mother_earn_loss_UC	0.1365325	0.1660379	0.193644	-0.3218415	-0.4466381	-0.294699	-0.3242446
FTtoFTPT_mother_wage_loss	0.1073163	0.1299246	0.1447096	-0.0864744	-0.3060364	-0.283487	-0.315292
FTtoFTPT_mother_wage_loss_LC	0.1030267	0.1258073	0.1407216	-0.090511	-0.3112686	-0.2884841	-0.3200068
FTtoFTPT_mother_wage_loss_UC	0.1116058	0.1340419	0.1486977	-0.0824379	-0.3008043	-0.27849	-0.3105772

	4	5	6	7	8	9	10
FTtoFTPT_mother_earn_loss	-0.2426297	-0.2133973	-0.1969312	-0.1862943	-0.1673754	-0.1552699	-0.139725
FTtoFTPT_mother_earn_loss_LC	-0.2506093	-0.2209526	-0.2043339	-0.1936701	-0.1745976	-0.1624538	-0.1468597
FTtoFTPT_mother_earn_loss_UC	-0.23465	-0.2058421	-0.1895285	-0.1789184	-0.1601532	-0.148086	-0.1325904
FTtoFTPT_mother_wage_loss	-0.2520969	-0.231812	-0.2159734	-0.2067134	-0.1872773	-0.171892	-0.1533198
FTtoFTPT_mother_wage_loss_LC	-0.2570588	-0.2369985	-0.2213627	-0.2123084	-0.1930611	-0.1778464	-0.1594619
FTtoFTPT_mother_wage_loss_UC	-0.247135	-0.2266255	-0.2105841	-0.2011184	-0.1814936	-0.1659376	-0.1471778

	11	12	13	14	15
FTtoFTPT_mother_earn_loss	-0.1232904	-0.1085565	-0.0888318	-0.0632034	-0.0494033
FTtoFTPT_mother_earn_loss_LC	-0.1304169	-0.115715	-0.0959934	-0.0703697	-0.0567093
FTtoFTPT_mother_earn_loss_UC	-0.1161639	-0.1013981	-0.0816701	-0.0560371	-0.0420973
FTtoFTPT_mother_wage_loss	-0.1371699	-0.1186001	-0.0972574	-0.0728717	-0.0518849
FTtoFTPT_mother_wage_loss_LC	-0.1435265	-0.1251635	-0.1040125	-0.0798146	-0.0590399
FTtoFTPT_mother_wage_loss_UC	-0.1308133	-0.1120366	-0.0905022	-0.0659287	-0.04473

TABLE B.3: Exact values corresponding to Figure 3.4. The table shows values of motherhood losses, for FT pre-motherhood and FT or PT post-motherhood spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3
FT_mother_earn_loss	0.0727459	0.084536	0.0934626	-0.3413076	-0.353148	-0.237296	-0.26434
FT_mother_earn_loss_LC	0.0691597	0.080884	0.0897371	-0.3502845	-0.3628123	-0.2445113	-0.2720519
FT_mother_earn_loss_UC	0.076332	0.0881881	0.0971881	-0.3323308	-0.3434837	-0.2300807	-0.2566281
FT_mother_wage_loss	0.0691686	0.0792995	0.0831226	-0.1397996	-0.238083	-0.2351574	-0.2633488
FT_mother_wage_loss_LC	0.0662259	0.0764679	0.0803705	-0.1426041	-0.2420084	-0.2391309	-0.2672103
FT_mother_wage_loss_UC	0.0721113	0.0821312	0.0858746	-0.136995	-0.2341576	-0.2311839	-0.2594873

	4	5	6	7	8	9	10
FT_mother_earn_loss	-0.1563441	-0.1330426	-0.1185761	-0.1038317	-0.0900637	-0.0794665	-0.0733358
FT_mother_earn_loss_LC	-0.1623097	-0.1389436	-0.1245712	-0.1099471	-0.0963204	-0.0858934	-0.0799541
FT_mother_earn_loss_UC	-0.1503785	-0.1271416	-0.1125811	-0.0977163	-0.083807	-0.0730396	-0.0667175
FT_mother_wage_loss	-0.1916783	-0.1728381	-0.157831	-0.1441198	-0.1309476	-0.1158225	-0.106256
FT_mother_wage_loss_LC	-0.195983	-0.177498	-0.1628092	-0.1494076	-0.1365213	-0.1216572	-0.1123267
FT_mother_wage_loss_UC	-0.1873736	-0.1681782	-0.1528528	-0.138832	-0.125374	-0.1099878	-0.1001853

	11	12	13	14	15
FT_mother_earn_loss	-0.0684268	-0.0596961	-0.0523217	-0.0452323	-0.0404032
FT_mother_earn_loss_LC	-0.0752733	-0.0667474	-0.059597	-0.0527093	-0.048122
FT_mother_earn_loss_UC	-0.0615803	-0.0526449	-0.0450465	-0.0377552	-0.0326845
FT_mother_wage_loss	-0.1000352	-0.0865381	-0.0752908	-0.068499	-0.0572414
FT_mother_wage_loss_LC	-0.1063628	-0.0931142	-0.0821193	-0.0755503	-0.0645412
FT_mother_wage_loss_UC	-0.0937075	-0.0799619	-0.0684624	-0.0614477	-0.0499417

TABLE B.4: Exact values corresponding to Figure 3.4. The table shows values of motherhood losses, for FT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.3 Figure 3.3

Year	-3	-2	-1	0	1	2	3
FTPT_earn_all	0.0944391	0.1076637	0.1151026	-0.3894929	-0.4561693	-0.3264739	-0.3515861
FTPT_earn_all_LC	0.0905491	0.1036528	0.1110228	-0.3997187	-0.4681847	-0.3353739	-0.3610019
FTPT_earn_all_UC	0.0983291	0.1116746	0.1191824	-0.3792672	-0.4441539	-0.3175739	-0.3421702
FTPT_wage_all	0.0801452	0.0893559	0.0902799	-0.1192413	-0.3307258	-0.3174412	-0.3449128
FTPT_wage_all_LC	0.077111	0.0864503	0.0874697	-0.1221186	-0.3343375	-0.3208876	-0.348161
FTPT_wage_all_UC	0.0831794	0.0922616	0.0930901	-0.116364	-0.3271141	-0.3139948	-0.3416647
FTPT_earn_low	0.0595391	0.0769921	0.0804266	-0.4039492	-0.3092961	-0.1967044	-0.2183759
FTPT_earn_low_LC	0.0512625	0.0690203	0.0727744	-0.4180363	-0.3221017	-0.207291	-0.229028
FTPT_earn_low_UC	0.0678158	0.0849638	0.0880788	-0.3898621	-0.2964906	-0.1861179	-0.2077238
FTPT_wage_low	0.0505487	0.0608371	0.0675094	-0.1106157	-0.1527206	-0.1452164	-0.158999
FTPT_wage_low_LC	0.0431996	0.0539073	0.0609251	-0.1172516	-0.1607415	-0.1532267	-0.1666434
FTPT_wage_low_UC	0.0578977	0.0677669	0.0740936	-0.1039799	-0.1446997	-0.137206	-0.1513546
FTPT_earn_medium	0.0730979	0.0824709	0.0851359	-0.3537342	-0.4235854	-0.3196033	-0.3393678
FTPT_earn_medium_LC	0.0693272	0.0786041	0.0812655	-0.3649008	-0.4369689	-0.3299125	-0.3501686
FTPT_earn_medium_UC	0.0768687	0.0863376	0.0890063	-0.3425676	-0.4102018	-0.309294	-0.3285671
FTPT_wage_medium	0.0713352	0.0799607	0.0811904	-0.1263483	-0.3648131	-0.3568524	-0.3857166
FTPT_wage_medium_LC	0.0679702	0.0767166	0.0780304	-0.1295991	-0.3689694	-0.360744	-0.3893327
FTPT_wage_medium_UC	0.0747003	0.0832048	0.0843505	-0.1230976	-0.3606568	-0.3529608	-0.3821005
FTPT_earn_high	0.5441746	0.6586952	0.8481729	-2.39235	-3.063297	-1.909265	-2.066025
FTPT_earn_high_LC	0.0918511	0.112987	0.1471987	-4.361094	-5.583155	-3.480831	-3.76677
FTPT_earn_high_UC	0.9964982	1.204403	1.549147	-0.4236051	-0.5434397	-0.3376997	-0.3652809
FTPT_wage_high	0.0666793	0.0838316	0.0946097	-0.1402345	-0.4218111	-0.3378213	-0.3390655
FTPT_wage_high_LC	0.0567999	0.0743971	0.0854695	-0.1495903	-0.4324343	-0.3485175	-0.3499411
FTPT_wage_high_UC	0.0765587	0.0932661	0.1037499	-0.1308786	-0.4111879	-0.3271251	-0.3281898

	4	5	6	7	8	9	10
FTPT_earn_all	-0.2675775	-0.2449385	-0.2288689	-0.2186243	-0.203352	-0.1919245	-0.176976
FTPT_earn_all_LC	-0.2751313	-0.2520637	-0.235723	-0.2253436	-0.2098398	-0.1982627	-0.183121
FTPT_earn_all_UC	-0.2600236	-0.2378133	-0.2220149	-0.211905	-0.1968642	-0.1855864	-0.170831
FTPT_wage_all	-0.2881525	-0.2709904	-0.2562268	-0.2453803	-0.229779	-0.2139917	-0.1965034
FTPT_wage_all_LC	-0.291574	-0.2745677	-0.2599445	-0.2492356	-0.2337637	-0.2180882	-0.2007244
FTPT_wage_all_UC	-0.284731	-0.2674132	-0.252509	-0.241525	-0.2257942	-0.2098952	-0.1922823
FTPT_earn_low	-0.1246489	-0.1107917	-0.1019666	-0.101727	-0.0885046	-0.0788275	-0.0706301
FTPT_earn_low_LC	-0.1341821	-0.1205033	-0.1119326	-0.1119721	-0.0989171	-0.0893942	-0.0814137
FTPT_earn_low_UC	-0.1151158	-0.1010801	-0.0920006	-0.0914819	-0.0780921	-0.0682607	-0.0598466
FTPT_wage_low	-0.1225947	-0.1101652	-0.1090544	-0.1067044	-0.0980523	-0.0922094	-0.0823719
FTPT_wage_low_LC	-0.1305775	-0.1184702	-0.1176939	-0.1156149	-0.1072261	-0.1015927	-0.092006
FTPT_wage_low_UC	-0.1146118	-0.1018602	-0.1004149	-0.0977939	-0.0888785	-0.0828262	-0.0727377
FTPT_earn_medium	-0.2646455	-0.2467604	-0.2328419	-0.2215863	-0.2065791	-0.1961716	-0.1820105
FTPT_earn_medium_LC	-0.2733757	-0.2550459	-0.2408041	-0.2293124	-0.2139695	-0.2033541	-0.1889081
FTPT_earn_medium_UC	-0.2559153	-0.238475	-0.2248796	-0.2138603	-0.1991887	-0.1889892	-0.1751129
FTPT_wage_medium	-0.3230119	-0.3055764	-0.2889087	-0.2749115	-0.2566297	-0.2396122	-0.2216117
FTPT_wage_medium_LC	-0.3268058	-0.3095279	-0.293001	-0.2791479	-0.260997	-0.2440958	-0.2262214
FTPT_wage_medium_UC	-0.3192179	-0.3016249	-0.2848165	-0.270675	-0.2522624	-0.2351286	-0.217002
FTPT_earn_high	-1.664757	-1.397773	-1.210331	-1.163639	-1.090963	-1.023138	-0.9284878
FTPT_earn_high_LC	-3.036024	-2.549855	-2.20892	-2.124132	-1.992499	-1.869637	-1.698626
FTPT_earn_high_UC	-0.29349	-0.2456915	-0.2117421	-0.203147	-0.1894262	-0.1766376	-0.1583495
FTPT_wage_high	-0.2863676	-0.2588916	-0.2251485	-0.2182857	-0.2056574	-0.1893016	-0.1663027
FTPT_wage_high_LC	-0.2980579	-0.2713224	-0.2382939	-0.2320661	-0.2202034	-0.2045394	-0.1822968
FTPT_wage_high_UC	-0.2746773	-0.2464607	-0.212003	-0.2045054	-0.1911114	-0.1740638	-0.1503086

	11	12	13	14	15
FTPT_earn_all	-0.1623434	-0.1456896	-0.1277108	-0.1057913	-0.087942
FTPT_earn_all_LC	-0.168329	-0.1515052	-0.1333659	-0.1112728	-0.09335
FTPT_earn_all_UC	-0.1563579	-0.139874	-0.1220558	-0.1003098	-0.0825339
FTPT_wage_all	-0.1785758	-0.1583349	-0.1373302	-0.1166712	-0.0935105
FTPT_wage_all_LC	-0.1829307	-0.1628247	-0.1419523	-0.1214253	-0.0984016
FTPT_wage_all_UC	-0.1742209	-0.1538452	-0.1327081	-0.1119171	-0.0886193
FTPT_earn_low	-0.0644962	-0.0537902	-0.043528	-0.0305237	-0.0122847
FTPT_earn_low_LC	-0.0754948	-0.0649857	-0.0548817	-0.0420841	-0.0240865
FTPT_earn_low_UC	-0.0534975	-0.0425948	-0.0321744	-0.0189633	-0.0004829
FTPT_wage_low	-0.0759116	-0.0660988	-0.052765	-0.0411463	-0.0266798
FTPT_wage_low_LC	-0.0857739	-0.0761908	-0.0630397	-0.0516431	-0.0374224
FTPT_wage_low_UC	-0.0660492	-0.0560067	-0.0424903	-0.0306496	-0.0159372
FTPT_earn_medium	-0.1672243	-0.1521282	-0.1343412	-0.1138178	-0.0967006
FTPT_earn_medium_LC	-0.173853	-0.1585007	-0.1404312	-0.1196115	-0.1023126
FTPT_earn_medium_UC	-0.1605956	-0.1457557	-0.1282511	-0.1080241	-0.0910887
FTPT_wage_medium	-0.2014659	-0.1800701	-0.1584468	-0.1362941	-0.1109896
FTPT_wage_medium_LC	-0.2062173	-0.1849632	-0.1634797	-0.1414646	-0.1163036
FTPT_wage_medium_UC	-0.1967145	-0.1751769	-0.1534139	-0.1311236	-0.1056757
FTPT_earn_high	-0.8380417	-0.6936748	-0.5654336	-0.4018268	-0.3309392
FTPT_earn_high_LC	-1.534794	-1.274527	-1.044444	-0.7537915	-0.6316112
FTPT_earn_high_UC	-0.141289	-0.1128223	-0.0864229	-0.049862	-0.0302672
FTPT_wage_high	-0.1454	-0.1206122	-0.0820556	-0.0629467	-0.0430044
FTPT_wage_high_LC	-0.1622263	-0.1382922	-0.1007263	-0.0825542	-0.0635968
FTPT_wage_high_UC	-0.1285737	-0.1029322	-0.063385	-0.0433391	-0.0224121

TABLE B.5: Exact values corresponding to Figure 3.5. The table shows values of motherhood losses, for FT and PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.4 Figure 3.4

Year	-3	-2	-1	0	1	2	3
FTPT_earn_all	0.0944391	0.1076637	0.1151026	-0.3894929	-0.4561693	-0.3264739	-0.3515861
FTPT_earn_all_LC	0.0905491	0.1036528	0.1110228	-0.3997187	-0.4681847	-0.3353739	-0.3610019
FTPT_earn_all_UC	0.0983291	0.1116746	0.1191824	-0.3792672	-0.4441539	-0.3175739	-0.3421702
FTPT_wage_all	0.0801452	0.0893559	0.0902799	-0.1192413	-0.3307258	-0.3174412	-0.3449128
FTPT_wage_all_LC	0.077111	0.0864503	0.0874697	-0.1221186	-0.3343375	-0.3208876	-0.348161
FTPT_wage_all_UC	0.0831794	0.0922616	0.0930901	-0.116364	-0.3271141	-0.3139948	-0.3416647
FTPT_earn_low	0.0595391	0.0769921	0.0804266	-0.4039492	-0.3092961	-0.1967044	-0.2183759
FTPT_earn_low_LC	0.0512625	0.0690203	0.0727744	-0.4180363	-0.3221017	-0.207291	-0.229028
FTPT_earn_low_UC	0.0678158	0.0849638	0.0880788	-0.3898621	-0.2964906	-0.1861179	-0.2077238
FTPT_wage_low	0.0505487	0.0608371	0.0675094	-0.1106157	-0.1527206	-0.1452164	-0.158999
FTPT_wage_low_LC	0.0431996	0.0539073	0.0609251	-0.1172516	-0.1607415	-0.1532267	-0.1666434
FTPT_wage_low_UC	0.0578977	0.0677669	0.0740936	-0.1039799	-0.1446997	-0.137206	-0.1513546
FTPT_earn_medium	0.0730979	0.0824709	0.0851359	-0.3537342	-0.4235854	-0.3196033	-0.3393678
FTPT_earn_medium_LC	0.0693272	0.0786041	0.0812655	-0.3649008	-0.4369689	-0.3299125	-0.3501686
FTPT_earn_medium_UC	0.0768687	0.0863376	0.0890063	-0.3425676	-0.4102018	-0.309294	-0.3285671
FTPT_wage_medium	0.0713352	0.0799607	0.0811904	-0.1263483	-0.3648131	-0.3568524	-0.3857166
FTPT_wage_medium_LC	0.0679702	0.0767166	0.0780304	-0.1295991	-0.3689694	-0.360744	-0.3893327
FTPT_wage_medium_UC	0.0747003	0.0832048	0.0843505	-0.1230976	-0.3606568	-0.3529608	-0.3821005
FTPT_earn_high	0.5441746	0.6586952	0.8481729	-2.39235	-3.063297	-1.909265	-2.066025
FTPT_earn_high_LC	0.0918511	0.112987	0.1471987	-4.361094	-5.583155	-3.480831	-3.76677
FTPT_earn_high_UC	0.9964982	1.204403	1.549147	-0.4236051	-0.5434397	-0.3376997	-0.3652809
FTPT_wage_high	0.0666793	0.0838316	0.0946097	-0.1402345	-0.4218111	-0.3378213	-0.3390655
FTPT_wage_high_LC	0.0567999	0.0743971	0.0854695	-0.1495903	-0.4324343	-0.3485175	-0.3499411
FTPT_wage_high_UC	0.0765587	0.0932661	0.1037499	-0.1308786	-0.4111879	-0.3271251	-0.3281898

	4	5	6	7	8	9	10
FTPT_earn_all	-0.2675775	-0.2449385	-0.2288689	-0.2186243	-0.203352	-0.1919245	-0.176976
FTPT_earn_all_LC	-0.2751313	-0.2520637	-0.235723	-0.2253436	-0.2098398	-0.1982627	-0.183121
FTPT_earn_all_UC	-0.2600236	-0.2378133	-0.2220149	-0.211905	-0.1968642	-0.1855864	-0.170831
FTPT_wage_all	-0.2881525	-0.2709904	-0.2562268	-0.2453803	-0.229779	-0.2139917	-0.1965034
FTPT_wage_all_LC	-0.291574	-0.2745677	-0.2599445	-0.2492356	-0.2337637	-0.2180882	-0.2007244
FTPT_wage_all_UC	-0.284731	-0.2674132	-0.252509	-0.241525	-0.2257942	-0.2098952	-0.1922823
FTPT_earn_low	-0.1246489	-0.1107917	-0.1019666	-0.101727	-0.0885046	-0.0788275	-0.0706301
FTPT_earn_low_LC	-0.1341821	-0.1205033	-0.1119326	-0.1119721	-0.0989171	-0.0893942	-0.0814137
FTPT_earn_low_UC	-0.1151158	-0.1010801	-0.0920006	-0.0914819	-0.0780921	-0.0682607	-0.0598466
FTPT_wage_low	-0.1225947	-0.1101652	-0.1090544	-0.1067044	-0.0980523	-0.0922094	-0.0823719
FTPT_wage_low_LC	-0.1305775	-0.1184702	-0.1176939	-0.1156149	-0.1072261	-0.1015927	-0.092006
FTPT_wage_low_UC	-0.1146118	-0.1018602	-0.1004149	-0.0977939	-0.0888785	-0.0828262	-0.0727377
FTPT_earn_medium	-0.2646455	-0.2467604	-0.2328419	-0.2215863	-0.2065791	-0.1961716	-0.1820105
FTPT_earn_medium_LC	-0.2733757	-0.2550459	-0.2408041	-0.2293124	-0.2139695	-0.2033541	-0.1889081
FTPT_earn_medium_UC	-0.2559153	-0.238475	-0.2248796	-0.2138603	-0.1991887	-0.1889892	-0.1751129
FTPT_wage_medium	-0.3230119	-0.3055764	-0.2889087	-0.2749115	-0.2566297	-0.2396122	-0.2216117
FTPT_wage_medium_LC	-0.3268058	-0.3095279	-0.293001	-0.2791479	-0.260997	-0.2440958	-0.2262214
FTPT_wage_medium_UC	-0.3192179	-0.3016249	-0.2848165	-0.270675	-0.2522624	-0.2351286	-0.217002
FTPT_earn_high	-1.664757	-1.397773	-1.210331	-1.163639	-1.090963	-1.023138	-0.9284878
FTPT_earn_high_LC	-3.036024	-2.549855	-2.20892	-2.124132	-1.992499	-1.869637	-1.698626
FTPT_earn_high_UC	-0.29349	-0.2456915	-0.2117421	-0.203147	-0.1894262	-0.1766376	-0.1583495
FTPT_wage_high	-0.2863676	-0.2588916	-0.2251485	-0.2182857	-0.2056574	-0.1893016	-0.1663027
FTPT_wage_high_LC	-0.2980579	-0.2713224	-0.2382939	-0.2320661	-0.2202034	-0.2045394	-0.1822968
FTPT_wage_high_UC	-0.2746773	-0.2464607	-0.212003	-0.2045054	-0.1911114	-0.1740638	-0.1503086

	11	12	13	14	15
FTPT_earn_all	-0.1623434	-0.1456896	-0.1277108	-0.1057913	-0.087942
FTPT_earn_all_LC	-0.168329	-0.1515052	-0.1333659	-0.1112728	-0.09335
FTPT_earn_all_UC	-0.1563579	-0.139874	-0.1220558	-0.1003098	-0.0825339
FTPT_wage_all	-0.1785758	-0.1583349	-0.1373302	-0.1166712	-0.0935105
FTPT_wage_all_LC	-0.1829307	-0.1628247	-0.1419523	-0.1214253	-0.0984016
FTPT_wage_all_UC	-0.1742209	-0.1538452	-0.1327081	-0.1119171	-0.0886193
FTPT_earn_low	-0.0644962	-0.0537902	-0.043528	-0.0305237	-0.0122847
FTPT_earn_low_LC	-0.0754948	-0.0649857	-0.0548817	-0.0420841	-0.0240865
FTPT_earn_low_UC	-0.0534975	-0.0425948	-0.0321744	-0.0189633	-0.0004829
FTPT_wage_low	-0.0759116	-0.0660988	-0.052765	-0.0411463	-0.0266798
FTPT_wage_low_LC	-0.0857739	-0.0761908	-0.0630397	-0.0516431	-0.0374224
FTPT_wage_low_UC	-0.0660492	-0.0560067	-0.0424903	-0.0306496	-0.0159372
FTPT_earn_medium	-0.1672243	-0.1521282	-0.1343412	-0.1138178	-0.0967006
FTPT_earn_medium_LC	-0.173853	-0.1585007	-0.1404312	-0.1196115	-0.1023126
FTPT_earn_medium_UC	-0.1605956	-0.1457557	-0.1282511	-0.1080241	-0.0910887
FTPT_wage_medium	-0.2014659	-0.1800701	-0.1584468	-0.1362941	-0.1109896
FTPT_wage_medium_LC	-0.2062173	-0.1849632	-0.1634797	-0.1414646	-0.1163036
FTPT_wage_medium_UC	-0.1967145	-0.1751769	-0.1534139	-0.1311236	-0.1056757
FTPT_earn_high	-0.8380417	-0.6936748	-0.5654336	-0.4018268	-0.3309392
FTPT_earn_high_LC	-1.534794	-1.274527	-1.044444	-0.7537915	-0.6316112
FTPT_earn_high_UC	-0.141289	-0.1128223	-0.0864229	-0.049862	-0.0302672
FTPT_wage_high	-0.1454	-0.1206122	-0.0820556	-0.0629467	-0.0430044
FTPT_wage_high_LC	-0.1622263	-0.1382922	-0.1007263	-0.0825542	-0.0635968
FTPT_wage_high_UC	-0.1285737	-0.1029322	-0.063385	-0.0433391	-0.0224121

TABLE B.6: Exact values corresponding to Figure 3.6. The table shows values of motherhood losses by education, for FT and PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3
FT_earn_all	0.0727459	0.084536	0.0934626	-0.3413076	-0.353148	-0.237296	-0.26434
FT_earn_all_LC	0.0691597	0.080884	0.0897371	-0.3502845	-0.3628123	-0.2445113	-0.2720519
FT_earn_all_UC	0.076332	0.0881881	0.0971881	-0.3323308	-0.3434837	-0.2300807	-0.2566281
FT_wage_all	0.0691686	0.0792995	0.0831226	-0.1397996	-0.238083	-0.2351574	-0.2633488
FT_wage_all_LC	0.0662259	0.0764679	0.0803705	-0.1426041	-0.2420084	-0.2391309	-0.2672103
FT_wage_all_UC	0.0721113	0.0821312	0.0858746	-0.136995	-0.2341576	-0.2311839	-0.2594873
FT_earn_low	0.0660956	0.0840715	0.0882306	-0.375602	-0.2419816	-0.1361959	-0.1530214
FT_earn_low_LC	0.0571476	0.0754152	0.0798758	-0.3895821	-0.254249	-0.14717	-0.1640601
FT_earn_low_UC	0.0750436	0.0927277	0.0965854	-0.361622	-0.2297143	-0.1252218	-0.1419827
FT_wage_low	0.0560299	0.0701957	0.0777331	-0.1056177	-0.0951045	-0.0846426	-0.0972978
FT_wage_low_LC	0.0488398	0.0633933	0.0712403	-0.1121204	-0.1030942	-0.0930071	-0.1055163
FT_wage_low_UC	0.06322	0.0769981	0.0842259	-0.099115	-0.0871148	-0.0762781	-0.0890792
FT_earn_medium	0.056817	0.0657987	0.0728828	-0.3290698	-0.3610162	-0.25496	-0.2821264
FT_earn_medium_LC	0.0531179	0.0620361	0.0690421	-0.3398187	-0.3731168	-0.2641077	-0.2919349
FT_earn_medium_UC	0.060516	0.0695613	0.0767234	-0.3183208	-0.3489157	-0.2458122	-0.2723178
FT_wage_medium	0.0607497	0.0707956	0.0751632	-0.1493643	-0.2732471	-0.2720905	-0.3043728
FT_wage_medium_LC	0.0575017	0.0676473	0.0720808	-0.1525216	-0.2778199	-0.2766597	-0.30876
FT_wage_medium_UC	0.0639976	0.0739439	0.0782456	-0.146207	-0.2686744	-0.2675213	-0.2999855
FT_earn_high	0.2243217	0.2769664	0.3439205	-1.070047	-1.253683	-0.7372654	-0.7894928
FT_earn_high_LC	0.1250927	0.1569016	0.1966873	-1.518568	-1.778773	-1.048345	-1.122555
FT_earn_high_UC	0.3235508	0.3970312	0.4911538	-0.6215261	-0.7285941	-0.4261857	-0.4564304
FT_wage_high	0.0558507	0.0685731	0.0810225	-0.1633518	-0.3255543	-0.2808635	-0.2837931
FT_wage_high_LC	0.046437	0.0594855	0.0721569	-0.172446	-0.3372718	-0.2930068	-0.2964224
FT_wage_high_UC	0.0652645	0.0776608	0.0898881	-0.1542575	-0.3138368	-0.2687201	-0.2711638

	4	5	6	7	8	9	10
FT_earn_all	-0.1563441	-0.1330426	-0.1185761	-0.1038317	-0.0900637	-0.0794665	-0.0733358
FT_earn_all_LC	-0.1623097	-0.1389436	-0.1245712	-0.1099471	-0.0963204	-0.0858934	-0.0799541
FT_earn_all_UC	-0.1503785	-0.1271416	-0.1125811	-0.0977163	-0.083807	-0.0730396	-0.0667175
FT_wage_all	-0.1916783	-0.1728381	-0.157831	-0.1441198	-0.1309476	-0.1158225	-0.106256
FT_wage_all_LC	-0.195983	-0.177498	-0.1628092	-0.1494076	-0.1365213	-0.1216572	-0.1123267
FT_wage_all_UC	-0.1873736	-0.1681782	-0.1528528	-0.138832	-0.125374	-0.1099878	-0.1001853
FT_earn_low	-0.0598733	-0.0457141	-0.0353425	-0.0304072	-0.0171645	-0.0098598	-0.0030624
FT_earn_low_LC	-0.0707068	-0.0571301	-0.0473382	-0.0429801	-0.0302719	-0.0234224	-0.0171544
FT_earn_low_UC	-0.0490398	-0.0342981	-0.0233468	-0.0178342	-0.004057	0.0037028	0.0110296
FT_wage_low	-0.0597951	-0.0509867	-0.0490203	-0.0452985	-0.0371961	-0.03774	-0.0314402
FT_wage_low_LC	-0.0686159	-0.0603543	-0.0589009	-0.0556707	-0.0480317	-0.0489592	-0.0431005
FT_wage_low_UC	-0.0509743	-0.0416191	-0.0391397	-0.0349263	-0.0263604	-0.0265209	-0.01978
FT_earn_medium	-0.1770534	-0.1564128	-0.1430657	-0.1254587	-0.1122431	-0.0987124	-0.0898881
FT_earn_medium_LC	-0.1844354	-0.1636052	-0.1502543	-0.1326147	-0.1194517	-0.1059977	-0.097287
FT_earn_medium_UC	-0.1696713	-0.1492203	-0.1358772	-0.1183027	-0.1050345	-0.0914271	-0.0824893
FT_wage_medium	-0.2269444	-0.2073431	-0.1902532	-0.174454	-0.1587569	-0.1376191	-0.1258447
FT_wage_medium_LC	-0.2318481	-0.2126508	-0.1959146	-0.1804681	-0.1650855	-0.1442514	-0.1327222
FT_wage_medium_UC	-0.2220407	-0.2020355	-0.1845919	-0.1684398	-0.1524283	-0.1309868	-0.1189673
FT_earn_high	-0.4848366	-0.3377253	-0.2720905	-0.2464471	-0.1824724	-0.1906286	-0.2211267
FT_earn_high_LC	-0.6938271	-0.4894486	-0.4010791	-0.368282	-0.286294	-0.3004034	-0.3440758
FT_earn_high_UC	-0.2758461	-0.1860019	-0.1431018	-0.1246122	-0.0786509	-0.0808539	-0.0981776
FT_wage_high	-0.1995404	-0.1670084	-0.1361976	-0.1191841	-0.1132747	-0.1116655	-0.1175291
FT_wage_high_LC	-0.2140193	-0.1830723	-0.1538121	-0.1382431	-0.1339623	-0.1338424	-0.1413229
FT_wage_high_UC	-0.1850615	-0.1509446	-0.118583	-0.1001251	-0.092587	-0.0894886	-0.0937354

	11	12	13	14	15
FT_earn_all	-0.0684268	-0.0596961	-0.0523217	-0.0452323	-0.0404032
FT_earn_all_LC	-0.0752733	-0.0667474	-0.059597	-0.0527093	-0.048122
FT_earn_all_UC	-0.0615803	-0.0526449	-0.0450465	-0.0377552	-0.0326845
FT_wage_all	-0.1000352	-0.0865381	-0.0752908	-0.068499	-0.0572414
FT_wage_all_LC	-0.1063628	-0.0931142	-0.0821193	-0.0755503	-0.0645412
FT_wage_all_UC	-0.0937075	-0.0799619	-0.0684624	-0.0614477	-0.0499417
FT_earn_low	-0.0053818	-0.0055768	-0.0028487	0.0059052	0.0052821
FT_earn_low_LC	-0.0198415	-0.0205234	-0.0181562	-0.0097437	-0.0109006
FT_earn_low_UC	0.0090779	0.0093699	0.0124588	0.0215541	0.0214648
FT_wage_low	-0.0244531	-0.0233883	-0.01646	-0.0103422	-0.0076931
FT_wage_low_LC	-0.0364168	-0.035755	-0.0291261	-0.0232902	-0.0210829
FT_wage_low_UC	-0.0124893	-0.0110217	-0.0037939	0.0026058	0.0056967
FT_earn_medium	-0.0830526	-0.0731324	-0.0634829	-0.0559677	-0.0504481
FT_earn_medium_LC	-0.0906609	-0.0809092	-0.071466	-0.0641446	-0.0588646
FT_earn_medium_UC	-0.0754443	-0.0653555	-0.0554997	-0.0477908	-0.0420317
FT_wage_medium	-0.1208427	-0.1036316	-0.0914559	-0.0834714	-0.0697474
FT_wage_medium_LC	-0.1280283	-0.1110985	-0.0992215	-0.0914922	-0.0780476
FT_wage_medium_UC	-0.1136571	-0.0961647	-0.0836903	-0.0754505	-0.0614471
FT_earn_high	-0.2067639	-0.1360602	-0.1274054	-0.1015502	-0.0649297
FT_earn_high_LC	-0.3287935	-0.2435699	-0.2386226	-0.2135116	-0.1760952
FT_earn_high_UC	-0.0847343	-0.0285505	-0.0161881	0.0104113	0.0462359
FT_wage_high	-0.0986274	-0.0749879	-0.058199	-0.0595404	-0.0462331
FT_wage_high_LC	-0.1240024	-0.1017876	-0.0869085	-0.090043	-0.0779625
FT_wage_high_UC	-0.0732524	-0.0481881	-0.0294894	-0.0290377	-0.0145036

TABLE B.7: Exact values corresponding to Figure 3.6. The table shows values of motherhood losses by education, for FT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.5 Figure 3.5

Year	-3	-2	-1	0	1	2	3
FTtoFTPT_earn_all	0.1310498	0.1601842	0.1873555	-0.3313079	-0.459548	-0.3039747	-0.3340394
FTtoFTPT_earn_all_LC	0.1255671	0.1543306	0.181067	-0.3407744	-0.4724579	-0.3132504	-0.3438342
FTtoFTPT_earn_all_UC	0.1365325	0.1660379	0.193644	-0.3218415	-0.4466381	-0.294699	-0.3242446
FTtoFTPT_wage_all	0.1073163	0.1299246	0.1447096	-0.0864744	-0.3060364	-0.283487	-0.315292
FTtoFTPT_wage_all_LC	0.1030267	0.1258073	0.1407216	-0.090511	-0.3112686	-0.2884841	-0.3200068
FTtoFTPT_wage_all_UC	0.1116058	0.1340419	0.1486977	-0.0824379	-0.3008043	-0.27849	-0.3105772
FTtoFTPT_earn_low	0.0899097	0.111236	0.1289125	-0.3780554	-0.313571	-0.1791025	-0.2040442
FTtoFTPT_earn_low_LC	0.0780105	0.0997992	0.117819	-0.3935493	-0.3295576	-0.1930407	-0.2178923
FTtoFTPT_earn_low_UC	0.101809	0.1226729	0.140006	-0.3625615	-0.2975844	-0.1651644	-0.1901961
FTtoFTPT_wage_low	0.0690971	0.0876823	0.0992196	-0.1082657	-0.1369833	-0.1249614	-0.1431291
FTtoFTPT_wage_low_LC	0.0585063	0.0777034	0.0897593	-0.1176924	-0.1486531	-0.1366929	-0.1544279
FTtoFTPT_wage_low_UC	0.079688	0.0976613	0.1086799	-0.098839	-0.1253134	-0.1132299	-0.1318302
FTtoFTPT_earn_medium	0.1035657	0.1255314	0.1456426	-0.30218	-0.4262567	-0.3016669	-0.3230866
FTtoFTPT_earn_medium_LC	0.0981875	0.1198198	0.1395448	-0.3125079	-0.4405943	-0.3123489	-0.3342006
FTtoFTPT_earn_medium_UC	0.1089439	0.1312429	0.1517403	-0.2918521	-0.4119192	-0.290985	-0.3119727
FTtoFTPT_wage_medium	0.0975628	0.1191026	0.1351215	-0.0940507	-0.3363411	-0.3196623	-0.3520669
FTtoFTPT_wage_medium_LC	0.0927771	0.1144826	0.1306147	-0.0986303	-0.3423949	-0.3253383	-0.3573375
FTtoFTPT_wage_medium_UC	0.1023485	0.1237227	0.1396283	-0.0894711	-0.3302873	-0.3139863	-0.3467963
FTtoFTPT_earn_high	0.4522298	0.6206135	0.8217818	-1.151073	-1.775673	-0.9474757	-1.093088
FTtoFTPT_earn_high_LC	0.2283185	0.317261	0.4224245	-1.708517	-2.632922	-1.407374	-1.623015
FTtoFTPT_earn_high_UC	0.6761411	0.923966	1.221139	-0.59363	-0.9184252	-0.4875776	-0.5631605
FTtoFTPT_wage_high	0.0988008	0.1350355	0.1653316	-0.0828541	-0.3943957	-0.2847412	-0.2892287
FTtoFTPT_wage_high_LC	0.0849385	0.1217244	0.1524101	-0.0960147	-0.4096939	-0.3000596	-0.3049095
FTtoFTPT_wage_high_UC	0.1126631	0.1483466	0.1782531	-0.0696935	-0.3790974	-0.2694228	-0.2735479

	4	5	6	7	8	9	10
FTtoFTPT_earn_all	-0.2426297	-0.2133973	-0.1969312	-0.1862943	-0.1673754	-0.1552699	-0.139725
FTtoFTPT_earn_all_LC	-0.2506093	-0.2209526	-0.2043339	-0.1936701	-0.1745976	-0.1624538	-0.1468597
FTtoFTPT_earn_all_UC	-0.23465	-0.2058421	-0.1895285	-0.1789184	-0.1601532	-0.148086	-0.1325904
FTtoFTPT_wage_all	-0.2520969	-0.231812	-0.2159734	-0.2067134	-0.1872773	-0.171892	-0.1533198
FTtoFTPT_wage_all_LC	-0.2570588	-0.2369985	-0.2213627	-0.2123084	-0.1930611	-0.1778464	-0.1594619
FTtoFTPT_wage_all_UC	-0.247135	-0.2266255	-0.2105841	-0.2011184	-0.1814936	-0.1659376	-0.1471778
FTtoFTPT_earn_low	-0.1186207	-0.0937502	-0.0864292	-0.0897245	-0.078605	-0.063856	-0.0578727
FTtoFTPT_earn_low_LC	-0.1319572	-0.1074086	-0.100521	-0.1042771	-0.0935492	-0.0790499	-0.0734957
FTtoFTPT_earn_low_UC	-0.1052841	-0.0800919	-0.0723374	-0.0751719	-0.0636608	-0.0486621	-0.0422498
FTtoFTPT_wage_low	-0.1139168	-0.0939305	-0.098928	-0.099229	-0.0920288	-0.0892043	-0.0781972
FTtoFTPT_wage_low_LC	-0.1256622	-0.1061596	-0.1116061	-0.1123199	-0.1055393	-0.1030057	-0.0924165
FTtoFTPT_wage_low_UC	-0.1021714	-0.0817013	-0.0862498	-0.0861381	-0.0785183	-0.0754029	-0.0639779
FTtoFTPT_earn_medium	-0.2389305	-0.2166034	-0.2013355	-0.1899142	-0.1710951	-0.1603265	-0.1441885
FTtoFTPT_earn_medium_LC	-0.2478728	-0.2250894	-0.2095689	-0.1980158	-0.1788992	-0.1680239	-0.1517085
FTtoFTPT_earn_medium_UC	-0.2299882	-0.2081175	-0.1931021	-0.1818127	-0.163291	-0.1526292	-0.1366685
FTtoFTPT_wage_medium	-0.2804205	-0.2601437	-0.2408582	-0.2283303	-0.2060725	-0.188818	-0.1688536
FTtoFTPT_wage_medium_LC	-0.2859489	-0.2658991	-0.2468227	-0.2345129	-0.2124457	-0.1953673	-0.1755959
FTtoFTPT_wage_medium_UC	-0.2748922	-0.2543884	-0.2348938	-0.2221478	-0.1996993	-0.1822687	-0.1621114
FTtoFTPT_earn_high	-0.8638564	-0.6691258	-0.5742265	-0.5257414	-0.4881402	-0.4558486	-0.4412107
FTtoFTPT_earn_high_LC	-1.284653	-0.9979698	-0.8592663	-0.7888876	-0.7352566	-0.6896296	-0.6701384
FTtoFTPT_earn_high_UC	-0.4430595	-0.3402819	-0.2891866	-0.2625952	-0.2410239	-0.2220675	-0.212283
FTtoFTPT_wage_high	-0.2364449	-0.2090047	-0.1760856	-0.1730286	-0.1537124	-0.1394482	-0.1297784
FTtoFTPT_wage_high_LC	-0.253316	-0.2269657	-0.195055	-0.1929916	-0.1747545	-0.1617238	-0.1531526
FTtoFTPT_wage_high_UC	-0.2195738	-0.1910437	-0.1571162	-0.1530655	-0.1326703	-0.1171726	-0.1064042

	11	12	13	14	15
FTtoFTPT_earn_all	-0.1232904	-0.1085565	-0.0888318	-0.0632034	-0.0494033
FTtoFTPT_earn_all_LC	-0.1304169	-0.115715	-0.0959934	-0.0703697	-0.0567093
FTtoFTPT_earn_all_UC	-0.1161639	-0.1013981	-0.0816701	-0.0560371	-0.0420973
FTtoFTPT_wage_all	-0.1371699	-0.1186001	-0.0972574	-0.0728717	-0.0518849
FTtoFTPT_wage_all_LC	-0.1435265	-0.1251635	-0.1040125	-0.0798146	-0.0590399
FTtoFTPT_wage_all_UC	-0.1308133	-0.1120366	-0.0905022	-0.0659287	-0.04473
FTtoFTPT_earn_low	-0.0558725	-0.0565369	-0.0417578	-0.020899	-0.0025671
FTtoFTPT_earn_low_LC	-0.0718492	-0.0728549	-0.0582547	-0.0376567	-0.0196288
FTtoFTPT_earn_low_UC	-0.0398957	-0.0402188	-0.0252609	-0.0041412	0.0144945
FTtoFTPT_wage_low	-0.072243	-0.0700882	-0.0538589	-0.038114	-0.020838
FTtoFTPT_wage_low_LC	-0.0867937	-0.0849527	-0.0689262	-0.0534531	-0.0364658
FTtoFTPT_wage_low_UC	-0.0576923	-0.0552237	-0.0387915	-0.0227748	-0.0052102
FTtoFTPT_earn_medium	-0.1287684	-0.1146096	-0.0964018	-0.0729741	-0.0597395
FTtoFTPT_earn_medium_LC	-0.1361861	-0.1219713	-0.1036807	-0.0801575	-0.0670009
FTtoFTPT_earn_medium_UC	-0.1213506	-0.107248	-0.089123	-0.0657907	-0.052478
FTtoFTPT_wage_medium	-0.1524612	-0.1316107	-0.1100083	-0.0849676	-0.0625972
FTtoFTPT_wage_medium_LC	-0.1594316	-0.1388032	-0.117411	-0.0925732	-0.0704295
FTtoFTPT_wage_medium_UC	-0.1454908	-0.1244183	-0.1026055	-0.0773621	-0.0547649
FTtoFTPT_earn_high	-0.3272278	-0.2573852	-0.1498334	-0.0651982	-0.0536416
FTtoFTPT_earn_high_LC	-0.5085586	-0.4136101	-0.2732508	-0.1752434	-0.1685709
FTtoFTPT_earn_high_UC	-0.1458969	-0.1011603	-0.026416	0.044847	0.0612877
FTtoFTPT_wage_high	-0.096241	-0.0793754	-0.0419846	-0.0222262	-0.0110672
FTtoFTPT_wage_high_LC	-0.1211048	-0.1056577	-0.0697123	-0.0514095	-0.0420356
FTtoFTPT_wage_high_UC	-0.0713771	-0.053093	-0.0142569	0.0069571	0.0199013

TABLE B.8: Exact values corresponding to Figure 3.7. The table shows values of motherhood losses by education, for FT pre-motherhood and FT and PT post-motherhood spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.6 Figure 3.6

Year	-3	-2	-1	0	1	2	3
motherhood_earn_all	0.0587932	0.0669858	0.0719797	-0.25617	-0.3232073	-0.2229695	-0.2249752
motherhood_earn_all_LC	0.0565682	0.0647758	0.0697805	-0.2606608	-0.328813	-0.2271551	-0.2291375
motherhood_earn_all_UC	0.0610181	0.0691958	0.074179	-0.2516792	-0.3176017	-0.2187839	-0.220813
motherhood_wage_all	0.0686688	0.0765744	0.078352	-0.1885792	-0.7066742	-0.4471643	-0.3322729
motherhood_wage_all_LC	0.0640715	0.0721724	0.0740942	-0.1929106	-0.7119358	-0.4523191	-0.3371954
motherhood_wage_all_UC	0.0732661	0.0809764	0.0826099	-0.1842478	-0.7014126	-0.4420095	-0.3273504
motherhood_earn_low	0.0319908	0.0428422	0.0446762	-0.2639038	-0.2274742	-0.1406585	-0.141302
motherhood_earn_low_LC	0.0265912	0.0377138	0.0397881	-0.2708126	-0.2346103	-0.1470304	-0.1474912
motherhood_earn_low_UC	0.0373904	0.0479706	0.0495642	-0.256995	-0.2203381	-0.1342866	-0.1351128
motherhood_wage_low	0.0184604	0.0301049	0.0353968	-0.1836476	-0.4480221	-0.2572034	-0.1653651
motherhood_wage_low_LC	0.005232	0.0176284	0.0235455	-0.1955276	-0.4620668	-0.271499	-0.1791318
motherhood_wage_low_UC	0.0316888	0.0425814	0.0472482	-0.1717675	-0.4339774	-0.2429078	-0.1515985
motherhood_earn_medium	0.0466926	0.0525835	0.0544917	-0.2377746	-0.308811	-0.2233055	-0.2223152
motherhood_earn_medium_LC	0.0444528	0.050357	0.0522888	-0.2428456	-0.315309	-0.2282504	-0.2271855
motherhood_earn_medium_UC	0.0489324	0.0548099	0.0566947	-0.2327037	-0.302313	-0.2183607	-0.2174449
motherhood_wage_medium	0.0640233	0.0712986	0.0732627	-0.1956922	-0.7914882	-0.504803	-0.3735561
motherhood_wage_medium_LC	0.0589344	0.0663933	0.0684843	-0.2005744	-0.7974946	-0.5106012	-0.3790254
motherhood_wage_medium_UC	0.0691122	0.0762039	0.0780411	-0.19081	-0.7854818	-0.4990049	-0.3680867
motherhood_earn_high	0.176774	0.2119535	0.2768022	-0.8043795	-1.054219	-0.64549	-0.6742135
motherhood_earn_high_LC	0.1243375	0.1508429	0.1988538	-1.023948	-1.341411	-0.8222709	-0.8589169
motherhood_earn_high_UC	0.2292105	0.2730642	0.3547507	-0.5848114	-0.7670281	-0.468709	-0.4895102
motherhood_wage_high	0.0643675	0.0768073	0.0936449	-0.2005212	-0.633471	-0.397504	-0.3204185
motherhood_wage_high_LC	0.0508299	0.0638867	0.081123	-0.2132806	-0.647772	-0.4120761	-0.3353199
motherhood_wage_high_UC	0.0779051	0.0897279	0.1061669	-0.1877617	-0.6191701	-0.3829319	-0.3055171

	4	5	6	7	8	9	10
motherhood_earn_all	-0.1708682	-0.1561997	-0.145716	-0.1389046	-0.1289051	-0.1213636	-0.1115324
motherhood_earn_all_LC	-0.1743992	-0.1596236	-0.1490882	-0.1422728	-0.1322388	-0.1246862	-0.1148377
motherhood_earn_all_UC	-0.1673372	-0.1527758	-0.1423437	-0.1355364	-0.1255715	-0.1180409	-0.1082271
motherhood_wage_all	-0.2753009	-0.2580024	-0.2425732	-0.230663	-0.2139896	-0.1970121	-0.1780032
motherhood_wage_all_LC	-0.2804866	-0.2634245	-0.2482083	-0.2365067	-0.2200296	-0.2032216	-0.1844015
motherhood_wage_all_UC	-0.2701153	-0.2525804	-0.2369381	-0.2248193	-0.2079496	-0.1908026	-0.1716048
motherhood_earn_low	-0.0818295	-0.0726227	-0.0667338	-0.0663073	-0.0573519	-0.0504893	-0.0445563
motherhood_earn_low_LC	-0.0878601	-0.0788417	-0.0731657	-0.0729312	-0.0641353	-0.0574049	-0.051639
motherhood_earn_low_UC	-0.075799	-0.0664038	-0.0603019	-0.0596834	-0.0505684	-0.0435737	-0.0374737
motherhood_wage_low	-0.1299017	-0.1170861	-0.1154436	-0.1126661	-0.1006543	-0.0910264	-0.0773416
motherhood_wage_low_LC	-0.144279	-0.1320456	-0.1310064	-0.1287179	-0.1171809	-0.1079307	-0.0946982
motherhood_wage_low_UC	-0.1155244	-0.1021265	-0.0998808	-0.0966142	-0.0841276	-0.0741221	-0.059985
motherhood_earn_medium	-0.1730612	-0.1611732	-0.1519067	-0.1442973	-0.1343454	-0.127363	-0.1179014
motherhood_earn_medium_LC	-0.1771549	-0.1651289	-0.1557726	-0.1481092	-0.1380687	-0.1310425	-0.1215164
motherhood_earn_medium_UC	-0.1689674	-0.1572175	-0.1480408	-0.1404854	-0.1306222	-0.1236835	-0.1142864
motherhood_wage_medium	-0.311095	-0.2931072	-0.276022	-0.2607179	-0.242216	-0.2244492	-0.2055036
motherhood_wage_medium_LC	-0.316834	-0.2990848	-0.2822127	-0.2671269	-0.248823	-0.2312322	-0.2124774
motherhood_wage_medium_UC	-0.3053559	-0.2871296	-0.2698313	-0.2543089	-0.2356089	-0.2176661	-0.1985297
motherhood_earn_high	-0.5416782	-0.45343	-0.3910631	-0.3750945	-0.3505609	-0.3286122	-0.2971546
motherhood_earn_high_LC	-0.6909485	-0.5793147	-0.5007476	-0.4808767	-0.4504438	-0.4232929	-0.3845238
motherhood_earn_high_UC	-0.3924079	-0.3275453	-0.2813786	-0.2693124	-0.250678	-0.2339315	-0.2097855
motherhood_wage_high	-0.2693846	-0.2402974	-0.2050058	-0.1971193	-0.1835393	-0.1685864	-0.1444877
motherhood_wage_high_LC	-0.285405	-0.2573337	-0.2230215	-0.2160056	-0.2034755	-0.1894714	-0.1664099
motherhood_wage_high_UC	-0.2533643	-0.2232611	-0.18699	-0.178233	-0.1636032	-0.1477014	-0.1225654

	11	12	13	14	15
motherhood_earn_all	-0.1019538	-0.0913377	-0.0797502	-0.0655552	-0.0539224
motherhood_earn_all_LC	-0.1052591	-0.0946453	-0.083064	-0.0688748	-0.0572784
motherhood_earn_all_UC	-0.0986486	-0.0880302	-0.0764363	-0.0622357	-0.0505665
motherhood_wage_all	-0.1591122	-0.1406051	-0.1198765	-0.0988157	-0.0748136
motherhood_wage_all_LC	-0.1657136	-0.147411	-0.1268831	-0.1060224	-0.0822281
motherhood_wage_all_UC	-0.1525109	-0.1337993	-0.1128699	-0.0916089	-0.0673991
motherhood_earn_low	-0.0396991	-0.0324002	-0.0253957	-0.0165278	-0.0041755
motherhood_earn_low_LC	-0.0469385	-0.0397937	-0.0329124	-0.0241986	-0.0120205
motherhood_earn_low_UC	-0.0324598	-0.0250068	-0.0178791	-0.0088571	0.0036695
motherhood_wage_low	-0.0649503	-0.0529202	-0.0372232	-0.0223675	-0.0034803
motherhood_wage_low_LC	-0.0827183	-0.0711025	-0.0557347	-0.0412795	-0.0228347
motherhood_wage_low_UC	-0.0471824	-0.034738	-0.0187116	-0.0034556	0.0158741
motherhood_earn_medium	-0.1080744	-0.0982964	-0.086591	-0.0730348	-0.0616895
motherhood_earn_medium_LC	-0.1116404	-0.1018242	-0.0900751	-0.0764749	-0.0651259
motherhood_earn_medium_UC	-0.1045084	-0.0947685	-0.0831069	-0.0695947	-0.0582531
motherhood_wage_medium	-0.1848617	-0.1659624	-0.1448386	-0.1225642	-0.0969245
motherhood_wage_medium_LC	-0.19205	-0.1733654	-0.1524532	-0.130387	-0.1049644
motherhood_wage_medium_UC	-0.1776734	-0.1585593	-0.1372241	-0.1147414	-0.0888846
motherhood_earn_high	-0.2674251	-0.2202768	-0.1787001	-0.1247856	-0.1018426
motherhood_earn_high_LC	-0.3479857	-0.2905055	-0.240824	-0.1777924	-0.1528524
motherhood_earn_high_UC	-0.1868645	-0.1500481	-0.1165763	-0.0717789	-0.0508329
motherhood_wage_high	-0.1232587	-0.100787	-0.0648776	-0.0464275	-0.0271783
motherhood_wage_high_LC	-0.1463215	-0.125021	-0.0904704	-0.0733054	-0.0554068
motherhood_wage_high_UC	-0.1001958	-0.076553	-0.0392849	-0.0195495	0.0010502

TABLE B.9: Exact values corresponding to Figure 3.8. The table shows values of motherhood losses by education, for FT and PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.7 Figure 3.7

Group / Year	-3	-2	-1	0	1	2	3	4	5	6	7
FTPT HS pre-reform	0.1779	0.2017	0.3065	-0.8233	-0.9956	-0.6854	-0.7355	-0.551	-0.5021	-0.4323	-0.3927
FTPT HS pre-reform LC	0.1071	0.1273	0.2078	-1.0614	-1.2825	-0.886	-0.9492	-0.7144	-0.6523	-0.5641	-0.5141
FTPT HS pre-reform UC	0.2487	0.2761	0.4053	-0.5852	-0.7087	-0.4848	-0.5217	-0.3875	-0.3518	-0.3006	-0.2714
FTPT MS pre-reform	0.0527	0.0573	0.056	-0.3654	-0.4373	-0.3518	-0.3764	-0.2775	-0.2567	-0.2395	-0.2242
FTPT MS pre-reform LC	0.0462	0.0509	0.0497	-0.377	-0.4517	-0.3638	-0.3883	-0.2873	-0.2661	-0.2486	-0.2332
FTPT MS pre-reform UC	0.0592	0.0637	0.0623	-0.3537	-0.4228	-0.3398	-0.3645	-0.2677	-0.2472	-0.2303	-0.2153
FTPT LS pre-reform	0.0903	0.0946	0.1088	-0.3939	-0.4272	-0.2884	-0.355	-0.1487	-0.1102	-0.0907	-0.0947
FTPT LS pre-reform LC	0.067	0.0721	0.0869	-0.4191	-0.4609	-0.318	-0.3809	-0.1734	-0.1355	-0.1169	-0.1218
FTPT LS pre-reform UC	0.1136	0.117	0.1306	-0.3687	-0.3935	-0.2587	-0.3291	-0.124	-0.0849	-0.0646	-0.0676
FTPT HS post-reform	0.3077	0.3838	0.4665	-1.2022	-1.8065	-1.038	-1.1588	-1.0555	-0.8837	-0.7524	-0.6377
FTPT HS post-reform LC	0.1746	0.221	0.2707	-1.6973	-2.548	-1.467	-1.637	-1.493	-1.253	-1.075	-0.9316
FTPT HS post-reform UC	0.4409	0.5467	0.6624	-0.7072	-1.065	-0.61	-0.6806	-0.6182	-0.5135	-0.4298	-0.3438
FTPT MS post-reform	0.0716	0.0834	0.0945	-0.3271	-0.5162	-0.3532	-0.3575	-0.3108	-0.3014	-0.2942	-0.2893
FTPT MS post-reform LC	0.0663	0.078	0.0891	-0.3379	-0.5326	-0.3653	-0.3698	-0.3226	-0.3139	-0.3083	-0.3079
FTPT MS post-reform UC	0.0769	0.0887	0.1	-0.3163	-0.499	-0.3411	-0.3453	-0.299	-0.2889	-0.2801	-0.2708
FTPT LS post-reform	0.1665	0.2305	0.2534	-0.2403	-0.4198	-0.1726	-0.1682	-0.0564	-0.0496	0.0073	0.0328
FTPT LS post-reform LC	0.1496	0.2131	0.2358	-0.2585	-0.4464	-0.1961	-0.1919	-0.0848	-0.0845	-0.0392	-0.0397
FTPT LS post-reform UC	0.1835	0.2479	0.271	-0.222	-0.3932	-0.149	-0.1445	-0.0279	-0.0147	0.0539	0.1053
FT HS pre-reform	0.0862	0.0889	0.1325	-0.4681	-0.5627	-0.3951	-0.3939	-0.2499	-0.219	-0.188	-0.1766
FT HS pre-reform LC	0.0526	0.0562	0.0959	-0.5547	-0.6676	-0.4726	-0.4706	-0.3069	-0.2741	-0.2404	-0.2296
FT HS pre-reform UC	0.1197	0.1216	0.1691	-0.3815	-0.4578	-0.3175	-0.3172	-0.1928	-0.165	-0.1357	-0.1237
FT MS pre-reform	0.04847	0.05515	0.05688	-0.3008	-0.323	-0.2608	-0.3149	-0.2037	-0.1783	-0.1618	-0.1336
FT MS pre-reform LC	0.0422	0.049	0.0508	-0.3106	-0.3356	-0.2718	-0.3259	-0.2134	-0.1882	-0.1722	-0.1443
FT MS pre-reform UC	0.0546	0.0612	0.0629	-0.2911	-0.3104	-0.2498	-0.304	-0.194	-0.1683	-0.1514	-0.1229
FT LS pre-reform	0.0902	0.1079	0.1124	-0.3695	-0.3425	-0.2394	-0.337	-0.0998	-0.0487	-0.0083	-0.0032
FT LS pre-reform LC	0.0637	0.0823	0.0876	-0.3971	-0.383	-0.2769	-0.3693	-0.1332	-0.0851	-0.0471	-0.0446
FT LS pre-reform UC	0.1166	0.1335	0.1372	-0.3419	-0.302	-0.202	-0.3047	-0.0664	-0.0124	0.0305	0.038
FT HS post-reform	0.1396	0.1833	0.2189	-0.6302	-0.8901	-0.4982	-0.5547	-0.4424	-0.3505	-0.278	-0.1723
FT HS post-reform LC	0.0978	0.1328	0.1608	-0.7846	-1.1069	-0.6235	-0.6946	-0.5611	-0.4581	-0.3892	-0.3072
FT HS post-reform UC	0.1814	0.2338	0.277	-0.4758	-0.6734	-0.3729	-0.4148	-0.3236	-0.2429	-0.1668	-0.0374
FT MS post-reform	0.0578	0.067	0.0762	-0.2994	-0.4403	-0.2832	-0.287	-0.1881	-0.1715	-0.181	-0.1863
FT MS post-reform LC	0.0527	0.0619	0.0711	-0.3089	-0.4544	-0.2942	-0.2985	-0.2005	-0.1869	-0.2007	-0.217
FT MS post-reform UC	0.0629	0.0721	0.0814	-0.2899	-0.4262	-0.2722	-0.2754	-0.1756	-0.1561	-0.1613	-0.1557
FT LS post-reform	0.1625	0.212	0.2531	-0.2507	-0.424	-0.1796	-0.1444	0.0135	-0.0062	0.0816	-0.0137
FT LS post-reform LC	0.1423	0.1913	0.2319	-0.2727	-0.4579	-0.2124	-0.1788	-0.0326	-0.0648	0.0026	-0.1478
FT LS post-reform UC	0.1828	0.2327	0.2743	-0.2287	-0.39	-0.1467	-0.11	0.0597	0.0524	0.1606	0.1204
FTtoFTPT HS pre-reform	0.2902	0.3654	0.5676	-0.673	-1.014	-0.6252	-0.6764	-0.5076	-0.4568	-0.3956	-0.3338
FTtoFTPT HS pre-reform LC	0.1805	0.2392	0.3893	-0.88	-1.3186	-0.8203	-0.8846	-0.6705	-0.6064	-0.5296	-0.4527
FTtoFTPT HS pre-reform UC	0.3999	0.4915	0.7458	-0.4661	-0.7096	-0.43	-0.4682	-0.3447	-0.3073	-0.2615	-0.2149
FTtoFTPT MS pre-reform	0.1036	0.1268	0.1438	-0.3106	-0.4462	-0.3293	-0.3667	-0.2479	-0.219	-0.2013	-0.1847
FTtoFTPT MS pre-reform LC	0.0938	0.1169	0.1338	-0.3234	-0.464	-0.344	-0.3808	-0.2598	-0.2305	-0.2126	-0.1959
FTtoFTPT MS pre-reform UC	0.1134	0.1366	0.1537	-0.2978	-0.4283	-0.3147	-0.3526	-0.236	-0.2075	-0.1901	-0.1736
FTtoFTPT LS pre-reform	0.1581	0.1855	0.2166	-0.338	-0.4145	-0.2415	-0.3132	-0.0995	-0.046	-0.0146	-0.0574
FTtoFTPT LS pre-reform LC	0.1227	0.151	0.1832	-0.3732	-0.4634	-0.2865	-0.3517	-0.1377	-0.0853	-0.0547	-0.0988
FTtoFTPT LS pre-reform UC	0.1935	0.2199	0.2499	-0.3028	-0.3656	-0.1966	-0.2746	-0.0613	-0.0067	0.0254	-0.0161
FTtoFTPT HS post-reform	0.3716	0.528	0.664	-0.8886	-1.653	-0.8055	-0.991	-0.8644	-0.6062	-0.5049	-0.4099
FTtoFTPT HS post-reform LC	0.222	0.3224	0.4085	-1.2283	-2.2788	-1.1153	-1.371	-1.2002	-0.8548	-0.7312	-0.6465
FTtoFTPT HS post-reform UC	0.5211	0.7337	0.9196	-0.549	-1.0277	-0.4957	-0.6113	-0.5286	-0.3576	-0.2785	-0.1733
FTtoFTPT MS post-reform	0.1254	0.1523	0.1779	-0.2532	-0.5179	-0.324	-0.3221	-0.2648	-0.2509	-0.2416	-0.2352
FTtoFTPT MS post-reform LC	0.1176	0.1441	0.1694	-0.2635	-0.5362	-0.3373	-0.3355	-0.2781	-0.2657	-0.2592	-0.2601
FTtoFTPT MS post-reform UC	0.1333	0.1604	0.1865	-0.2428	-0.4997	-0.3108	-0.3088	-0.2514	-0.2361	-0.2239	-0.2103
FTtoFTPT LS post-reform	0.2594	0.3317	0.3793	-0.1691	-0.5065	-0.1731	-0.1827	-0.0874	-0.0438	0.0352	0.0757
FTtoFTPT LS post-reform LC	0.2342	0.3059	0.3527	-0.1948	-0.5465	-0.21	-0.2203	-0.1323	-0.0992	-0.0353	-0.0346
FTtoFTPT LS post-reform UC	0.2845	0.3575	0.406	-0.1434	-0.4665	-0.1363	-0.1451	-0.0425	0.0116	0.1058	0.1862

TABLE B.10: Exact values corresponding to Figure 3.9. The table shows values of motherhood losses in earnings, for FT and PT, FT, and FT to FT or PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3	4	5	6	7
FTPT HS pre-reform	0.0795	0.0932	0.1187	-0.1713	-0.4667	-0.3506	-0.3448	-0.2693	-0.2535	-0.2101	-0.1987
FTPT HS pre-reform LC	0.0561	0.0709	0.097	-0.1934	-0.4913	-0.3741	-0.3672	-0.2922	-0.2765	-0.2332	-0.2218
FTPT HS pre-reform UC	0.1404	0.1154	0.1404	-0.1492	-0.4422	-0.3271	-0.3224	-0.2465	-0.2305	-0.1871	-0.1756
FTPT MS pre-reform	0.0493	0.0513	0.0499	-0.2047	-0.4637	-0.4442	-0.4715	-0.373	-0.345	-0.3224	-0.294
FTPT MS pre-reform LC	0.0412	0.0434	0.0422	-0.2128	-0.4744	-0.4536	-0.4795	-0.3811	-0.3532	-0.3307	-0.3023
FTPT MS pre-reform UC	0.0574	0.0592	0.0577	-0.1967	-0.453	-0.4347	-0.4635	-0.3649	-0.3367	-0.3141	-0.2856
FTPT LS pre-reform	0.064	0.0649	0.0808	-0.1655	-0.2863	-0.216	-0.2494	-0.1494	-0.1262	-0.1217	-0.0964
FTPT LS pre-reform LC	0.0421	0.0437	0.0603	-0.1869	-0.3162	-0.243	-0.272	-0.1725	-0.1501	-0.1464	-0.122
FTPT LS pre-reform UC	0.086	0.086	0.1013	-0.1441	-0.2565	-0.1889	-0.2268	-0.1263	-0.1024	-0.097	-0.0709
FTPT HS post-reform	0.0886	0.1125	0.119	-0.1191	-0.4466	-0.3488	-0.353	-0.3204	-0.2956	-0.2563	-0.2293
FTPT HS post-reform LC	0.075	0.0993	0.106	-0.1324	-0.4619	-0.3647	-0.3706	-0.3409	-0.3204	-0.2873	-0.2734
FTPT HS post-reform UC	0.1022	0.1257	0.1319	-0.1058	-0.4312	-0.3328	-0.3353	-0.3	-0.2709	-0.2253	-0.1852
FTPT MS post-reform	0.0694	0.0814	0.0884	-0.1308	-0.4222	-0.3978	-0.4184	-0.3749	-0.3551	-0.3358	-0.331
FTPT MS post-reform LC	0.0637	0.0759	0.0829	-0.1365	-0.4298	-0.4051	-0.4259	-0.3835	-0.3654	-0.3489	-0.3502
FTPT MS post-reform UC	0.0751	0.087	0.0939	-0.1251	-0.4146	-0.3906	-0.411	-0.3662	-0.3447	-0.3228	-0.3117
FTPT LS post-reform	0.1588	0.201	0.2213	-0.0095	-0.1403	-0.1278	-0.108	-0.0442	-0.0158	-0.0231	0.0083
FTPT LS post-reform LC	0.1435	0.1859	0.2063	-0.0253	-0.1625	-0.1494	-0.1298	-0.0708	-0.0486	-0.0669	-0.0597
FTPT LS post-reform UC	0.174	0.216	0.2363	0.0062	-0.1181	-0.1063	-0.0862	-0.0175	0.0168	0.0205	0.0764
FT HS pre-reform	0.0471	0.0496	0.0676	-0.2389	-0.4818	-0.383	-0.3819	-0.2687	-0.2494	-0.2165	-0.2026
FT HS pre-reform LC	0.0258	0.0291	0.0476	-0.2594	-0.5082	-0.4085	-0.4061	-0.2949	-0.2772	-0.2455	-0.2333
FT HS pre-reform UC	0.0684	0.07	0.0876	-0.2185	-0.4553	-0.3576	-0.3577	-0.2424	-0.2216	-0.1874	-0.1719
FT MS pre-reform	0.0495	0.0551	0.0559	-0.1986	-0.3695	-0.3652	-0.4287	-0.3259	-0.2886	-0.2596	-0.2269
FT MS pre-reform LC	0.0419	0.0477	0.0486	-0.206	-0.3814	-0.3761	-0.4379	-0.336	-0.2996	-0.2714	-0.2394
FT MS pre-reform UC	0.057	0.0625	0.0632	-0.1911	-0.3576	-0.3543	-0.4195	-0.3157	-0.2776	-0.2479	-0.2143
FT LS pre-reform	0.0753	0.0811	0.0887	-0.1597	-0.2479	-0.173	-0.2129	-0.1024	-0.0871	-0.0566	-0.0303
FT LS pre-reform LC	0.0525	0.0591	0.0675	-0.1817	-0.2819	-0.2048	-0.2396	-0.1312	-0.1185	-0.0902	-0.0662
FT LS pre-reform UC	0.0981	0.1031	0.11	-0.1377	-0.2139	-0.1411	-0.1863	-0.0736	-0.0557	-0.0229	-0.0054
FT HS post-reform	0.0644	0.0809	0.0927	-0.1476	-0.3557	-0.3065	-0.3238	-0.2651	-0.2576	-0.2147	-0.1445
FT HS post-reform LC	0.0517	0.0685	0.0805	-0.1601	-0.3723	-0.3244	-0.3445	-0.2914	-0.2917	-0.2601	-0.2106
FT HS post-reform UC	0.0771	0.0933	0.1049	-0.1351	-0.339	-0.2887	-0.3032	-0.2389	-0.2235	-0.1692	-0.0785
FT MS post-reform	0.0542	0.0614	0.0614	-0.1639	-0.3604	-0.3344	-0.3546	-0.2628	-0.2359	-0.2315	-0.2148
FT MS post-reform LC	0.0485	0.0558	0.0559	-0.1695	-0.3693	-0.3436	-0.3646	-0.276	-0.253	-0.2537	-0.25
FT MS post-reform UC	0.0568	0.0669	0.0668	-0.1582	-0.3515	-0.3253	-0.3446	-0.2496	-0.2188	-0.2092	-0.1796
FT LS post-reform	0.1237	0.1617	0.178	-0.0456	-0.1627	-0.1268	-0.1179	-0.0367	-0.0027	0.0194	-0.0224
FT LS post-reform LC	0.1067	0.1448	0.161	-0.0633	-0.1899	-0.1547	-0.1473	-0.0765	-0.0532	-0.0486	-0.1381
FT LS post-reform UC	0.1406	0.1787	0.195	-0.0278	-0.1354	-0.0988	-0.0884	0.0031	0.0478	0.0875	0.0931
FTtoFTPT HS pre-reform	0.1117	0.1526	0.2072	-0.1024	-0.4447	-0.3104	-0.2922	-0.2172	-0.2072	-0.1695	-0.1681
FTtoFTPT HS pre-reform LC	0.0797	0.1217	0.1771	-0.133	-0.479	-0.343	-0.3234	-0.2488	-0.2389	-0.2012	-0.1998
FTtoFTPT HS pre-reform UC	0.1437	0.1834	0.2372	-0.0719	-0.4105	-0.2779	-0.2611	-0.1855	-0.1755	-0.1378	-0.1363
FTtoFTPT MS pre-reform	0.0969	0.1152	0.1307	-0.1315	-0.3987	-0.3696	-0.4041	-0.2911	-0.2578	-0.2344	-0.2065
FTtoFTPT MS pre-reform LC	0.0856	0.1041	0.1198	-0.1426	-0.4138	-0.3832	-0.4155	-0.3026	-0.2695	-0.2462	-0.2184
FTtoFTPT MS pre-reform UC	0.1083	0.1263	0.1417	-0.1204	-0.3835	-0.356	-0.3927	-0.2795	-0.2461	-0.2226	-0.1946
FTtoFTPT LS pre-reform	0.0989	0.1228	0.1472	-0.1118	-0.2677	-0.1634	-0.168	-0.0913	-0.0547	-0.0511	-0.0267
FTtoFTPT LS pre-reform LC	0.0659	0.0909	0.1165	-0.1435	-0.3123	-0.2051	-0.2032	-0.1271	-0.0916	-0.0888	-0.0656
FTtoFTPT LS pre-reform UC	0.1319	0.1548	0.178	-0.0801	-0.2232	-0.1216	-0.1328	-0.0555	-0.0178	-0.0135	0.012
FTtoFTPT HS post-reform	0.1084	0.1464	0.1737	-0.0601	-0.4299	-0.3003	-0.3178	-0.2773	-0.2479	-0.2014	-0.1911
FTtoFTPT HS post-reform LC	0.09	0.1285	0.1561	-0.0781	-0.4512	-0.3222	-0.3423	-0.3059	-0.2827	-0.2451	-0.255
FTtoFTPT HS post-reform UC	0.1269	0.1644	0.1913	-0.0421	-0.4086	-0.2783	-0.2933	-0.2488	-0.2132	-0.1577	-0.1272
FTtoFTPT MS post-reform	0.1194	0.1469	0.167	-0.0448	-0.3632	-0.3341	-0.3533	-0.297	-0.2698	-0.2515	-0.2563
FTtoFTPT MS post-reform LC	0.1115	0.1391	0.1594	-0.0527	-0.3742	-0.3444	-0.3639	-0.3094	-0.2845	-0.2701	-0.2839
FTtoFTPT MS post-reform UC	0.1273	0.1546	0.1746	-0.0369	-0.3523	-0.3238	-0.3427	-0.2847	-0.2551	-0.2329	-0.2287
FTtoFTPT LS post-reform	0.2206	0.2657	0.2943	0.0849	-0.1419	-0.1109	-0.1096	-0.0599	-0.0097	-0.0005	0.0423
FTtoFTPT LS post-reform LC	0.1982	0.2434	0.2718	0.0613	-0.1765	-0.145	-0.1444	-0.1019	-0.0616	-0.0666	-0.0609
FTtoFTPT LS post-reform UC	0.2429	0.288	0.3168	0.1084	-0.1073	-0.0767	-0.0748	-0.018	0.0421	0.0655	0.1456

TABLE B.11: Exact values corresponding to Figure 3.9. The table shows values of motherhood losses in wages, for FT and PT, FT, and FT to FT or PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

B.1.8 Figure 3.8

Year	-3	-2	-1	0	1	2	3	4	5	6	7
FTPT HS pre-reform	0.197095	0.195792	0.307999	-0.79857	-0.95898	-0.65055	-0.6874	-0.54274	-0.50122	-0.41313	-0.37501
FTPT HS pre-reform LC	0.11666	0.117077	0.205847	-1.02653	-1.23116	-0.84	-0.88558	-0.70335	-0.65118	-0.54104	-0.49354
FTPT HS pre-reform UC	0.27753	0.274507	0.410152	-0.57062	-0.6868	-0.4611	-0.48921	-0.38213	-0.35126	-0.28523	-0.25648
FTPT MS pre-reform	0.055313	0.06177	0.064676	-0.34749	-0.41615	-0.33321	-0.35194	-0.25853	-0.23639	-0.21669	-0.20369
FTPT MS pre-reform LC	0.04706	0.053672	0.056675	-0.35984	-0.43163	-0.34619	-0.36432	-0.26921	-0.24676	-0.22682	-0.2137
FTPT MS pre-reform UC	0.063567	0.069867	0.072678	-0.33513	-0.40067	-0.32022	-0.33956	-0.24785	-0.22602	-0.20656	-0.19367
FTPT LS pre-reform	0.106316	0.112533	0.121616	-0.3752	-0.43052	-0.29395	-0.34921	-0.13855	-0.11403	-0.09236	-0.0696
FTPT LS pre-reform LC	0.076878	0.083937	0.093642	-0.40602	-0.47444	-0.33154	-0.38106	-0.16992	-0.14642	-0.12628	-0.10532
FTPT LS pre-reform UC	0.135754	0.141128	0.149591	-0.34439	-0.38659	-0.25635	-0.31736	-0.10719	-0.08165	-0.05845	-0.03388
FTPT HS post-reform	0.225742	0.280112	0.330025	-0.79666	-1.13693	-0.623	-0.71506	-0.61932	-0.48471	-0.37633	-0.27936
FTPT HS post-reform LC	0.146074	0.188423	0.226363	-1.02594	-1.46127	-0.8047	-0.92174	-0.8002	-0.63203	-0.502	-0.40218
FTPT HS post-reform UC	0.30541	0.3718	0.433688	-0.56738	-0.81259	-0.4413	-0.50838	-0.43843	-0.33739	-0.25065	-0.15653
FTPT MS post-reform	0.058461	0.067261	0.079358	-0.33527	-0.49838	-0.33373	-0.33482	-0.28151	-0.26828	-0.25683	-0.24737
FTPT MS post-reform LC	0.051392	0.060295	0.072424	-0.34669	-0.51446	-0.34554	-0.34625	-0.29197	-0.27943	-0.26946	-0.26421
FTPT MS post-reform UC	0.06553	0.074227	0.086292	-0.32385	-0.4823	-0.32192	-0.3234	-0.27105	-0.25714	-0.24421	-0.23052
FTPT LS post-reform	0.139103	0.208331	0.219065	-0.2728	-0.44324	-0.17716	-0.18611	-0.06769	-0.05843	0.000535	0.029273
FTPT LS post-reform LC	0.114479	0.184112	0.195394	-0.29792	-0.47767	-0.20649	-0.21316	-0.09673	-0.09366	-0.04601	-0.0427
FTPT LS post-reform UC	0.163727	0.23255	0.242735	-0.24768	-0.40881	-0.14782	-0.15905	-0.03866	-0.02319	0.047079	0.101242
FT HS pre-reform	0.071372	0.081428	0.132119	-0.45144	-0.53559	-0.3873	-0.3666	-0.23671	-0.20297	-0.1681	-0.14533
FT HS pre-reform LC	0.034857	0.045388	0.092353	-0.53426	-0.63512	-0.46416	-0.4397	-0.29506	-0.25974	-0.22374	-0.20193
FT HS pre-reform UC	0.107887	0.117468	0.171884	-0.36861	-0.43606	-0.31044	-0.2935	-0.17835	-0.1462	-0.11245	-0.08874
FT MS pre-reform	0.051445	0.059632	0.061848	-0.28909	-0.29541	-0.24892	-0.29329	-0.19289	-0.16696	-0.1463	-0.1135
FT MS pre-reform LC	0.043638	0.051919	0.054243	-0.29963	-0.30956	-0.26149	-0.30519	-0.20421	-0.17893	-0.15909	-0.12707
FT MS pre-reform UC	0.059253	0.067344	0.069454	-0.27855	-0.28125	-0.23635	-0.28139	-0.18157	-0.15498	-0.13351	-0.09993
FT LS pre-reform	0.09429	0.106877	0.119277	-0.37748	-0.37839	-0.23453	-0.32151	-0.09066	-0.07462	-0.02996	0.007265
FT LS pre-reform LC	0.059726	0.073705	0.086935	-0.41289	-0.43251	-0.28297	-0.36219	-0.13354	-0.12186	-0.08129	-0.04878
FT LS pre-reform UC	0.128855	0.140048	0.15162	-0.34207	-0.32427	-0.18609	-0.28083	-0.04778	-0.02738	0.021374	0.063309
FT HS post-reform	0.098064	0.140781	0.17231	-0.46185	-0.58371	-0.31061	-0.34228	-0.26658	-0.19241	-0.13007	-0.04508
FT HS post-reform LC	0.063595	0.102534	0.130649	-0.54861	-0.69294	-0.37629	-0.41274	-0.32825	-0.25296	-0.19991	-0.14032
FT HS post-reform UC	0.132532	0.179029	0.213971	-0.37509	-0.47448	-0.24493	-0.27182	-0.2049	-0.13185	-0.06023	0.050158
FT MS post-reform	0.050886	0.061415	0.073958	-0.28342	-0.41608	-0.2558	-0.25737	-0.16202	-0.14322	-0.14819	-0.14874
FT MS post-reform LC	0.043998	0.054605	0.067169	-0.29329	-0.43061	-0.26736	-0.26871	-0.17356	-0.15755	-0.16656	-0.1774
FT MS post-reform UC	0.057774	0.068225	0.080747	-0.27355	-0.40156	-0.24424	-0.24603	-0.15048	-0.1289	-0.12981	-0.12008
FT LS post-reform	0.139377	0.192601	0.233194	-0.24702	-0.42345	-0.15491	-0.1412	0.015184	-0.00171	0.087979	-0.00329
FT LS post-reform LC	0.11011	0.1638	0.204692	-0.27653	-0.46654	-0.19497	-0.1799	-0.03129	-0.06031	0.009401	-0.13633
FT LS post-reform UC	0.168643	0.221402	0.261696	-0.2175	-0.38035	-0.11484	-0.1025	0.061656	0.056901	0.166557	0.129747
FTtoFTPT HS pre-reform	0.269929	0.345624	0.550509	-0.67846	-0.99658	-0.62223	-0.64556	-0.51645	-0.48487	-0.39959	-0.32981
FTtoFTPT HS pre-reform LC	0.156376	0.217735	0.373821	-0.88835	-1.29523	-0.81928	-0.84734	-0.68546	-0.64594	-0.54031	-0.45467
FTtoFTPT HS pre-reform UC	0.383481	0.473514	0.727198	-0.46856	-0.69792	-0.42518	-0.44378	-0.34744	-0.3238	-0.25887	-0.20495
FTtoFTPT MS pre-reform	0.103304	0.129418	0.147942	-0.296	-0.42378	-0.31306	-0.34252	-0.23523	-0.20187	-0.18221	-0.16655
FTtoFTPT MS pre-reform LC	0.091111	0.117254	0.135768	-0.31043	-0.44359	-0.32961	-0.35785	-0.24897	-0.21527	-0.19548	-0.17979
FTtoFTPT MS pre-reform UC	0.115496	0.141583	0.160116	-0.28158	-0.40397	-0.29651	-0.32719	-0.2215	-0.18847	-0.16894	-0.15331
FTtoFTPT LS pre-reform	0.185622	0.217715	0.231862	-0.31869	-0.39571	-0.20875	-0.31019	-0.08188	-0.0462	-0.00401	-0.02139
FTtoFTPT LS pre-reform LC	0.141166	0.174081	0.189733	-0.36301	-0.45881	-0.26627	-0.35807	-0.13015	-0.09596	-0.05481	-0.07462
FTtoFTPT LS pre-reform UC	0.230079	0.26135	0.273991	-0.27437	-0.33262	-0.15123	-0.2623	-0.03362	0.003568	0.046797	0.031849
FTtoFTPT HS post-reform	0.283535	0.409293	0.511087	-0.70897	-1.18302	-0.56913	-0.72062	-0.6188	-0.41012	-0.32253	-0.23658
FTtoFTPT HS post-reform LC	0.176028	0.272262	0.347703	-0.92712	-1.53715	-0.74917	-0.94179	-0.8125	-0.55456	-0.45902	-0.39434
FTtoFTPT HS post-reform UC	0.391042	0.546323	0.674472	-0.49083	-0.8289	-0.38909	-0.49946	-0.42511	-0.26568	-0.18604	-0.07882
FTtoFTPT MS post-reform	0.107689	0.133757	0.159891	-0.28304	-0.51764	-0.32362	-0.32003	-0.25821	-0.24243	-0.23101	-0.22234
FTtoFTPT MS post-reform LC	0.097216	0.123246	0.149247	-0.29586	-0.53728	-0.33812	-0.33375	-0.27107	-0.25666	-0.24792	-0.24623
FTtoFTPT MS post-reform UC	0.118162	0.144268	0.170535	-0.27022	-0.498	-0.30911	-0.3063	-0.24534	-0.2282	-0.21409	-0.19845
FTtoFTPT LS post-reform	0.241985	0.301456	0.332149	-0.22303	-0.5414	-0.16247	-0.21918	-0.10751	-0.06276	0.017284	0.060726
FTtoFTPT LS post-reform LC	0.204004	0.264586	0.295791	-0.25942	-0.59392	-0.20811	-0.26217	-0.15346	-0.11889	-0.05361	-0.04935
FTtoFTPT LS post-reform UC	0.279966	0.338326	0.368508	-0.18664	-0.48887	-0.11682	-0.17619	-0.06157	-0.00663	0.088182	0.170798

TABLE B.12: Exact values corresponding to Figure 3.10. The table shows values of motherhood losses in earnings, for FT and PT, FT, and FT to FT or PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Year	-3	-2	-1	0	1	2	3	4	5	6	7
FTPT HS pre-reform	0.082252	0.100389	0.129554	-0.16891	-0.47925	-0.33059	-0.32038	-0.25705	-0.25108	-0.19678	-0.1859
FTPT HS pre-reform LC	0.053605	0.07278	0.102475	-0.19655	-0.50962	-0.35964	-0.3481	-0.28521	-0.27918	-0.22497	-0.21413
FTPT HS pre-reform UC	0.110899	0.127998	0.156634	-0.14127	-0.44887	-0.30154	-0.29265	-0.22889	-0.22298	-0.16858	-0.15767
FTPT MS pre-reform	0.052579	0.057735	0.061675	-0.2143	-0.43336	-0.4146	-0.44886	-0.34326	-0.31749	-0.29262	-0.26605
FTPT MS pre-reform LC	0.042266	0.047671	0.051761	-0.22455	-0.44695	-0.42653	-0.459	-0.35357	-0.32793	-0.30316	-0.27672
FTPT MS pre-reform UC	0.062892	0.067798	0.071589	-0.20406	-0.41977	-0.40266	-0.43872	-0.33296	-0.30706	-0.28207	-0.25539
FTPT LS pre-reform	0.073744	0.073128	0.083192	-0.17015	-0.26421	-0.20473	-0.25521	-0.13931	-0.12404	-0.12896	-0.07447
FTPT LS pre-reform LC	0.045931	0.046143	0.056838	-0.1976	-0.30429	-0.23958	-0.28395	-0.16888	-0.15465	-0.1611	-0.10837
FTPT LS pre-reform UC	0.101556	0.100112	0.109546	-0.14271	-0.22413	-0.16989	-0.22648	-0.10973	-0.09343	-0.09683	-0.04058
FTPT HS post-reform	0.092464	0.112101	0.118422	-0.11414	-0.42044	-0.31996	-0.32981	-0.28952	-0.25782	-0.21036	-0.17506
FTPT HS post-reform LC	0.069815	0.090209	0.097154	-0.13599	-0.44398	-0.34216	-0.35145	-0.31171	-0.28398	-0.24257	-0.22011
FTPT HS post-reform UC	0.115113	0.133992	0.13969	-0.0923	-0.3969	-0.29776	-0.30817	-0.26733	-0.23165	-0.17816	-0.13
FTPT MS post-reform	0.065349	0.073785	0.081854	-0.1376	-0.4375	-0.40602	-0.4231	-0.36744	-0.34313	-0.31867	-0.30827
FTPT MS post-reform LC	0.056708	0.065357	0.073598	-0.14619	-0.44831	-0.4155	-0.43173	-0.37634	-0.35368	-0.33186	-0.32765
FTPT MS post-reform UC	0.073989	0.082213	0.090109	-0.12902	-0.4267	-0.39655	-0.41447	-0.35854	-0.33257	-0.30548	-0.28889
FTPT LS post-reform	0.134265	0.174333	0.199525	-0.00804	-0.18883	-0.12045	-0.12589	-0.05453	-0.02468	-0.02999	0.003491
FTPT LS post-reform LC	0.111176	0.152044	0.177865	-0.03076	-0.21928	-0.14793	-0.15112	-0.08208	-0.05814	-0.07424	-0.06493
FTPT LS post-reform UC	0.157355	0.196623	0.221185	0.01468	-0.15837	-0.09297	-0.10067	-0.02699	0.008784	0.014263	0.071908
FT HS pre-reform	0.044022	0.0538	0.081293	-0.23278	-0.49625	-0.34336	-0.32359	-0.24286	-0.24065	-0.17821	-0.16873
FT HS pre-reform LC	0.018411	0.029069	0.056883	-0.2576	-0.52819	-0.37392	-0.35301	-0.27472	-0.27448	-0.21387	-0.20671
FT HS pre-reform UC	0.069633	0.07853	0.105703	-0.20796	-0.46431	-0.3128	-0.29417	-0.21099	-0.20682	-0.14254	-0.13075
FT MS pre-reform	0.054749	0.065095	0.064437	-0.22237	-0.33376	-0.35018	-0.41267	-0.31131	-0.27182	-0.24124	-0.19637
FT MS pre-reform LC	0.045029	0.055549	0.055045	-0.23203	-0.34902	-0.36399	-0.42451	-0.32425	-0.28599	-0.25672	-0.21312
FT MS pre-reform UC	0.064469	0.074641	0.073828	-0.21272	-0.3185	-0.33637	-0.40083	-0.29838	-0.25764	-0.22577	-0.17962
FT LS pre-reform	0.08813	0.075006	0.088414	-0.16615	-0.25278	-0.15077	-0.19651	-0.09598	-0.0844	-0.06291	-0.01373
FT LS pre-reform LC	0.058167	0.046293	0.060468	-0.19541	-0.29885	-0.19249	-0.23089	-0.13321	-0.12546	-0.10756	-0.06248
FT LS pre-reform UC	0.118093	0.103719	0.116359	-0.1369	-0.20671	-0.10905	-0.16212	-0.05875	-0.04335	-0.01825	0.035031
FT HS post-reform	0.061336	0.082673	0.090476	-0.15552	-0.35425	-0.27896	-0.28604	-0.24031	-0.22819	-0.17935	-0.10396
FT HS post-reform LC	0.040351	0.062257	0.07056	-0.17598	-0.3796	-0.30407	-0.31138	-0.26805	-0.26347	-0.22581	-0.17096
FT HS post-reform UC	0.082321	0.103088	0.110391	-0.13507	-0.32891	-0.25385	-0.26071	-0.21257	-0.19291	-0.13289	-0.03695
FT MS post-reform	0.054824	0.06527	0.069191	-0.15537	-0.38701	-0.33604	-0.35182	-0.25215	-0.22208	-0.21367	-0.19257
FT MS post-reform LC	0.046412	0.057032	0.061089	-0.16372	-0.39948	-0.34792	-0.36332	-0.26553	-0.23931	-0.23604	-0.2279
FT MS post-reform UC	0.063236	0.073509	0.077293	-0.14703	-0.37455	-0.32415	-0.34031	-0.23876	-0.20485	-0.1913	-0.15724
FT LS post-reform	0.099035	0.145936	0.170868	-0.03331	-0.18862	-0.10534	-0.12401	-0.03881	-0.00325	0.020826	-0.01949
FT LS post-reform LC	0.073802	0.121357	0.146807	-0.05825	-0.22459	-0.14001	-0.15753	-0.07929	-0.0543	-0.04759	-0.13539
FT LS post-reform UC	0.124268	0.170515	0.194928	-0.00837	-0.15264	-0.07066	-0.0905	0.001672	0.047807	0.089246	0.096403
FTtoFTPT HS pre-reform	0.103312	0.154229	0.216628	-0.10649	-0.4605	-0.31306	-0.29045	-0.2081	-0.22042	-0.16456	-0.16442
FTtoFTPT HS pre-reform LC	0.064368	0.116399	0.179524	-0.1441	-0.50256	-0.35284	-0.32876	-0.24681	-0.25907	-0.20321	-0.203
FTtoFTPT HS pre-reform UC	0.142256	0.192058	0.253733	-0.06889	-0.41845	-0.27329	-0.25214	-0.16939	-0.18177	-0.12591	-0.12585
FTtoFTPT MS pre-reform	0.096748	0.121011	0.138806	-0.14582	-0.36795	-0.34576	-0.37764	-0.26926	-0.23731	-0.20854	-0.18596
FTtoFTPT MS pre-reform LC	0.082366	0.106933	0.124948	-0.16	-0.38699	-0.36268	-0.39197	-0.28383	-0.25204	-0.2234	-0.201
FTtoFTPT MS pre-reform UC	0.11113	0.135089	0.152664	-0.13164	-0.3489	-0.32883	-0.3633	-0.25469	-0.22259	-0.19368	-0.17092
FTtoFTPT LS pre-reform	0.120168	0.136102	0.142964	-0.11546	-0.23059	-0.13768	-0.17418	-0.07877	-0.04167	-0.04925	0.001748
FTtoFTPT LS pre-reform LC	0.078666	0.095513	0.103881	-0.15619	-0.28894	-0.1915	-0.21839	-0.12414	-0.08849	-0.09706	-0.04835
FTtoFTPT LS pre-reform UC	0.16167	0.17669	0.182046	-0.07474	-0.17225	-0.08387	-0.12997	-0.03341	0.00515	-0.00144	0.051846
FTtoFTPT HS post-reform	0.098531	0.133285	0.158442	-0.06211	-0.40155	-0.2804	-0.30872	-0.26591	-0.23326	-0.18294	-0.16797
FTtoFTPT HS post-reform LC	0.067439	0.103229	0.12905	-0.09229	-0.43439	-0.31147	-0.33889	-0.29684	-0.26993	-0.22816	-0.23303
FTtoFTPT HS post-reform UC	0.129624	0.163341	0.187834	-0.03194	-0.36871	-0.24933	-0.27854	-0.23498	-0.19658	-0.13771	-0.10291
FTtoFTPT MS post-reform	0.113217	0.138571	0.160059	-0.06258	-0.39374	-0.34744	-0.36688	-0.30142	-0.27199	-0.25124	-0.25346
FTtoFTPT MS post-reform LC	0.101151	0.126785	0.148506	-0.07447	-0.4091	-0.36083	-0.37912	-0.31406	-0.28695	-0.27001	-0.28124
FTtoFTPT MS post-reform UC	0.125282	0.150357	0.171612	-0.05069	-0.37838	-0.33404	-0.35465	-0.28878	-0.25702	-0.23246	-0.22568
FTtoFTPT LS post-reform	0.206031	0.234058	0.259347	0.056958	-0.18432	-0.10078	-0.12466	-0.0752	-0.0242	-0.01385	0.030675
FTtoFTPT LS post-reform LC	0.170884	0.200363	0.226395	0.023211	-0.23148	-0.14357	-0.16473	-0.11842	-0.07709	-0.08069	-0.07308
FTtoFTPT LS post-reform UC	0.241177	0.267753	0.292299	0.090704	-0.13717	-0.05799	-0.08459	-0.03198	0.028688	0.052984	0.134424

TABLE B.13: Exact values corresponding to Figure 3.10. The table shows values of motherhood losses in wages, for FT and PT, FT, and FT to FT or PT spells of employment. LC denotes lower boundary and UC upper boundary on a 95% confidence interval.

Appendix C

Appendix B: Additional tables and figures for Chapter 4

Industry	Ref	Industry	Ref
Food and beverages	F1	Coke and refined petroleum products	X1 / Z1
Electricity, water, sewage	F2	Chemicals and chemical products	X2 / Z2
Textiles, wearing apparel and leather products	F3	Basic pharmaceutical products and pharmaceutical preparations	X3 / Z3
Furniture	F4	Other manufacturing	X4 / Z4
Motor vehicles	F5	Constructions and construction works	X5 /Z5
Computer, electronic and optical products	F6	Mining and quarrying	X6 / Z6
Wholesale and retailing	F7	Land and water transport	X7 / Z7
Hotels, restaurants, pubs, etc.	F8	Advertising	X8 / Z8
Air transport	F9	Other professional, scientific and technical services	X9 / Z9
Public transport	F10	Scientific research and development	X10 / Z10
Telecommunication services	F11	Public administration	X11 / Z11
Postal and courier services	F12		
Financial, insurance and legal services	F13		
Rents	F14		
Other real estate services	F15		
Compulsory education	F16		
Non-compulsory education	F17		
Public health services	F18		
Private health services	F19		
Services of households as employers	F20		
Arts and culture (both live and digital)	F21		
Sports	F22		
Other services	F23		

FIGURE C.1: Industries included in the questionnaire.
Note: Industries in the left column were considered for final household demand, with values of the responses being referred to as F1-F23; industries in the right column were considered for exports and supply of intermediate goods and services, with values of the responses being referred to as X1-X11 and Z1-Z11 respectively.

	Industry		Direct Multiplier of Lockdown on Final Consumption (Exports ecluded)	Direct Multiplier of Lockdown on Exports	Direct Multiplier of Lockdown on Supply of Intermediate Inputs
1	A	Products of agriculture, hunting and related services	F1	F1	F1
2	A	Products of forestry, logging and related services	Z4	X4	Z4
3	A	Fish and other fishing products; aquaculture products; support services to fishing	F1	F1	F1
4	BDE	Mining and quarrying	Z6	X6	Z6
5	C	Food products, beverages and tobacco products	F1	F1	F1
6	C	Textiles, wearing apparel and leather products	F3	X4	Z4
7	C	Wood and of products of wood and cork, except furniture; articles of straw and plaiting materials	Z4	X4	Z4
8	C	Paper and paper products	Z4	X4	Z4
9	C	Printing and recording services	Z4	X4	Z4
10	C	Coke and refined petroleum products	Z1	X1	Z1
11	C	Chemicals and chemical products	Z2	X2	Z2
12	C	Basic pharmaceutical products and pharmaceutical preparations	Z3	X3	Z3
13	C	Rubber and plastics products	Z4	X4	Z4
14	C	Other non-metallic mineral products	Z4	X4	Z4
15	C	Basic metals	Z4	X4	Z4
16	C	Fabricated metal products, except machinery and equipment	Z4	X4	Z4
17	C	Computer, electronic and optical products	F6	F6	Z4
18	C	Electrical equipment	Z4	X4	Z4
19	C	Machinery and equipment n.e.c.	Z4	X4	Z4
20	C	Motor vehicles, trailers and semi-trailers	F5	F5	Z4
21	C	Other transport equipment	Z4	Z4	Z4
22	C	Furniture; other manufactured goods	F4	F4	Z4
23	C	Repair and installation services of machinery and equipment	Z4	X4	Z4
24	BDE	Electricity, gas, steam and air-conditioning	F2	X6	Z6
25	BDE	Natural water; water treatment and supply services	F2	X6	Z6
26	BDE	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services	F2	Z4	Z4
27	F	Constructions and construction works	Z5	X5	Z5
28	G	Wholesale and retail trade and repair services of motor vehicles and motorcycles	F5	F7	F7
29	G	Wholesale trade services, except of motor vehicles and motorcycles	F7	F7	F7
30	G	Retail trade services, except of motor vehicles and motorcycles	F7	F7	F7
31	H	Land transport services and transport services via pipelines	F10	X7	Z7
32	H	Water transport services	F9	X7	Z7
33	H	Air transport services	F9	F9	F9
34	H	Warehousing and support services for transportation	Z7	X7	Z7
35	H	Postal and courier services	F12	F12	F12
36	I	Accommodation and food services	F8	F8	F8
37	J	Publishing services	F21	X9	Z9
38	J	Motion picture, video and television programme production services, sound recording and music publishing; programming and broadcasting services	Z9	X9	Z9
39	J	Telecommunications services	F11	F11	F11
40	J	Computer programming, consultancy and related services; information services	Z9	X9	Z9
41	K	Financial services, except insurance and pension funding	F13	F13	F13
42	K	Insurance, reinsurance and pension funding services, except compulsory social	F13	F13	F13
43	K	Services auxiliary to financial services and insurance services	F13	F13	F13
44	L	Real estate services excluding imputed rents	(F14+F15/2)	(F14+F15/2)	(F14+F15/2)
45	L	Imputed rents of owner-occupied dwellings			
46	M	Legal and accounting services; services of head offices; management consulting	F13	F13	F13
47	M	Architectural and engineering services; technical testing and analysis services	F23	X9	Z9
48	M	Scientific research and development services	Z10	X10	Z10
49	M	Advertising and market research services	Z8	X8	Z8
50	M	Other professional, scientific and technical services; veterinary services	Z9	X9	Z9
51	N	Rental and leasing services	Z9	X9	Z9
52	N	Employment services	Z9	X9	Z9
53	N	Travel agency, tour operator and other reservation services and related services			
54	N	Security and investigation services; services to buildings and landscape; office administrative, office support and other business support services	Z9	X9	Z9
55	O	Public administration and defence services; compulsory social security services	Z11	X11	Z11
56	P	Education services	(F16+F17)/2	(F16+F17)/2	(F16+F17)/2
57	Q	Human health services	(F18+F19)/2	(F18+F19)/2	(F18+F19)/2
58	Q	Social work services	F23	F23	F23
59	RST	Creative, arts and entertainment services; library, archive, museum and other cultural services; gambling and betting services	F21	F21	F21
60	RST	Sporting services and amusement and recreation services	F22	F22	F22
61	RST	Services furnished by membership organisations	F23	F23	F23
62	RST	Repair services of computers and personal and household goods	F23	F23	F23
63	RST	Other personal services	F23	F23	F23
64	RST	Services of households as employers; undifferentiated goods and services produced by households for own use	F20	F20	F20

FIGURE C.2: Mapping from results of the consensus analysis to parameters used for the macro model.
Note: Values referred to as per Table A1.

Variable	mean	sd	min	max
Employment to Non-employment transition = 1	0.0237		0	1
Age	43.19	12.77	16	69
Sex (1 = Male)	0.482		0	1
Single	0.324		0	1
Married	0.555		0	1
Separated	0.025		0	1
Divorced	0.082		0	1
Widowed	0.014		0	1
Total usual hours worked in main job (incl. overtime)	36.00	12.73	0	97
Months continuously employed	109.4	110.2	0	696
Public sector = 1	0.290		0	1
% change in employment in industry	0.469	2.372	-16.67	36.36

TABLE C.1: Employment transition model: Descriptive statistics

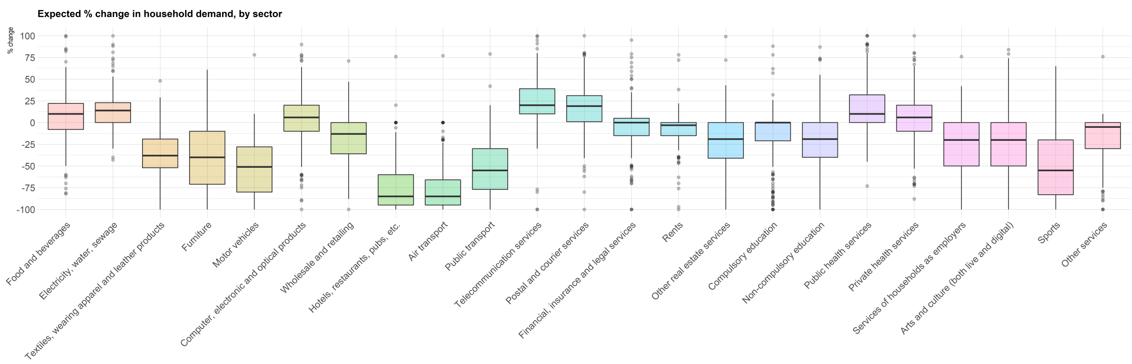


FIGURE C.3: Box-plot for the expected change in household demand, by sector.
Responses to the question: Please provide your estimates of the effects on final household demand for goods and services of the Covid-19 related lock-down measures implemented by the UK Government on March 23: these are due to constraints preventing consumers from physically visiting sellers.
Note: Statistics based on 257 valid responses to this question.

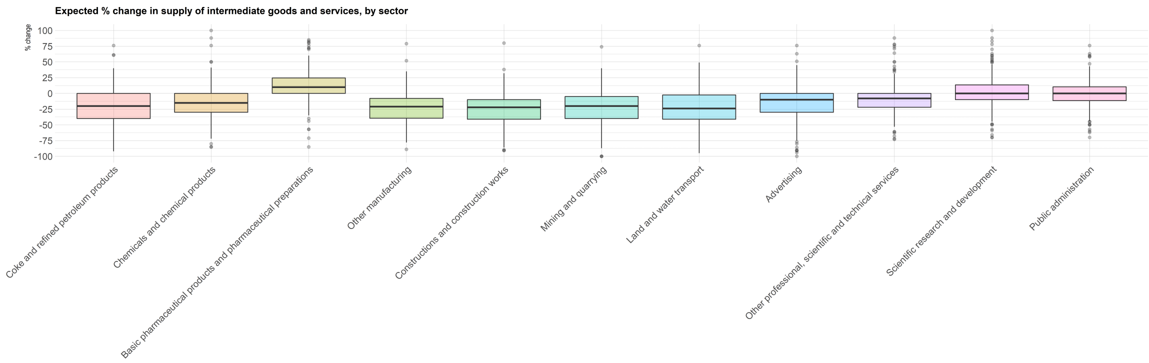


FIGURE C.4: Box-plot for the expected change in supply of intermediate goods and services, by sector.
Responses to the question: Please provide your estimates of the effects on the supply of intermediate goods and services to businesses of the Covid-19 related lock-down measures implemented by the UK Government on March 23: these are due to social distancing and smart working measures reducing the output of intermediate goods and services, which producers sell to other producers.
Note: Statistics based on 223 valid responses to this question.

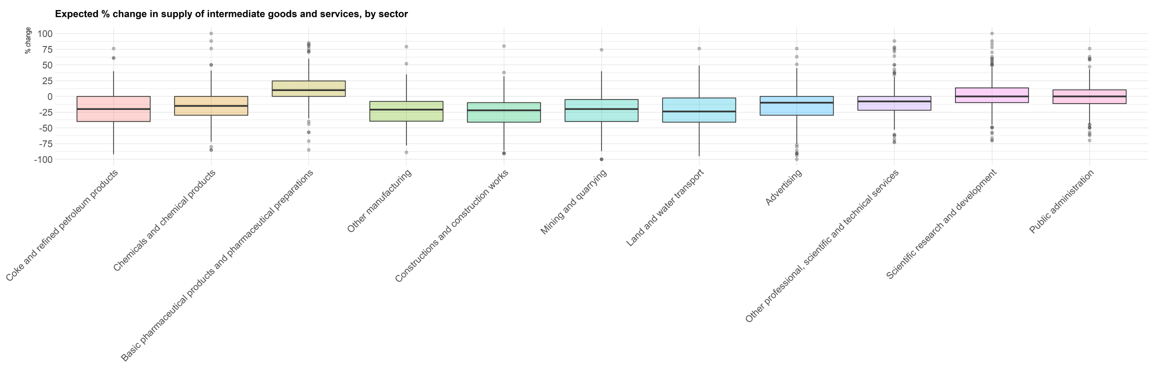


FIGURE C.5: Responses to the question: Please provide your estimates of the effects on the supply of intermediate and final goods and services of the Covid-19 related lock-down measures implemented by the UK Government on March 23: these are due to due to reduction in the demand from importers, or to difficulties to get the goods and services through the border.
Note: Statistics based on 208 valid responses to this question.

Appendix D

Appendix C: Modifications to UKMOD input data and modelling assumptions for Chapter 4

UKMOD runs on the Family Resources Survey (FRS). This survey contains weekly information on incomes. For most analyses, incomes are simply extrapolated to months in UKMOD (and to years in our fiscal overview). Since we are simulating that the COVID-19 crisis lasts for part of the year, we modify incomes from employment (yem), self-employment (yse) and contributory-based Job Seekers Allowance (bunct_s) to obtain weighted average amounts that reflects the months during and after the crisis (while we do not modify hours of work), as detailed in Table D.1.

We consider as employed (self-employed) individuals, people with positive employment (self-employment) income and whose incomes from this source are higher than those from self-employment (employment).

Var	Scenario 1	Scenario 2	Scenario 3
yem	yem	yem*(8/12)	MISS=1 =>as in Scenario 2 + min(0.8*yem,2500)*(4/12)
			MISS=0 =>as in Scenario 2
yse	yse	yse*(8/12) + new_emp*yse*(4/12)	as in Scenario 2 + min(0.8*(yse-new_emp*yse), 2500) *(4/12)
bunct_s	0	bunct_s *(4/12) [this & yem removed from disregard]	MISS=1 =>0
			MISS=0 =>bunct_s *(4/12) [as in Scenario 2]
lhw	lhw	(not modified)	(not modified)

TABLE D.1: Changes to UKMOD variables.

Job Retention Scheme (JRS) JRS is a grant that covers 80% of usual monthly wage costs, up to £2,500 a month, plus the associated Employer National Insurance contributions and pension contributions (up to the level of the minimum automatic enrolment employer pension contribution). UKMOD does not simulate employer pension contributions; therefore, we do not assess their impact of revenue changes. Employees pay the taxes they normally pay, which includes automatic pension contributions, unless the employee has opted out or stopped saving into their pension. We do not have information on the latter, and therefore assume they continue to pay pension contributions. Employer National Insurance contributions are paid by the government instead of the employers under the JRS. Accordingly, for the fiscal overview we made those contributions negative.

$$yem = yem * (8/12) + min(0.8 * yem, 2500) * (4/12) \tag{D.1}$$

Self-Employment Income Support Scheme (SEISS) SEISS is taxable grant of 80% of average monthly trading profits, paid out in a single instalment covering 3 months, and capped at £7,500 altogether. UKMOD uses the FRS variable on gross earnings from self-employed Opt 2 (yse). SEISS is subject to Income Tax and self-employed National Insurance. The pseudo-code for the implementation of this policy is:

$$\begin{split} yse = yse * (8/12) + income_{r}eduction_{c}oeff * yse * (4/12) + \\ min(0.8 * (yse - income_{r}eduction_{c}oeff * yse), 2500) * (4/12) \end{split} \tag{D.2}$$

Contribution-based Job Seekers Allowance (Cb-JSA) UKMOD includes a Labour Market Adjustment (LMA) add-on to transition people across employment statuses. When transitioning people to unemployment during the crisis, we modify income from employment (in the LMA add-on) and contribution-based Job Seekers Allowance (in UKMOD) as in Table A4. In addition, for those transitioning we remove income from employment from the base for disregards in UKMOD (otherwise the income earned after the crisis would be part of this base). Furthermore, for the (very few) people considered as employed that also have some self-employment incomes, the latter incomes are maintained (and not put to 0 as by the default in the LMA add-on).

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