Three Essays on Labor Supply

Inaugural-Dissertation zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaft des Fachbereichs
Wirtschaftswissenschaft der
Freien Universität Berlin

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geboren in Berlin

Berlin, 2018

Gedruckt mit der Genehmigung des Fachbereichs Wirtschaftswissenschaft der Freien Universität Berlin

Erstgutachter: Prof. Dr. Peter Haan

Zweitgutachter: Prof. Georg Weizsäcker, Ph.D.

Tag der Disputation: 13. Juni 2018

Erklärung über Zusammenarbeit mit Koautoren und Vorveröffentlichungen

Die Dissertation ist in drei Kapitel gegliedert. Kapitel 1 und 2 wurden unter meiner alleinigen Autorenschaft verfasst. Bei Kapitel 3 handelt es sich um eine gemeinschaftliche Arbeit von Dr. Amelie Schiprowski, Luke Haywood, Ph. D., und mir.

Kapitel 3 ist bereits als Diskussionspapier unter folgendem Titel erschienen:

Sascha Drahs, L. Haywood und A. Schiprowski, „*Job Search with Subjective Wage Expectations*“, Discussion Paper No. 1725, DIW Berlin, 2018; Discussion Paper No. 75, SFB TRR 190, 2018.

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Introduction

Until the visionary age of robots will have fully arrived, the production of goods and services will demand human work, most of which will be traded in the labor market. In 2017, 44 million employees in Germany supplied a total amount of 51 billion hours of work to produce goods and services worth 3.1 trillion €[1]. This is what makes the labor market a central institution for the productive capacity of our society. Consequently, the importance of the labor market in politics and media seems unchallenged by any other market: next to output growth and inflation, it is usually the unemployment rate by which we judge the state of the economy. Still, one may argue: isn't the supply of energy or the price of computers essential for production, too?[2] What is it, then, that makes the labor market so unique?

In light of the topic of this dissertation, I would like to give the following answer: it is the importance of work for our personal lives. Most people find themselves to participate in the labor market at some point in their lives, and in many cases spend a significant part of their lifetime at the workplace. Work means more than trading leisure for consumption; the possibility of selling one's skills and work hours to the market provides the foundation for sustaining a standard of living, social status, and providing for one's children. Because conditions in the labor market have such far-reaching consequences in so many domains of life, understanding and improving these conditions is a rewarding goal.

In the most stylized version of the neoclassical model, the labor supply choice entails an optimal trade-off between leisure and consumption. To analyze the effects of labor market conditions or institutions on individual labor supply decisions, this framework – although true at a sufficient level of abstraction – does not possess enough depth of detail. In this dissertation, I analyze, chapter by chapter, three core aspects of individual labor supply, where each aspect will emphasize a concretization of the standard framework.

I start out from the origin of individual labor supply decisions: the private domain, or more succinctly, the family. Chapter 1 analyzes the labor supply decisions of women, taking into account family planning. The importance of the childbearing decision is evident from the fact that female labor supply declines sharply with the presence of children. Hence, the leisure-consumption trade-off of mothers is structurally different from that of

[1] Destatis [2018], GDP as of 2016.

[2] In 2017, each produced €'s worth used 59 seconds of work [Destatis , 2018, own calculations], but 89 grams of oil equivalent of energy [The World Bank Group , 2018, OECD , 2018, own calculations].

childless women. In the first chapter, I add two central ingredients to the model of labor supply – unemployment and dynamics – to analyze how parental leave policies can affect female labor supply and fertility. The presence of unemployment changes the whole game of labor supply: a job becomes a valuable asset, and leaving one's job to take care of children becomes a risky undertaking. As I show in the empirical analysis, this risk leaps far into the most private domain of family formation when women who work refrain from having children. Moreover, I argue that parental leave legislation provides policy makers with a powerful tool to cushion these adverse effects of job risk on fertility. The second key ingredient in a model of labor supply is dynamic optimization. The dynamic structure of the model presented in this chapter is nowadays a standard way to think about labor supply (and most other economic decisions), because economic actions such as working or family planning are taken under the deliberation of their future consequences.

In Chapter 2, it is taken as given that individuals have made up their minds about their preferred amount of labor supply. As in the preceding chapter, a distinction is made between non-work, part-time, or full-time work[3], allowing for the empirically relevant distinction between the extensive (participation) and the intensive (hours per week) decision margin. The goal of the second chapter is to shed light on the consequences for employees' labor supply when transitions between full-time and part-time work are not feasible. Looking at female employees in full-time jobs, I analyze the effects of a legal reform making it easier for employees of medium-sized and large firms to reduce their weekly work hours. Using a quasi-experimental research design, I show that women above the age of 50 reacted strongly to the reform by reducing their hours and leaving their jobs less often. Like in Chapter 1, it is again the private domain which helps to explain the age pattern in labor supply adjustment, as women often take care of own or in-law parents later in their working lives. In analogy to the fertility case, I find that the government can change the legal rules so as to alleviate a conflict between career and private life.

In the final chapter of my dissertation, I broaden the perspective on labor supply by analyzing the search effort of the unemployed.[4] As prolonged unemployment persists to be a pervasive and costly feature of labor markets, most advanced economies have adopted some kind of search assistance. In Chapter 3, my coauthors and I introduce subjective expectations as a new ingredient to the analysis of unemployment. Without further mentioning, the analysis in Chapter 1 and 2 assumed that economic agents base their decisions on realistic expectations of the future. We show this is not true of expectations of future wages; using the framework of a dynamic search model, we find that job seekers are optimistic about their future wage offers, which causes them to be unemployed longer than necessary. We suggest information provision as an innovative and cheap tool in job search assistance.

[3] That is, I have discretized the continuous hours-of-work choice into three broad categories.

[4] The decision to search harder implies finding work earlier and thus increases labor supply in expectation. This, in turn, implies frictional unemployment to decline and the aggreate employment level to rise [e.g., Pissarides, 2000].

As I have laid out above, the three chapters of my dissertation exemplify the policy-relevance of labor supply in three important contexts: the family, the workplace, and in unemployment. For completeness, I should comment on the relationship between labor supply and labor demand (i.e., firm behavior), or labor market equilibrium. Throughout the analysis, I have analyzed individual behavior *ceteris paribus*, i.e. under the assumption that firm behavior remain unchanged. This approach has both advantages and disadvantages. First, the motivating reason for abstracting from firm behavior is a trade-off between detail and comprehensiveness: the detailed insights from any of the three chapters of this dissertation could not have been gained without the simplifying assumption of exogenous labor demand. Second, the downside to the partial analysis presented here clearly is its agnosticism about equilibrium policy effects. To the policy maker, this may seem like only half of the analysis – and I agree: the analysis of firm's responses to changes in worker behavior may proceed in the same (partial) manner. Moreover, I think that the combination of credible "partial" evidence and a battery of plausible scenarios of firm response can be a better guide for policy than an equilibrium analysis that is based on too many far-fetched assumptions.

Chapter 1

The Effects of Parental Leave Policies in Labor Markets with Search Frictions

Parental leave policies contain two key components. First, parental leave job protection reduces the risk of involuntary unemployment for parents after taking parental leave; second, parental leave benefits help to reduce financial hardships during parental leaves. The goals of these policies are to increase both fertility and female labor supply.

However, there may be a target conflict between these policy goals, and assessing the impact of parental leave policies on both fertility and female labor supply is crucial in designing effective policies. Lalive et al. [2013] show that parental leave job protection and benefits provide incentconsideredives to take parental leave and return within the legal time frame. Since the fertility and the labor supply margin are innately connected, it is interesting to ask what consequences these policies have on fertility. To answer this question, I stress the importance of unemployment risk: in labor markets with search frictions[1], parental leave policies affect female labor supply by providing additional job security and financial support. By the same token, fertility decisions might be affected when these policies improve the situation of parents. In addition to evaluating the trade-off between fertility and labor supply effects, learning about the underlying economic mechanisms is necessary to understand how job protection and benefits interact to influence both outcomes.

I develop a dynamic discrete choice model of female labor supply and fertility similar to Adda et al. [2017] to evaluate parental leave policies based on longitudinal German micro data. In each time period, women face a joint decision of fertility and hours of work, provided in three broad hours-of-work categories. In each period, income is earned and labor market experience increases wages through a Mincer wage equation. Net incomes

[1] The term search friction denotes the fact that finding a job is not guaranteed to the job seeker.

are determined under consideration of taxes and social security payments, unemployment and child benefits using a microsimulation model. Women may be labor market rationed in the sense that no job offer is available. This is modeled by a pair of employment shocks – one for job loss and one for job finding. Importantly, job loss and job finding probabilities depend on labor market experience just like wages do. Moreover, I distinguish between fixed-term and permanent employment contracts; a labor market shock governs period-to-period transitions from fixed-term to permanent work contracts.

To quantify the effect of parental leave policies on fertility and female labor supply, I simulated counter-factual remaining life-cycles for samples of women affected by parental leave reforms at ages 20, 30 and 40. I consider a reduction of the parental leave job protection period from 3 to 2 years and an extension of the parental leave benefit period from 1 to 2 years, and consider the effects on parental leave hazard rates, age-specific and total remaining fertility rates, the employment rate and the part-time share among female employees.

I find that a reduction in job protection decreases remaining fertility by 4.1 % for the sample affected at age 20, and an extension of benefits increases fertility by 4.7 %. Life-cycle employment effects are rather small and seem to be dominated by indirect effects coming though changes in fertility. Effects on the employment rate are not persistent but effects on the part-time share among female employees are. I conclude that reform effects on parental leave durations tend to overestimate the employment effects of parental leave reforms. On the other hand, usually unobserved effects on total remaining fertility rates seem to be positive for both considered policies.

The paper contributes to at least three strands of literature. First, it adds to the large body of research on the economic determinants of fertility [see Hotz et al., 1997, for a survey]. A recent series of papers have been looking at the causal effect of exogenous unemployment shocks on fertility. Using evidence from plant closures in Austria, Del Bono et al. [2012] found that experiencing a job loss reduces subsequent fertility. Del Bono et al. [2015] extended this analysis and found that the fertility effect of job loss incidence remains even after separately controlling for a subsequent unemployment status. Using data from plant closures in Finland, Huttunen and Kellokumpu [2016] showed a negative fertility effect for women who have lost their job, and no effect for women whose partner has experienced a job loss. One can conclude from these studies that women's own employment prospects matter for their childbearing decisions, and that adverse labor market shocks translate into lower subsequent childbearing. Using German survey data, women who perceive a high risk of becoming unemployed have been shown to have a reduced hazard rate of having a next child [Kreyenfeld, 2010, Hofmann and Hohmeyer, 2013]. Moreover, women who lose their job during recessions display a more pronounced reduction in subsequent fertility [Hofmann et al., 2017]. These findings further highlight the importance of labor market search frictions for the childbearing decision. The dynamic structural model in this paper features job risk prominently: the future risk of involuntary unemployment is taken into account when the childbearing decision is made. Therefore, the important empirical relationship between unemployment risk and fertility is considered in the evaluation of parental leave policies.

In the last decades, there has been a growing interest in the evaluation of parental leave policies. A number of studies have used quasi-experimental methods to analyze the fertility and labor supply effects of parental leave policies exploiting temporal variation of benefits and job protection policies. The literature documents strong positive effects of financial incentives and parental leave job protection periods on the duration of the parental leave: Spiess and Wrohlich [2008] performed an ex-ante policy simulation of a German parental leave benefit reform, which showed that front-loading parental leave benefits reduces the average parental leave duration. Wrohlich et al. [2012] and Kluve and Tamm [2013] confirmed this prediction ex-post. Using several reforms of the parental leave benefit duration and job protection period in Switzerland, Lalive and Zweimüller [2009] showed that increasing the entitlement period for both benefits and job protection for a current child reduces subsequent employment of mothers. In line with this, Schönberg and Ludsteck [2014] found that several extensions of the parental leave job protection period in Germany have increased average parental leave durations of mothers. Findings on fertility effects are more sparse but generally positive. Lalive and Zweimüller [2009] showed in the Swiss context that extensions of the length of the parental leave job protection and benefit period for a current child have a positive effect on the probability to have a next child. Using a similar approach with data from Germany, Cygan-Rehm [2016] showed that reducing parental leave benefit payments for the current child reduced the probability to have a next child. Directly looking at short-term birth rates, Raute [2017] exploited a parental leave benefit reform in Germany and found that increasing benefits had positive fertility effects, which are more pronounced for women being older than 35. Thus, existing studies have found compelling evidence of the effectiveness of parental leave policies on both fertility and female labor supply. These findings are in line with the economic model of female labor supply and fertility presented in this paper. However, conventional reform evaluations face limitations in analyzing the effects of parental leave policies on first-birth hazards and lifetime completed fertility rates: available reforms are invariably only sharp at the birth date of the child, such that women in the control group will move into the treatment group as time progresses. This challenge is overcome by using the structural modeling approach in this paper. I simulate counter-factual parental leave reforms to assess a causal effect of parental leave on first-birth hazards, completed fertility rates, and life-cycle female labor supply.

Finally, the paper adds to the literature on structural models of female labor supply and fertility. Starting with Heckman and Macurdy's [1980] analysis of female labor supply under certainty, a vast literature have used dynamic structural models to answer questions relating to female labor supply. Wolpin [1984] analyzed female life-cycle fertility using a dynamic discrete choice model. Francesconi [2002] estimated a joint model of female labor supply and fertility under earnings uncertainty. Adda et al. [2017] estimated a dynamic discrete choice model of female labor supply and fertility with search frictions and occupational choice. They found that a large part of the lifetime income losses from having children are due to occupational sorting. Moreover, they evaluate the effects of a monetary child benefit to find that life-cycle employment outcomes and completed fertility are only mildly affected by such a reform when long-term adjustments are taken into account. Lalive et al. [2013] revisited the reduced-form findings of Lalive and Zweimüller [2009] to show that parental leave job protection and benefits have their strongest impact when used together. My approach extends their analysis by adding a child-bearing decision in a dynamic discrete choice model. This allows me to identify important trade-offs between fertility and labor supply effects of parental leave policies. I stress the importance of job risk by modeling a detailed process for the risk of job loss and the chance of job finding and making a distinction between fixed-term and permanent work contracts. I identify processes for the various labor market shocks using detailed survey information from the German Socio-economic Panel (GSOEP).

The next section provides an outline of the benefits and job protection policies in Germany. This will give an insight into the important economic considerations in the timing of childbirth, parental leave, and life-cycle labor supply. Following next, I propose a dynamic discrete choice model of female labor supply and fertility (Section 1.2). Afterwards, I discuss the micro data used for the empirical analysis, which is retrieved from the GSOEP (Section 1.3). I then describe the estimation method and identification of the labor market frictions (Section 1.4). Estimation results ans poicy simulations are presented in Sections 1.5-1.6. Section 1.7 concludes.

1.1 Institutions

Similar to other countries, parental leave policies in Germany consist of two parts: a parental leave benefit payment (benefits) and the parental leave job protection (job protection).

Parental Leave Benefit. The parental leave benefit[2] is a wage replacement parents can receive for up to twelve months following the birth of a child. In 2007 it replaced the prior means-tested benefits by an earnings-related payment: for up to 12 months following childbirth, parents on parental leave receive 65 % of their previous year's net earnings as a wage replacement in the baseline scenario. If parents choose to work part-time while on parental leave, net income from part-time work is deducted from the benefits amount. Moreover, a minimum amount of 300 Euro is paid for low-income earners, and the ceiling amount for the parental leave benefit payout is 1,800 Euro. In addition to that, some

[2] Elterngeld.

special provisions apply. Most importantly, parents who choose to share parental leave months between partners are eligible for two extra months of benefit payments.

Parental leave job protection. Contrary to benefits, parental leave job protection[3] constitutes an employee right for parents who are in an employment relationship at the time of childbirth. Within the first three years following childbirth, each parent has the right to reduce work hours or interrupt employment altogether without being at risk of being displaced. Thus, parents who wish or need to take (full-time) care of a newborn can do so flexibly without having to abandon their work position. Therefore, this type of policy is often seen as a means to foster mothers' labor force attachment. On the other hand, eligibility for job protection is not universal: the work contract is only protected if it does not expire during the parental leave. As temporary contracts are common especially for labor market entrants, a substantial fraction of parents can not fully benefit from the job protection policy.

Fertility and Labor Supply Effects. It is easily seen that both benefits and job protection policies make it easier to take some time off after childbirth for previously employed mothers. Moreover, the time limited nature of these policies provides incentives for the timing of return to work. All else being equal, benefits make the first year of parental leave financially more attractive than parental leave in any other year. Somewhat distinctly, job protection induces a sharp decrease in the value of returning to work right at job protection exhaustion. For an in-depth discussion of the economic incentives of both policies in a labor supply framework with unemployment risk, see Lalive et al. [2013]. The central labor market implication of parental leave job protection is that labor force attachment of mothers is strengthened, while parental leave benefits reduce the employment rate within the benefit period.

Fertility effects of parental leave policies are ambiguous. On the one hand, the additional job security and benefit payments increase the value of having a child, with a positive effect on fertility. Parental leave policies, on the other hand, are conditional on labor market aspects such as the wage and the duration of the job contract. When additional labor market experience is expected to lead to higher benefit payments and a longer effective period of parental leave job protection, then deferring the next childbirth might be optimal. This opposing effect on fertility may be called entitlement effect in analogy to the effect of unemployment benefits on labor supply [see, e.g. Hamermesh, 1979], and renders the total fertility effect theoretically ambiguous.

Finally, higher fertility might decrease the overall level of labor supply when there is a complementarity between the number of (small) children and the amount of non-market-work time. This means that a positive fertility effect of parental leave policies might lead

[3] Elternzeit.

to a lower participation rate and a higher part-time share. This effect partially offsets any positive effect of these policies on the labor force attachment of women.

In the next section, I will outline the dynamic discrete choice model of female labor supply and fertility, which I will then use to analyze these mechanisms and the role that parental leave policies play in this context.

1.2 Model

To analyze the incentives provided by parental leave policies, I employ a dynamic discrete choice model of female labor supply and fertility. Individuals are assumed to derive utility from consumption, leisure, and from the presence of children. Hence, they choose an optimal amount of hours worked and an optimal number (and birth time) of children in each period of time. Furthermore, individuals are forward looking and foresee that labor supply has a positive externality on wages in future periods of time. Thus, there is a career rationale that also affects the timing of children. For example, when complementarities exist between children and consumption, women may choose to defer child bearing until a higher wage level is attained. Moreover, labor market frictions exist that pose the threat of involuntary unemployment. The risk of unemployment is also affected by labor market experience, providing an additional career incentive to individuals. Finally, jobs may be of a temporary nature at first, with a period-by-period chance of conversion to a permanent contract with associated lower risk of job loss.

This economic framework captures the policy incentives outlined in Section 1.1. In particular, parental leave benefits will lead to postponements of births for individuals with low wages. Likewise, parental leave job protection will induce postponements of births for individuals with temporary work contracts.

1.2.1 Utility and Income

Since parental leave policies have their strongest impact on the labor supply of women before childbearing age and until a few years after children have been born, I restrict the model's time horizon to the end of the fertile period at age $T^1 = 45$. The life-cycle starts after completion of education at T^0. For simplicity, I do not make individual subscripts explicit.

The model focuses on the economic determinants of women's fertility and labor supply choices. To this end, many non-economic factors and private circumstances are not explicitly modeled. Note that this does not imply that choices are made independently of such private circumstances, but that they rather add to the set of unobserved choice characteristics that affect choice through a random utility component.

At each age $t, t = T^0, \ldots, T^1$, a simultaneous joint decision on the number of hours worked $x_t^w \in \{NW, PT, FT\}$ and conception of a child $x_t^c \in \{C, NC\}$ is made such that

$X_t \equiv [x_t^W, x_t^C]$. Individuals can supply hours of work in three broad categories: full-time (FT), part-time (PT), and non-work (NW). The child decision is binary, conception being denoted by C and non-conception by NC. I define indicator variables ft_t, pt_t, and $conceive_t$ for convenience.

Denote by $S_t \equiv [x_{t-1}^w, edu_t, exper_t, perm_t, jpro_t, nc_t, ac_t, h_t]$ the state variables of the decision maker (individual) at age t. The state space consists of the following elements:

- labor supply in $t-1$ x_{t-1}^w
- education $edu_t \in \{1, 2, 3\}$
- labor market experience $exper_t \in [0, T^1 - T^0] \subset \mathbb{R}$
- permanent work contract in $t-1$ $perm_t \in \{0, 1\}$
- parental leave job protection in $t-1$ $jpro_t \in \{0, 1\}$
- number of children $nc_t \in \{0, 1, 2, 3\}$
- inverse age of youngest child $ac_t \in \{0, 1, \frac{1}{2}, \frac{1}{3}, \ldots, \frac{1}{19}\}$
- presence of a partner $h_t \in \{0, 1\}$

where labor market experience is defined as the cumulative number of years worked, with part-time experience being downward adjusted by a factor of 0.5 to account for working hours[4]. Furthermore, ac_t is defined as $\frac{1}{1+\text{age of youngest child at age } t}$ and $ac_t = 0$ when $nc_t = 0$.

Instantaneous utility Given the state variables and choices, an individual's instantaneous utility at age t has the following mixed-CRRA linear form:

$$\begin{aligned} u_t = & \frac{\tilde{c}_t^{1-\eta} - 1}{1-\eta} \exp\left(\alpha_{c_t}^0 + \alpha_{c,nc}^1 \cdot nc_t\right) + \ldots \\ & \alpha_{pt}^0 \cdot pt_t + \alpha_{ft}^0 \cdot ft_t + \ldots \\ & \alpha_{nc}^0(edu_t) \cdot nc_t + \alpha_{nc^2}^0(edu_t) \cdot nc_t^2/100 + \ldots \\ & \alpha_{ac,t}^1 \cdot ac_t \cdot \tilde{t}(edu_t) + \alpha_{ac,t^2}^1 \cdot ac_t \cdot \tilde{t}(edu_t)^2/100 + \ldots \\ & \left[\alpha_{nc,pt}^1 \cdot nc_t + \alpha_{ac,pt}^1 \cdot ac_t\right] \cdot pt_t + \ldots \\ & \left[\alpha_{nc,ft}^1 \cdot nc_t + \alpha_{ac,ft}^1 \cdot ac_t\right] \cdot ft_t + \ldots \\ & \epsilon_t^u, \end{aligned} \tag{1.1}$$

where ϵ_t^u is an i.i.d. type-1 extreme value distributed random utility shock capturing unobserved choice characteristics. η denotes the coefficient of relative risk aversion, with

[4] This adjustment reflects the relation of mean hours of work in full-time and part-time jobs, as shown in Table 1.B.10 in Appendix 1.B.

$\eta \neq 1$[5], and $\tilde{c}_t \equiv \frac{c_t}{\sqrt{1+h_t+nc_t}}$ is the per-capita consumption according to an equivalence scale, depending on the presence of a husband. The second term in (1.1) captures the overall consumption weight and a complementarity between consumption and the number of children. The following two lines reflect baseline preferences for non-market-work time, and a quadratic preference for the overall number of children. To capture age-dependent preferences for fertility, I assume that mothers have age-dependent preferences for the presence of young children. This is captured by the following line as a quadratic interaction between mother's age and the age of the youngest child. Furthermore, I allow the utility derived from the ages and number of children to interact with leisure as given by any of the two work categories. To account for heterogeneity in fertility preferences across education groups, I define $\tilde{t}(edu_t) \equiv t + \alpha^2_{edu=1} \cdot \mathbb{1}_{\{edu_t=1\}} + \alpha^2_{edu=2} \cdot \mathbb{1}_{\{edu_t=2\}} + \alpha^2_{edu=3} \cdot \mathbb{1}_{\{edu_t=3\}}$ as the shifted age and further allow the preference for the number of children to be heterogeneous across education groups by writing shorthand $\alpha^0_{nc}(edu_t) \equiv \alpha^1_{nc,edu=1} \cdot \mathbb{1}_{\{edu_t=1\}} + \alpha^1_{nc,edu=2} \cdot \mathbb{1}_{\{edu_t=2\}} + \alpha^1_{nc,edu=3} \cdot \mathbb{1}_{\{edu_t=3\}}$.

Income Consumption in each period of time is equal to income y_t, that is, there is no savings. Income is equal to own net labor market income y^o_t including all transfers, plus the net labor income of any partner y^h_t:

$$y_t = y^o_t + y^h_t, \tag{1.2}$$

such that

$$y^o_t = \tau(w_t(ft_t + \beta^{pt} pt_t)), \tag{1.3}$$

where τ denotes the tax- and transfer function, w_t is the full-time equivalent gross wage, and β^{pt} is the share of part-time relative to full-time hours.

Wage equation The wage process assumed in the estimation of the model follows a Mincer type wage equation depending on labor market experience and education:

$$\begin{aligned}\log w_t =& \beta^0 + \beta^1_{edu=2} \cdot \mathbb{1}_{\{edu_t=2\}} + \beta^1_{edu=3} \cdot \mathbb{1}_{\{edu_t=3\}} + \dots \\ & \beta^1_{exper} \cdot exper_t + \beta^1_{exper^2} \cdot exper^2_t/100 + \dots \\ & \beta^1_{pt} \cdot pt_t + \epsilon^w_t,\end{aligned} \tag{1.4}$$

where $\epsilon^w_t \sim \mathcal{N}(0, \sigma_w)$ denotes a normally distributed measurement error. That is, the wage process is deterministic from the perspective of the decision maker but not of the researcher. The parameter β^1_{pt} reflects a part-time wage penalty.

[5] For $\eta = 1$, the CRRA term $\frac{\tilde{c}_t^{1-\eta} - 1}{1-\eta}$ is replaced by $\log \tilde{c}_t$.

1.2.2 Labor Market Shocks

As described in the introduction to Section 1.2, labor market shocks can be of three kinds: job finding, job loss, and obtaining a permanent contract. For ease of exposition, I will first denote these shocks by a vector $Z_t = (z_t^1, z_t^2, z_t^3)$ with attached probabilities $\pi_t = (\pi_t^1, \pi_t^2, \pi_t^3)$ and then summarize the outcomes of Z_t in relevant labor market states.

Let the employment shocks be denoted by z_t^1 for finding a job, and z_t^2 for losing a job such that the random labor market status can be characterized by o_t equal to one if a job is offered (inherited) and zero otherwise. If no job is offered, then there is no hours of work choice and NW is chosen trivially. In addition to the availability of a job offer, offered contracts can be of a temporary or permanent type, governed by the third labor market shock z_t^3 equal to one when changing into a permanent contract is possible. Importantly, a change to a permanent contract is not only possible from non-employment but also from an existing non-permanent position. This is summarized by the variable s_t^p being equal to zero when no contract or a temporary contract is offered, switching to one whenever a permanent job is found or a temporary job is transformed to a permanent one. An on-the-job transition from a permanent to a non-permanent contract is therefore not possible.

I assume that the probabilities of these three random events are independent conditional on the state variables and are given by the following logit functional form:

$$\begin{aligned}\pi_t^j(S_t) = \Big[1 + \exp\Big(&\gamma^{j,0} + \gamma^{j,1}_{edu=2} \cdot \mathbb{1}_{\{edu_t=2\}} + \gamma^{j,1}_{edu=3} \cdot \mathbb{1}_{\{edu_t=3\}} + \dots \\ &\gamma^{j,1}_{exper} \cdot exper_t + \gamma^{j,1}_{exper_t^2} \cdot exper_t^2 \cdot 10^{-2} + \gamma^{j,1}_{exper_t^3} \cdot exper_t^3 \cdot 10^{-3} + \dots \\ &\gamma^{j,1}_{perm} \cdot perm_t\Big)\Big]^{-1},\end{aligned} \tag{1.5}$$

for $j = 1,2,3$, $\gamma^{j,1}_{perm} = 0$ for $j = 1,3$ and $\gamma^{j,1}_{exper_t^3} = 0$ for $j = 1,2$. Equation (1.5) reflects the dependence of labor market frictions on human capital. Importantly, it can be seen that education and labor market experience can work as an insurance against involuntary joblessness. This mechanism can be an important incentive for human capital accumulation when unemployment risk is present. Furthermore, the dynamic model considered makes explicit reference to the term of the job contract, which is an important determinant of job security. This relationship between job security and contract type is modeled via a dependence of the job loss probability on the contract term $perm_t$ in (1.5).

1.2.3 Job Offers

The labor market shocks are governed by the transition probabilities shown in (1.15). The availability of a job offer o_t at age t depends on the previous employment status: when the individual worked in the previous period, then a job is inherited with probability $(1 - \pi_t^2)$ and lost with probability π_t^2. On the contrary, if no job was held previously, then the job availability depends purely on the search outcome π_t^1. However, as explained in Section 1.1, job loss is not possible when the individual is within the legal job protection period. To reflect the heterogeneity in job quality with respect to the job loss probability, I make a distinction between fixed-term and permanent job offers. Whenever an individual in non-employment or on a fixed-term contract gets a job offer in the next period, this job offer may be permanent with probability π_t^3. A permanent work contract may not be revoked for the same job, and a permanent work contract remains permanent upon returning from parental leave. For a mathematical representation of the job offer availability and job term, see Appendix 1.A.

Offered and realized jobs In this model with labor supply choices and frictions, a subtle distinction is made between offered jobs o_t and actually realized labor supply amounts x_t^w: naturally, the set of possible labor supply choices is restricted by the availability of a job offer. Therefore, when $o_t = 0$, the only feasible choice is $x_t^w = NW$. This state may be referred to as unemployment. Likewise does the availability of a permanent job offer s_t^p not determine the status of the realized permanent work contract or its lagged value $perm_t$. Rather, $perm_{t+1} = 1$ will require $s_t^p = 1$ and $x_t^w \neq NW$ in the standard case outside of the job protection period.

1.2.4 Law of Motion

Given current choices X_t, current state S_t, and current labor shocks Z_t the state in the next period $t+1$ is implied by the law of motion g, written

$$S_{t+1} = g(X_t, S_t, Z_t, E_t), \tag{1.6}$$

where E_t denotes a vector of all other shocks affecting the state variables at age $t+1$.

Deterministic state variables Once state variables S_t and choices X_t are known, updating of the deterministic state variables proceeds as follows. First, edu_t is treated as constant across time. Second, one period of full-time work adds one additional year to $exper_{t+1}$, whereas one period of part-time work only adds 0.5. Third, nc_{t+1} and ac_{t+1} are chosen in accordance with x_t^C. That is, $x_t^C = C$ adds an additional child to nc_{t+1} and sets ac_{t+1} to 1. Conversely, $x_t^C = NC$ increases the denominator of ac_{t+1} by one if children are present. Moreover, when the youngest child reaches the age of 18, it is removed from the household such that $nc_{t+1} = 0$.

Stochastic state variables The stochastic state variables are not fully determined from state variables in time t and choices in time t. Rather, they depend on the unobserved labor market shocks Z_t and all other shocks summarized by E_t.

First of all, three independent labor market shocks determine the availability of a job contract and its term: when a job is held, a job can be lost. When this is the case, a job may be found immediately or in the future. Transitions to permanent jobs are possible from a fixed-term job and from unemployment, respectively, but transitions from permanent to fixed-term contracts require intermittent job loss or voluntary quit.

Importantly, the parental leave job protection safeguards a permanent job when the return to work is within the legal time frame. Parental leaves beyond the legal protection period result in layoff. For fixed-term contracts, parental leaves beyond one years result in layoff in the baseline specification[6]. For a mathematical exposition of the law of motion for $perm_t$ and $jpro_t$, see Section 1.A of the appendix.

Finally, the presence of a partner in the household is governed by an age and education specific Markov chain. That is, E_t represents the error term of a logistic regression model of the presence of a partner on a fully interacted set of variables containing lagged outcome, a second-order age polynomial, and education dummies. For details of the estimation, see Appendix 1.B.

1.2.5 Value Functions and Policy Incentives

At each age t, agents maximize expected discounted lifetime utility with respect to the current choice X_t:

$$V_t(S_t) := \mathsf{E}_{Z_t,E_t}\left(\max_{X_t}\left\{\mathsf{E}_{g,ZE}\left(\sum_{s=t}^{T^1}\beta^{s-t}u_s|S_t,X_t,Z_t,E_t\right)\right\}|S_t\right), \tag{1.7}$$

where β denotes the per-period discount factor and V_t is called the individual's value function at the age t. Furthermore, note that the value function depends solely on the state S_t, and consequently $\mathsf{E}_{g,ZE} \equiv \mathsf{E}_{g,(Z_{t+1},E_{t+1}),(Z_{t+2},E_{t+2}),\ldots}$ is the expectation with respect to future shocks and the law of motion for the state variables.

Using standard results from dynamic optimization theory, the value function can be written out recursively for each t as

$$V_t(S_t) = \mathsf{E}_{Z_t,E_t}\left(\max_{X_t}\left\{u_t + \beta\mathsf{E}_{g,Z_{t+1},E_{t+1}}(V_{t+1}(S_{t+1})|S_t,X_t,Z_t,E_t)\right\}|S_t\right). \tag{1.8}$$

The recursive notation of the value functions shows that the value of any given choice alternative X_t at age t depends on the immediate utility flow u_t associated with that choice, and its impact on future expected utilities. The latter dependence is important in the analysis of fertility and female labor supply, as these are highly dynamic choices: considerations of the future employment and family situation are central to the analysis of these

[6] This reflects the fact that parental leave job protection also protects fixed-term contracts, but only up to the end of their term.

behavioral margins.

Conditional Value Functions To shed light on the role of labor market frictions on dynamic decision making, it is useful to define labor market shock specific value functions. Recall that the relevant aspects of the outcome of Z_t are fully captured by the realizations of o_t and s_t^p. Therefore, we can distinguish between three different conditional value functions: the value of being unemployed, employed on a temporary contract, and employed on a permanent contract.

The conditional value of being unemployed is thus:

$$\begin{aligned} U_t(S_t) = \max_{x_t^c} \Big\{ & u^{NW,x_t^c}(S_t, E_t) + \epsilon_t^{x^c} + \dots \\ \beta \mathsf{E}_{g,E_t} & \left[(1 - \Pr(o_{t+1}|S_{t+1}))U_{t+1}(S_{t+1}) + \dots \right. \\ & \Pr(o_{t+1}|S_{t+1})(1 - \Pr(s_{t+1}^p|S_{t+1}, o_{t+1}))V_{t+1}^0(S_{t+1}) + \dots \\ & \left. \Pr(o_{t+1}|S_{t+1}) \Pr(s_{t+1}^p|S_{t+1}, o_{t+1})V_{t+1}^1(S_{t+1})|S_t, Z_t, X_t \right] \Big\}, \end{aligned} \tag{1.9}$$

where E_{g,E_t} denotes the expectation of tomorrow's state S_{t+1} given S_t, Z_t and X_t, following from the expectation of E_t and the law of motion g. Similarly, the extensive form for the other labor market shocks is as follows:

$$\begin{aligned} V_t^j(S_t) = \max_{(x_t^w, x_t^c)} \Big\{ & u^{x_t^w, x_t^c}(S_t) + \epsilon_t^{x^w, x^c} + \dots \\ \beta \mathsf{E}_{g,E_t} & \left[(1 - \Pr(o_{t+1}|S_{t+1}))U_{t+1}(S_{t+1}) + \dots \right. \\ & \Pr(o_{t+1}|S_t + 1)(1 - \Pr(s_{t+1}^p|S_{t+1}, o_{t+1}))V_{t+1}^0(S_{t+1}) + \dots \\ & \left. \Pr(o_{t+1}|S_t) \Pr(s_{t+1}^p|S_{t+1}, o_{t+1})V_{t+1}^1(S_{t+1})|S_t, Z_t, X_t \right] \Big\}, j \in \{0, 1\}. \end{aligned} \tag{1.10}$$

The extensive form highlights two dynamic considerations that the individual has to make when making choices in t: first, choices X_t affect future value functions through the updating of S_t as determined by the law of motion g. Second, future labor market shocks depend on future state variables, such that actions X_t influence future labor market risk through this channel.

Terminal value. At age $T^1 = 45$, the individual receives the terminal value V_{T^1} equal to

$$V_{T^1} = \omega u_{T^1}, \tag{1.11}$$

such that ω denotes the weight that is given to the utility at age T^1 from a life-course perspective.

1.3 Data

I estimate a dynamic discrete choice model of fertility and female labor supply using the microeconomic panel data of the German Socio-economic Panel (GSOEP)[7] from the years of 2007-2014. Estimation based on these fairly recent data has two main advantages. First, changes in fertility patterns are arguably influenced by changes in preferences and social norms over time. Thus, a narrower observation window reduces the risk of confusing policy effects and secular trends in preferences. Second, in 2007 there has been a comprehensive reform of the German parental leave benefit system, changing from a means-tested to an earnings-proportional benefit. To reduce the complexity of the structural model I do not model the pre-reform period.

Descriptive Statistics of Estimation Sample The sample prepared for the structural estimation consists of 7,545 individuals (see Table 1.1). The total number of observed individual-years is 23,118, which makes on average 3.06 time periods observed per sample member, or about 48 % of the observation window (8 years).

The education variable is fixed per individual. I defined three education categories (low, medium, high) according to the maximum education observed for these individuals in the sample[8]. The largest group has up to “medium” education (vocational training, about 60 %), whereas about 27 % belong to the highest education group (higher vocational training and university education).

The second part of Table 1.1 shows the descriptive statistics of the time-varying state variables. Here, the unit of observation is a person-year. Sample members are on average 35.84 years old and have about 8.73 years of hours-adjusted years of labor market experience, where the adjustment factor reflects the mean number of hours worked in part-time jobs relative to mean full-time hours. The adjustment factor is roughly 50 %. Further information on full-time and part-time work experience as well as the hours distribution in full-time and part-time jobs can be found in Appendix 1.3. The mean number of children in the sample is 1.35, where the sample restriction to women with less than or equal to three children has very little effect. On average, the youngest child in the household is 9.9 years old, albeit with substantial variation (standard deviation: 6.64).

Of all female households in the sample, a share of 73 % cohabitates with a partner. Among these, the net income of the partner contributes on average 2,090 € to the household income.

A total of 16,667 women in the estimation sample are observed as employed, which means that the employment share in the sample is 72.1 %. The average monthly full-time equivalent gross wage of employed women is 2,390 €, with a standard deviation of

[7] The GSOEP data used in this working paper are provided by the German Institute for Economic Research (DIW Berlin). I use the 1984-2014 version (v31).

[8] See Appendix 1.B for a detailed description and raw distributions of the variables used from the SOEP.

	Mean	Std	Min	Max	N
Time-Invariant Characteristics					
Low Education	0.12	0.11	0	1	7,545
Medium Education	0.60	0.24	0	1	7,545
High Education	0.27	0.20	0	1	7,545
Time-Varying Characteristics					
Age	35.84	6.38	19	45	23,118
Experience	8.73	5.89	0	29.79	23,118
Number of Children	1.35	1.02	0	3	23,118
Age of Youngest Child	9.90	6.64	0	18	23,118
Partner in Household	0.73	0.20	0	1	23,118
Net Income of Partner	2.09	1.45	0	30	14,940
Gross Wage (in 1,000 €)	2.39	1.22	0.10	9.89	16,677
Permanent Contract	0.86	0.12	0	1	16,677

Table 1.1: Summary Statistics of Estimation Sample

Source: Socio-economic Panel, Years 2007-2014. This table shows the summary statistics for the estimation sample, obtained from row deletion of missings for person-year observations. The descriptive statistics of the time-invariant state variables are based on one observation for each sample member. Descriptive statistics of the time-varying state variables are based on all individual-year observations. Descriptive statistics for the job characteristics are based on all observations where a positive amount of labor was supplied.

1,220 €. The full-time equivalent wage is calculated by multiplying the hourly wage by the average number of weekly work hours observed in full-time jobs (39.11 hours, see Table 1.B.10 in Appendix 1.B). The share of all employed women who had a permanent work contract was 86 %.

Observed Choice Combinations As described in Section 1.2, the model allows for six different choice combinations: three labor supply choices (non-work, part-time work, full-time work), and a binary fertility choice of whether to have a child in the next year (conceive) or not (not conceive). The observed counts of these choice combinations in the estimation sample are shown in Table 1.2. It can be seen that a total of 1,010 births are observed in the estimation sample, and roughly an even share of all births is to women with a non-work, part-time, or full-time status in the year before child birth. However, the total number of non-working women is considerably lower (5,937) than the number of part-time (8,604) or full-time working women (7,568), which means that the empirical probability to conceive a child is highest for the non-working group (5.17 % versus 4.09 % among the employed).

	Fertility	
Labor Supply	Not Conceive	Conceive
No Work	5,937	324
Part-Time	8,604	313
Full-Time	7,568	373

Table 1.2: Observed Choice Combinations

Source: Socio-economic Panel, Years 2007-2014. This table shows the observed numbers of all six possible choice combinations for fertility (columns) and labor supply (rows).

Age Patterns for Labor Supply, Fertility, and Labor Market Risks The descriptive statistics in Tables 1.1 and 1.2 do not reveal the heterogeneity of the sample characteristics over the age at observation. This heterogeneity is important, as changes in labor supply, fertility, and labor market frictions over the life-cycle reflect the inter-temporal trade-offs that are crucial to measuring the impact of parental leave polices on employment and fertility outcomes. However, one should keep in mind that the estimation sample is not a balanced sample of full fertility life-cycles. Rather, differences between age groups also reflect compositional changes in the estimation sample, for example with respect to the education distribution. This will be discussed in Section 1.6 on the counter-factual policy simulation.

Figure 1.1 shows the share of women working part-time and full-time, respectively. It can be seen that – although part-time and full-time work are similar in terms of total observed person-years (see Table 1.2) – part-time work is relatively rare before age 30 (about 15-20 %), while full-time work is the predominant labor market status (45-50 %) in this age group.[9] However, part-time work exhibits a steady upward trend, reaching a maximum of almost 40 % for ages above 40. Full-time work, on the other hand, decreases and levels off to about 30 % from age 35 on. Despite the possibility for compositional changes driving some of this pattern, it is in line with a fertility-driven reduction in the hours of work over the life-cycle. In fact, Figure 1.2 confirms that childbearing is highest around the age of 30, when full-time work is decreasing rapidly. The second graph in Figure 1.2 further shows that the fraction of female households cohabitating with a partner increases in parallel to the birth probability and part-time share, which seems to indicate that the (financial) contribution of the partner to the household (income) is important to explaining life-cycle fertility and employment patterns.

Finally, I emphasize the importance of labor market risks for fertility, female labor supply, and the effectiveness of parental leave policies (see Section 1.1). Figure 1.3 shows that jobs become increasingly secure with age: the probability to lose one's job exhibits a gradual decline over time, being above 5 % per year for women below the

[9] The downward spike for age 20 can be attributed to extremely few observations for the initial ages.

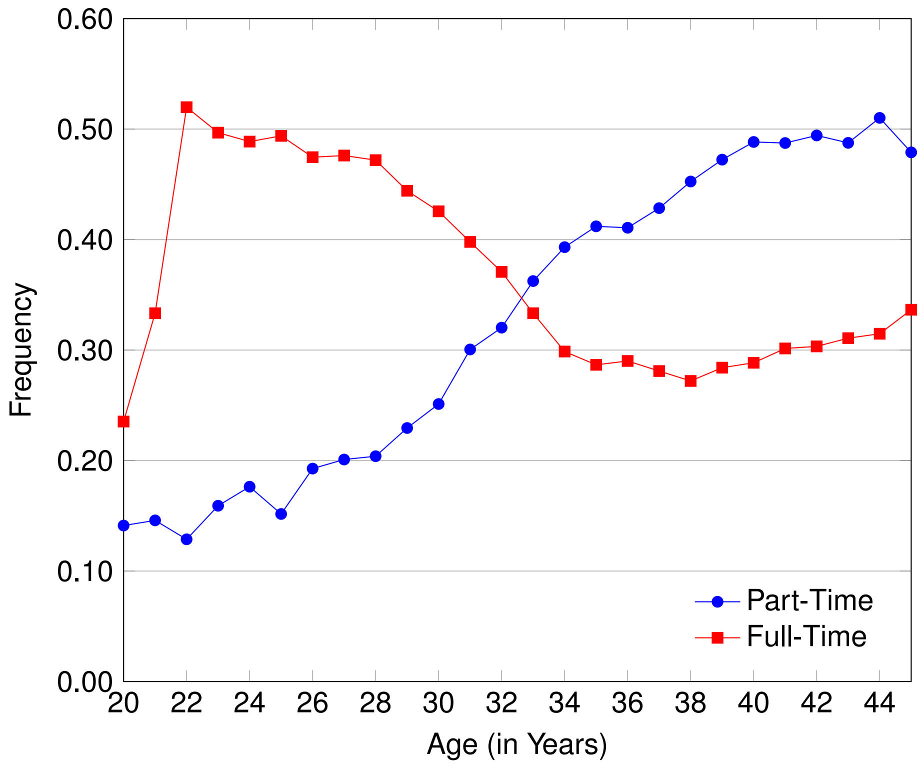


Figure 1.1: Distribution of Part-Time and Full-Time Work over Age

Source: Socio-economic Panel, years 1984-2014. This figure shows the shares of women working part-time and full-time relative to all women in the estimation sample.

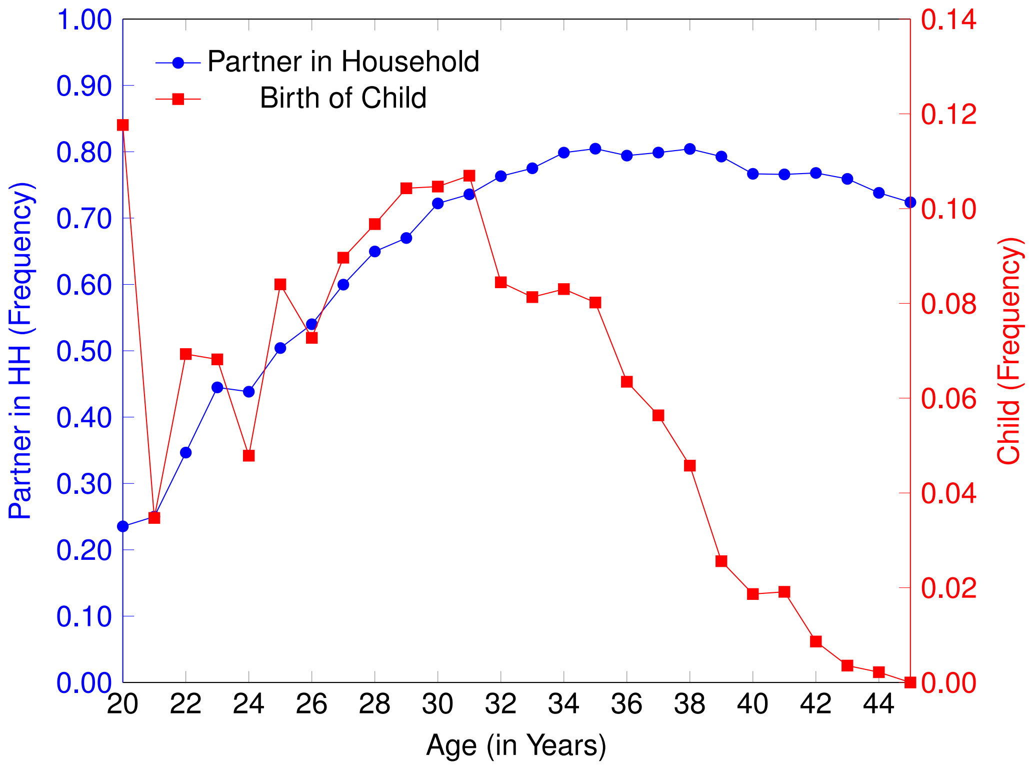


Figure 1.2: Observed Fraction of Women with a Partner and Observed Birth Probabilities by Age

Source: Socio-economic Panel, years 1984-2014. This figure shows the shares of female households in the estimation sample for whom a cohabitating partner is observed, and the age-specific probability of giving birth to a child in the estimation sample.

age of 30. For higher age groups, the risk to lose one's job reaches its lowest point around 3 % toward the age of 45. Conversely, the probability to have a permanent job for all previously non-employed or non-permanently employed working women shows an upward age trend, but is consistently high and between 40 and 70 %. Thus, labor market risk declines with age, which might pose a disincentive for having children at younger ages. Importantly, birth probabilities in Figure 1.2 are rising strongest at ages 25-30, which is when labor market risks are reduced most drastically.

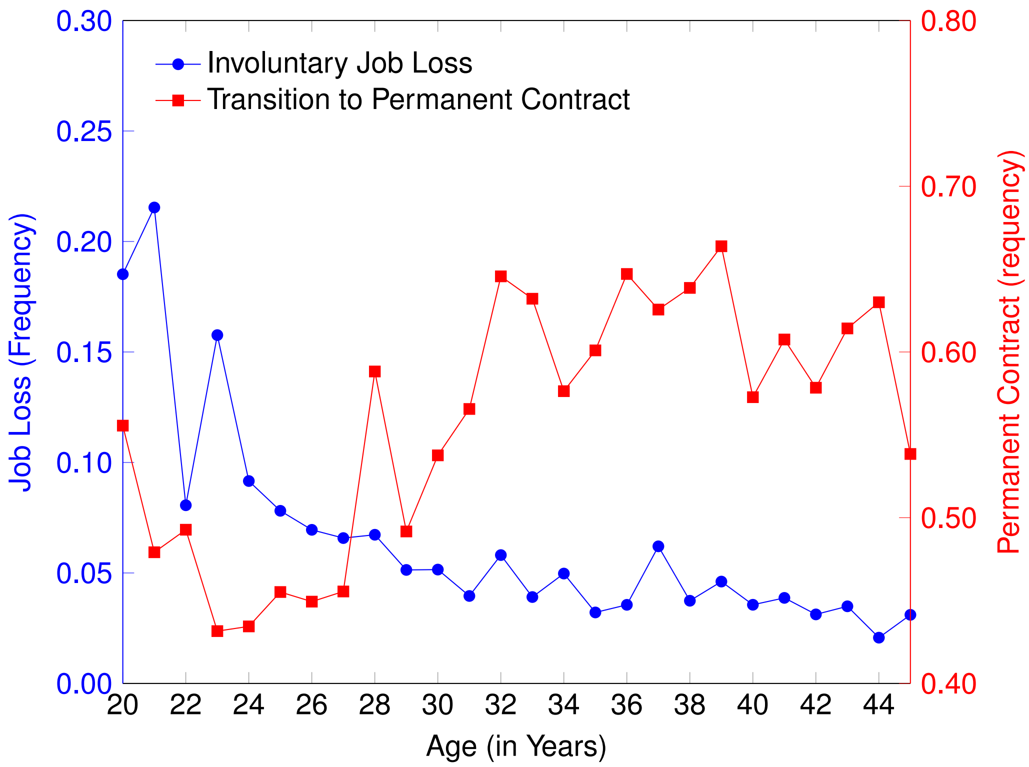


Figure 1.3: Risk of Involuntary Job Loss and Transitions to Permanent Contract by Age

Source: Socio-economic Panel, years 1984-2014. This figure shows the observed risk of being displaced for employed women and the observed risk of obtaining a permanent work contract for all women who were either non-employed or employed on a fixed-term contract in the previous period.

1.4 Estimation Method

I estimate the model using maximum likelihood estimation, where the likelihood function includes additional terms in order to utilize available information on observable labor market shocks. In Section 1.4.2, I discuss the identification of labor market frictions in detail.

1.4.1 Likelihood Function

To define the likelihood function for the dynamic model, first consider that we have four types of data at hand: 1. state variables $s \equiv (s_{it})_{i=1,\dots,N;t=1,\dots,T}$ with s_{it} being a vector of state variables for observation i, t, 2. choice variables $x \equiv (x_{it})_{i=1,\dots,N;t=1,\dots,T}$ with x_{it} being the two-dimensional vector of the labor market choice $x_{it}^W \in \{NW, PT, FT\}$ and choice of conception $x_{it}^C \in \{C, NC\}$, 3. labor market frictions $z \equiv (z_{it})_{i=1,\dots,N;t=1,\dots,T}$ such that $z_{it} \equiv [z_{it}^1, z_{it}^2, z_{it}^3]$ denotes job finding, job loss, and transition to a permanent contract, receptively, 4. wages w_{it}, and 5. the stochastic arrival of a partner e_{it}.

Denote the conditional probability density of one observation i, t given state s_{it} and model parameters θ by $f(x_{it}, z_{it}, w_{it}, e_{it}|s_{it}, \theta)$. From the model assumptions, we know that z_{it} and $, e_{it}$ do not depend on x_{it} (conditionally on s_{it}) from the timing of labor market, non-labor market shocks and choices, and that z_{it} and e_{it} are independent conditionally on s_{it}. Similarly, wages w_{it} are independent of (x_{it}, z_{it}, e_{it}) conditionally on s_{it}. Therefore, the i, t-th likelihood contribution $\mathcal{L}_{it}^1$ can be written in the following simple form:

$$\widetilde{\mathcal{L}}_{it}^1 \equiv \widetilde{\mathcal{L}}^1(\theta|x_{it}, z_{it}, w_{it}, e_{it}, s_{it}) = \Pr(x_{it}|z_{it}, e_{it}, s_{it}, \theta) \Pr(z_{it}|s_{it}, \theta) \Pr(e_{it}|s_{it}, \theta) f(w_{it}|s_{it}, \theta), \tag{1.12}$$

where $\Pr(x_{it}|z_{it}, e_{it}, s_{it}, \theta)$ is called the conditional choice probability (CCP) of choice x_{it}, and f denotes the (normal) density function of the wage measurement error. This likelihood function is, however, not feasible for estimation, since labor market shocks z and wages w are unobserved in many cases.

For wages, this is the case in all periods with no work, i.e. $x_{it}^w = NW$. Missing wage observations with $x_{it}^w \neq NW$ are assumed to be missing at random. In any case, the likelihood with a missing wage observation is given by

$$\widetilde{\mathcal{L}}_{it}^0 \equiv \widetilde{\mathcal{L}}^0(\theta|x_{it}, z_{it}, e_{it}, s_{it}) = \Pr(x_{it}|z_{it}, e_{it}, s_{it}, \theta) \Pr(z_{it}|s_{it}, \theta) \Pr(e_{it}|s_{it}, \theta). \tag{1.13}$$

The treatment of missing labor market shocks applies the same logic, but the dependence of the CCPs on the realization of the labor market shocks makes things slightly more complicated. Again, we assume that the observability of the variable in question is either fully determined by the observed variables in i, t, or missing at random. The first case arises, for example, when we cannot observe a transition to a permanent contract because $x_{it}^w = NW$. Also, as explained in Section 1.3 the GSOEP does not provide information on job finding, such that z^1 is never observed. In all cases with missing labor market shocks, the likelihood contribution is obtained from integration. Thus, the likelihood contribution for the i, t-th observation is given by

$$\mathcal{L}_{it}^{j} = \begin{cases} \sum_{z^1} \sum_{z^3} \widetilde{\mathcal{L}}_{it}^{j} & \text{if } z_{it}^{2} \text{ observed,} \\ \sum_{z^1} \sum_{z^2} \widetilde{\mathcal{L}}_{it}^{j} & \text{if } z_{it}^{3} \text{ observed,} \\ \sum_{z^1} \widetilde{\mathcal{L}}_{it}^{j} & \text{if } z_{it}^{2},\ z_{it}^{3} \text{ observed,} \\ \sum_{z^1} \sum_{z^2} \sum_{z^3} \widetilde{\mathcal{L}}_{it}^{j} & \text{if no } z_{it}^{k} \text{ observed,} \end{cases} \tag{1.14}$$

for $j \in \{0, 1\}$ and $k \in \{1, 2, 3\}$.

1.4.2 Identification of Labor Market Frictions

A vital element of the model of female labor supply and fertility is the effect of work and fertility decisions on future unemployment risk. Classical estimation of the dynamic discrete choice model from CCPs alone is not sufficient for estimation in this case. To see this, consider the corresponding fourth case in (1.14). Since z_{it} is never observed in this case, likelihood estimation solely based on CCPs and wages cannot observationally distinguish a situation with low job availability (low job finding, high job loss) from a situation with high leisure preference. Therefore, information on demand constraints in the labor market is included in the likelihood.

Directly observed labor market shocks are available from the GSOEP for job loss events and a transition to a permanent job contract. Identification of the transition process from fixed-term to permanent positions is straightforward from all observed such transitions. Given the survey information on a job loss in the recent survey year, it is necessary to distinguish leisure preferences from (unobserved) job finding rates. Following Haan and Prowse [2014], leisure preferences can be determined from transitions from work to non-work when no job loss has been observed (voluntary transition to non-work). Then, job finding probabilities are identified from transitions from non-work into work when a job loss is observed.

1.4.3 Two-Step Estimation

To estimate the parameters of the model, I perform a two-step estimation, where the wage equation (1.4), the observed labor market frictions (job loss and transition to permanent contract) in (1.5), and the stochastic process for the presence of a partner are estimated in a first step. Estimation of the remaining model parameters, i.e. preference parameters and job finding probabilities, then proceeds by maximizing (1.14) conditional on the pre-estimated parameters. In general, this causes a loss in efficiency compared to joint estimation.

1.5 Results

In this section, I provide estimation results from a full likelihood based estimation of the dynamic discrete choice model of female labor supply and fertility.[10] Estimation is performed using full maximum likelihood estimation as described in Section 1.4.1 based on the SOEP data described in Section 1.3. Given the utility function, the wage equation and transition equations in Section 1.2, assessing the plausibility of the parameter estimates is an important specification check. Moreover, I will discuss the in-sample fit of the two decision margins graphically.

1.5.1 Parameter Estimates

Parameter	Estimate (Std.-Err.)		
Consumption			
η			0.71 (0.33)
ω			1.41 (0.07)
α_c^0			-1.56 (0.40)
$\alpha_{c,nc}^1$			0.46 (0.05)
Leisure			
α_{pt}^0			0.46 (0.05)
α_{ft}^0			1.47 (0.07)
$\alpha_{ac,pt}^1$			-3.19 (0.11)
$\alpha_{ac,ft}^1$			-6.21 (0.13)
$\alpha_{nc,pt}^1$			0.25 (0.02)
$\alpha_{nc,ft}^1$			-0.63 (0.03)
$\alpha_{ac,T}^1$			-5.74 (0.82)
Family composition			
$\alpha_{ac,t}^1$			0.39 (0.02)
α_{ac,t^2}^1			-1.47 (0.12)
Heterogeneity parameters	*Low edu*	*Mid edu*	*High edu*
$\alpha_{nc,edu=*}^1$	-0.02 (0.06)	0.20 (0.05)	0.27 (0.06)
$\alpha_{nc^2,edu=*}^1$	-0.07 (0.01)	-0.16 (0.01)	-0.20 (0.01)
$\alpha_{edu=*}^2$	3.45 (0.91)	1.05 (0.85)	-0.96 (0.85)

Table 1.3: Estimated Parameters of Utility Function

Source: Socio-economic Panel, years 2007-2014. This table shows the observed numbers of all six possible choice combinations for fertility (colums) and labor supply (rows).

[10]The author would like to thank the HPC Service of ZEDAT, Freie Universität Berlin, for computing time.

Table 1.3 shows the parameter estimates[11] of the utility function (1.1). As a whole, utility estimates are well in line with economic intuition. First, I estimate a coefficient of relative risk aversion of 0.71, lower than the estimate obtained by Adda et al. [2017]. This is against the backdrop of a lower discount rate of $r = 10\%$, but without modeling savings.

As to the utility parameters for the family composition, the estimation results point to (a) decreasing marginal utility of the total number of children ($\hat{\alpha}^1_{nc,edu=*}$ and $\hat{\alpha}^1_{nc^2,edu=*}$), and (b) an inverted-U shaped age pattern with respect to the utility of having young children in the household ($\hat{\alpha}^1_{ac,t}$ and $\hat{\alpha}^1_{ac,t^2}$). Furthermore, it can be seen that the reference age for the fertility preferences is roughly 2.5 years later for middle educated than for low educated, and further one year later for the high education group ($\hat{\alpha}^2_{edu=*}$).

Parameter estimates on leisure complementarities with family composition are quite plausible. Specifically, there is a positive complementarity between income and family size, as indicated by positive sign of $\hat{\alpha}^1_{c,nc}$. Moreover, the inverse age of the youngest child ac has a detrimental effect on working for both work categories ($\hat{\alpha}^1_{ac,pt}$ and $\hat{\alpha}^1_{ac,ft}$), which is stronger for full-time work. However, having many children has a negative effect on working full-time ($\hat{\alpha}^1_{nc,ft}$) but even a positive effect of working part-time ($\hat{\alpha}^1_{nc,pt}$).

	Est.	Std.-Err.
$\beta^1_{edu=2}$	0.163***	(0.022)
$\beta^1_{edu=3}$	0.539***	(0.023)
β^1_{exper}	0.047***	(0.004)
$\beta^1_{exper^2}$	-0.113***	(0.016)
β^1_{pt}	-0.078***	(0.011)
β^0	0.206***	(0.025)
N		16,678
Adjusted R^2		0.204

Table 1.4: Estimated Parameters of Wage Equation

Source: Socio-economic Panel, years 2007-2014, own calculations. This table shows the estimated parameters of the wage equation (1.4), obtained from a linear regression of the logarithmic monthly wage in 1,000 € on education, experience, and a dummy variable indicating part-time work.

The estimated wage equation in Table 1.4 shows that accumulating work experience is rewarded in the labor market, with an initial 5 % gain from full-time work ($\hat{\beta}^1_{exper}$) and decreasing returns to experience ($\hat{\beta}^1_{exper^2}$). There exists a wage penalty for working part-time in the amount of 7.8 %.

Turning to the estimates of the labor market frictions in Table 1.5, the intuition from earlier sections can be confirmed: accumulating human capital through labor supply serves

[11] Parameter estimates shown are for the model with effective maximal parental leave job protection for fixed-term contracts P^{fix} of 1 year. Alternative values of $P^{fix} = 0, 2, 3$ have been shown to yield inferior in-sample fit in robustness estimations.

	Find Job		Lose Job		Get Permanent	
	Est.	Std.-Err.	Est.	Std.-Err.	Est.	Std.-Err.
$\gamma^{*,1}_{edu=2}$	0.329***	(0.068)	-0.254	(0.172)	0.127	(0.143)
$\gamma^{*,1}_{edu=3}$	0.669***	(0.081)	-0.468**	(0.184)	-0.244	(0.150)
$\gamma^{*,1}_{exper}$	-0.051***	(0.014)	-0.147***	(0.028)	0.124***	(0.025)
$\gamma^{*,1}_{exper^2}$	0.165**	(0.073)	0.488***	(0.129)	-0.473***	(0.126)
$\gamma^{*,1}_{exper^3}$	-		-		-	
$\gamma^{*,1}_{perm}$	-		-1.420***	(0.101)	-	
$\gamma^{*,0}$	-0.606***	(0.073)	-1.045***	(0.187)	-0.318**	(0.147)
N	-		11,624		11,624	
Pseudo-R^2	-		0.079		0.079	

Table 1.5: Parameter Estimates of Labor Market Shocks

Source: Socio-economic Panel, years 2007-2014, own calculations. This table shows the estimated parameters of the equations for the labor market frictions in (1.5). The parameters of π_t^2 (job loss shock, column 2) and π_t^3 (transition to permanent position, column 3) were obtained from a logistic regression of the binary outcome variables on education and experience, and additionally a dummy variable indicating a permanent work contract in period $t-1$ for the job loss probability. The parameter estimates for π_t^1 were obtained from likelihood estimation of the structural model.

as an insurance in the labor market. This happens via two different channels. First, labor market experience has a negative but decreasing effect on the probability to be displaced ($\hat{\gamma}^{2,1}_{exper}$ and $\hat{\gamma}^{2,1}_{exper^2}$). Second, there is an indirect channel from transitions to a permanent position: being in a permanent contract drastically reduces the job loss probability ($\hat{\gamma}^{2,1}_{perm}$), and gaining experience increases the probability of acquiring such a job contract ($\hat{\gamma}^{3,1}_{exper}$ and $\hat{\gamma}^{3,1}_{exper^2}$). These two effects are somewhat offset by a negative but decreasing effect of labor market experience on the probabiloty to find a new job. Overall, the results show that experience may increase both earnings and job security.

1.5.2 Goodness of Fit

In order to assess the in-sample fit of the estimated structural model, I compare actual to simulated choice frequencies at different ages. To simulate the labor supply and fertility choices I replicated each sample observation M $(= 30)$ times, thus giving me 30 times 23,118 (=693,540) simulated person-years. Then I forward-simulated a complete path of choices and states for each of the 30 times 7,545 (=226,350) synthetic sample members, starting at the age at entry into the sample. When there were missing observations, these observations were set to missing in the simulated sample as well. This simulation technique preserves the sample composition not only in terms of the distribution of education, but also with respect to the distribution of the individual observation window patterns.

The prediction error from forward simulation accumulates with the age of the simulated individuals, as misprediced choices feed back into the prediction of the state variables. Thus, the fit compares the paths of individual choices observed in the sample. Thus, this is a stricter test for model adequacy than comparing the choice probabilities conditional on the observed values of the state variables. However, the potential for accumulation of large prediction errors over the life-cycle is limited by the fact that only very few individuals exhibit uncensored spells, with a majority of spells being observed less than five time periods.

To analyze the goodness of fit, I compared observed and simulated full-time and part-time work proportions for different ages, age-specific average birth probabilities, and the wage distribution. Note that the age patterns shown in the goodness-of-fit statistics are not directly interpretable, as the sample composition (for example in terms of education) changes for different ages due to the generation of the data set described in Appendix 1.B. For the estimation of the model, this is unproblematic as long as the conditional choice probabilities are correctly specified, but the counter-factual policy simulations in Section 1.6 must account for compositional changes.

Fit of Employment Outcomes Figure 1.4 shows the fraction of part-time and full-time work over the life-cycle, for the actual and simulated data. Overall, it can be confirmed that the fit looks reasonably well in that the model is able to replicate the marked hump shape in age specific full-time probabilities and the steady increase in the proportion of part-time work seen in the sample. At this point, note that the model does not allow for any age-dependence in leisure preferences.

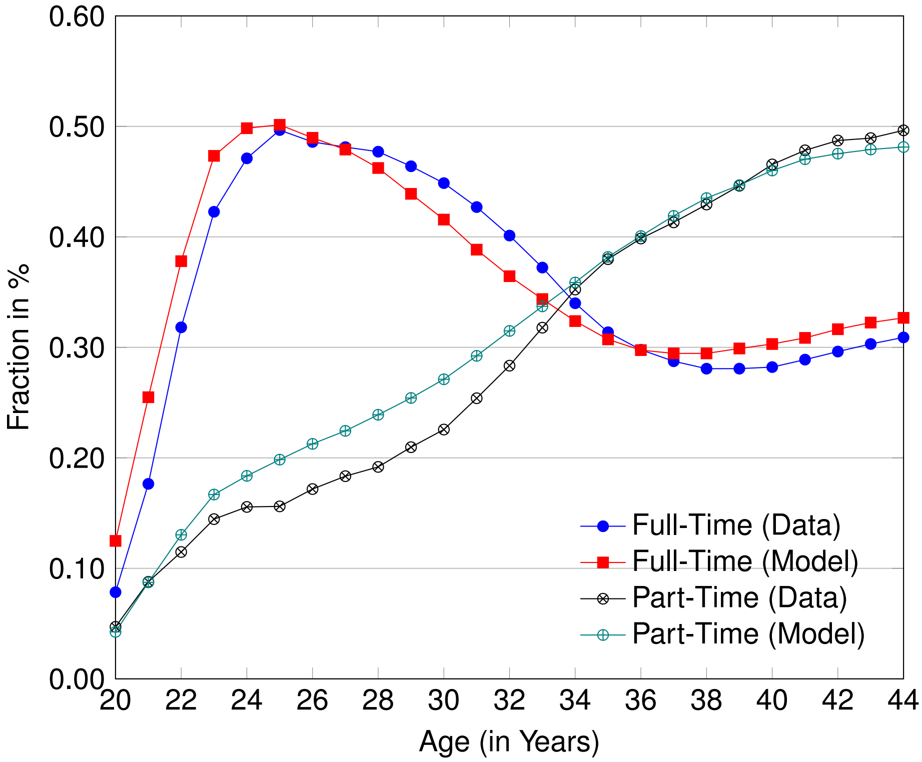


Figure 1.4: In-Sample Fit for the Fraction of Observed Part-Time (PT) and Full-Time (FT) Choices by Age

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the actual and fitted distribution of the age-specific probabilities to work part-time and full-time, respectively. Data and fitted values were smoothed using a moving average filter. For the simulation, each sample observation was replicated $M = 30$ times, and the simulated wages include a normally distributed measurement error.

Fit of Birth Probabilities The overall fit of the age-specific birth probabilities is quite good. The slight under-prediction of the fertility rate for ages below 25 is completely explained by women with low education, for whom also lower (full-time) employment rates are seen at these ages. This may point to a pattern of preferences over the career-family margin that is unique in the group of low educated women. However, it should be noted that the observed sample at these ages is rather small.

Fit of Wage Distribution Figure 1.6 displays the in-sample fit for the distribution of observed full-time equivalent wages (in 1,000 €, logarithmized). To simulate wages, the normally distributed measurement error was added to predicted wages. The model places

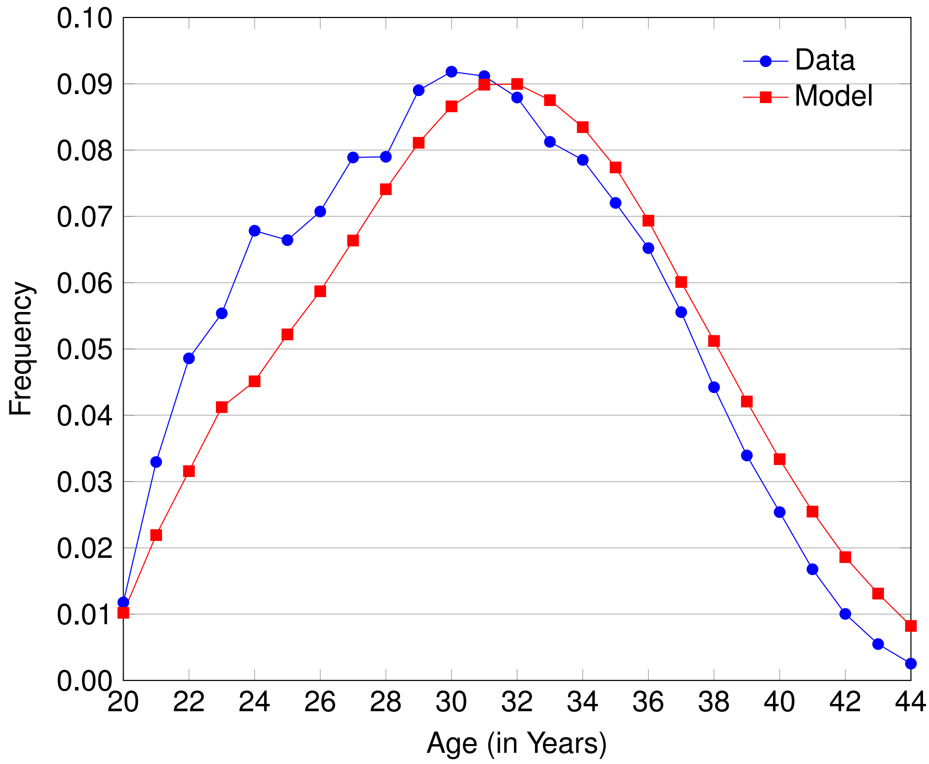


Figure 1.5: In-Sample Fit for the Probability of Giving Birth to a Child by Age

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the actual and fitted distribution of the age-specific probability to give birth to a child. Data and fitted values were smoothed using a moving average filter. For the simulation, each sample observation was replicated $M = 30$ times, and the simulated wages include a normally distributed measurement error.

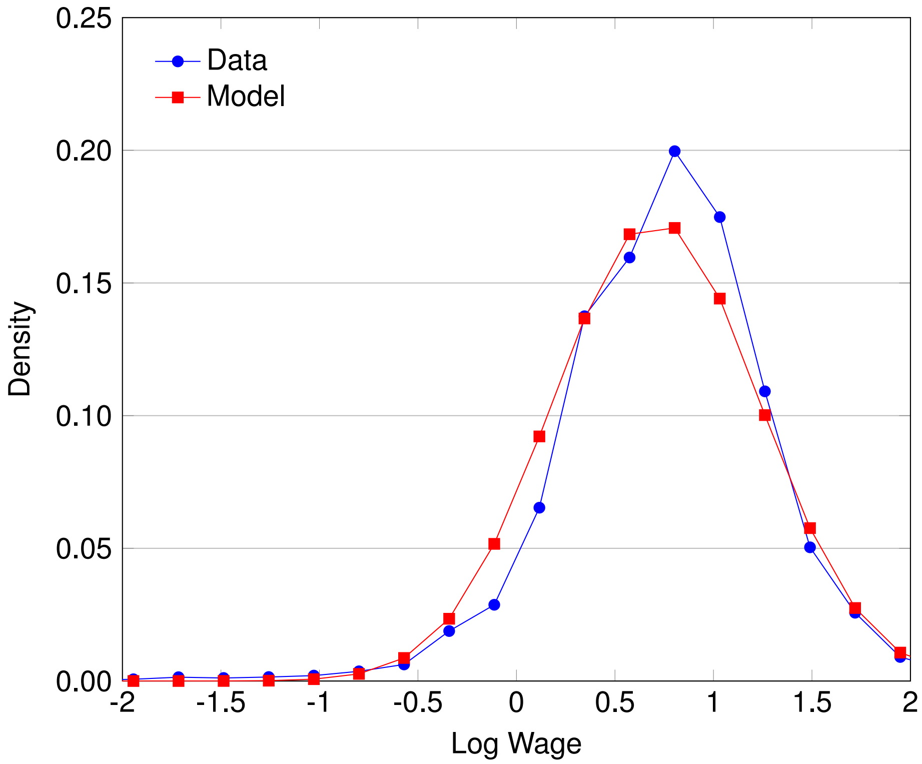


Figure 1.6: In-Sample Fit for the Distribution of Wages

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the empirical density for the actual and fitted distribution of the full-time equivalent monthly gross wage in 1,000 €, logarithmized, with a bin width of 0.5. For the simulation, each sample observation was replicated $M = 30$ times, and the simulated wages include a normally distributed measurement error.

a slightly higher mass on wages around 1,000 €, and instead under-predicts the fraction of women earning about 2,500 €. However, this difference does not appear to be economically significant to the extent that it would change the results of the estimation.

1.6 Policy Simulation

The estimated structural model of female labor supply and fertility is useful for a comprehensive assessment of the impact of parental leave policies on employment and fertility outcomes. Specifically, the framework of the model can distinguish the effects of changes in the parental leave job protection period and parental leave benefits. To compare these policy instruments, I consider one-year changes in the legal entitlement period of these policies as “marginal effects”. The baseline entitlement period is three years for job protection and one year for benefits.

To simulate the reform effect, it must be decided at what age the reform affects the economic agents. The earlier in life a decision maker is affected by a reform, the more time the reform has to unfold its full potential in terms of lifetime outcomes. In the given context, this means that any observed response to a policy may influence subsequent decisions through, for example, changes in human capital accumulation or the family composition. One notable example of the importance of these life-cycle effects is the relationship between timing and completed fertility effects: short-run fertility effects typically observed in reduced-form studies do not have to say much about this distinction. However, the direction of these long-run effects is not ex-ante clear: short-run effects may be compensated or amplified throughout the life-cycle.

To analyze the impact of parental leave policies on (remaining) life-cycle effects at different ages, I select the cross-section of individuals at ages 20, 30, and 40, respectively, and forward-simulate the full remaining life-cycle from that age on, for a synthetic sample of 10,000 replicants[12]. In principle, the effect for individuals at age 20 at reform phase-in will come closest to the long-run fertility effect for the full population. However, since individuals only enter the sample upon completion of their education, the forward-simulation for this age group is biased towards the effect in the low education group. However, the impact of the reform at age 30 will be representative in terms of education.

Scenario I considers a change in the parental leave job protection period. Since the baseline period is already quite extensive at three years, I consider a one-year reduction of the job protection period, i.e. to two years. Scenario II considers a one-year extension of the maximal entitlement to parental leave benefits, keeping the replacement rate the same. To analyze the employment effects, I first look at parental leave durations (Section 1.6.1). Since I consider parental leave policies, this is is the most natural employment outcome. By definition, parental leave durations are conditional on fertility (Section 1.6.2).

[12] That is, the simulation sample is a balanced panel with 10,000 individuals. Moreover, the distribution of initial conditions at the starting ages 20, 30, and 40 reflects the distribution in the data.

However, life-cycle employment is affected not only by the duration of parental leaves, but also on their incidence, i.e. fertility. Moreover, long-run employment effects occurring after a return from parental leave or among women who were not employed (immediately) before childbirth. These “indirect” employment effects may also take the form of changes in the share of part-time jobs among all employment. Life-cycle employment effects will be discussed in Section 1.6.3.

1.6.1 Parental Leave Durations

The parental leave reforms simulated in scenario I and II directly affect the incentives to take parental leave: all other things equal, reducing the maximal parental leave job protection period reduces the incentives to take parental leaves of three years and makes early return to work more attractive. Likewise, extending the maximal benefit period for parental leave benefits from one to two years increases the financial incentives to take a second year of parental leave.

To compare the counter-factual parental leave durations for the different scenarios, I plot discrete-time (yearly) hazard rates for the simulation samples starting at age 20, 30, and 40. Figures 1.7-1.9 display the hazard rate, which is defined as the hazard rate of returning to work after a certain number of elapsed years on parental leave. The parental leave duration is defined as the number of consecutive years in non-employment starting in the year of child birth, for women who were employed immediately before their child was born.

Baseline Simulation First of all, looking at the reform phase-in at age 20 depicted in Figure 1.7, it can be seen that the baseline regime produces a pronounced peak of the hazard rate after three years of parental leave: while only very few women (7.2 %) do not take a full year of parental leave, 37.7 % of the remaining mothers return after one year, and the hazard rate gradually increases until it reaches 58.4 % after three years of parental leave. After that, the hazard rate levels off to somewhat between 20 and 30 %.

For the baseline simulations from age 30 and 40 in Figures 1.8 and 1.8, the picture looks similar, although exit rates are higher for these age groups, possibly reflecting the on average higher education and higher labor market experience in these age groups.

Scenario I: Reduction of Parental Leave Job Protection As expected, reducing the maximal period of parental leave job protection has a strong effect on actual parental leave durations: women who would otherwise return after year three now face an earlier expiration of their legal claim to return to their job, which is reflected in a shift of the peak in the hazard rate from year 3 to year 2. Interestingly, exit hazards in subsequent years (year 4 and beyond) are falling significantly in response to the reform. To understand this, it should be pointed out that the only group affected by the reform is mothers who would

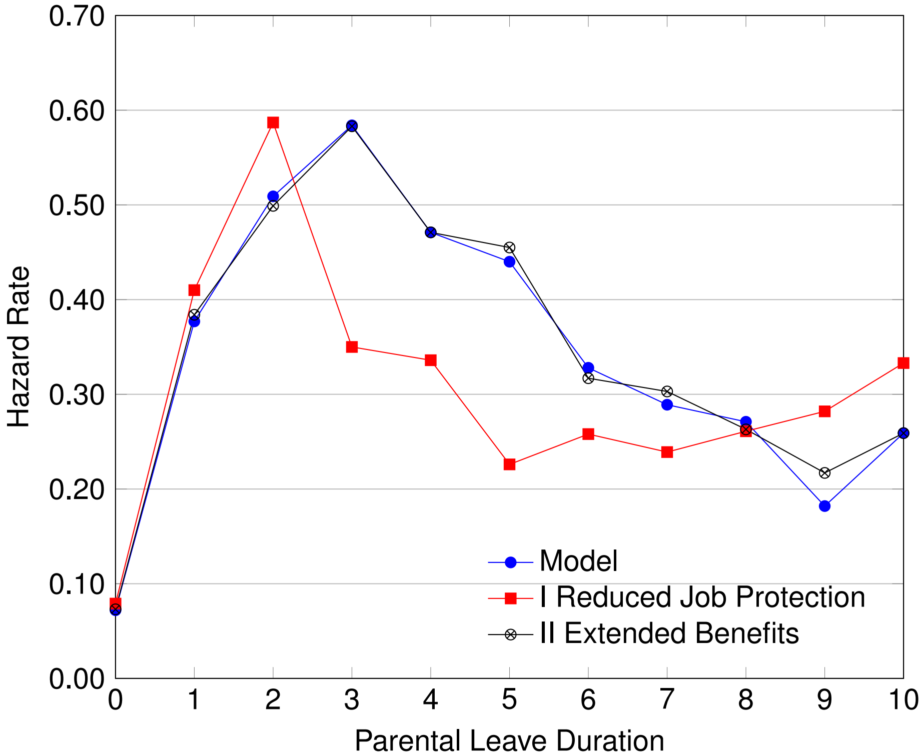


Figure 1.7: Simulated Hazard Rate for Parental-Leave Durations: Reform at Age 20

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the discrete-time exit hazard from parental leave, for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). The hazard rate after duration d is defined as the risk of taking up employment for women on parental leave for d years. Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 20-year old women in the original data set, who were forward-simulated until age 45.

have otherwise returned after exactly three years. As can be seen from figures 1.7-1.9, only about one third of these women decide to return earlier in response to the reform.[13] The remaining mothers actually forgo their right to return and need to find a new job if they want to. Moreover, it is possible that the reform changed the composition of mothers, such that this pattern would reflect this compositional change.

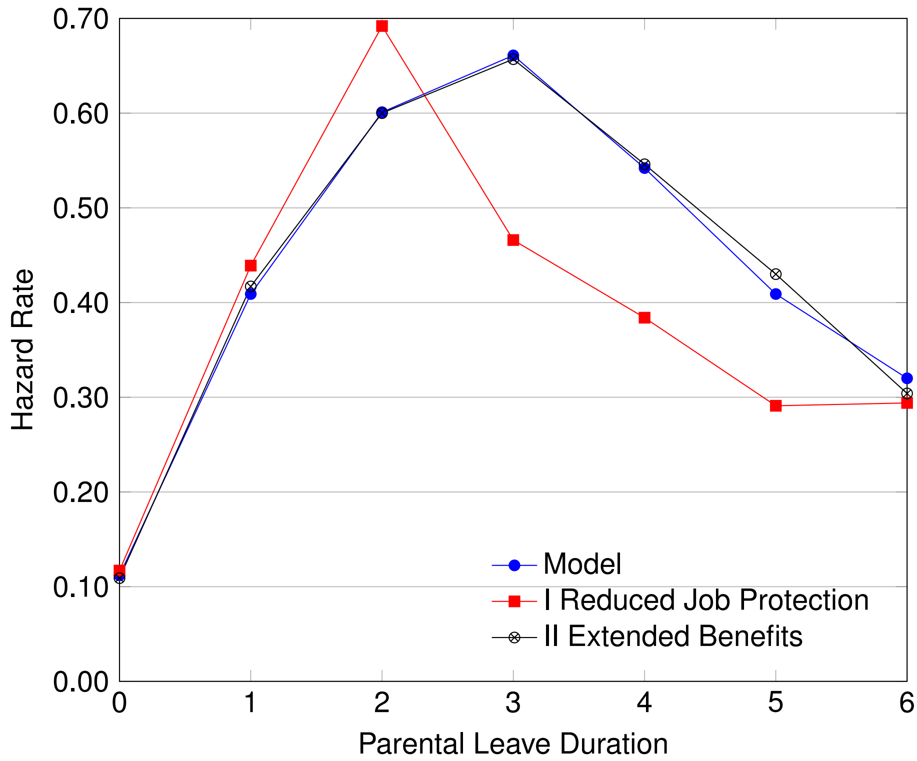


Figure 1.8: Simulated Hazard Rate for Parental-Leave Durations: Reform at Age 30

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the discrete-time exit hazard from parental leave, for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). The hazard rate after duration d is defined as the risk of taking up employment for women on parental leave for d years. Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 30-year old women in the original data set, who were forward-simulated until age 45.

Scenario II: Extension of Parental Leave Benefits As described in Section 1.1, extending parental leave benefits to two years increases mothers' incentives to reduce work hours in the second year after child birth. However, the policy does not require benefit recipients to not work as long as their working hours are lower than before the birth of the child. Figures 1.7-1.9 do not indicate that the extension of parental leave benefits to

[13] For the starting age 20, the calculation is as follows: about 40.9 % $\times$ 58.4 % = 28.6 % of mothers taking at least two years of parental leave would return exactly after three years, whereas the increase in the hazard rate at year 2 is only 7.8 %, which amounts to a fraction of 27.2 % of affected women returning earlier. For the other starting ages, the fractions of shifters are 26 % and 34.5 %, respectively.

two years changed the return-to-work hazard functions. Taken at face value, this suggests that the parental leave duration is far more responsive to changes in the legal job protection period than to changes in financial benefits. Given the existing evidence on measured responses to changes in parental leave benefits, for example by Lalive et al. [2013], this result is surprising. However, there are important differences between the simulated reform and previously evaluated cases. First, parental leave benefits in Germany do require non-work for eligibility. This means that parents can benefit from a longer benefit duration even when no adjustment of parental leave durations is observed. Secondly, existing evaluation studies do not account for any adjustment in birth spacing: to identify the causal effect of longer parental leave benefit periods on parental leave durations, usually a time discontinuity in the eligibility period with respect to the birth date of the child is exploited. This means that parents do not have the option to adjust to the reform, which is one reason why evidence on fertility responses is much less abundant that on parental leave durations *conditional on conception*. As I show in Section 1.6.2, fertility indeed changes in the simulation of Scenario II, which indicates that financial benefits matter. However, I cannot rule out completely that the model fails to capture some aspects of the employment response to parental leave benefits.

As the parental leave policies are conditional on having worked prior to having a child, the parental leave durations shown in this section are for (previously) working women only.

1.6.2 Fertility

Parental leave policies are considered to foster female labor supply and at the same time increase fertility. However, to measure the effects on parental leave reforms on fertility outcomes, three main challenges have to be faced. First, causal identification of the reform impact requires a credible quasi-experimental (treatment-control) setting. Second, to decide whether an increase in the individual-specific hazard rate of having a next child is an effect on completed fertility or a mere timing effect, high data requirements covering a long time horizon have to be met. Third, the age at which women are affected by a reform matters for their ability to respond to a reform: while women in higher age groups adjust their subsequent fertility choices based on past choices optimal under the old regime, younger women might adjust their full path of employment and childbearing decisions. This means that age-specific fertility rates are differently affected depending on the age at the reform date.

To overcome these problems, I perform counter-factual policy simulations of full remaining fertility life-cycles, starting at ages 20, 30, and 40. As described in Section 1.5, the sample of women at age 20 is not representative with respect to the education distribution, and will be biased towards the response for women with low and medium education. However, this sample will come closest to the fully adjusted lifetime response

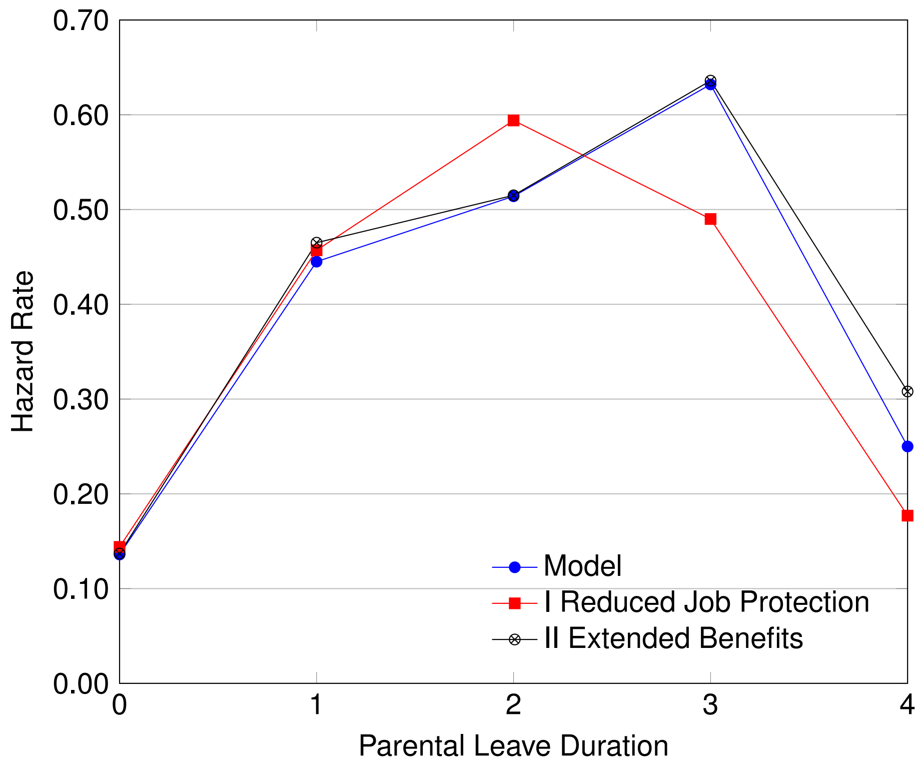


Figure 1.9: Simulated Hazard Rate for Parental-Leave Durations: Reform at Age 40

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the discrete-time exit hazard from parental leave, for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). The hazard rate after duration d is defined as the risk of taking up employment for women on parental leave for d years. Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 40-year old women in the original data set, who were forward-simulated until age 45.

	21-25	26-30	31-35	36-40	41-45	Total	% Change
Reform at Age 20:							
Model	0.250	0.393	0.343	0.143	0.026	1.155	-
I Reduced Job Protection	0.244	0.379	0.330	0.137	0.024	1.113	-4.1
II Extended Benefits	0.251	0.406	0.361	0.156	0.028	1.202	4.7
Reform at Age 30:							
Model	-	-	0.426	0.223	0.051	0.700	-
I Reduced Job Protection	-	-	0.414	0.219	0.050	0.683	-1.7
II Extended Benefits	-	-	0.457	0.243	0.055	0.755	7.2
Reform at Age 40:							
Model	-	-	-	-	0.063	0.063	-
I Reduced Job Protection	-	-	-	-	0.062	0.062	-0.1
II Extended Benefits	-	-	-	-	0.071	0.071	0.8

Table 1.6: The Effect of Parental Leave Policies on Fertility Rates by Age

Source: Socio-economic Panel, years 1984-2014, own calculations. This table shows the simulated age-specific fertility rates for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Column 7 displays the remaining total fertility rate, obtained from summing over the columns 2-6. Column 8 shows the percentage change versus the baseline scenario. Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 20/30/40-year old women (block 1/2/3) in the original data set, who were forward-simulated until age 45.

that one would expect in the long-run, i.e. when the new policy would be in place for a sufficiently long time.

Age-Specific Fertility Rates Table 1.6 shows the response in age-specific fertility rates (ASFR) to the counter-factual policy Scenarios I and II. Columns 2-6 show the age-specific fertility rates, defined as the average number of children born per woman in the shown age groups.[14] Simulation results show that both a reduction in the job protection period and an extension in the benefit period affect the ASFR in an economically significant way.

First of all, and in line with the hypothesis from Section 1.1, the reduction in the job protection period from 3 to 2 years reduces the probability to have a child, as the privilege of a 3-year job protected leave of absence is taken away from parents. Conversely, an extension of parental leave policies increases the ASFR. This is also in line with economic intuition, as money is only paid out conditionally on child birth.

Second, the effects on the ASFR show a pronounced age pattern both in absolute and relative terms. For the simulated reform onset at age 20, reducing the job protection period lowers the ASFR strongest at age 26 and 35, which is also when baseline fertility is highest: in these age brackets, the ASFR decreases by 0.013 to 0.014. This means that the number of children reacts most strongly to parental leave policies at ages when most children are born. Looking at percentage changes reveals a different picture: the sensitivity of fertility with respect to job protection increases with age, starting from 2.6 % at ages 20-24 and reaching 4.4 % in the highest age group 40-45. The same is true of the simulations for Scenario II: increases in fertility are somewhat higher in magnitude and show a similar age gradient in the relative reform effects. Especially for ages above 30, relative changes in the ASFR are higher than under Scenario I, ranging between 5.2 (30-34) and 8.9 (40-45) %.

Third, reform effects are stronger when long-term adjustments are taken into account. This is seen from block 2 and 3 of Table 1.6 showing the reform effects when women are only affected from age 30 and 40, respectively. Results show that for women affected from age 30, Scenario I reduces the ASFR by at most 0.012 at ages 30-34, then quickly levels off. This contrasts with the findings from early-reform sample, especially in view of the fact that the baseline is considerably higher for this sample. On the other hand, absolute and relative responses to an extension of parental leave benefits (Scenario II) are higher. As explained earlier, it is not possible to infer from these differences directly a trade-off between immediate responses and long-term adjustments. The results are consistent with two findings. First, short-term reform effects under-estimate long-term effects, as women will adjust their whole fertility and labor supply path so as to increase the rewards to longer benefits (and decrease the rewards to job protection, e.g. through higher labor supply). Second, the imbalance of the age-20 reform sample with respect to

[14] The ASFR is calculated by summing the age-specific birth rates for all ages in each ages group.

the education composition suggests that women with higher education benefit more from parental leave benefits and less from job protection.

Total Fertility Rates The total fertility rate is the most commonly used fertility measure. Just like the ASFR, it is calculated from summing over the age-specific birth probabilities, and it has the interpretation as the average number of children being born to a woman. Column 7 depicts a version of this measure that is useful for comparison of the policies in terms of completed fertility. It should be noted that this measure really only captures the total remaining fertility, as I exclude ages below 21 and only consider age-specific fertility after any reform date. Therefore, even the number shown for the age-20 reform group in the first block is below the actual TFR by about 0.2. To make the changes in remaining fertility comparable, column 7 expresses them in percentage terms.

Overall, it can be summarized that the third year of parental leave job protection increases fertility by about 4.1 %, and an additional year of parental leave benefits would increase fertility by roughly the same amount (4.7 %). Moreover, changes in remaining fertility are smaller when the reform sets in at later ages, suggesting that fertility effects of reforms amplify with time. Mild evidence of this might come from looking at the age-40 reform group, which is comparable to the previous group in terms of education.

1.6.3 Employment

In Section 1.6.1, I considered the effect of parental leave policies on parental leave durations. I showed that a simulated reduction in the parental leave job protection period shifts the peak of the parental leave exit hazard to the left. In contrast, an extended payment of parental leave benefits did not seem to affect exit hazards in the expected direction. On the other hand, both policies seem to affect fertility. To quantify the impact of parental leave policies on employment over the whole life-cycle, both direct changes (changes in parental leave durations) and indirect changes (changes coming through fertility effects) have to be taken into account. I consider two outcomes that are central to the discussion on female labor supply: the employment rate and the part-time share among female employees.

Employment Rates The baseline employment rate is similar for the samples at different ages at reform[15]: the employment rate increases with age and exhibits a dip between ages 25 and 32, when age-specific birth probabilities are highest.[16]

First of all, when looking at the sample of women affected by the reform at age 20 (Figure 1.10 and Table 1.7), the simulated changes in employment rates are inconclusive.

[15] Of course, a comparison of employment rates and part-time shares to the subgroups which are at age 30 and 40 at the time of the reform is only possible for ages 30 onwards and 40 onwards, respectively.

[16] Overall, female employment rates in 2014 were still about 10 percentage points below the employment rate of men, see Figure 2.B.1 of the appendix of Chapter 2.

Especially for the simulated reduction in the job protection period this is surprising, given the marked shift in the hazard rate. However, this was also seen in Section 1.6.1 that an increase in the hazard rate after two years of parental leave was accompanied by a decrease in any subsequent hazard rate. In total, the age-specific employment rates do not change in Scenario I despite an decrease in the fertility rate shown in Section 1.6.2.

When looking at higher ages at reform date, some evidence of employment effects is found, although only for Scenario II: employment decreases by about 0.4 and 0.6 percentage points in some age groups (see Table 1.8) for the group affected at age 30. This is interpretable as a pure indirect (fertility) effect given the lack of evidence on parental leave durations. To further back up this claim, Table 1.10 shows the employment rates of women with different numbers of children. However, here it seems that the decrease in employment rates seems to be driven to some extent by women with no and up to one children. I interpret this finding as a compositional change in these groups in response to the reform.

Finally, employment effects for a reform at age 40 are not economically significant.

Part-Time Shares Concerning the effects on part-time shares among the female workforce, Figures 1.10-1.12 and Tables 1.7-1.9 show that part-time shares are closely connected to fertility changes: reducing parental leave job protection decreases the part-time share by up to one percentage point especially in higher age groups and in the early reform scenario. The milder response for women who were 30 or 40 years old when the reform set in is likely attributable to the milder fertility response. Similarly, the benefit extension in Scenario II shows a marked increase especially in the group affected at age 30. This is also in line with the stronger fertility reaction in this group.

Overall, it can be seen that differences in employment shares occur around the typical ages of childbirth while differences in part-time shares occur after that and become more pronounced with age. This suggests that the effects of parental leave policies on labor market participation are only of a limited-term nature. Part-time shares, on the other hand, change persistently as mothers switch to part-time work when they have more, not necessarily younger children.

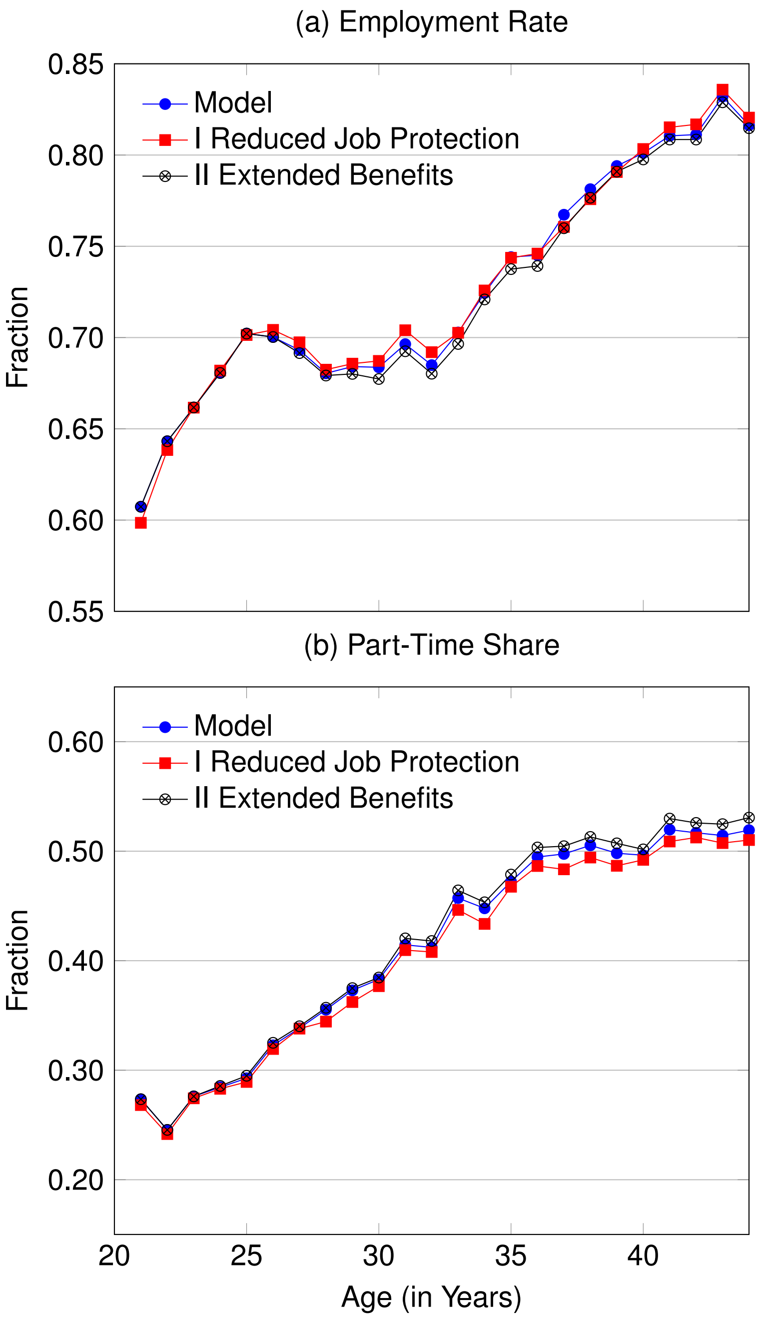


Figure 1.10: Employment Effects for Reform at Age 20

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the simulated age-specific employment rates (Panel a) and part-time shares among employed women (Panel b) for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 20-year old women in the original data set, who were forward-simulated until age 45.

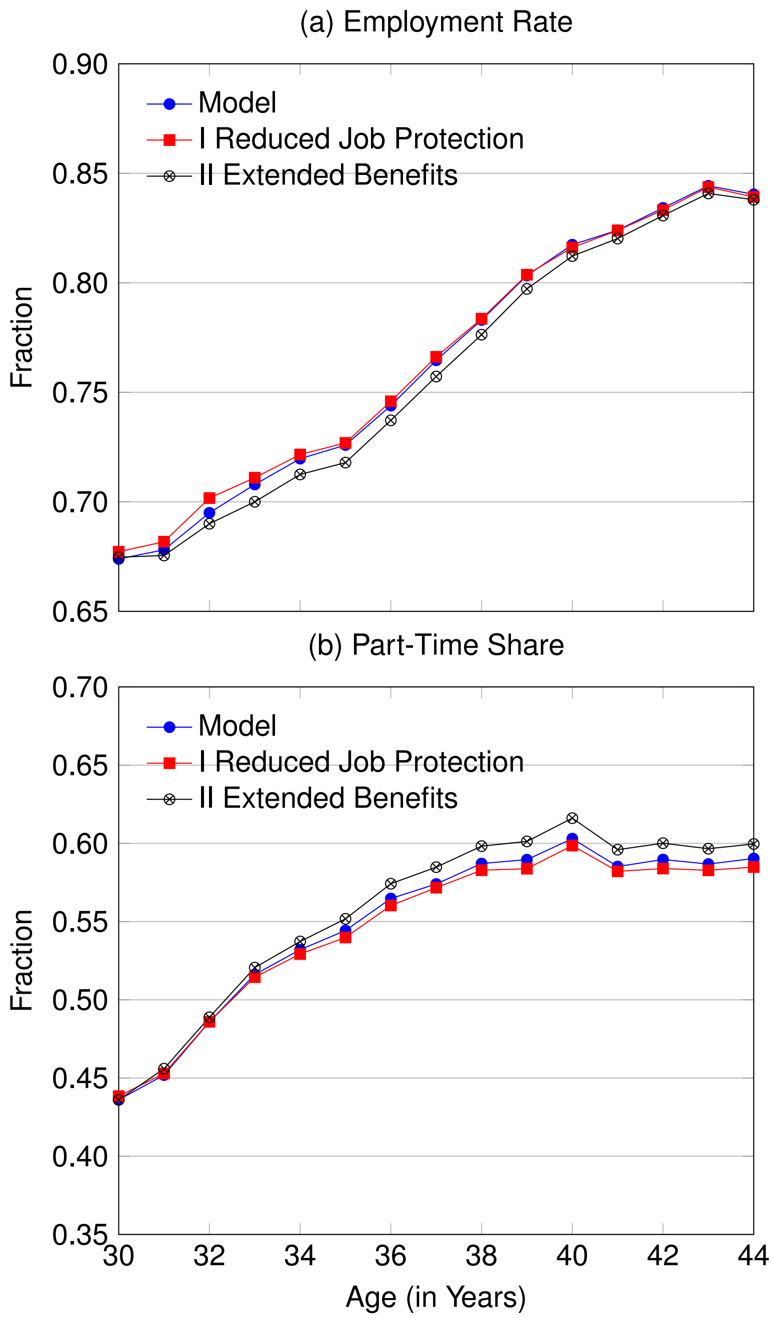


Figure 1.11: Employment Effects for Reform at Age 30

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the simulated age-specific employment rates (Panel a) and part-time shares among employed women (Panel b) for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 30-year old women in the original data set, who were forward-simulated until age 45.

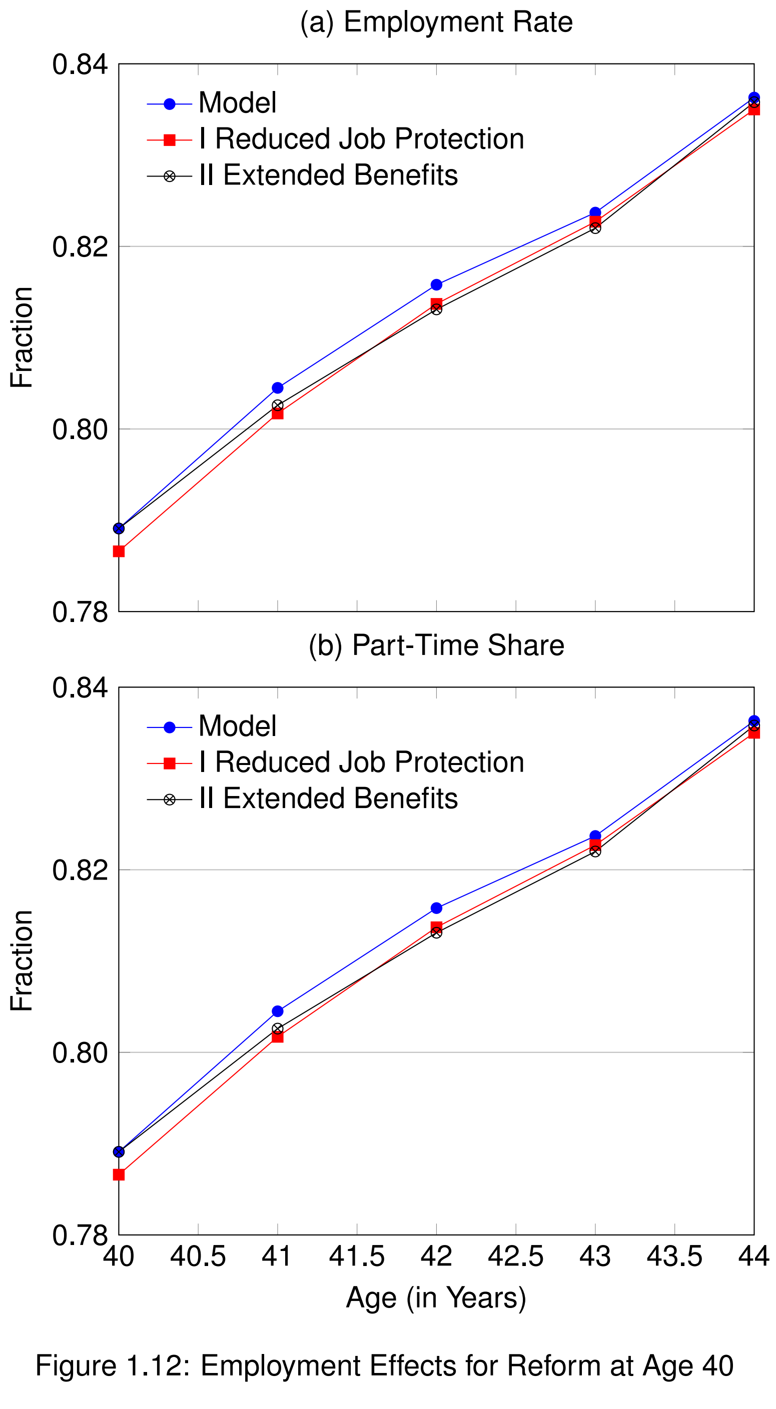


Figure 1.12: Employment Effects for Reform at Age 40

Source: Socio-economic Panel, years 1984-2014, own calculations. This figure shows the simulated age-specific employment rates (Panel a) and part-time shares among employed women (Panel b) for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 40-year old women in the original data set, who were forward-simulated until age 45.

	20-24	25-29	30-34	35-39	40-44
Employment Rate (in %):					
Model	64.8	69.2	69.8	76.6	81.4
I Reduced Job Protection	64.5	69.4	70.2	76.3	81.8
II Extended Benefits	64.8	69.1	69.3	76.1	81.1
Part-Time Share (in %):					
Model	27.0	33.6	42.3	49.4	51.2
I Reduced Job Protection	26.7	33.1	41.5	48.4	50.5
II Extended Benefits	27.0	33.8	42.8	50.1	52.0

Table 1.7: Age-Specific Employment Rates and Part-Time Shares: Reform at Age 20

Source: Socio-economic Panel, years 1984-2014, own calculations. This table shows the simulated age-specific employment rates (block 1) and part-time shares among employed women (block 2) for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 20-year old women in the original data set, who were forward-simulated until age 45.

	20-24	25-29	30-34	35-39	40-44
Employment Rate (in %):					
Model	-	-	69.5	76.4	83.0
I Reduced Job Protection	-	-	69.9	76.5	82.9
II Extended Benefits	-	-	69.1	75.7	82.6
Part-Time Share (in %):					
Model	-	-	48.4	57.2	59.1
I Reduced Job Protection	-	-	48.4	56.8	58.7
II Extended Benefits	-	-	48.8	58.2	60.2

Table 1.8: Age-Specific Employment Rates and Part-Time Shares: Reform at Age 30

Source: Socio-economic Panel, years 1984-2014, own calculations. This table shows the simulated age-specific employment rates (block 1) and part-time shares among employed women (block 2) for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 30-year old women in the original data set, who were forward-simulated until age 45.

	20-24	25-29	30-34	35-39	40-44
Employment Rate (in %):					
Model	-	-	-	-	80.8
I Reduced Job Protection	-	-	-	-	80.6
II Extended Benefits	-	-	-	-	80.7
Part-Time Share (in %):					
Model	-	-	-	-	61.7
I Reduced Job Protection	-	-	-	-	60.4
II Extended Benefits	-	-	-	-	60.4

Table 1.9: Age-Specific Employment Rates and Part-Time Shares: Reform at Age 40

Source: Socio-economic Panel, years 1984-2014, own calculations. This table shows the simulated age-specific employment rates (block 1) and part-time shares among employed women (block 2) for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 40-year old women in the original data set, who were forward-simulated until age 45.

	0 Children	1 Child	2 Children	3 Children	Full Sample
Employment Rate:					
I Reduced Job Protection	0.11	-0.04	-0.73	-0.49	0.10
II Extended Benefits	-0.15	-0.36	0.02	0.52	-0.29
Part-Time Share:					
I Reduced Job Protection	0.01	-0.42	-0.29	0.53	-0.77
II Extended Benefits	-0.07	0.34	0.01	0.11	0.57

Table 1.10: The Effect of Parental Leave Policies on Employment Rates by Number of Children: Reform at Age 20

Source: Socio-economic Panel, years 1984-2014, own calculations. This table shows the simulated employment rates (block 1) and part-time shares among employed women (block 2) for women with different numbers of children for the baseline scenario, as well as Scenario I (reduction of parental leave job protection period from 3 to 2 years) and II (extension of parental leave benefit period from 1 to 2 years). Simulations are based on 10,000 randomly re-sampled individuals from the cross-section of 40-year old women in the original data set, who were forward-simulated until age 45.

1.7 Conclusion

I estimated a dynamic structural life-cycle model to quantify the effect of parental leave policies on fertility and female labor supply.

To this end, I simulated counter-factual remaining life-cycles for samples of women affected by parental leave reforms at ages 20, 30 and 40. I considered a reduction of the parental leave job protection period from 3 to 2 years (Scenario I) and an extension of the parental leave benefit period from 1 to 2 years, and considered the effects on parental leave hazard rates, age-specific and total remaining fertility rates, the employment rate and the part-time share among female employees.

I find that both job protection and benefits affect fertility outcomes in an economically significant way: a reduction in job protection decreases remaining fertility by 4.1 % for the sample affected at age 20, and an extension of benefits increases fertility by a similar amount of 4.7 %. In line with theory, the effects of longer benefit payments are higher when women are affected at age 30, but the effects of job protection reforms are lower: these women have higher work experience, higher previous earnings, and higher job finding probabilities. However, a higher education level for the sample affected at age 30 and 40, respectively, might explain part of this finding, too.

Life-cycle labor market outcomes are less affected by the simulated reforms: while reducing the job protection period shifts the peak of the exit hazard out of parental leave to the left, this is accompanied by lower hazard rates for the non-shifters. Overall, employment effects seem to be dominated by indirect effects coming through changes in fertility. Effects on the employment rate are in the lower one-digit percentage point area for most ages, for both reforms, and do not persist beyond the ages when childbearing is highest (ages 25-35). On the other hand, effects on part-time shares are stronger and last for a longer period of time.

I conclude that reform effects on parental leave durations tend to overestimate the employment effects of parental leave reforms. On the other hand, usually unobserved effects on total remaining fertility rates seem to be positive for both considered policies.

Appendix

1.A Supplementary Modeling Information

Job Offer o_t and Permanent Contract s_t^p The transition probabilities for the job offer o_t are:

$$\Pr(o_t = 1|S_t) = \begin{cases} 1 & \text{if } jpro_t = 1, \\ \pi_t^1(S_t) & \text{if } jpro_t = 0,\, x_{t-1}^w = NW \\ \begin{matrix}\left[1 - \pi_t^2(S_t) + \dots \right. \\ \left. \pi_t^1(S_t)\pi_t^2(S_t)\right]\end{matrix} & \text{if } jpro_t = 0,\, x_{t-1}^w \neq NW \end{cases} \tag{1.15}$$

The current permanent contract status s_t^p depends on the availability of a job offer, previous existence of a permanent contract, labor market shocks, and parental leave job protection.

The transition probabilities are shown in (1.16). The third line of (1.16) reflects the fact that a permanent contract is inherited with the employment relationship. However, even a job with a permanent contract can be lost, such that the overall probability is below one. Finally, the fourth line states that a parental leave safeguards a permanent contract.

$$\Pr(s_t^p = 1|S_t, o_t) = \begin{cases} 0 & \text{if } o_t = 0, \\ \pi_t^3(S_t) & \text{if } o_t = 1,\, perm_t = 0, \\ \begin{matrix}\left[\frac{1-\pi_t^2(S_t)}{(1-\pi_t^2(S_t)+\pi_t^1(S_t)\pi_t^2(S_t)} \times \dots \right. \\ \left. \left(1 + \pi^3(S_t)\frac{\pi_t^1(S_t)\pi_t^2(S_t)}{1-\pi_t^2(S_t)}\right)\right]\end{matrix} & \text{if } o_t = 1,\, perm_t = 1, \\ 1 & \text{if } jpro_t = 1. \end{cases} \tag{1.16}$$

Law of Motion for Permanent Contract Status and Parental Leave The contract status and parental leave job protection status are not fully determined from state and choice variables in t. Rather, they depend on the unobserved labor market shocks Z_t. For one, the lagged permanent-job indicator is equal to one if either a permanent contract was inherited or obtained in period t, or a legal job protection period was taken:

$$perm_{t+1} = \mathbb{1}_{\{x_t^w \neq NW\}} \cdot s_t^p + \mathbb{1}_{\{x_t^w = NW\}} \cdot jpro_t \cdot perm_t \tag{1.17}$$

The first term in (1.17) states that a working woman has a permanent contract if it has been offered to her as determined by (1.16). When she is on parental leave, then the contract status is permanent if she went on parental leave out of a permanent contract, which is reflected in the second term of (1.17).

The legal job protection status in any period t in turn is granted for the first three life years of a child. However, only permanent work contracts can fully benefit from this job protection, since a temporary contract may expire within the legal job protection period. This is modeled by granting women on fixed-term contracts a shorter maximal job protection period $P^{fix} = 1$[17]. Thus, the law of motion for the lagged value of parental leave job protection is given by:

$$\begin{aligned} jpro_{t+1} = \mathbb{1}_{\{x_t^w = NW\}} \cdot \mathbb{1}_{\{nc_t > 0\}} \Big[& \mathbb{1}_{\{ac_t = 1\}} \cdot perm_t + \dots \\ & \mathbb{1}_{\{ac_t < 1/3\}} \cdot jpro_t \cdot perm_t + \mathbb{1}_{\{ac_t < 1/(1+P^{fix})\}} \cdot jpro_t \cdot (1 - perm_t) \Big] \end{aligned} \tag{1.18}$$

The first term in the square brackets of (1.18) indicates that parental leave can be taken from the first birth year of a child ($ac_t = 0$). The second term allows parents with a permanent contract to go on with parental leave until their child has completed the third life year. The third term allows parents with a temporary contract to go on with parental leave until their child has completed the P^{fix}-th life year.

1.B Data Appendix

1.B.1 Dataset Generation

Time-Invariant Variables

Education The education variable is based on the ISCED-97 classification. Education is classified into three groups, and the maximum attained education in the observation window is used as a time-invariant education measure. The distribution of the time-varying ISCED-97 variable is seen in Table 1.B.1. To construct the education variable edu, the education information was classified into three categories: low education if considered any ISCED-97 level up t the general elementary level, medium education consists of vocational training including vocational training and highschool (Abitur) degree, and high education pertains to the educaiton levels above vocational training. Individuals in school were dropped from the sample.

Time-Varying Variables

Birth Information For each sample member, the birth history is taken from the BIOBIRTH file. The information is used to construct a panel containing a birth incident, as

[17] Other values of P^{fix} have been applied in estimation as robustness checks.

	Number	Per cent
N/A	1,741	2.83
In school	2,202	3.58
Inadequ.	1,242	2.02
Gen. elem.	7,853	12.75
Mid. voc.	27,539	44.73
Voc. + Abi	6,539	10.62
Higher voc.	2,740	4.45
Higher ed.	11,713	19.02
Total	61,569	100

Table 1.B.1: Education (ISCED-97)

Source: Socio-economic Panel, Years 1984-2014. This table shows the raw distribution of the education variable for women between the age of 18 and 45, for the years 2007-2014.

well as the number of children nc, and the age of the youngest child ac. To regularize the sample, all individuals giving birth to multiples are dropped from the sample. Table 1.B.2 shows the frequency of births for each year, separately by birth parity.

Labor Market Experience For each person-year, information on cumulative labor market experience (in years) is available, separately for full-time and part-time experience. To derive a composite measure of labor market experience, I weight any part-time experience by the mean relative amount of working hours in both work categories shown in Table 1.B.10. That is, one year of full-time work contributes a full year of labor market experience, while one year of part-time work contributes the fraction of mean part-time to mean full-time hours. The summary statistics for both raw variables and for the generated labor market experience *exper* is shown in Table 1.B.3.

Gross Wage Labor market earnings are taken from the gross monthly labor market earnings variable. From the monthly earnings measure, a full-time equivalent monthly wage is calculated by using the individual weekly working hours information displayed in Table 1.B.10. In particular, an individual hourly wage is calculated and then rescaled to the average working hours in the full-time work category. Wage is measured in 1,000 €, and observed wages higher than 10,000 € and lower than 100 € have been deleted as an outlier correction. The distributional information is shown in Figure 1.B.1.

Permanent work contract *perm*. For all individuals reporting a work relationship, information on the term of the contract is available from the variable *plb0037* in the SOEPlong file. The distribution of all valid observations if shown in Table 1.B.4.

Birth Parity	2007	2008	2009	2010	Year 2011	2012	2013	2014	Total
1	115	96	95	465	104	102	123	107	1,207
2	54	75	87	434	157	161	127	124	1,219
3	26	27	32	163	97	72	68	64	549
4	13	11	5	52	41	42	28	15	207
5	3	3	3	23	7	13	19	4	75
6	1	1	1	7	2	3	3	4	22
7	0	0	0	2	1	1	1	1	6
8	1	0	0	1	1	0	1	0	4
9	0	0	0	1	0	2	0	0	3
Total	213	213	223	1,148	410	396	370	319	3,292

Table 1.B.2: Observed Births by Birth Parity and Survey Year

Source: Socio-economic Panel, Years 1984-2014. This table shows the raw distribution of all births observed to women between the age of 18 and 45, for the years 2007-2014, separately by the birth parity of the child.

	Mean	Std	Min	Max	N
Full-Time Exp.	5.36	5.77	0	34	52,184
Part-Time Exp.	2.86	3.93	0	29	52,184
$exper$	6.77	6.02	0	34	52,184

Table 1.B.3: Full-Time and Part-Time Labor Market Experience

Source: Socio-economic Panel, Years 1984-2014, own calculations. This table shows summary statistics for the labor market experience, separately for full-time and part-time experience, for women between the age of 18 and 45, for the years 2007-2014. The last line is the calculated composite labor market experience, where each year of part-time experience contributes in proportion to the mean weekly hours of work for part-time jobs relative to full-time jobs. The hours-of-work statistics used for the calculation are displayed in Table 1.B.10.

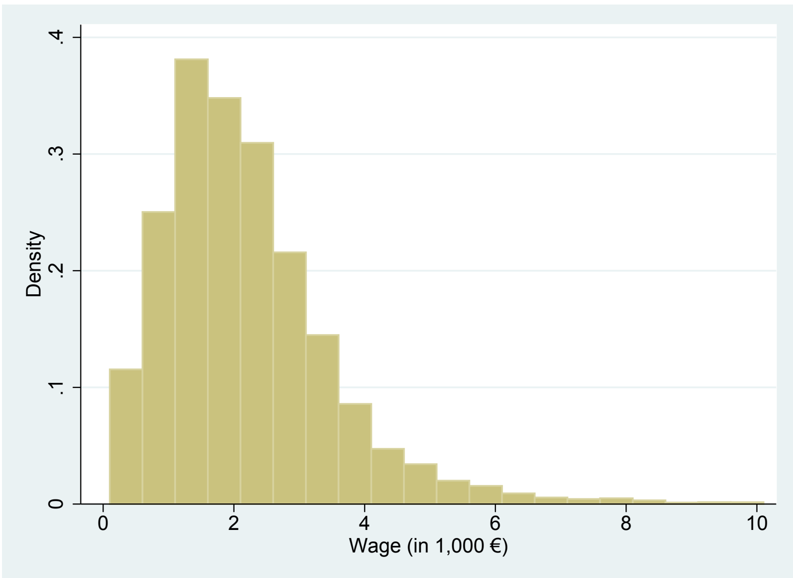


Figure 1.B.1: Gross Wage Distribution

Source: Socio-economic Panel, Years 1984-2014. This figure shows a histogram (bin width=0.5) for gross monthly wages of female employees between the age of 18 and 45, for the years 2007-2014. Wages are measured in 1,000 € and cropped below 100 € and above 10,000 €.

	Number	Per Cent
N/A	21,958	35.66
Permament Job	27,571	44.78
Temporary Job	7,969	12.94
Self-Employed	4,071	6.61
Total	61,569	100.00

Table 1.B.4: Contract Term

Source: Socio-economic Panel, Years 1984-2014. This table shows the distribution of contract terms for female employees between the age of 18 and 45, for the years 2007-2014. If the employment status is "non-employment", then the contract term information does not apply ("N/A").

Parental Leave and Parental Leave Job Protection The parental leave variable pl_t indicates if a mother was on parental leave in the *previous* year. Starting at time a child is born, this variable takes the value one if the mother was in employment in the year preceding the birth of her child and was non-employed from then on until and including the year prior to the current year of observation. If the youngest child is older than three years ($ac_t > 3$), then previous non-employment is not tracked as a parental leave in pl_t. If a next child is born within three years from the birth year of the previous child such that parental leave spells are neighboring each other, then this is also reflected in the variable pl_t.

According to the institutional setting, parental leaves taken from a permanent contract benefit from parental leave job protection. Leaves taken from a fixed-term contract are defined to benefit from job protection only for a parental leave duration of up to a year.

Involuntary Job Displacememt To identify labor work incentives in the presence of labor market frictions, survey information on involuntay job separations is used. The SOEP provides information on the reason for a previous job discontinuation in the variable *pgjobend*. Table 1.B.5 displays the raw distribution of the variable. A job discontinuation qualifies as an involuntary displacement if the job was either terminated by the employer, or ended due to expiration of a nonpermanent contract, or ended due to plant closure. In all other cases, any job separation is treated as voluntary.

Presence of a Partner Presence of a partner is retrieved from the *partner* variable in the PPFADL file. Out of the five possible values of *partner* shown in Table 1.B.6, I summarized all positive values indicating (probable) presence of a partner or spouse to generate a binary partner indicator h_t. To model the stochastic arrival or departure of a partner, I estimated a logistic regression of the presence of a husband h_t on a fully interacted set of variables: the lagged dependent variable h_{t-1}, age, age (squared)

	Number	Per cent
N/A	54,481	88.49
Terminated by Employer	906	1.47
Own Resignation	2,096	3.40
Mutual Termination	546	0.89
Ended Self-Employment	198	0.32
Contract Expired	1,254	2.04
Company Closed	327	0.53
Retirement	12	0.02
Sabbatical	888	1.44
Parental Leave	861	1.40
Total	61,569	100.00

Table 1.B.5: Reasons for Job Change

Source: Socio-economic Panel, Years 1984-2014. This table shows the reasons for a job change observed since the last survey period for women between the age of 18 and 45, for the years 2007-2014.

	Number	Per cent
No Partner	18,920	35.38
Spouse	26,693	49.92
Partner	7,577	14.17
Probably spouse	93	0.17
Probably partner	193	0.36
Total	53,476	100.00

Table 1.B.6: Partnership Status

Source: Socio-economic Panel, Years 1984-2014. This table shows the partnership status of women between the age of 18 and 45, for the years 2007-2014.

divided by 100, and education group dummies. The parameter estimates are shown in Table 1.B.7.

Partner Income As described in the main text, I account for the contribution of partner's net labor income to household income whenever a partner is present. To reduce the computational burden, the partner income in the structural estimation is the predicted value from the individual's exogenous characteristics: age, age (squared and divided by 100), and education. Table 1.B.8 shows the parameter estimated and Figure 1.B.2 shows raw distribution of the partner's net labor income in 1,000 €.

	Est.	Std.-Err.
Partner in $t-1$	0.524	(3.418)
Age	0.069	(0.149)
Age$^2/100$	-0.181	(0.236)
Medium Education	-4.393*	(2.624)
High Education	-4.115	(3.386)
Age*Partner in $t-1$	0.185	(0.222)
Age$^2/100$*Partner in $t-1$	-0.097	(0.346)
Medium Education *Age	0.296*	(0.173)
High Education *Age	0.289	(0.214)
Medium Education *Age$^2/100$	-0.455*	(0.271)
High Education *Age$^2/100$	-0.443	(0.328)
Medium Education *Partner in $t+1$	2.898	(4.046)
High Education *Partner in $t+1$	-1.867	(5.527)
Medium Education *Partner in $t+1$*Age	-0.189	(0.259)
High Education *Partner in $t+1$*Age	0.079	(0.339)
Medium Education *Partner in $t+1$*Age$^2/100$	0.294	(0.398)
High Education *Partner in $t+1$*Age$^2/100$	-0.061	(0.506)
Constant	-2.695	(2.226)
N		23,118
Pseudo-R^2		0.696

Table 1.B.7: Logistic Regression for Presence of Partner

Source: Socio-economic Panel, Years 1984-2014. This table shows parameter estimates from a logistic regression of the presence of a husband on a fully interacted set of variables: the lagged dependent variable, age, age (squared) divided by 100, and education group dummies for medium and high education, for women between the age of 18 and 45, for the years 2007-2014.

	Est.	Std.-Err.
Age	0.176***	(0.020)
Age$^2/100$	-0.183***	(0.028)
Medium Education	0.379***	(0.033)
High Education	0.784***	(0.035)
Constant	-2.321***	(0.339)
N		14,885
Adjusted R^2		0.092

Table 1.B.8: Linear Regression for Partner Income

Source: Socio-economic Panel, Years 1984-2014. This table shows parameter estimates from a linear regression of the net income of the partner on the variables: age, age (squared) divided by 100, and education group dummies for medium and high education, for women between the age of 18 and 45, for the years 2007-2014.

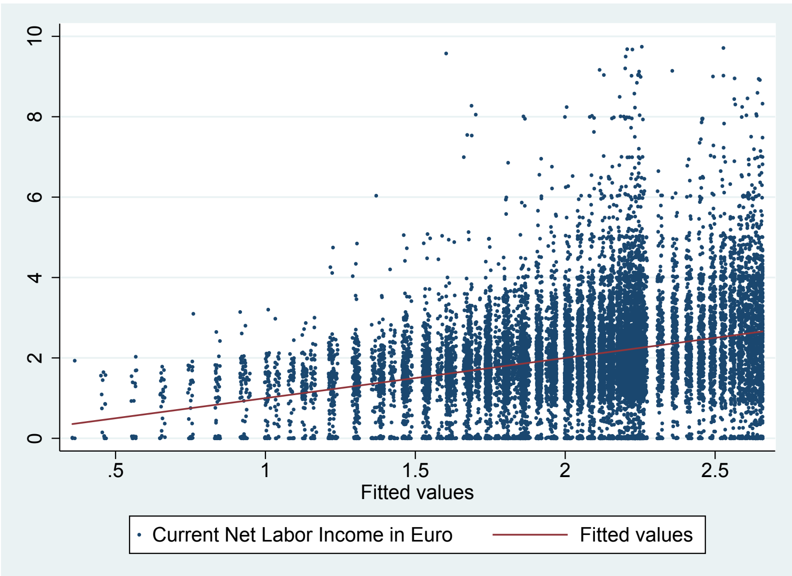


Figure 1.B.2: Fit of Partner Income Regression

Source: Socio-economic Panel, Years 1984-2014. This figure displays the scatter plot of observed net labor incomes of the partner if a partner was present of women between the age of 18 and 45, for the years 2007-2014. Net labor incomes are measured in 1,000 € and cropped below 100 € and above 10,000 €. The red line indicates the linear in-sample fit of regression shown in Table 1.B.8.

	Number	Per Cent
N/A	1	0.00
Full-Time	16,333	26.53
Regular Part-Time	15,593	25.33
Training	2,292	3.72
Marginal	6,171	10.02
Not Employed	21,087	34.25
Sheltered Workshop	92	0.15
Total	61,569	100.00

Table 1.B.9: Distribution of Employment Status

Source: Socio-economic Panel, Years 1984-2014. This table shows the distribution of the employment status of women between the age of 18 and 45, for the years 2007-2014.

Mean	Std	Min	Max	N	
Part-time	19.56	8.90	1	80	21,312
Full-time	39.11	6.09	1	80	16,150
midrule Total	27.98	12.45	1	80	37,462

Table 1.B.10: Distribution of Weekly Hours of Work by Work Category

Source: Socio-economic Panel, Years 1984-2014. This table shows summary statistics for the weekly hours of work by full-time or part-time work status, for female employees between the age of 18 and 45, for the years 2007-2014. Part-time work includes marginal employment.

Choice Variables

Labor Market Status The labor market status variable is generated from the SOEPlong employment status variable *pgemplst*. The raw distribution of the variable is shown in Table 1.B.9. Individuals in vocational training or working in a sheltered workshop are dropped from the sample. The labor market status variable is obtained from grouping the employment status into three categories, treating marginal employment as part-time employment.

Table 1.B.10 shows the average weekly working hours per labor market category. Where possible, data on contractually agreed working hours were used. In some cases, this information is missing. As it it likely that contractual hours are positively selected, missing observations are imputed from the actual weekly work hours observed in the SOEP for most working individuals[18].

[18] Imputation through the mean contractual hours in the work choice category leads to severly lower implied hourly wages, which suggests that positive selection is indeed present.

	Mean	Std	P50	N
Low	18.9	3.5	19	2,047
Middle	21.1	3.5	20	7,417
High	24.5	4.1	24	3,409
Total	21.7	4.1	21	12,873

Table 1.B.11: Age at Labor Market Entry by Education Group

Source: Socio-economic Panel, Years 1984-2014. This table shows summary statistics for last year in education for women between the age of 18 and 45, for the years 2007-2014. Part-time work includes marginal employment.

Sample Selection

The structural model is estimated on a sample of women between age 18 and 45 in years 2007-2014.

Age at Labor Market Entry. I assume that women enter the labor market one year after the last year of education as observed in the biographical spell file PBIOSPE. The age distribution of the last year in education is seen in Table 1.B.11.

Chapter 2

The Effects of Hours Constraints on Work Hours and Labor Market Participation

Over the last decades the number of arrangements for working time flexibility has grown [Chung and Tijdens, 2013]: besides temporary contracts, overtime, or leave periods, part-time work has gained in importance [Anttila et al., 2015, Absenger et al., 2014]. This development is related to the labor market attachment of women, whose employment rates have grown in most OECD countries, especially in Germany. Part-time work is generally more prevalent among women, for whom the part-time share has risen above 35 % in Germany (see Figure 2.B.1 in Appendix 2.B). Part-time employment is selective in terms of job qualification, tasks, and prestige [Fagan et al., 2014, Booth and Van Ours, 2013, Connolly and Gregory, 2008]. It thus prevails in specific occupations or sectors and pays lower wages [Aaronson and French, 2004, Hirsch, 2005, Manning and Petrongolo, 2008]. Part-time employment does not necessarily go along with time flexibility. Many employees would rather work longer hours, but are not able to find such jobs or face time restrictions [Weber and Zimmert, 2017]. On the other hand, full-time workers who prefer to reduce their hours of work at different stages of their life, for example because of care responsibilities for children or adults, also face constraints in their current jobs [Drago et al., 2009, Rengers et al., 2017].

Patterns are rather similar for men and women and in most European countries: the share of people who prefer to work longer hours increases as their actual hours decrease. At the same time, employees wish to reduce hours more often the higher their actual working time is [Steiber and Haas, 2015]. Therefore, discussions about causes and adequate policy responses persist [Müller et al., 2018a,b]. The mismatch between actual and desired working hours has been repeatedly discussed in the labor supply literature, often in combination with part-time work and hours constraints [Reynolds, 2014]. Yet, it is often hard to relate constraints to some underlying mechanisms on the supply or demand side of the labor market [Müller et al., 2018b].

In this paper, I exploit a policy reform in Germany – the introduction of the Part-Time and Limited-Term Employment Act – to derive the causal effect of a legal claim to working part-time on subsequent hours of work and the probability to continue to work. To identify the effect, I use the fact that the reform only affected firms with more than 15 employees: focusing on full-time employees only, I use employees of firms with at most 15 employees as a control group in a difference-in-differences setting. Since the treatment/control status is determined at the individual level, I am able to (a) precisely estimate the effect of the reform on individual hours of work, (b) estimate an effect on the participation margin, and (c) consider important individual heterogeneity in terms of age groups. Thus, I am able to answer the following questions.

First, do full-time employees in firms affected by the reform exhibit a higher transition probability to move to a part-time job? This would indicate that constraints were reduced. Second, does the legal right to work part-time have an effect on the probability to continue working? If this is true, then a resolution of the working time conflict at the workplace can potentially avoid a full retreat from the labor market in some instances. Alternatively, employees who reduced their working hours may have suffered from a higher risk of layoff, implying continuation probabilities to fall in response to the reform. Third, do some subgroups of the female full-time workforce respond differently to the reform? The literature provides compelling evidence that the presence of hours constraints is not homogeneously distributed across the workforce but affects some individuals and age groups more than others. This suggests that average reform effects mask substantial heterogeneity.[1]

Note that in terms of the extensive margin of labor supply I can only investigate flows out of employment. An increase in the demand for part-time jobs in response to the legal right for part-time may have led to a higher overall participation rate because more individuals decided to work. This second dimension of labor market participation, i.e. flows from non- into part-time employment can, however, not be considered based on this reform-induced variation and empirical design. The treatment assignment is based on firm size and thus only well-defined for already employed persons. People out of work do not belong to either group. I will argue below that the distinction between these two dimensions of participation is important in the context of this reform as they correspond to quite different aspects of the labor supply behavior of women.

Based on the difference-in-differences research design used in this paper only short-term effects of more generous working time regulations can be identified. However, short-run and long-run effects might diverge due to several types of inertia. Most importantly, one can argue that information about the new policy rules requires time to disseminate,

[1] There is a discussion in the literature that working time flexibility is mainly achieved through job, i.e. employer changes [Knaus and Otterbach, 2016, Altonji and Paxson, 1992]. In order to address this additional question, the transition to part-time work is also assessed conditional on remaining in the same establishment.

and employers' (as well as employees') norms and working-time cultures could require more time to adjust. Potentially, peer effects [see Cornelissen et al., 2017, Mas and Moretti, 2009, Hesselius et al., 2009, Welteke and Wrohlich, 2017, for evidence on peer effects at the workplace] may lead to short-run effects underestimating the total reform effect. I address this issue by comparing effects of the first and second year after the reform. Although dissemination may take longer, this should hint at potentially diverging medium- or long-term effects.

The empirical analysis is based on the Sample of Integrated Labor Market Biographies (SIAB), an administrative data set on employees [Antoni et al., 2016]. It contains information on labor market states (full- and part-time employment, unemployment) and basic establishment characteristics (e.g. number of employees). Individuals can be assigned to the treatment group of firms affected by the reform, or a control group. Additional employee and firm characteristics allow to consider effect heterogeneity. Most importantly, I look at different age groups as a particularly important dimension, as time conflicts are heterogeneous over the life course. I focus on a sample of women who were in full-time employment before the reform came into effect. Part-time work among men was negligible during the observation period (see Figure 2.B.1 and Section 2.3 below).

I contribute to one particular strand of the labor supply literature on hours constraints by investigating the importance of demand side restrictions. In addition, I also provide evidence on an important policy reform that affected working time regulations in Germany. Existing studies evaluated the aggregate effect on the incidence and share of part-time work with firm-level data [Munz, 2007, Schank et al., 2009]. These studies were not able to focus on the transition from full- to part-time employment. Moreover, they could not investigate whether the work continuation probability of people affected by the reform has changed. Other papers that looked at individual transitions were based on survey data and suffered from imprecise firm size information, small samples [Munz, 2007], or used an extended window of observation after the reform an thus lack clear identification [Sopp and Wagner, 2016]. In this paper, first, I investigate the individual labor market transitions which were targeted by the reform. Second, I use individual characteristics in the data to analyze effect heterogeneity and focus on groups of people that were most likely affected by the legal right to work part-time. Third, I assess the reform affect on work continuation probabilities.

I find only moderate positive effects on the transition rate to work part-time for women employed in firms with more than 200 employees. However, I find considerable effect heterogeneity with respect to the age group: for full-time employees above the age of 50, I find that the introduction of the Part-Time and Limited-Term Employment Act had increased the transition rate from full-time to part-time work by 1-2.5 percentage points (baseline: 39 %; in percentage terms: 25 to 50 %). Moreover, I find an increase in the one-year ahead probability to work by 1 percentage point for this age group. I find mild evidence for compensating employment effects for other age groups and little support for any lagged reform effects.

The structure of the paper is as follows. Section 2.1 gives a brief review of the literature on hours constraints in general and evaluations of the legal right to part-time work in particular. Then I describe the introduction of the legal right to work part-time in Germany and relate intention and scope of this reform to labor market groups and outcomes most affected (Section 2.2). Having described the data and sample, some descriptive evidence is provided on part-time work and transitions out of full-time employment (Section 2.3). In Section 2.4, the empirical strategy is detailed by discussing the difference-in-differences estimator (sub-Section 2.4.1), the consistency of estimated standard errors (Section 2.4.2), the definition of treatment and control groups (Section 2.4.3), and the identifying assumptions (sub-Section 2.4.4). The following Section 2.5 contains the results. After showing baseline estimates for all employees and different firm sizes (Section 2.5.1), I present effect heterogeneity by worker age (Section 2.5.2). Section 2.6 provides a discussion of the findings and conclusions.

2.1 Related Literature

2.1.1 Hours Constraints

In the labor supply literature, hours constraints are mainly analyzed within some kind of structural labor supply framework. Moffitt [1982], who extended a Tobit model to account for institutional restrictions on part time work was one of the first studies to do this. Van Soest et al. [1990] augmented a Hausman [1980] type labor supply model with hours constraints by letting individuals choose between a finite set of wage-hours packages. Tummers and Woittiez [1991], Dickens and Lundberg [1993], Aaberge et al. [1995] and Bloemen [2000] followed this route and refined the approach in various aspects. The main challenge in this literature is to separately identify preferences and the job offer distribution only from observed working hours. A recent study by Beffy et al. [2015] exploited situations in which employees face non-convex budget sets. The extreme working hours they observe under these circumstances cannot be rationalized within a labor supply model without introducing choice restrictions. Bloemen [2008] incorporated stated desired hours of work into a job search model.

Euwals and van Soest [1999] exploited survey information on labor market eligibility and individual search activities as well as actual and desired hours. They estimate preferences and restrictions with a labor supply model that integrates participation and hours constraints. Müller et al. [2018b] extended the framework to couple households in Germany. Restrictions at the extensive and intensive margin were allowed to vary across individuals with observed and unobserved characteristics. Müller et al. distinguished different restriction mechanisms. They modeled labor demand rationing, working hours norms varying across occupations, and restrictions on the childcare market. They found that both demand and supply restrictions matter for individual labor supply and estimate that removing all demand and supply side barriers would increase participation by about 10 % and hours of work by about 25 %.

Apart from the structural approaches, some reduced-form studies also investigated different types of hours restrictions. There is an interdisciplinary literature that primarily focuses on supply side constraints (e.g. the availability of childcare, or employment state of partners) in a household and life-cycle perspective [Drago et al., 2009, Booth and Van Ours, 2013, Weber and Zimmert, 2017, Steiber and Haas, 2012]. In addition, various comparative and descriptive papers looked at the mismatch between actual and preferred working hours [e.g. Chung and Tijdens, 2013]. Some of these studies related observed actual or preferred working hours to cultural or institutional factors, mostly without convincing identification strategies [e.g. Pollmann-Schult, 2016].

Few papers looked explicitly at hours constraints on the demand side of the labor market. Altonji and Paxson [1986] compared the variance in the change of working hours across time between job changers and job stayers. They argued that preferences are constant and any discrepancy reflects varying demand side restrictions between different jobs. They found the variance to be 2-4 times higher across compared to within jobs and concluded that more attention should be devoted to demand side constraints. Dunn [1990] analyzed constraints on the choice of working hours under equilibrium conditions of different sectors in the US. He estimated the marginal rate of substitution between income and leisure and related it to the wage rate. Results are consistent with variation in overtime premiums and fixed employment costs between these sectors. In another paper Altonji and Paxson [1992] reversed the perspectives. They started from changes in labor supply preferences and argued these should lead to larger hours adjustments after a job change when hours restrictions were binding in the current job. They compared within- and between-job changes in working hours and empirically confirm their hypothesis. They concluded that employees cannot adjust hours of work according to their preferences in the current job.

Martinez-Granado [2005] confirmed earlier results of Altonji and Paxson [1986] for more recent data on prime age males in the US. Martinez-Granado controlled for endogenous switching between firms. The results of Gielen [2009] and Bell and Rutherford [2013] underline the importance of hours constraints for older workers, in particular older women on the U.K. labor market. More recently, Chetty et al. [2011] presented indirect evidence for the existence of hours constraints set by firms. Based on a stylized labor supply model they argued that hours constraints inherent in jobs offered by firms interact with workers' search costs attenuating micro-econometric estimates of labor supply elasticities. This provides and explanation for different empirical macro and micro elasticities.

2.1.2 Policy Evaluations: The Legal Right to Work Part-Time

The first group of previous evaluation studies focused on identifying an aggregate effect of the German Part-Time and Limited-Term Employment Act (TzBfG[2]; Part Time Law hereafter) at the establishment level. Schank et al. [2009] used the IAB establishment panel [Fischer et al., 2009] with an observation period of three years before and after the introduction of the legal right to part-time and estimated the reform effect on the incidence and the share of part-time employment in establishments in a difference-in-differences framework. They found no reform effect on the incidence of part-time work at the establishment level[3], but a significantly positive effect on the part-time share in larger establishments. They concluded that the TzBfG enhanced part-time work in Germany. Using the same data, Munz [2007] estimated the reform effect on aggregate employment at the firm level in a structural labor demand framework controlling for plant- and aggregate-level control variables. She found no effect of the reform on the number of employees and total employment volume at the establishment level.[4]

Similar to my approach, a second strand of evaluation studies looks at individual labor market transitions. However, previous papers on individual outcomes rely on survey data from the German Socio-economic Panel [Wagner et al., 2007]. First, Munz [2007] analyzed determinants of time flexibility within and between employers for working-age women in Germany using structural equations for job changes and work hour adjustments. Accounting for, among others, survey-measured individual discrepancies between actual and desired work hours, she showed that job changers adjusted their working hours more frequently than stayers.[5] Another study by Sopp and Wagner [2016] could not find evidence for a reform effect. However, their study lacks convincing identification for the different policy reforms considered. Askenazy [2013] discussed various studies evaluating the consequences of different reforms of working time regulations in France. One outcome of interest is the working time flexibility of employers and employees.

Thus, previous studies suffered from either of two shortcomings: first, important individual level heterogeneity is possibly "averaged out" when looking at establishment level effects. Second, survey data allow to consider these individual characteristics but lack the data quality and sample size to identify a causal effect of the reform. Using administrative individual level data from the SIAB (see Section 2.3 for details), I overcome these problems.

[2] Gesetz über Teilzeitarbeit und befristete Arbeitsverträge.

[3] This does not come as a surprise given the nearly comprehensive pre-reform incidence of part-time in the treatment group.

[4] There were significantly positive effects for some of the estimators in the equations for the employment volume. Result patterns are not particularly convincing as effects are larger for small firms above the threshold of 15 employees. Munz also critically discussed the identification assumptions for some of these significant results.

[5] However, the fact that the legal right to work part-time was found to have significantly increased this gap within her model casts some doubt on her structural estimates.

2.2 The Legal Right to Part-Time and Working Time Flexibility

The Part-Time Law came into effect on 1 January 2001. §8 TzBfG establishes a legal right for employees to reduce their working hours under certain circumstances for the first time in Germany. In addition, employers may refuse the employee's wish to shorten hours of work for "business-related reasons", e.g. when adjustment costs get too high for the firm. However, the law does not contain a formal right to return to full-time employment.[6]

One intention of the TzBfG was to to increase the general acceptance of, and prevent discrimination against, part-time work. Thereby existing jobs should be secured, or new jobs should be created more easily for those employees who are able to work only reduced hours. The wording in the TzBfG addresses specifically transitions from full to part-time work of employees within existing jobs. Various employee-related restrictions may emerge over the course of an individual's life cycle [Drago et al., 2009]: classic examples are those duties arising in the household when children are born or when older relatives or friends become chronically ill and need to be cared for [Reynolds and Johnson, 2012]. In most cases women take up these unpaid tasks and reduce their working hours to reconcile gainful employment and care work. Moreover, these time conflicts usually cluster around specific stages of the life-course, for example around childbirth or at the end of the working career.

It is thus paramount to analyze effect heterogeneity with respect to age. Moreover, the TzBfG should be much more relevant for women than for men, who were mostly in full-time employment when the reform was introduced. That is, the analysis of participation effects only pertains to transitions out of employment. In particular, assessing whether the reform changed re-entry behavior into the labor market for women on maternal leave is beyond the scope of this analysis.

Besides these supply side constraints, employers play a significant role by providing (denying) opportunities for (to) their employees' working-time flexibility [Zapf and Weber, 2017]. As indicated above, part-time employment had been traditionally concentrated in certain occupations and sectors [Fagan et al., 2014, Booth and Van Ours, 2013]. Employers were hesitant to allow more part-time work in jobs with higher qualification and pay. The legal right is intended to force employers to remove some of these constraints. Apart from actual cost considerations the refusal to offer more flexible work arrangements is often shaped by longstanding work-cultures and norms concerning traditional, standard employment relationships.

Due to their limited internal flexibility, employers with 15 employees or less were exempted from the regulation. Therefore, the introduction of the TzBfG created a natural experiment: all establishments with 16 or more employees were affected by the law; small

[6] Jurisdiction from the German Federal Labor Court has strengthened the position of employees in this matter. Moreover, the new government announced in their coalition agreement from 2018 to establish a legal right to return to the previous work hours.

establishments with a workforce below 16 employees form a natural control group. I exploit this situation for the identification (cf. Section 2.4). As Schank et al. [2009] noted, the incidence and share of part-time employment increases with firm size. It is straightforward to estimate heterogeneous reform effects by establishment size expecting that the effect increases with the size of the workforce.

2.3 Data, Sample, and Descriptive Evidence

As mentioned in Section 2.1.2, evaluating the effect of the Part-Time Law has high data demands. First, the empirical literature emphasizes individual level heterogeneity in hours constraints. This implies that reform effects should be allowed to vary along important dimensions like worker age. Second, causal identification of a reform effect requires a credible research design. I use the Sample of Integrated Labor Market Biographies[SIAB, see Antoni et al., 2016] to analyze the reform impact at the individual level. Using a differences-in-differences design, I take the precisely measured firm size to define a control group according to a reform-induced firm size cutoff at 15 employees.

2.3.1 Data

The SIAB is a large process-generated administrative data set, comprising a representative two-percent sample of all individuals for whom an employer's record to the social security system exist. It does not cover the self-employed or civil servants. Information on the entire employment history is available for all individuals in the sample:

- employment subject to social security (in the data since 1975),
- marginal or part-time employment (in the data since 1999),
- benefit receipt according to the German Social Code III or II (SGB III since 1975, SGB II since 2005),
- officially registered as job-seeking at the German Federal Employment Agency,
- (planned) participation in programs of active labor market policies (since 2000).

The data is provided in spell format with daily information for each individual. As a result of the data-generating process the number of individual characteristics is limited. There is daily information available on wages, unemployment benefits, age, tenure, occupation, and qualification. Importantly, the exact working hours at the individual level are not available. The SIAB only contain the type of employment, i.e. full-time, part-time or marginal employment, where part-time work is defined as working less than 20 hours per week. This means that not all part-time relationships are classified as such in the data, and a reduction of work hours is only detected when crossing the threshold of 20 work hours.

In addition, some establishment characteristics are available in the SIAB, among them the number and structure of employees, sector, or location. It is therefore possible to assign each employee to the treatment group of firms affected by the reform, or to the control group according to the number of workers in their establishment. The large sample size allows the estimation of effect heterogeneity with respect to various employer and employee characteristics.

2.3.2 Part-Time Work Heterogeneity

Despite the fact that part-time employment relationships are more and more common not only in Germany, but also internationally, it cannot be concluded that part-time work is determined by a single factor. It is rather a multi-faceted phenomenon both driven by the preferences and constraints of workers and the demands of firms. To properly understand how work hours constraints may affect labor supply decisions, it is therefore important to investigate the heterogeneity in part-time work between different types of employees and firms.[7] In the following, I report part-time shares among female employees, for different sub-groups defined by age, education, firm size, and occupation.

The Supply Side: Age and Education The individual preference[8] for working part-time is not constant throughout life. Figure 2.1 (a) shows that female employees supply significantly more hours of work during the first third of their working life, with only 17 % working less that 20 hours per week before age 35, rising to 37 % and beyond during later life stages. This corresponds to the strong and persistent increase of part-time work and decrease of labor force participation after childbirth [Fitzenberger et al., 2013], while the mean maternal age at childbirth in Germany was 31.1 years between 2000 and 2015 Destatis [2018, own calculations]. This supports the presumption that family formation is the main driver of part-time work during the second third of the working life. At later stages in life, the duty of caring for own or in-law parents often falls to women. In addition to age-related physical impediments to work full-time, this may help to explain the age gradient towards the end of the working life: part-time shares reach their maximum of 39 % in the highest age group from age 50 to age 65.

While age factors have been argued to be closely related to the private, family-related domain, differences in part-time shares across education levels may shed light on the

[7] It should be noted that the distinction between supply and demand side is not as clear cut as it may seem: in fact, *none* of the considered dimensions is strictly and uniquely attributable to either supply or demand side.

[8] In the following, I will use the terms *preference for part-time work* and *individual time constraints* interchangeably. Analyzing the household-level rationale for a reduction in women's labor supply decisions is beyond the scope of the analysis.

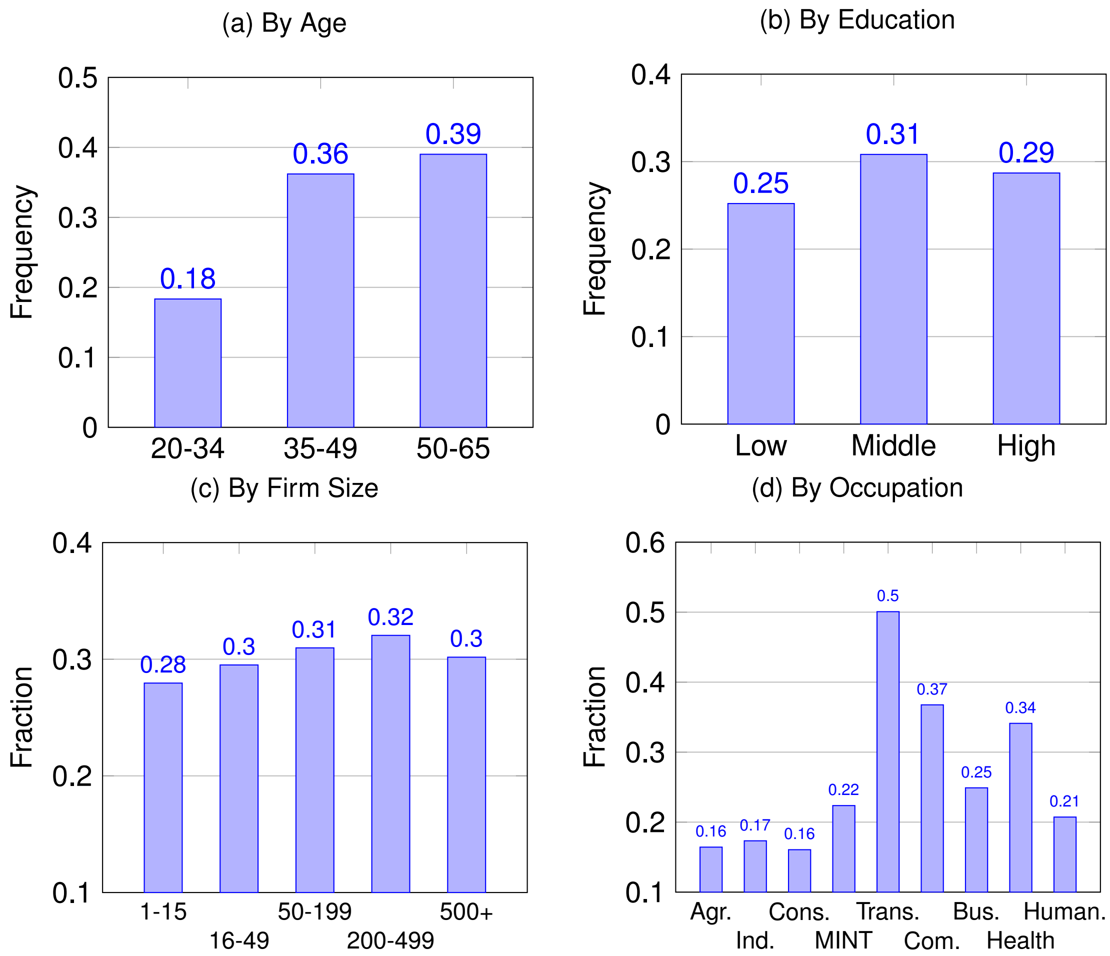


Figure 2.1: Prevalence of Part-Time Work Among Female Employees

Source: SIAB 7514, own calculations. Panels (a)-(d) show part-time rates for female employees (conditional on employment), separately for subgroups defined by (a) age (368,274 obs.), (b) education (374,433 obs.), (c) firm size (374,757 obs.), and (d) occupation (374,133 obs.). "Low" education denotes at most a non-high-school degree, "middle" education at most an apprenticeship degree with and a high school diploma, and "high" education denotes college or university degree. Firm size corresponds to the number of employees of the firm. Occupation is grouped by top-level KldB codes: 1) agriculture, landscaping, 2) industrial production, raw materials, 3) construction, 4) MINT, 5) transportation, security, cleaning, 6) commercial services, gastronomy, 7) business, accounting, law, 8) health, social, education, 9) humanities.

human capital dimension of part-time work. With part-time work being associated with substantial cumulative losses in human capital and hence lower hourly wages [Connolly and Gregory, 2009, Blundell et al., 2016a], and wage-experience profiles being steeper for employees with higher education levels [Blundell et al., 2016a], one should expect a negative education gradient for part-time work. However, Figure 2.1 (b) shows that overall part-time shares are very similar (roughly 30 %) in all three educational groups, being somewhat lower in the group with "middle" education, i.e. high school or apprenticeship level education.

The Demand Side: Firm Size and Occupation In order to analyze the workplace-level determinants of part-time work, I look at part-time shares for different firm sizes and occupations. First, I divided the firms of all employees into five size groups to confirm that larger firms generally have more part-time employment relationships.[9] This is in line with the presumption that part-time work is associated with somewhat higher administrative overhead. Figure 2.1 (c) shows that roughly quadrupling firm size leads to a one to two percentage point in increase in the part-time share among employed persons, although this does not carry over to very large firms, i.e. those with more than 500 employees.

Finally, Panel (d) of Figure 2.1 displays the prevalence of part-time work across different occupations/industries.[10] It can be seen that the part-time share is particularly high in groups 5 (transportation, security, cleaning: 50 %), 6 (commercial services, gastronomy: 37 %), and 8 (health, social services, and education: 34 %). Thus, even when restricting attention to the female work force, part-time work is concentrated in service sector occupations. These occupations are labor intensive, with many low-qualified jobs, and a high share of female workers [see Wrohlich and Zucco, 2017].

2.3.3 Transitions From Full-Time Employment

The previous analysis provided indicative evidence that both supply and demand factors play a role in explaining the heterogeneity in part-time work among female employees. In this section, I will perform the complementary analysis in terms of transitions between full-time work and part-time work, as well as between full-time work and non-work. This will shed light on those subgroups of the female workforce which are at high risk of leaving their full-time employment. This exercise is particularly useful in the context of female labor supply, where employment statuses are highly influenced by life events.[11]

[9] The firm size cutoffs are similar to those used in Schank et al. [2009].

[10] Technically, the KldB 2010 classification used here is an attribute of the individual job position.

[11] Note that the analysis is not trivial in the sense that full-time workers must leave full-time more often where full-time work is rare. Although this mechanical effect is possibly contributing to the observed heterogeneity in transition rates, it is not a necessary condition for heterogeneity in part-time shares to emerge. As an extreme counter-example, one may think of a world where transitions between the different hours of work categories do not occur at all, such that working hours are fixed across time.

	Work in $t+1$	Part-Time in $t+1$
By Age Group:		
20-34	0.966	0.030
35-49	0.969	0.030
50-65	0.950	0.040
By Education:		
Low	0.953	0.030
Medium	0.966	0.032
High	0.971	0.036
By Wage Group:		
Low	0.929	0.046
Medium	0.958	0.031
High	0.984	0.026
By Firm Size:		
1-15	0.953	0.029
16-49	0.961	0.030
50-199	0.964	0.032
200-499	0.969	0.033
500+	0.980	0.035

Table 2.1: Probability of Work and Part-Time Work in $t+1$ for Full-Time Employees by Subgroups

Source: SIAB 7514, own calculations. The first and second columns display the probability to work in $t+1$ and the probability to switch to part-time work within one year, for currently full-time employed women. The baseline period is always Q4. The first block separates by age group, the second by education, where "low" education denotes at most a non-high-school degree, "mid" education at most an apprenticeship degree with and a high school diploma, and "high" education denotes college or university degree. The third block separates by the wage received per 30 calender days in the initial time period. The fourth block separates by the number of total employees of a firm in the initial period.

Transitions from Full-Time to Part-Time Work Over time, some women in full-time employment reduce their work hours. Empirically, I find that the probability to work part-time within a year from now for current full-time employees is roughly 3 % (see Table 2.1). However, transitions to part-time work are heterogeneous. The first striking observation is that transition rates are significantly higher in the highest age group of women above the age of 50, contrasting sharply with the finding that most of the increase in part-time shares over the lifetime happens between the lower two age groups. In fact, transition rates for the age groups 20-34 and 35-49 are practically identical. This emphasizes the importance of distinguishing between transitions out-of and into (part-time) employment: while motherhood may well be the driver of the part-time share, this comes through transitions into part-time work from non-work rather than full-time work. The higher transition rate among the highest age group is compatible with the hypothesis that care work necessitates a reduction in work hours or a gradual retreat from the labor market in this age group. Looking at the transition rates by education group, it can be seen that education is positively associated with transition from full-time to part-time work. Interestingly, this pattern is not mirrored by the thord block of Table 2.1 showing transitions for different wage groups, although wage and education are highly positively correlated. This suggests that neither wage nor education differences in part-time work can be reduced to a single "quality of work" dimension. Finally, the transition rates are not very different for different firm sizes. However, there seems to be a small size gradient, most likely attributable to the fact that part-time work arrangements are more common in larger establishments with professionalized human resource departments.

Work-Continuation Probabilities for Full-Time Employees Next to a high share of part-time work, the second characteristic feature of female careers is a lower participation rate compared to men (see Figure 2.B.1). In theory, the economic mechanisms are identical for the intensive and the extensive labor supply margin, with non-participation being the "corner solution" of the optimal labor supply problem. With hours constraints, i.e. a lack of opportunities to reduce work hours in the current job, the transition to non-participation might be left as the only remaining, sub-optimal alternative to full-time work. Put differently, part-time work and non-participation may be regarded as substitutes in a situation where a reduction of work hours is desired.

Table 2.1 shows that, in age groups where part-time transitions are frequent, also transitions to non-work are frequent for full-time employees. The same is true of different wage groups shown in the table. These patterns are consistent with an employee-driven impulse to reduce work hours, which might be associated with age and socio-economic group. On the other hand, it is plausible that employers might themselves drive employees of certain subgroups (age, hierarchy level) out of full-time employment. Interestingly, part-time work and non-employment do not always pair up: higher education is associated with higher transitions to part-time and lower transitions to non-work. The same is true of firm size. This provides some evidence in favor of job quality being one driver of transitions to part-time work and work continuation.

Summing up, transitions to part-time work and continuation probabilities display substantial heterogeneity along the dimensions of age, education, wage, and firm size. These differences can plausibly be explained by labor demand and supply factors. Complementing these descriptive findings, the following analysis provides causal evidence on the existence of hours constraints and its relation to transitions to non-employment at the employee level.

2.4 Empirical Strategy

To identify the causal effect of hours constraints on work hours and labor market participation, I use the introduction of a legal right to switch from full-time to part-time work as a natural experiment, which took place in the year 2001. Using the difference-in-differences research design described in Section 2.4.1, I use a control group of employees not affected by the reform to infer a causal effect on the transition from full-time to part-time hours and the continuation rate of full-time employees, respectively.

2.4.1 The Difference-in-Differences Estimator

I am interested in how a removal of hours constraints affects labor supply y_{it+k} of individual i, k periods ahead of time period t (the current period). y_{it+k} will be an indicator variable of part-time work or employment status for the main analysis, but for now it can be anything.[12] Denote by $d_{it} \in \{0, 1\}$ a variable indicating whether the firm of employee i is affected by the reform in period t or not. Since each worker chooses his or her preferred amount of labor supply subject to the constraints imposed by the employer, the counter-factual labor supply in the current ($k = 0$) or any future period ($k > 0$) can be denoted by

$$y^0_{it+k} \equiv y_{it+k}(d_{it} = 0); y^1_{it} \equiv y_{it+k}(d_{it} = 1). \tag{2.1}$$

To identify the causal effect of the policy reform on the employment outcome is to consistently estimate

$$\delta \equiv \mathsf{E}(y^1_{it+k}) - \mathsf{E}(y^0_{it+k}). \tag{2.2}$$

The Basic Approach Denote the date of the reform by t^*, and suppose that the set of firms in the treatment group is the same before and after the reform.[13] Then, we can

[12] The reform evaluation thus reflects transitions from full-time work to other employment statuses as examined in Section 2.3.3.

[13] I abstract from any fluctuations in the firms size.

denote by $\mathcal{D}_t$ the set of all workers who belong to a firm in the treatment group in time period t. Of course, firms in the treatment group are only treated after t^*. To start with, one could estimate the reform effect on work hours for all individuals as

$$\mathsf{E}(y_{it+k}|t \geq t^*, i \in \mathcal{D}_t) - \mathsf{E}(y_{it+k}|t < t^*, i \in \mathcal{D}_t), \tag{2.3}$$

i.e., through a before-after comparison among all those affected by the reform. As it is well-known, the causal identification of the reform effect is threatened in this case by any time trends unrelated to the reform (e.g. secular time trends, other reforms in t^*). Using the notation of (2.1), this would mean that observed changes in outcomes are associated with a change in $y_{it+k}(\cdot)$ instead of a change in d_{it}. The difference-in-differences (diff-in-diff) estimator addresses this problem by use of an appropriately chosen control group. If the time trend in the absence of the reform is similar in the treatment and control group, then the causal effect of the reform is consistently estimated from

$$\begin{aligned} &[\mathsf{E}(y_{it+k}|t \geq t^*, i \in \mathcal{D}_t) - \mathsf{E}(y_{it+k}|t < t^*, i \in \mathcal{D}_t)] \\ - &[\mathsf{E}(y_{it+k}|t \geq t^*, i \notin \mathcal{D}_t) - \mathsf{E}(y_{it+k}|t < t^*, i \notin \mathcal{D}_t)]\,. \end{aligned} \tag{2.4}$$

Regression Diff-in-Diff In practice, the reform effect δ is often estimated with the following regression equation:

$$y_{it+k} = \alpha + \gamma \mathbb{1}\{i \in \mathcal{D}_t\} + \tau_t + \delta \mathbb{1}\{t \geq t^*; i \in \mathcal{D}_t\} + \varepsilon_{it}, \tag{2.5}$$

where α is an intercept, γ a group fixed effect, τ_t a time fixed effect, and ε_{it} an error term. Here, the common trends assumption is reflected by the time fixed effects, capturing all time trends unrelated to the reform.

When the parallel trends assumption holds only within subgroups defined by a vector of covariates x_{it}, then consistent inference is possible with the conditional diff-in-diff, which results from replacing expectations in (2.4) by $\mathsf{E}(y_{it}|t, i, x_{it})$. The corresponding regression equation is given by:

$$y_{it} = \alpha + \gamma \mathbb{1}\{i \in \mathcal{D}_t\} + \tau_t + \delta \mathbb{1}\{t \geq t^*; i \in \mathcal{D}_t\} + \beta' x_{it} + \varepsilon_{it}. \tag{2.6}$$

Similarly, heterogeneous treatment effects are obtained from the following specification:

$$y_{it} = \alpha + \gamma \mathbb{1}\{i \in \mathcal{D}_t\} + \tau_t + \delta'[1 \vdots x'_{it}]' \mathbb{1}\{t \geq t^*; i \in \mathcal{D}_t\} + \beta' x_{it} + \varepsilon_{it}. \tag{2.7}$$

2.4.2 Consistency and Standard Errors

Consistency The conditional diff-in-diff model in equation (2.6) (and quite naturally the extension (2.7)) is consistent under the weak exogeneity of the treatment dummy $d_{it} \equiv$

$\mathbb{1}\{t \geq t^*; i \in \mathcal{D}_t\}$ controlling for x_{it}, that is, $\mathrm{E}(\tilde{d}_{it}\varepsilon_{it}) = 0$,[14] where $\tilde{d}_{it}$ is the residual from a regression of d_{it} on x_{it}. In words, this means that there should not be any selection into the treatment group *after* the reform date which is not explained by the variables in x_{it}.[15] The sample considered is a random draw from the population of social security insured individuals, with up to two time periods per person in a two-period model. Therefore, large-N, fixed-T asymptotics apply and standard errors have to take into account the time correlation within individuals and possibly any cross-sectional clustering.

Clustering As sampling is random at the individual level but treatment assignment is at the firm level, I follow the logic of Abadie et al. [2017] to cluster standard errors at the firm level. Thus, I allow for arbitrary correlation between individuals and time periods within firms. As the number of firms is large, the cluster robust standard errors are consistently estimated.

As Bertrand et al. [2004] have pointed out, serial correlation of labor supply outcomes may significantly increase standard errors in diff-in-diff estimations, especially with a long time series dimension. They show that using cluster robust standard errors provides credible inference for an intermediate number of clusters (in their example, 50). As there are many clusters (with very few observations per cluster) in my setting, I expect the clustering problem to be captured well by the chosen approach.

2.4.3 Definition of Treatment and Control Group

I analyze the question of how a legal right to work part-time affects transitions from full-time work to part-time and to non-employment. Both the restriction to an ex-ante full-time employment status and the consideration of k-year ahead employment are motivated methodologically and conceptually.

Restriction to Full-Time Employed Women To analyze the effect of a legal right to work part-time, I focus on a sample of employees who work full-time. That is, hours constraints that restrict people from extending their work hours are beyond the scope of this analysis. As mentioned earlier, the same is true of the effects the Part Time Law had on non-participants, i.e. the transitions into employment.

Determination of Treatment Status As described in the introduction, the Part-Time Law affected only firms with more than 15 employees, rendering employees of firms with 1-15 employees as candidates for a control group. As discussed above, the central requirement for the validity of the control group is the parallelity of counter-factual trends.

[14] $\mathrm{E}(d_{it}\varepsilon_{it}|x_{it}) = 0$ may be more familiar but is not sufficient for consistency in (2.6) when x_{it} is not a full set of stratum dummies.

[15] Note that selection on unobservables into the treatment or control group does not harm the consistency of the estimator. This is the whole trick behind diff-in-diff.

Therefore, the diff-in-diff design does not preclude ex-ante selection of workers into the treatment or control group, so long as the counter-factual trend in both groups remains the same. It is, however, problematic if the selection takes place in response to the treatment after the reform date, which may lead to spurious estimates reflecting merely a compositional change in the treatment and the control group.

To solve this problem, I define the treatment and control group solely based on their firm size just before the introduction of the Part-Time Law in 2001, i.e. in the fourth quarter of 2000. Since the k-step ahead outcomes do not depend on future (post-reform) firm size, they do not suffer from the selection problem described above.

Moreover, looking at subsequent employment paths for employees in firms up to and above 15 employees, respectively, has two main advantages for the interpretation of the results. The first is conceptual: while hours constraints may play a role for current and prospective jobs alike (for example, when job offers feature high work hours), it is primarily for incumbent workers that hours constraints deny a change in work hours when personal life circumstances change. Depending on the nature of the given time conflict, employees will subsequently work inconveniently high work hours or be at higher risk of quitting. This temporal dimension is captured well by the chosen definition of treatment and control group. The second point is methodological: by definition, the treatment and control group are only defined for employees. This means that inference on the participation margin would not be possible using the suggested diff-in-diff design. However, the relationship between hours constraints and labor market participation is an extremely relevant policy dimension.

2.4.4 Discussion of Identifying Assumptions

Parallel Reforms The identifying assumption of parallel counter-factual trends implies that no other reforms or major events took place in 2001 that affected the treatment and control group differently. One concern may be that the Part Time Law does not only regulate contractual work hours but also the applicability of employment protection. At the time of its introduction, employment protection applied to employees in firms with more than 5 full-time equivalents (FTE), such that individuals in the control group were subject to less employment protection on average. However, employment protection at this threshold was already in place before 2001.[16] Therefore, the introduction of the Part Time-Law in 2001 changed nothing.

Policy Endogeneity The size threshold of 15 employees has not been chosen randomly. Rather, a plausible motivation for excluding small firms from expanding employee rights was to prevent these firms from overly hardships: in small firms, hours of work

[16] In fact, subsequent reforms change the form size threshold from 5 to 10 FTE in 1996 and back to 5 FTE in 1999

reductions of few employees may have caused severe impediments to established work flows, allocation of human resources, and the capability of meeting production goals. Although employers may reject a request for part-time work on the basis of important operational reasons even in firms with more than 15 employees, lawmakers might have instituted an exemption for small firms to reduced bureaucratic burdens. These policy concerns do not constitute a threat to the causal identification of the reform effect, but warrant caution when generalizing any reform effect. In particular, the diff-in-diff estimator identifies an average treatment effect on the treated and cannot be expected to generalize to the group of very small firms.

To threaten the identification in the diff-in-diff design, the policy must be endogenous with respect to the *timing* of the reform as well: had policymakers aimed at correcting (or amplifying) an anticipated differential development between small and large firms or had the reform been motivated by an unobserved confounder which also affected treatment and control differently, then policy endogeneity would be a problem. To the best of my knowledge, no such endogeneity was present for the considered reform.

Differential Trends The most basic threat to identification is, of course, the possibility of fundamentally different counter-factual time trends for the treatment and control group. This can happen mainly for two reasons. First, there may be truly diverging counter-factual trends one can think of as causally related to the treatment or control status. For example, if firms with less than 15 employees for some reason find part-time employment less and less attractive over time, and these reasons do not apply to larger firms, then the diff-in-diff estimator will display an upward bias in the reform effect. Second, differential time trends may be the result of selection. This happens when large firms increasingly attract part-time workers such that counter-factual time trends diverge. When differential trends can be explained by selection on observable characteristics, then controlling for these characteristics will restore comparability. This is the motivation for the conditional diff-in-diff introduced in Section 2.4.1.

Since the assumption of (conditionally) parallel trends can be required to hold also in other time periods, it is possible to validate the assumption by plotting pre-trends for the treatment and control group.[17] To check whether the parallel trends assumption holds conditionally on the set of control variables, it is possible to look at the trends of residuals from a regression of outcomes on the control variables. To establish comparability of both groups, I plotted unconditional and conditional pre-trends of the one-year ahead employment probability in Figures 2.1 and 2.2, respectively.[18]

The raw trend in the treatment and control group show that up until the reform date

[17] Note that this is a test of an implication of the parallel trends assumption and not the assumption itself, which would require comparing the untreated treatment group to the control group after the reform date.

[18] Plotting trends in the part-time variable hA_{it} was not feasible due to unreliable availability of this variable prior to 1999 [Antoni et al., 2016].

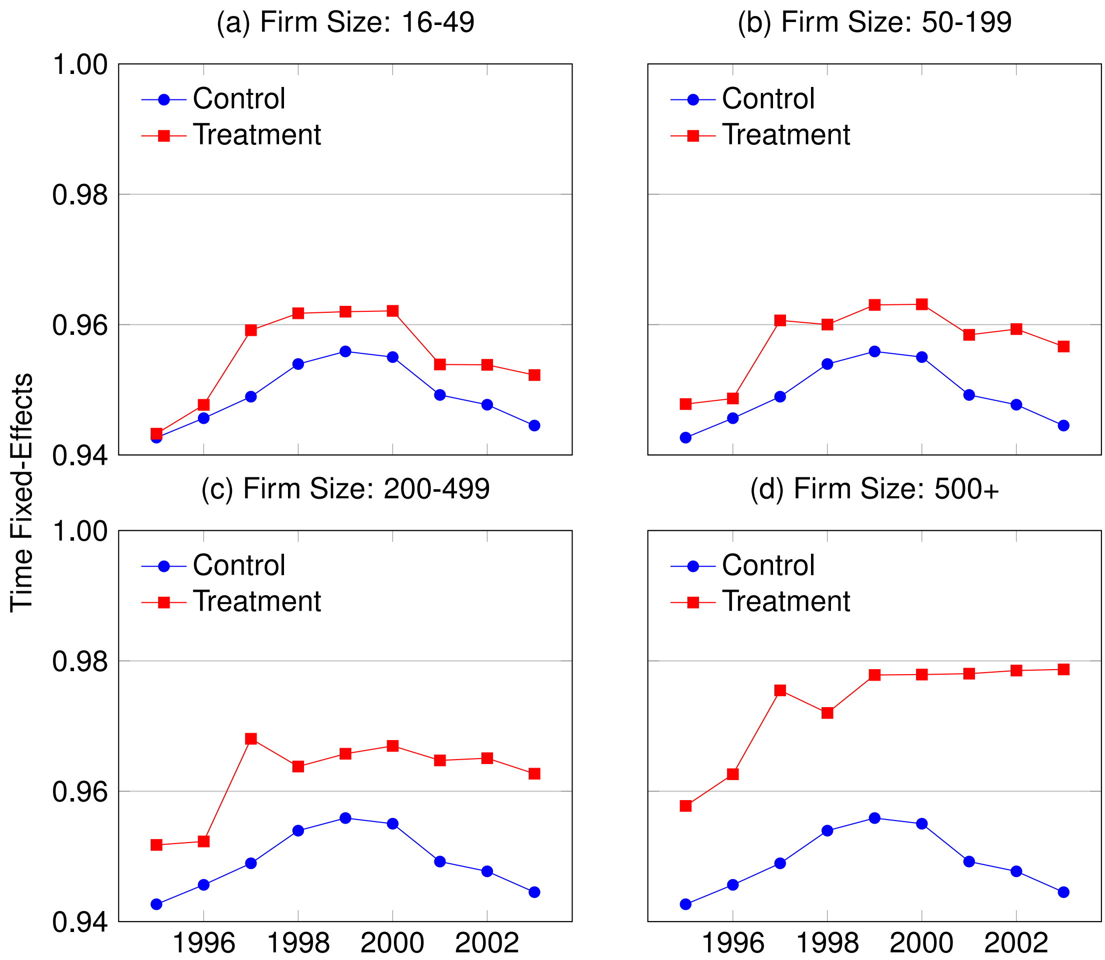


Figure 2.1: Time Trends for the Continuation Probability in the Treatment and Control Group

Source: SIAB 7514, own calculations. The figure shows the time trends for the treatment and control group for the one-year ahead continuation probability to work, for different definitions of the treatment group.

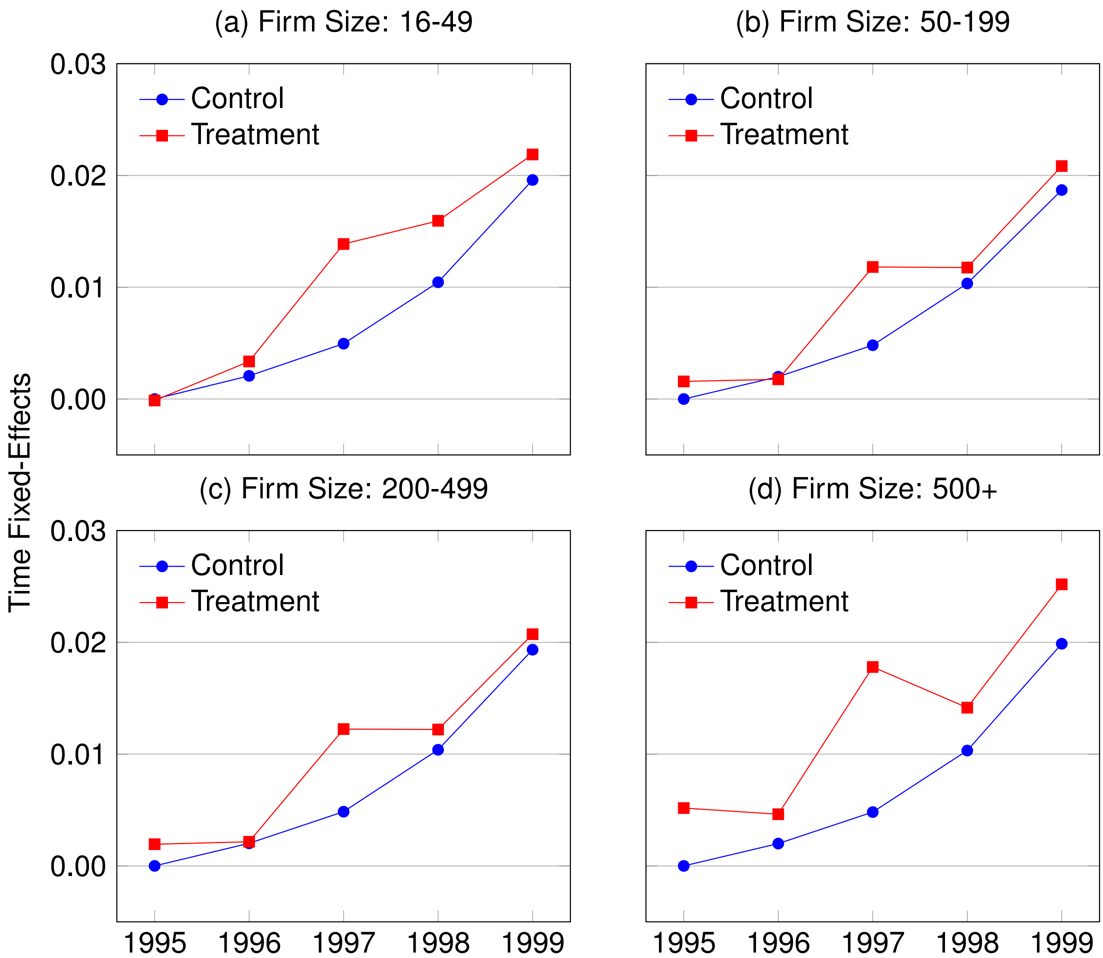


Figure 2.2: Conditional Pre-Trends for the Continuation Probability for Different Treatment Groups

Source: SIAB 7514, own calculations. The figure shows the estimated time trends for the treatment and control group for the one-year ahead continuation probability to work, for different definitions of the treatment group. Estimates were obtained from a regression of the outcome variable in the pre-reform years 1995-1998 on time-group dummies and controlling for age group, education, wage group, occupation and East/West region. The dashed lines indicate a “perfect parallel trend” by shifting the control group trend to match the treatment group time effect in the last year 1998. Regression output tables are available on request.

at the end of 2000, the trends in the treatment and control group show roughly the same trend, although not perfectly. Especially the continuation probabilities at 1997/Q4 exhibit a marked jump in the treatment groups. To further investigate whether accounting for compositional changes improves comparability of the treatment and control groups, Figure 2.2 displays the estimated pre-trends from a regression of the one-year continuation probability on treatment/control specific time trends and control variables for age group, education, wage group, occupation and East/West region. Visually, the pre-trends look roughly parallel: in the time period between 1995 and 1998, the increase in the continuation probability is at about one percent in the treatment and in the control group. An exception is the smallest treatment group of firms with less than 16 employees shown in panel (a), which seems to exhibit a one-half percent shift in 1997. For all other treatment groups, the years 1995, 1996, 1998 and 1999 are remarkably parallel to the trend in the control group. Though it seems that in 1998 something affected all larger treatment groups in 1998 so as to temporarily increase the one-year continuation probability in December 1997 in these groups. In summary, the assumption of parallel trends is satisfied in most pre-reform years. I interpret this as mild evidence for the validity of the diff-in-diff approach. However, the possibility of a violation of the identifying assumptions and the generation of spurious results cannot be ruled out.[19] Therefore, additional weight will be given to the plausibility of the obtained estimates.

2.5 Results

As described above, I analyze the 2001 introduction of the Part Time Law to assess whether (a) this reform had increased transitions from full-time to part-time work, and (b), whether this had an effect on transitions from full-time work to non-work. To this end, I estimate diff-in-diff regression equations for the outcome variables of one-year ahead employment and one-year ahead part-time work, respectively. Due to data restrictions for the part-time work variable, I use a two-period framework comparing one-year ahead probabilities from December 1999 and December 2000.[20]

All results are reported for four different definitions of the treatment group. This has two advantages. First, a single treatment group from all firms with more than 15 employees can be structurally very different from the control group of small firms having less than 15 employees. By this, I aim to find firms with a similar number of employees to be better comparable. Second, as it is shown in sections 2.3.2 and 2.3.3, greater firm size is associated with a higher part-time share, more transitions to part-time work, and higher

[19] This is in light of the fact that parallel pre-trends are neither a necessary nor a sufficient condition for the parallel trends assumption to hold in the reform period.

[20] For the pre-reform year, I considered observations from December 1999 with one-year ahead outcome from December 2000. For the post-reform year, I considered observations from December 2000 with one-year ahead outcome from December 2001. Thus, the one-year ahead outcome in the pre-reform period was never affected by the reform.

continuation probabilities. These observations, and the findings of Schank et al. [2009] suggest that firm size is a key variable for demand-side restrictions to work part-time.

In Section 2.5.1, I start by presenting the estimated effect of the 2001 reform on transitions to part-time work for full-time employed women. This will shed light on the effectiveness of the policy device of a legal right to work part-time. Moreover, any response to the law is indicative of the existence of hours constraints in the female workforce. Next, I assess the effect of the reform on the one-year continuation probabilities, to find out whether the option of part-time work increases employment stability or even decreases subsequent employment, for example through a punishment of the part-time worker.

In line with the change of time conflicts over the life cycle, Section 2.5.2 shows the same results allowing for heterogeneous effects for different age groups. Since it has been argued that transitions to part-time work mostly come through employer changes [Knaus and Otterbach, 2016, Altonji and Paxson, 1992], Section 2.5.3 analyzes the transitions to part-time for firm-stayers only.

2.5.1 Reform Effects for the Full Sample

Figure 2.1 shows the estimated treatment effects of the 2001 introduction of the Part Time Law on subsequent employment and part-time work. Diff-in-diff estimates are reported are reported separately for different firm sizes. I find no significant increase in transitions to part-time work for the lowest treatment group of size 16-49 but significant positive effects for firms with more than 200 employees. According to my estimations, the introduction of the law increased the probability to reduce work hours for full-time employees by 0.5 to 0.6 percentage points for firms with 200-499 and more than 500 employees, respectively. Given that the baseline probability ranges between 3 to 4 %, this is a sizable relative effect of 9 to 16 %.

The pattern of results is in line with the findings of [Schank et al., 2009] which are based on firm-level data.[21] The fact that firm size is positively associated with the reform effect comes as no surprise: larger firms can more easily accommodate an employees request to reduce work hours due to more professionalized human resource practices. Moreover, it might have been easier for smaller firms to reject such a request claiming "business-related reasons" (see Section 2.2).

The second outcome of interest is the work continuation probability. I can test whether firms shift adjustment costs of higher working time flexibility requirements to employees or whether employees are more likely to stay employed. Figure 2.1 shows that no reform effect could be detected for the re-employment probability in the full sample. This means that any reform-induced increase of part-time work did neither lead to additional lay-offs,

[21] Schank et al. distinguish between the probability of part-time work at the firm level and the share of part-time work among firms with at least one part-time contract, and find that the share of part-time workers in these firms was on average 1.4 to 2.7 % higher than for the control firms in the post-treatment period of 2001-2003.

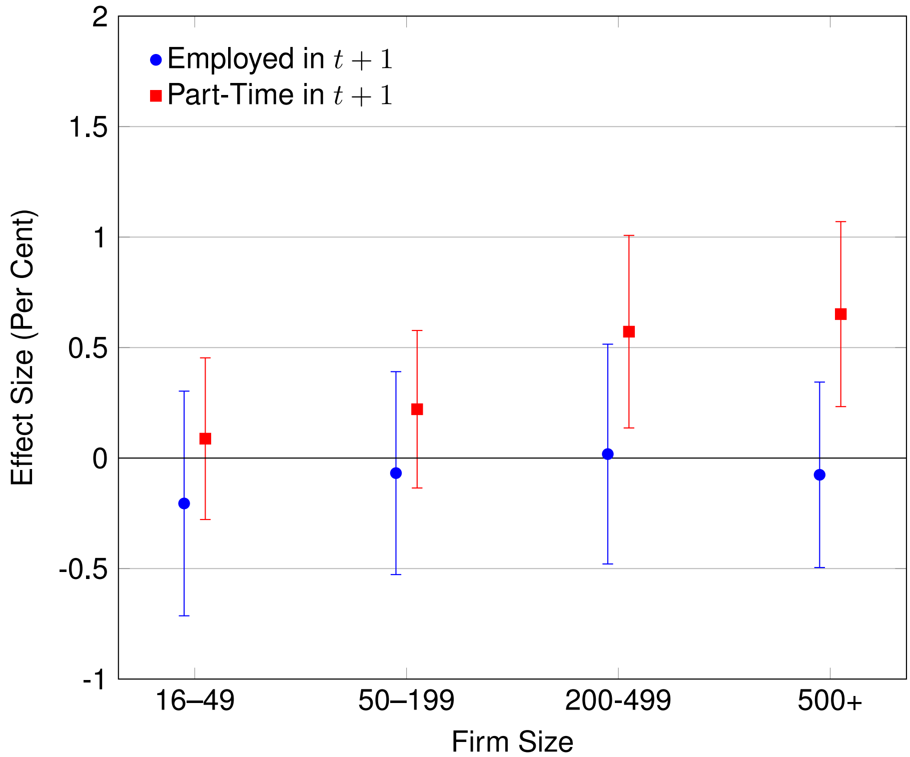


Figure 2.1: Baseline

Source: SIAB 7514, own calculations. The figure shows difference-in-differences estimates and 95-% confidence intervals for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level. Regression output tables can be found in Table 2.A.1 in the appendix.

nor did it enable workers to stay in employment at a significant scale. Another possibility is that these effects exist but that positive and negative employment effects are distributed between different subgroups of employees. As it turns out in the next section, I find this to be the case.

2.5.2 Heterogeneous Effects for Different Age Groups

As discussed in Section 2.2, it is important to distinguish between the phenomenon of hours constraints at different life stages. Moreover, the response to a legal claim to reduce work hours might be different depending on the age of an employee. Reasons for this could be, for example, that older employees do not fear negative consequences of filing such a claim as much as younger workers.

Figure 2.2 and Table 2.1 show the estimated reform effect for the age group of women between 50 and 65 years of age. In contrast to the average effect from the previous section, the magnitude of the reform-induced increase in part-time transitions is much larger, and ranges around one to 2.5 percentage points, i.e. relative increases of 25 to over 50 % (see Figure 2.4.4). It is similarly striking that for this age group I am able to identify a significantly positive effect on the continuation probability: depending on the choice of the treatment group, the reform seems to have increased subsequent employment of full-time employees by roughly one percentage point. Given that the baseline continuation probabilities range at 95 %, the reform has reduced their transition to non-work by about 20 %.

Thus, it seems like a legal right to work part-time has indeed allowed female workers to stay in employment longer than before. Without further decomposing the age group, it can, however, not be concluded that every second of these additional transitions to part-time was associated with longer subsequent employment. Instead, the effect on work continuation might be composed of increases in employment for compliers, as well as decreases in employment for other, if not younger employees, for example due to increased layoffs. In fact, other, if not younger employees, could have been laid off earlier had this fraction been even larger.

Together with the small average effect, the positive employment effect for the highest age group implies that younger age groups must have faced a reduction in subsequent employment due to the reform. Figures 2.B.2 and 2.B.3 in Appendix 2.B show that especially the age group of 20 to 34 year-olds might have faced lower continuation probabilities in the wake of the reform, although most results are statistically insignificant.

The observed pattern is thus consistent with a theory where especially larger firms allowed female employees above the age of 50 to work part-time after the reform; absent the reform, (some of) these employees would have left employment. The additional workforce in turn caused the companies to not continue employment contracts with younger workers. Furthermore, discontinuing the work contracts of younger workers is consistent

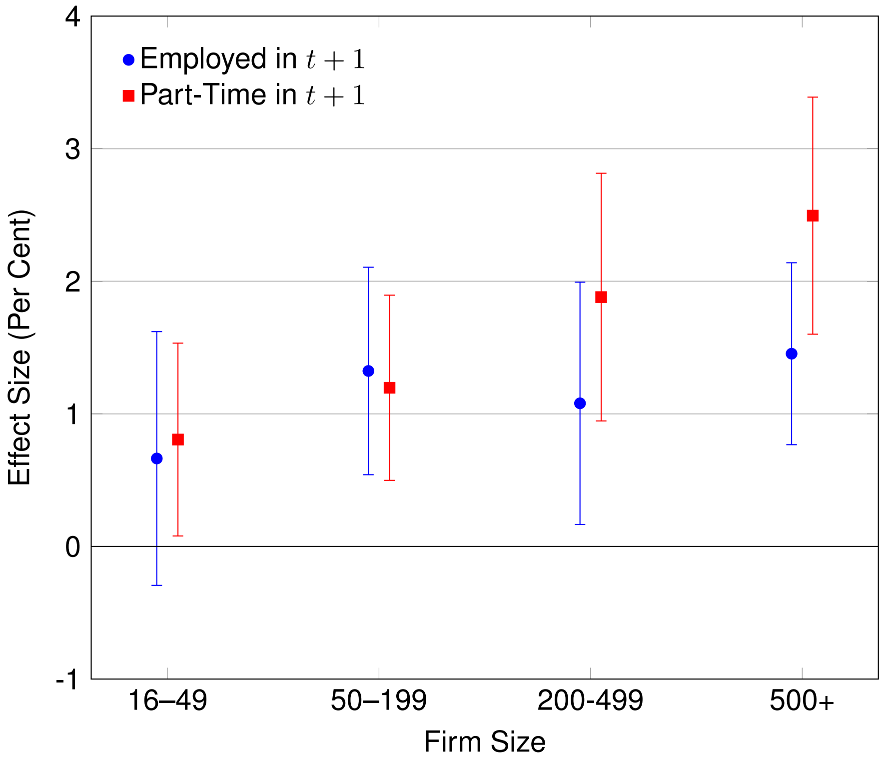


Figure 2.2: Effects for Age 50–65

Source: SIAB 7514, own calculations. The figure shows difference-in-difference estimates and 95-% confidence intervals for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level. Regression output tables can be found in Tables 2.1 and 2.A.5 in the appendix.

	16-49		50-199		200-499		500+	
Employment in $t+1$:								
Treat*Post								
– 20-34	0.005	(0.003)	-0.008***	(0.003)	-0.005*	(0.003)	-0.006**	(0.003)
– 35-49	0.003	(0.003)	0.000	(0.003)	0.001	(0.003)	-0.003	(0.002)
– 50-65	0.007	(0.005)	0.013***	(0.004)	0.011**	(0.005)	0.015***	(0.004)
Treat	0.008***	(0.002)	0.006***	(0.002)	0.008***	(0.002)	0.015***	(0.002)
Post	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Obs.	95,469		110,424		90,660		107,684	
Part-Time in $t+1$:								
Treat*Post								
– 20-34	0.003	(0.003)	-0.001	(0.003)	0.003	(0.003)	0.002	(0.003)
– 35-49	-0.002	(0.003)	0.000	(0.002)	0.000	(0.003)	-0.002	(0.003)
– 50-65	0.011***	(0.004)	0.014***	(0.004)	0.021***	(0.005)	0.029***	(0.004)
Treat	0.004**	(0.002)	0.011***	(0.002)	0.011***	(0.002)	0.016***	(0.002)
Post	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Obs.	95,469		110,424		90,660		107,684	

Table 2.1: Effect Heterogeneity by Age

Source: SIAB 7514, own calculations. The table shows estimates from difference-in-difference estimates for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level.

with a first-in-first-out layoff practice.[22]

2.5.3 Robustness Analysis

Timing of the Reform Effect In the main analysis, I looked at a rather short time horizon of one year. However, it may be that the effects of the reform take effect rather slowly, for example through information frictions and/or peer effects. In this case, the estimated effect would only discover part of the full reform effect.[23]

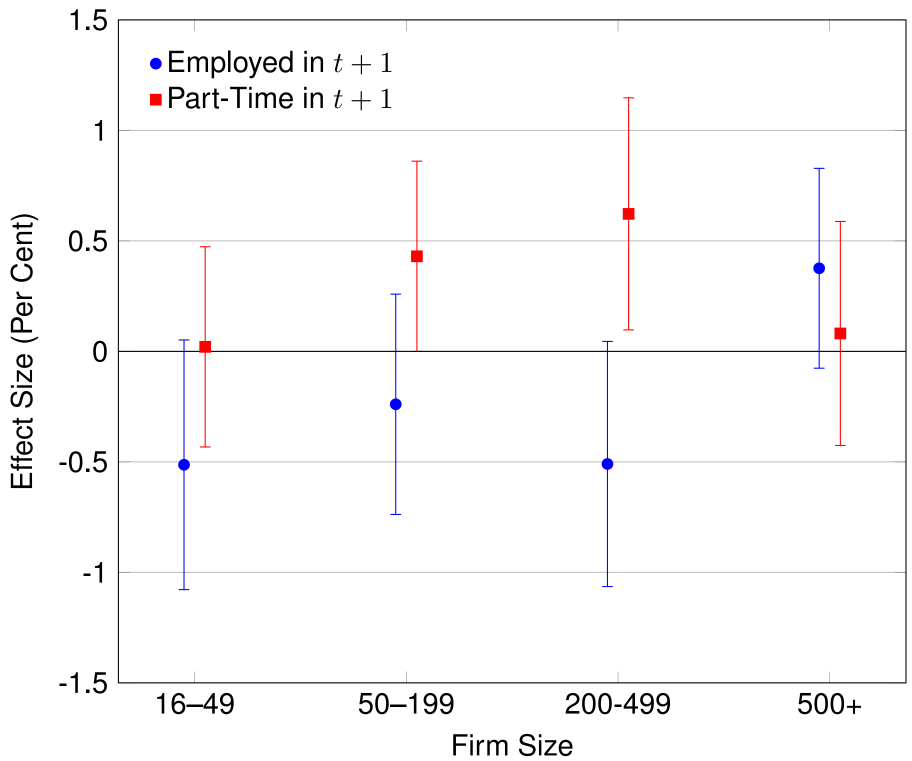


Figure 2.3: Effects Over 2 Years

Source: SIAB 7514, own calculations. The figure shows difference-in-differences estimates and 95-% confidence intervals for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level. Regression output tables can be found in Table 2.A.3 in the appendix.

To analyze these questions on the timing of the reform effect, I have repeated the regression analysis from Section 2.5.1, exchanging one-year ahead outcomes for two-year ahead outcomes. Note that, in this estimation, the two-year ahead outcomes in the pre-reform period overlap with the post-reform period. The resulting reform effect

[22] This practice may have been optimal for firms due to tenure-dependence in employment protection, severance payments, or firm-specific human capital accumulation, among others.

[23] At the other extreme, the long-run effect of a reform might invert the short-run effect. In the given context, this seems rather implausible.

compares two years of treatment to only one year of treatment. As such, it estimates the additional effect of the second year under the reform.

Figure 2.3 suggests that there is no significant lag in the reform effect: only for the treatment group of firms with 200-499 employees, the second-year effect is positive and significant for the part-time transitions. I interpret this observation as evidence of a quick reform implementation, such that the vast majority of workers who would have liked to change working hours realized their preferences immediately after the reform had been implemented.

Part-Time Transitions for Firm Stayers The outcomes defined for use in the main analysis did not distinguish between within-firm and between-firm transitions between different employment statuses. As Knaus and Otterbach [2016], Altonji and Paxson [1992], Martinez-Granado [2005] note, employer changes may play an important role in this context. More precisely, changing one's employer may be a response to experience hours constraints at the work place. This makes the estimation of reform effects for firm stayers a good robustness check: should the observed changes in the outcome variables be causally related to the reform, then these should be close to the estimated main effects.

Tables 2.A.2 and 2.A.5 in Appendix 2.A show that the estimated effects are very similar to the main effects for the full sample and the heterogeneous-effects specifications. Moreover, the estimates are a bit larger in magnitude, consistent with the fact that a reform effect could only be there for firm stayers. This means that all observed cases of reform-related transitions to part-time must be present in the smaller sub-group of firm stayers as well, which scales up the estimates.

2.6 Discussion and Conclusion

In this paper, I exploit a reform in working-time regulations that established a legal right to part-time employment in Germany. Under certain conditions full-time employees are entitled to reduce their hours of work within an existing employment relationship. The reform provides a unique opportunity to investigate the impact of working time regulations on hours constraints at the demand side of the labor market without changing financial incentives.

I identify groups of individuals that are particularly confronted with time conflict and might face hours constraints. Individual level evidence from administrative employment records on worker and firm heterogeneity in female part-time rates and transitions from full-time to part-time confirm these conjectures: comparing part-time rates and transitions to part-time for female employees of different age and education groups, I find substantial heterogeneity along both these dimensions. Moreover, although the highest increase in part-time shares is between the ages 20-49, the highest transition rates from full- to part-time are found for women above the age of 50. This highlights the importance of distinguishing transitions into and out-of employment when dealing with the female part-time share. Demand side characteristics further contribute to heterogeneity in part-time shares and transitions to part-time.

When there is insufficient demand for part-time work, full-time employment and non-participation may become competing employment states for female employees who are confronted with time conflicts. The necessary condition for an effective reduction of hours constraints is that transitions to from full- to part-time to be increasing. The sufficient condition is that transitions to non-participation for full-time employed women are non-increasing. The link between those mechanisms becomes visible in the descriptive findings: subgroups with frequent transitions from full- to part-time employment also exhibit higher transition rates to non-work (i.e. lower continuation probabilities). The education dimension is an exception in this regard: the relationship is inverted in this case.

The main contribution of this study is to estimate the reform effect on these particular individual transitions allowing for heterogeneity along individual characteristics. Previous evaluations based on firm-level data [Schank et al., 2009, Munz, 2007] were only able to detect effects on the aggregate level or share of part-time employment, but did not focus on the transitions from full-to part-time employment for those groups where the need for part-time employment is highest. Furthermore, previous studies did not relate the aggregate effect on part-time to the work-continuation probability of affected and non-affected individuals.

In the main analysis I estimated the causal effect of the legal claim to work part-time for all women. I employed a diff-in-diff research design, using the fact that the reform did not apply to firms with less than 15 employees. For the full sample, I find only moderate positive effects on the transition rate to part-time for employees in firms with more than 200 employees. However, this finding masks important heterogeneity along the age dimension: for employees above the age of 50, I find that the 2001 reform had increased the transition rate to part-time work by one to 2.5 percentage points, or 25 to 50 %. Moreover, I find subsequent employment to increase by about one percentage point in this age group. At the same time, subsequent employment in the other age groups decreased due to the reform, possibly due to firm strategies to counterbalance the additional workforce. Robustness checks did not indicate the presence of any significant lagged reform effect and confirmed that the effects came about via firm stayers.

These findings are in line with previous evidence that confirm the relevance of hours constraints for Germany [Müller et al., 2018b] an other countries [Altonji and Paxson, 1986, 1992, Martinez-Granado, 2005, Gielen, 2009, Bell and Rutherford, 2013, Chetty et al., 2011]. The results suggest that establishing a legal right to work part-time helped those employees in need of more time flexibility. Negative effects for overall employment could not be identified. Quite on the contrary, for older women who showed higher transitions to part-time work this seems to be strategy to keep them in the labor market.

This is an important insight given the ongoing discussions about the right to return from temporary part-time to full-time employment in Germany.

Appendix

2.A Additional Tables

	16-49		50-199		200-499		500+	
Employment in $t+1$:								
Treat*Post	-0.002	(0.003)	-0.001	(0.002)	0.000	(0.003)	-0.001	(0.002)
Treat	0.008***	(0.002)	0.006***	(0.002)	0.008***	(0.002)	0.015***	(0.002)
Post	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Obs.	95,469		110,424		90,660		107,684	
Part-Time in $t+1$:								
Treat*Post	0.002	(0.002)	0.002	(0.002)	0.005**	(0.002)	0.006**	(0.002)
Treat	0.004**	(0.002)	0.011***	(0.002)	0.011***	(0.002)	0.016***	(0.002)
Post	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Obs.	78,346		91,764		75,838		91,793	

Table 2.A.1: Reform Effect on Employment and Part-Time Work for Different Firm Sizes

Source: SIAB 7514, own calculations. The table shows estimates from difference-in-difference estimates for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level.

	16-49		50-199		200-499		500+	
Part-Time in $t+1$ (Stayers):								
Treat*Post	0.001	(0.002)	0.002	(0.002)	0.006**	(0.002)	0.007***	(0.002)
Treat	0.004***	(0.001)	0.012***	(0.001)	0.013***	(0.002)	0.021***	(0.002)
Post	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)
Obs.	78,346		91,764		75,838		91,793	

Table 2.A.2: Reform Effect on Part-time Work for Firm Stayers

Source: SIAB 7514, own calculations. The table shows estimates from difference-in-difference estimates for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level.

	16-49		50-199		200-499		500+	
Employment in $t+1$:								
Treat*Post	-0.005*	(0.003)	-0.002	(0.003)	-0.005*	(0.003)	0.004	(0.002)
Treat	0.010***	(0.002)	0.010***	(0.002)	0.016***	(0.002)	0.023***	(0.002)
Post	-0.005***	(0.002)	-0.005***	(0.002)	-0.005***	(0.002)	-0.005***	(0.002)
Obs.	91,490		106,132		87,083		103,542	
Part-Time in $t+1$ (Stayers):								
Treat*Post	0.001	(0.003)	0.004*	(0.002)	0.006**	(0.003)	0.003	(0.003)
Treat	0.008***	(0.002)	0.018***	(0.002)	0.022***	(0.003)	0.034***	(0.003)
Post	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)	0.000	(0.002)
Obs.	91,490		106,132		87,083		103,542	

Table 2.A.3: Effects on Employment and Part-Time Work over 2-Year Horizon

Source: SIAB 7514, own calculations. The table shows estimates from difference-in-difference estimates for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level.

	16-49		50-199		200-499		500+	
Part_Time in $t+1$ (Stayers):								
Treat*Post	0.000	(0.002)	0.004*	(0.002)	0.006**	(0.003)	0.001	(0.003)
Treat	0.009***	(0.002)	0.023***	(0.002)	0.030***	(0.003)	0.047***	(0.003)
Post	0.002	(0.001)	0.001	(0.001)	0.002	(0.001)	0.001	(0.001)
Obs.	65,408		77,512		64,306		78,848	

Table 2.A.4: Effects on Part-Time Work (Stayers) over 2-Year Horizon

Source: SIAB 7514, own calculations. The table shows estimates from difference-in-difference estimates for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level.

	16-49		50-199		200-499		500+	
Part-Time in $t+1$ (Stayers):								
Treat*Post								
– 20-34	0.001	(0.002)	-0.001	(0.002)	0.004	(0.003)	0.004*	(0.003)
– 35-49	-0.002	(0.002)	0.000	(0.002)	0.002	(0.003)	0.000	(0.002)
– 50-65	0.008**	(0.004)	0.012***	(0.004)	0.019***	(0.005)	0.025***	(0.005)
Treat	0.004***	(0.001)	0.012***	(0.001)	0.013***	(0.002)	0.021***	(0.002)
Post	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)	0.000	(0.001)
Obs.	78,346		92,473		75,838		91,793	

Table 2.A.5: Effect Heterogeneity by Age for Stayers

Source: SIAB 7514, own calculations. The table shows estimates from difference-in-difference estimates for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level.

2.B Additional Figures

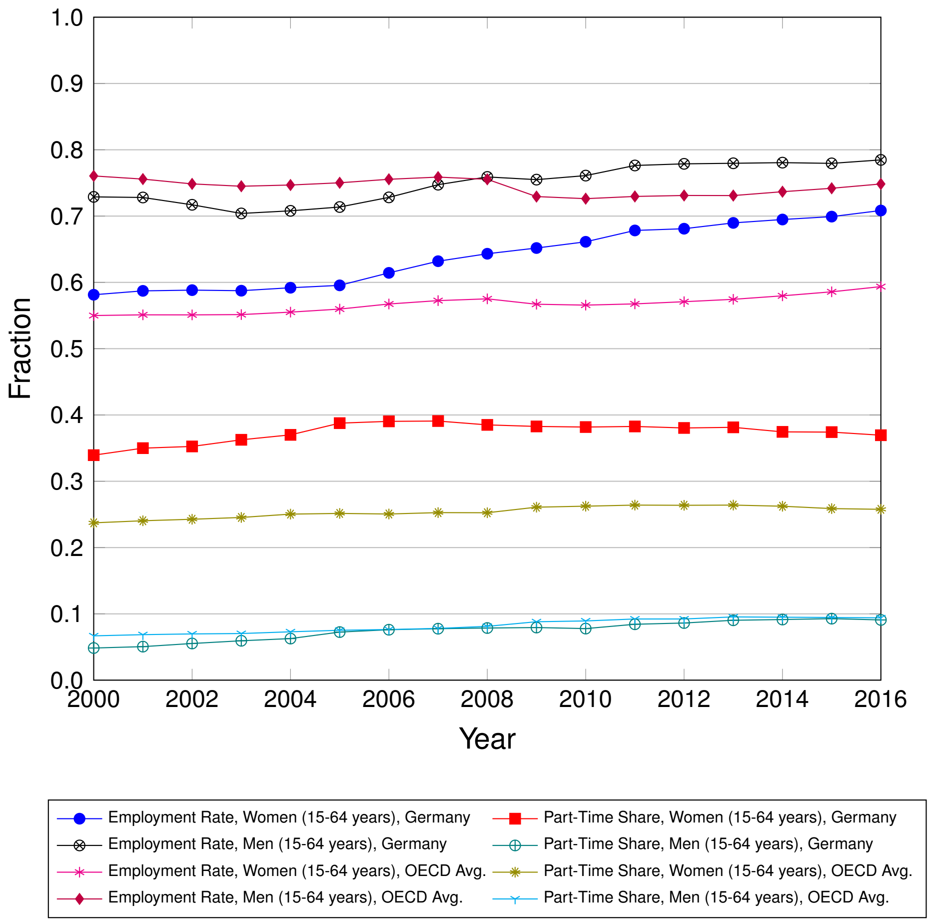


Figure 2.B.1: Part-Time Work Among Female Employees Over Time
Source: SIAB 7514, own calculations. This figure shows female and male employment rates and part-time rates of female and male employed individuals, for Germany and the OECD average. Source: OECD [2018].

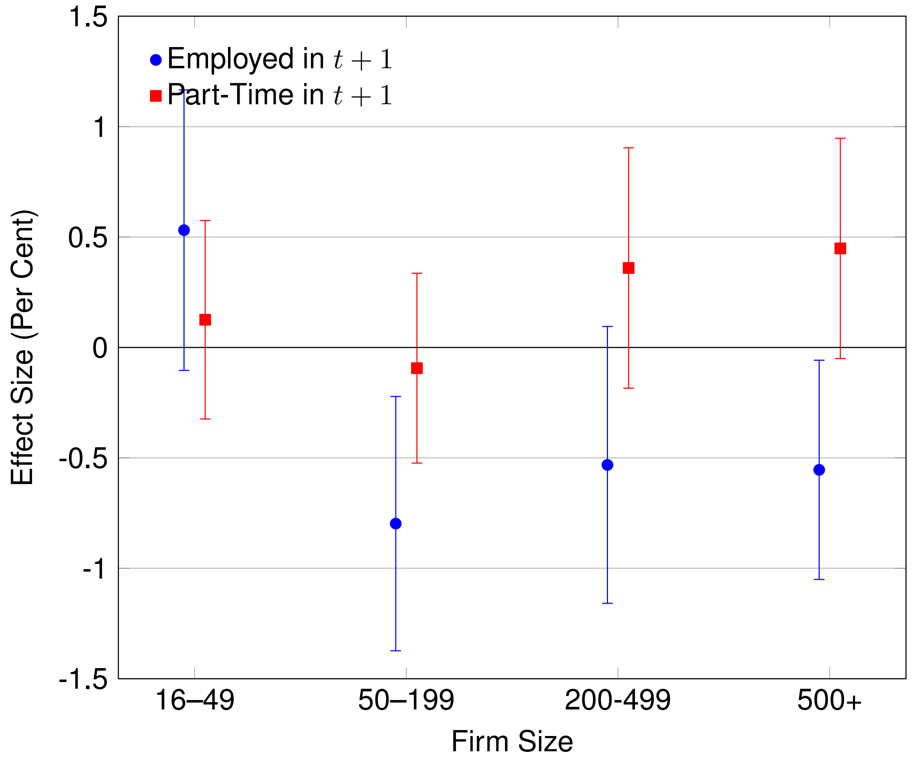


Figure 2.B.2: Effects for Age 20–34

Source: SIAB 7514, own calculations. The figure shows difference-in-difference estimates and 95-% confidence intervals for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level. Regression output tables can be found in Tables 2.1 and 2.A.5 in the appendix.

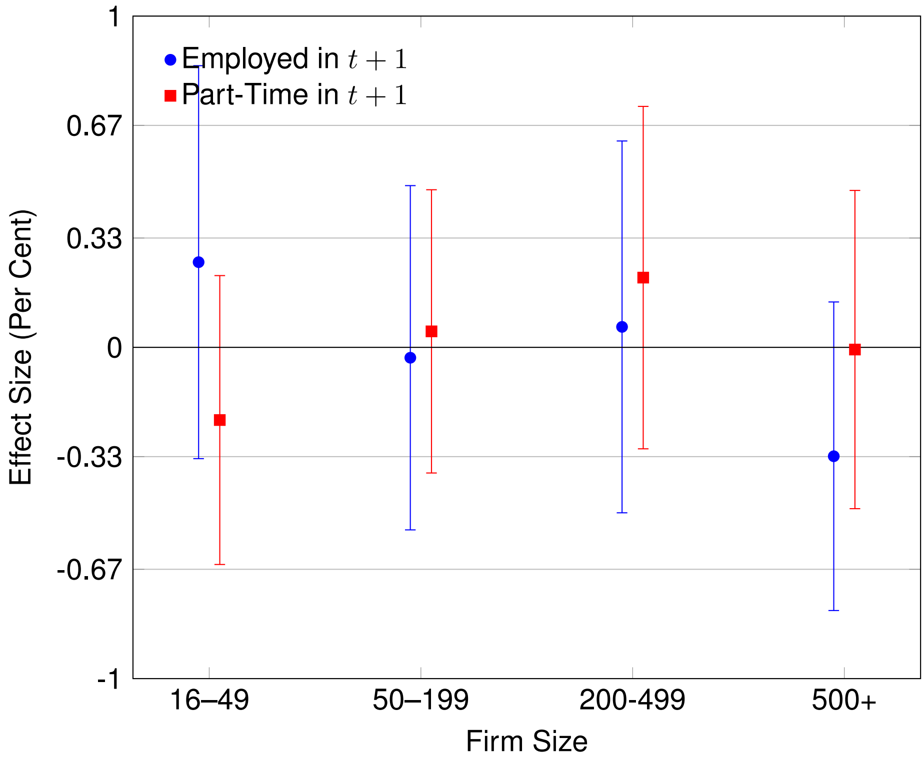


Figure 2.B.3: Effects for Age 35–49

Source: SIAB 7514, own calculations. The figure shows difference-in-difference estimates and 95-% confidence intervals for the effect of the introduction of the Part Time Law in 2001 using different firm sizes as alternative treatment groups. In all regressions, the control group comprises firms with 1-15 employees. All regressions include controls for age group, education, wage group, occupation and East/West region. Standard errors are adjusted for clustering at the firm level. Regression output tables can be found in Tables 2.1 and 2.A.5 in the appendix.

Chapter 3

Job Search with Subjective Wage Expectations

Most welfare states support unemployed workers in their search for a job. This has been justified by the costs imposed by unemployment on both public finances and individuals' work careers. In particular, previous research has shown that prolonged unemployment decreases job finding prospects [Kroft et al., 2013, Eriksson and Rooth, 2014], as well as the quality of wage offers [Schmieder et al., 2016]. These studies provide strong evidence that the returns to job search decrease with elapsed duration in unemployment. Less knowledge exists on how individuals perceive these returns, and how they react to their beliefs. Such knowledge is, however, important to effectively counsel and inform unemployed individuals. Given the wide use of counseling in modern welfare states, it is crucial to take into account beliefs held by unemployed individuals, and to understand how these beliefs affect job search behavior.

In this paper, we focus on the expectations held by newly unemployed job seekers about their wage prospects. We show descriptively that the average job seeker over-estimates her future wage outcome. We then use a structural dynamic job search model to analyze how this "wage optimism" affects the decision to search for work at different stages of the unemployment spell.

The data on subjective wage expectations stem from the 'Linked IZA/IAB Evaluation Dataset', which contains both survey data on subjective expectations and administrative records on labor market histories and outcomes. In line with previous evidence [e.g., by Schmieder et al., 2016], we observe that re-employment wages decrease over the unemployment spell, relative to prior wages. By contrast, subjective expectations do not take account of future reductions in the quality of wage offers. Rather, expectations are heavily anchored in past wages. The average gap between initial expectations and actually realized re-employment wages amounts to 10 % in net terms. Even after one year out of employment, most individuals do not update their expectations.[1] These patterns

[1] Over-optimism by job seekers regarding future wages is consistent with evidence on the empirics of

reveal that unemployed individuals do not recognize that they are searching in a highly dynamic environment.

To assess the consequences of wage optimism for job search, we introduce subjective wage expectations into a non-stationary job search model similar to Card et al. [2007] and Frijters and van der Klaauw [2006]. In these models, unemployed workers choose their optimal job search effort across their unemployment spell. We model individuals as holding potentially incorrect beliefs about both the average value of wage offers and, importantly, about the evolution of wage offers over the unemployment spell. We identify these two key parameters using the data on subjective expectations about future wages. Additionally, we model three sources of dynamics in the job search environment: First, the quality of the average wage offer can evolve over the duration out of employment. Second, search costs are allowed to change over time, capturing the phenomenon that job seekers find it increasingly difficult to generate job offers.[2] Third, UI benefits are paid for a limited amount of time. After exhausting UI payments, benefits are reduced to the level of social assistance. Additionally, the model controls for observable heterogeneity in search costs and wage offers. Similar to Card et al. [2007] and DellaVigna et al. [2017], we focus on search effort instead of reservation wage dynamics and assume that every wage offer is accepted.[3] We provide a range of estimates for different choices of the discount rate.

We use the parameter estimates to simulate a hypothetical scenario in which individuals are perfectly informed about the stochastic evolution of wage offers. The simulation results show that wage optimism affects the trajectory of job search in a highly dynamic way. At first, the knowledge about falling wage prospects creates an incentive for unemployed workers to search more. As a consequence, having correct information about the labor market increases job finding by around 8 % early in an unemployment spell compared to the optimistic benchmark. This effect weakens over the spell and eventually switches sign after about 8 months of unemployment. From then onward, the information about worsened wage offers discourages search and thereby decreases job finding by up to 15 %. Long-term unemployed individuals thus search less when they are well-informed about the wage offers they face. As most individuals exit during early stages of the unemployment spell, optimism prolongs the average unemployment duration by around 0.7 months (6.5 %). The amount of UI benefits paid to the average recipient therefore increases by 450 €. Average accepted wages decrease by about 1 %. Nevertheless, the dynamic pattern renders the overall implications of wage optimism ambiguous: optimism discourages search at early stages of the spell, while encouraging it at later stages. This

reservation wages by Krueger and Mueller [2016] and Koenig et al. [2016], who find that workers persistently misjudge their prospects and set their reservation wage according to their previous wage.

[2]See, e.g., Kroft et al. [2013] and Eriksson and Rooth [2014] for evidence that the probability of a callback decreases over the unemployment spell.

[3]In line with this assumption, Schmieder et al. [2016] find that reservation wages of German job seekers are not binding, suggesting that they are not a meaningful driver of search dynamics in the context of our analysis.

qualitative pattern persists for different choices of the discount rate, while the estimated size of the initial negative effect of optimism decreases in the discount rate.

Our results contribute to the understanding of job search behavior in a dynamic setting and under potentially non-rational expectations. A growing literature analyzes job search under alternative behavioral assumptions than those made by standard models. For instance, DellaVigna and Paserman [2005] and Paserman [2008] study job search with non-exponential discounting. DellaVigna et al. [2017] introduce reference-dependent preferences into a job search model, making the case for a benefit schedule in which UI benefits decrease step-wise over the duration in unemployment. Caliendo et al. [2015] analyze job search strategies when the subjective job offer arrival rate depends on the locus of control. They find that a more internal locus of control is associated with higher job search effort. Spinnewijn [2015] shows that job seekers in the U.S. are overly optimistic regarding their job finding prospects.[4] He presents theoretical evidence that optimal unemployment insurance design is affected by the presence of biased beliefs. Arni and Wunsch [2014] observe a negative relationship between subjective wage expectations and the exit rate out of unemployment. Altmann et al. [2017] show that the provision of information to unemployed individuals via a brochure increases job finding among individuals with low re-employment prospects. We add to this literature by providing a first structural analysis of dynamic job search behavior under subjective wage expectations: based on our model, we trace search choices over the unemployment spell and contrast choices made by over-optimistic agents to choices made by perfectly rational agents.

The remainder of the paper is structured as follows: Section 3.1 presents a search model with subjective expectations about the wage offer distribution. Section 3.2 describes the matched administrative and survey data. Section 3.3 provides reduced form evidence on wage expectations and outcomes. We describe the structural estimation in Section 3.4 and present results in Section 3.5. Section 3.6 concludes.

3.1 Model

We set up a discrete-time, non-stationary job search model similar to Card et al. [2007], where job seekers choose the level of search intensity in each period of time. In a context where wage offers decline in value over the unemployment spell, non-stationarity is central to analyze how subjective wage expectations affect behavior.[5] We first present a rational-expectations version of the model and then introduce the possibility of diverging subjective expectations.

In each period of time t, a worker is either employed at a job paying gross wage

[4] Evidence on persistent over-optimism also exists from other labor market contexts. Hoffman and Burks [2017] show that truck drivers over-estimate their (future) productivity without updating their beliefs.

[5] Non-stationarity in job search models was formalized by Van den Berg [1990], who presents a non-stationary job search model in continuous time.

w, or unemployed with unemployment benefits b_t. At the beginning of each period, job seekers determine their level of search intensity $s_t \in [0, 1]$, which directly translates into their per-period probability of finding a job. Upon finding a job, workers remain employed for the entire future. As in Card et al. [2007] and DellaVigna et al. [2017], we focus on search effort instead of reservation wage dynamics and assume that every wage offer is accepted.[6] We discuss alternative assumptions on reservation wages below.

Value functions The resulting value functions are given by:

$$V(w) = \frac{1+r}{r} u(\tau(w)), \tag{3.1}$$

$$U_t = u(b_t) + \frac{J_{t+1}}{1+r}, \text{ and} \tag{3.2}$$

$$J_t = \max_{s \in [0,1]} s\mathsf{E}_{F_t} V(w) + (1-s)U_t - c_t(s), \tag{3.3}$$

where u denotes the utility of consumption, r is the time discount rate, c_t is the strictly convex effort cost function in period t, F_t is the wage distribution of job offer arrivals in period t, and E_F designates the expectation over the wage offer distribution. The function τ denotes the tax and transfer function, such that consumption equals the net wage $\tau(w)$. In this problem, the job seeker's optimal search policy is the path $(s_t)_{t=1}^{\infty}$. It is determined by the first-order conditions

$$c_t'(s_t) = \mathsf{E}_{F_t} V(w) - U_t, \tag{3.4}$$

for $t = 1, \ldots$. Assuming that the job search environment becomes stationary after T time periods, we then get the stationary solution

$$U_T = \frac{1+r}{s_T + r} u(b_T) + \frac{1}{s_T + r} [s_T \mathsf{E}_{F_T} V(w) - c_T(s_T)], \tag{3.5}$$

$$c_T'(s_T) = \mathsf{E}_{F_T} V(w) - U_T, \tag{3.6}$$

such that a complete solution of the model is obtained by backward induction.

Subjective Wage Expectations The proposed model of job search allows for non-stationarity in the benefit level b_t, the cost of effort c_t and in the wage offer distribution F_t. As shown by the first-order conditions (3.4), the wage offer distribution enters the optimal search decision both directly through the value of finding a job today, $\mathsf{E}_{F_t} V(w)$, and indirectly through the value of finding a job in the future. Therefore, the perceived evolution of the wage offer distribution matters for search behavior. In what follows, we distinguish the objective (true) from the subjective wage offer distributions, the latter denoted F_t^{sub}

[6] Schmieder et al. [2016] provide empirical evidence supporting this assumption, by showing that reservation wages of German job seekers are not binding.

$(t = 1, \ldots)$.

Definition of Wage Optimism We allow for a difference between the true wage offer distribution and its subjective counterpart. Given the widely established evidence of optimism as a behavioral trait, optimism with respect to the subjective wage offer distribution seems plausible. Wage optimism can be defined as follows: denote by $(F_t)_{t=1}^{\infty}$ the *true* sequence of cumulative wage offer distributions, and allow the job seeker to face the job search problem with *subjective* wage expectations $(F_t^{sub})_{t=1}^{\infty}$. We call a job seeker *wage optimistic* if $F_t^{sub} \succ F_t$ for all $t \geq 1$ in the sense of first order stochastic dominance. Conversely, a job seeker is *wage pessimistic* if $F_t^{sub} \prec F_t$ for all $t \geq 1$ holds.

However, we must emphasize that wage optimism as it is defined above is just one possible deviation between subjective and true wage offer distributions. It is, for instance, conceivable that subjective wage distributions are below the true path of wage offers for some periods and above for others.

Consequences of Wage Optimism When individuals would display wage optimism as defined above, this would change job search behavior in a predictable manner. To see the implications of wage optimism, consider the following expanded expression of the value of unemployment:

$$\begin{aligned} U_t = & \sum_{\eta=0}^{\infty} \frac{1}{(1+r)^{\eta}} S_{t+1,t+\eta+1} u(b_{t+\eta}) + \ldots \\ & \sum_{\eta=1}^{\infty} \frac{1}{(1+r)^{\eta}} S_{t+1,t+\eta} \left(s_{t+\eta} \mathsf{E}_{F_{t+\eta}^{sub}} V(w) - c_{t+\eta}(s_{t+\eta}) \right), \end{aligned} \tag{3.7}$$

where $S_{t,t+\eta} = (1 - s_t) \ldots (1 - s_{t+\eta-1})$. The first term on the right hand side is the expected utility stream from unemployment benefits, conditional on the job seeker's search behavior. The second term is the expected value of finding a job in the future less any future effort costs, again conditional on searching. From this equation, it becomes clear that the chosen search intensity involves a trade-off between the current and any future value of taking up employment.

Consider a marginal change in the perceived wage offer distribution, e.g., a wage increase ϕ_W. The effect on the current expected value of work is $\partial \mathsf{E}_{F_t^{sub}} V(w) / \partial \phi_W$, and the effect on the value of unemployment is

$$\frac{\partial U_t}{\partial \phi_w} = \sum_{\eta=1}^{\infty} \frac{1}{(1+r)^{\eta}} S_{t+1,t+\eta} s_{t+\eta} \frac{\partial \mathsf{E}_{F_{t+\eta}^{sub}} V(w)}{\partial \phi_W}. \tag{3.8}$$

This result can be used to derive qualitative predictions. First consider the case of wage optimism in a stationary job search model. In this case, the marginal effect of the increase in the subjectively expected wage on current and future values of employment is constant, i.e., $\partial \mathrm{E}_{F_t^{sub}} V(w)/\partial \phi_W = \partial \mathrm{E}_{F_{t+\eta}^{sub}} V(w)/\partial \phi_W$ for all $\eta = 1, \ldots$. Therefore, the effect of wage optimism on today's search effort is unambiguously positive.

It is, of course, more realistic to consider a duration-dependent wage offer distribution. The effect of optimism on search behavior is then composed of changes in both current and future payoffs. To fix ideas, first consider the decision of how much to search at the beginning of the unemployment spell. Optimism about current wage offers increases the incentive to search. Conversely, optimism about future wage offers reduces the search incentive, as the cost of remaining unemployed is lowered. The net effect of optimism on early job search is thus theoretically ambiguous and remains an empirical question. Considering the effect of optimism at later stages of the unemployment spell, theory predicts that wage optimism increases search. The intuition is that the search environment converges towards the stationary equilibrium as unemployment progresses. As described above, wage optimism under stationarity unambiguously increases search.

The effect of wage optimism on initial job search is thus ambiguous. By contrast, theory predicts that optimistic individuals search more at later stages in the unemployment spell, towards the stationary period.

Learning and Reservation Wages Our model assumes that job seekers accept every wage offer, thereby assuming that any reservation wage is not binding. This central assumption is motivated by recent empirical evidence suggesting that reservation wages are not the main driver of search dynamics and the job finding hazard [e.g. Card et al., 2007, Krueger and Mueller, 2016, Schmieder et al., 2016]. Given the popularity of job search models with reservation wages [c.f. the surveys by Eckstein and Van den Berg, 2007, Rogerson et al., 2005], a discussion of our modeling approach is, however, necessary.

When considering the initial periods of the unemployment spell, a model with reservation wages leads to similar predictions as our model. The main intuition is that individuals with optimistic wage expectations set their reservation wages too high, and potentially adjust them downward too little over time. If reservation wages are binding, wage optimism thus leads to an increased rejection of wage offers and therefore reduces job finding. At the initial periods of the unemployment spell, this is in line with our model, which also predicts a reduced job finding hazard in response to optimism. In later periods, our model implies that optimism can also encourage search by the long-term unemployed, and thereby increase job finding. In a model with reservation wages, this effect would be counteracted by the increased rejection of wage offers due to optimism. We thus conclude that the two models imply similar behavioral reactions at initial periods of the unemployment spell, but potentially diverging reactions during later periods.

Unfortunately, we do not observe rejected offers in our data and can therefore not test for a reservation wage policy directly. Instead, we show that individuals do not appear to learn about wage offers, an indication that reservation wages may not be relevant (see Section 3.3).

Finally, it is worth noting that acceptance of any wage offer is not the only possible interpretation of the search effort model. The model may also, as in Card et al. [2007], be viewed as one with a deterministic individual wage which is observed only with measurement error.

3.2 Data

Data Sources and Sampling We match administrative data on unemployed individuals from the German IAB Employment Biographies to survey data from the IZA Evaluation Dataset. The IZA Evaluation Dataset is a telephone survey of randomly chosen individuals who became unemployed and received payments from the German unemployment insurance (UI) between June 2007 and May 2008.[7] The interviews were realized around 5 to 12 weeks after entry into unemployment. We restrict the analysis to individuals aged between 20 and 55 years, who worked full-time prior to unemployment,[8] were unemployed for at least one full month and were searching for work.[9] After these restrictions, 7,492 individuals are potentially part of the sample.

To measure the relationship between pre-unemployment wages, wage expectations and re-employment wages in a consistent way, we needed to apply additional, non-standard sample restrictions. These ensure that our picture of optimistic wage expectations is not driven by confounding factors:

To focus on regular employment, we first excluded individuals whose net pre-unemployment monthly wage was below 631 € net, the level of social assistance (including housing benefits) for a single household (N=1032, 13.7 %). In addition, we dropped individuals whose pre-unemployment wage is top-coded by the IAB at monthly 4,470 € gross (N=217, 2.9 %). For these individuals it is impossible to infer the wage depreciation profile. We further exclude individuals whose self-reported pre-unemployment net wage exceeds the pre-unemployment gross wage reported in the administrative data (N=1118, 14.9 %). In these cases, self-reported and administratively reported wages are obviously inconsistent.[10] This is problematic in our context, as we study both wage expectations and re-employment wages in relation to the pre-unemployment wage. We finally dropped individuals who did not state a wage expectation although they were not yet re-employed

[7] Arni et al. [2014] provide a detailed description of the sampling method and content of the survey. The merged IZA/IAB data is described by Eberle et al. [2017].

[8] We exclude part-time workers to avoid that changes in working hours confound the wage effects we are interested in.

[9] Individuals who state that they are not searching for work are not asked for their wage expectation and are therefore not relevant for our analysis.

[10] Additionally, the administrative data can under-state the actual pre-unemployment gross wage in the cases of temporary sickness or maternity leave.

at the time of the survey (N=402, 5.4 %).[11] We did not exclude individuals who already found a job at the time of the interview and therefore do not have a stated expectation.[12] After applying these restrictions, the estimation sample contains 4,723 job seekers.

Measurement of Unemployment Duration and Wages The administrative data allow for a precise measurement of the realized unemployment duration, the pre-unemployment and the re-employment wage, the unemployment history and unemployment benefit payments. We observe entry into unemployment and can follow individuals until they are re-employed, independent of whether or not they receive unemployment benefits. Information on the employment status is reported on a monthly basis. An individual is defined as re-employed when entering a job whose wage exceeds monthly welfare benefits (631 €) and which lasts longer than one month.

Measurement of Subjective Wage Expectations The survey data were used, in particular, to measure subjective wage expectations held by job seekers at the time of the survey, i.e., 5 to 12 weeks after entry into unemployment. The corresponding question is: *"Now I am interested in your wage expectations concerning your next job. What do you expect to earn in net euros per month?"* The wage expectation is naturally available only for job seekers who are still searching for work at the time of the interview. 720 individuals (15.2 %) had already found a job at the time of the interview and therefore do not state a wage expectation.

For individuals who participated in the second survey wave and who were still unemployed after one year, the data report a second wage expectation (N=628, 13.3 %). This information is used to test for evidence of updating of expectations in both the descriptive analysis and the structural estimation.

Reported wage expectations are stated in net terms. As individuals also stated their net pre-unemployment wage, we observe how much individuals expect to earn, in net terms, relative to their pre-unemployment wage. In the administrative data, wages are reported in gross terms. There, we observe how the gross re-employment wage relates to the gross pre-unemployment wage.[13] To relate gross wages to net expectations, both in the descriptive analysis and the structural estimation, we converted gross re-employment wages into net terms according to the procedure described in Appendix 3.A. The procedure relies on both the theoretical tax schedule for 2008 and on the fact that we observe,

[11] We define an individual as re-employed when entering a job that exceeds monthly welfare benefits (=monthly wage $>$ 631 €) and lasts longer than one month. Individuals may consider themselves as re-employed when entering subsidized or marginal employment, and thus not answer the question on wage expectations.

[12] In the estimation, these individuals contribute to the likelihood of job finding, but not to the likelihood of wage expectations.

[13] For individuals who enter re-employment within 12 months and participate at the second survey wave, we also observe the re-employment wage in net terms. Due to attrition and the limited time horizon, we do not rely on this measure.

for the same individual, pre-unemployment wages in both gross and net terms.

Summary Statistics Table 3.1 contains summary statistics on the variables used in the baseline estimation. The average pre-unemployment gross wage is at 1,923 € gross per month. The average re-employment gross wage is 1,834 €, i.e. 90 € below. In turn, the average net expectation is 120 € above the average net pre-unemployment wage.

Variable	Obs	Mean	Std. Dev.	Data Source
UE Duration	4,723	8.891	7.373	Admin
Censored at T=20	4,723	0.239	0.427	Admin
Gross Pre-UE Wage	4,723	1923.125	744.296	Admin
Net Pre-UE Wage	4,723	1261.724	420.055	Survey
Gross Re-Employment Wage	3,592	1834.001	718.793	Admin
Net Re-Employment Wage	3,592	1227.857	434.990	Admin, own calc.
Net Expected Wage, Wave 1	4,005	1380.496	461.211	Survey
Net Expected Wage, Wave 2	628	1364.229	456.119	Survey
Education: Medium	4,723	0.487	0.500	Survey
Education: High	4,723	0.177	0.381	Survey
Female	4,723	0.387	0.487	Survey
UE in Prev 10 Yrs (Yes/No)	4,723	0.712	0.453	Admin
Work Experience $>$ Median	4,723	0.566	0.496	Admin
PBD in Months	4,723	11.318	2.269	Own calc.
UI Benefits (ALG I)	4,723	819.803	242.820	Admin
Welfare Benefits (ALG II)	4,723	631	0	Own calc.

Table 3.1: Summary Statistics

Source: IZA Evaluation Dataset (survey) & IAB Employment Biographies (admin). An exit from unemployment is defined as the transition to a job which is exceeds welfare benefits (631 euros per month) and lasts more than one month. Right-censoring applies if individuals are unemployed for more than 20 months. Wages are reported in monthly terms. “Education: Medium” takes the value one if the individual has finished the German Realschule or Fachoberschule. “Education: High” takes the value one if the individual holds the German Abitur. Prior unemployment and work experience both refer to the 10 years prior to entry into the current unemployment spell. The median work experience level over this period is 5 years. PBD is a function of the number of months worked during the 5 years prior to unemployment, and of age. UI benefits are a function of the pre-unemployment wage and of the number of children. Welfare benefits are means-tested and contain a payment for rent expenses and a payment for other living expenses. In practice, welfare benefits vary with household size. For simplification, we use here the average payment for a single individual.

3.3 Descriptive Evidence

In the following, we provide descriptive evidence on the realized and perceived evolution of wage offers after entry into unemployment. We first show that wages decrease with the time spent in unemployment. We then document that job seekers do not expect the fall in wage offers at the beginning of their spell, and that on average, they do not update their wage expectations later on.

Wage Depreciation Over the Unemployment Spell Figure 3.1 shows how average log monthly re-employment gross wages change with the realized duration of unemployment. Clearly, the average wage decreases over the spell. As illustrated by Figure 3.2, this pattern holds for all deciles of the wage distribution.

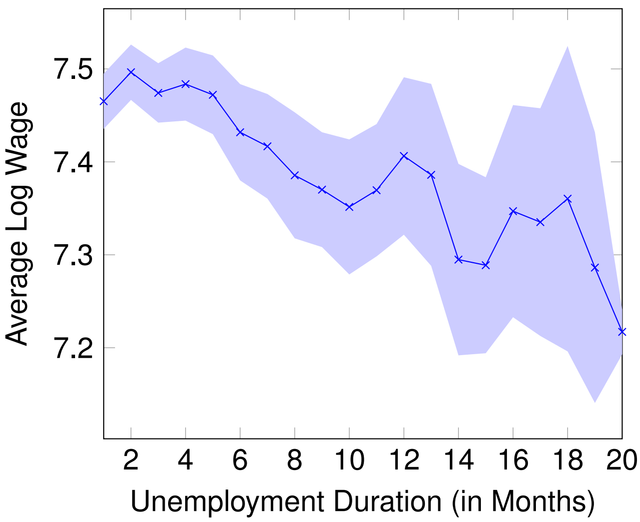


Figure 3.1: Re-Employment Log Wage (Gross)

Source: IAB Employment Biographies. The shaded area shows 95 % confidence bands. The graph includes individuals who enter re-employment within 20 months (N=3,592).

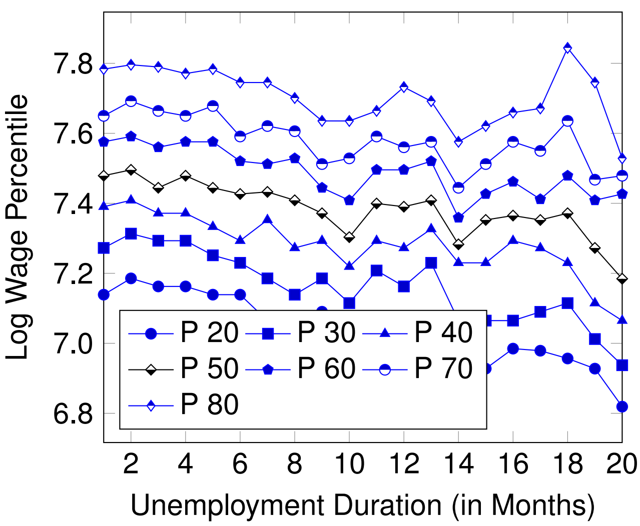


Figure 3.2: Deciles of Re-Employment Log Wage (Gross)

Source: IAB Employment Biographies. The graph includes individuals who enter re-employment within 20 months (N=3,592).

Since wage levels may be correlated with the time spent in unemployment for various reasons, a more relevant measure of wage depreciation results from a comparison between re-employment and pre-unemployment wages. Figure 3.3 shows the same graph for the difference between the log re-employment and the log pre-unemployment wage. The average difference increases strongly over the spell. While individuals who remain unemployed up to 4 months lose around 2 to 3 % relative to their pre-unemployment wage, longer spells are associated with significantly higher losses. In particular, individuals who are unemployed for longer than one year lose 10-20 % on average. According to a linear specification, the monthly depreciation factor is -1.2 %, i.e., slightly above the 0.8 % estimated with local discontinuities by Schmieder et al. [2016]. Figures 3.B.1 to 3.B.3 in the appendix show the same pattern for net wages. Tax progression slightly alleviates the wage depreciation, which is here 1 % per month according to a linear specification.

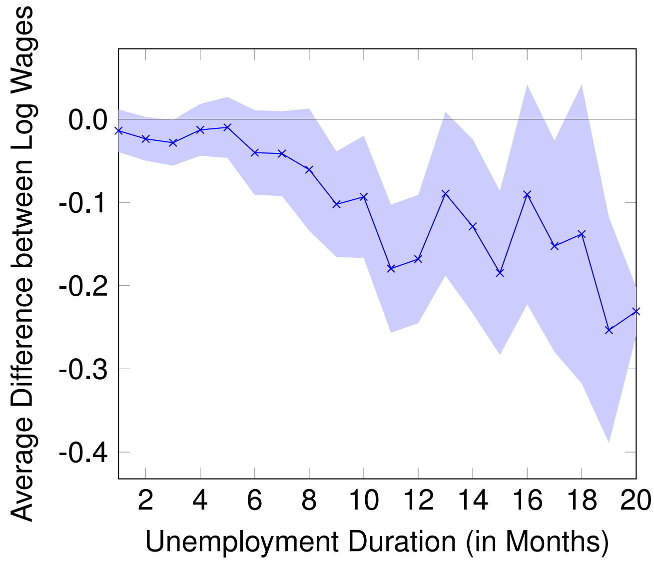


Figure 3.3: Re-Employment Minus Pre-Unemployment Log Wage (Gross)

Source: IAB Employment Biographies. The shaded area shows 95 % confidence bands. The graph includes individuals who enter re-employment within 20 months (N=3,592).

Subjective Expectations of Level of Wage Offers How do individuals perceive their wage prospects when entering unemployment? Figure 3.4 plots the sample distribution of the ratio of expected over pre-unemployment net wages. Clearly, most job seekers do not expect a wage loss. Almost 40 % expect to earn a wage which is very close to their last wage, and more individuals expect to gain than to lose relative to their pre-unemployment wage. As illustrated by Figure 3.5, this pattern results for many individuals in a gap between the expected and the realized net re-employment wage. Both the average and the median job seeker obtain only 90 % of their expected wage.

In Table 3.B.1 of Appendix 3.B, we regress the ratio of the re-employment wage over the expected wage on individual job seeker characteristics, to get a sense of the degree of heterogeneity in wage optimism. Column 1 shows that the ratio of the re-employment wage over the expected wage decreases in the pre-unemployment wage. This suggests that individuals with high pre-unemployment wages receive a smaller share of their expected wage. A higher degree of education, work experience and prior unemployment experience are associated with a more realistic expectation, i.e., with a higher ratio. The pattern also holds in column 2, where the dependent variable is an indicator for whether the ratio of the re-employment wage over the expected wage is lower than the sample median. While the table documents that the degree of optimism can be very heterogeneous across individuals, we focus in this paper on estimating the average effect of optimism on the exit from unemployment.

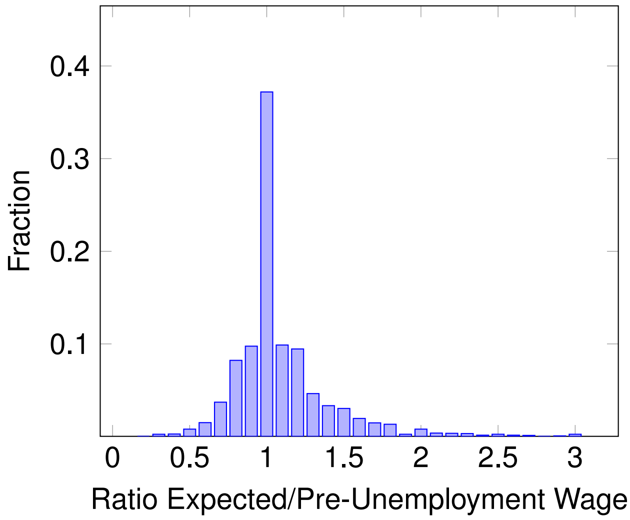


Figure 3.4: Initial Wage Expectation over Pre-Unemployment Wage (Net)

Source: IAB Employment Biographies (pre-unemployment wage) and IZA Evaluation Dataset (wage expectation). The graph includes individuals who have not entered re-employment at the interview date (N=4,005). Individuals with a ratio larger than 3 are excluded from the graph (<1 %)

Evolution of Subjective Wage Expectations A natural question arises: do individuals learn? Do individuals correct for their initial optimism while searching, i.e., is there evidence of learning over the unemployment spell? The data allow us to test for this in two ways. First, job seekers are initially interviewed at slightly different points in their unemployment spell, between week 5 and 12 after entry into unemployment. This provides a small degree of random variation in the time at which job seekers are asked for their initial expectation. Figure 3.6 plots the ratio of expected over last wages by the week of interview. It clearly shows that the distribution of expectations does not change over this time window: job seekers with 5 weeks of elapsed unemployment do not hold different expectations than job seekers whose elapsed unemployment is 12 weeks.

As an additional source of variation in the timing of stated expectations, we use panel

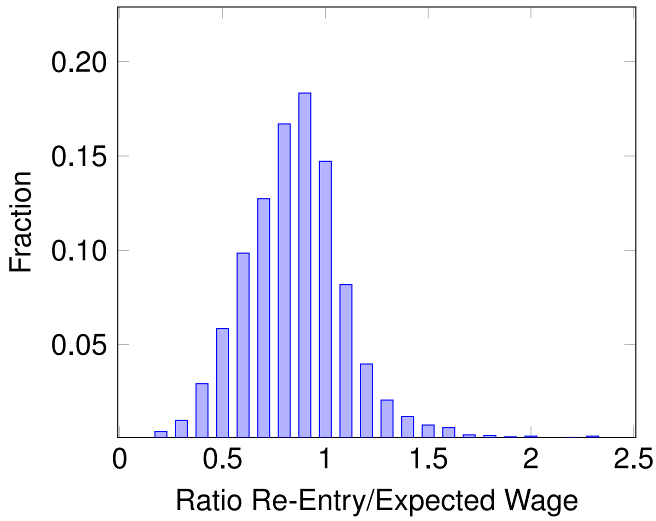


Figure 3.5: Re-Employment Wage over Wage Expectation (Net)

Source: IAB Employment Biographies (re-employment wage) and IZA Evaluation Dataset (wage expectation). The graph includes individuals who have not entered re-employment at the interview date and who enter re-employment within 20 months (N=2,874).

dimension, which is available for individuals participating at the second survey wave and still being unemployed in this period, i.e., after 12 months (N=628). Figure 3.7 plots the ratio of wage expectations reported in the second wave against the initial expectation of these individuals. It shows that more than 30 % of job seekers maintain their initial expectation after one year in unemployment. The average and median job seeker perform zero updating. Although individuals still unemployed after a year are a selective group and despite attrition, the pattern suggests that there is on average no relevant updating of wage expectations over the spell. This observation is in line with reservation wage data collected by Krueger and Mueller [2016], who show that the reservation wages of U.S. workers hardly adapt over the unemployment spell. Koenig et al. [2016] confirm the notion of reference dependence in reservation wages for UK and West German job seekers. Further, Hoffman and Burks [2017] document the absence of belief updating in a different labor market context. They show that truck drivers over-estimate the number of miles they will run over the pay week, without updating their beliefs over the week.

Figure 3.6: Subjective Wage Expectations (Net), by Week of Interview

Source: IZA Evaluation Dataset. The graph shows box plots on initial (log) net wage expectations over the job seeker's week of interview. The upper line of the box shows 75^{th} percentiles, the line inside the box shows medians and the lower line shows 25^{th} percentiles. Dots show outside values. The graph includes individuals who have not entered re-employment at the interview date (N=4,005).

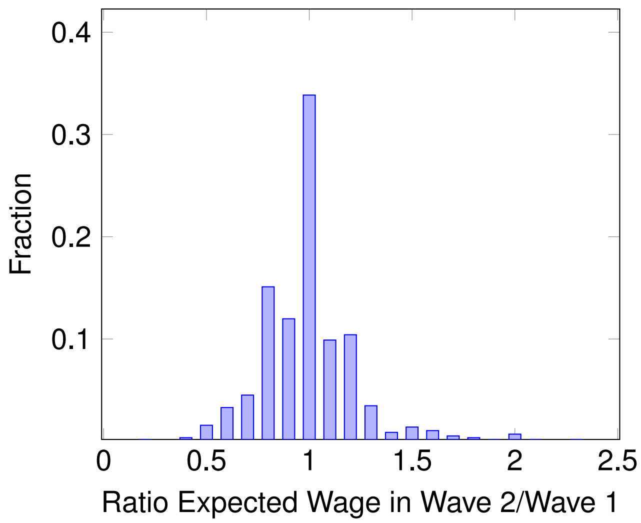


Figure 3.7: Net Wage Expectation in Wave 1 over Net Wage Expectation in Wave 2

Source: IZA Evaluation Dataset. Wave 1 takes place between 5 and 11 weeks after entry into unemployment. Wave 2 re-interviews all available job seekers after 12 months of unemployment. The graph includes individuals with a stated wage expectation in waves 1 and 2 (N=628).

3.4 Structural Estimation

The descriptive evidence indicates a neglect of actual wage dynamics by job seekers. From there, we can, however, not conclude whether this mis-perception (adversely) affects individual behavior. In the following, we want to find out whether "wage optimism" affects job search and the duration spent in unemployment. To this end, we set up a structural analysis of job search under subjective wage expectations.

In the following, we discuss the likelihood function, econometric specification and identification of the model presented in Section 3.1. Our goal is to obtain parameter estimates allowing to simulate how search behavior changes after the imposition of perfect information on actual wage opportunities.

3.4.1 Likelihood Function

We estimate the non-stationary job search model with subjective beliefs about wage offers using maximum likelihood. The likelihood function describes the joint density of observed wages w_i, job search durations d_i, and wage expectations w_i^{exp}. The parameter vector ϕ contains the wage offer distributions F_t, the benefit levels b_t, the utility function u, as well as the search cost function c_t. We allow subjective wage expectations to be subject to measurement error, with $\varepsilon^{exp} \equiv \log(\widetilde{w}^{exp}(\phi)) - \log(w^{exp})$, where w^{exp} is the reported subjective wage expectation and $\widetilde{w}^{exp}(\phi)$ the underlying subjective wage expectation. Denote the density of the measurement error as $h_{exp|\phi}$. The likelihood contribution for an uncensored observation i whose unemployment spell ends in month d_i is:

$$\mathcal{L}_i^{uncens}(\phi) = \prod_{\eta=1}^{d_i-1} (1 - s_\eta(\phi)) h_{exp|\phi}(w_\eta^{exp}|\widetilde{w}_{d_i}^{exp}(\phi))^{d_\eta^{exp}} s_{d_i}(\phi) f_{d_i}^{obj}(w_i|\phi), \tag{3.9}$$

where d_η^{exp} indicates if a wage expectation is observed in period η. Similarly, for observations censored at time $t = T_C$ (here: 20 months), we have:

$$\mathcal{L}_i^{cens}(\phi) = \prod_{\eta=1}^{T_C} (1 - s_\eta(\phi)) h_{exp|\phi}(w_\eta^{exp}|\widetilde{w}_\eta^{exp}(\phi))^{d_\eta^{exp}}. \tag{3.10}$$

3.4.2 Econometric Specification

Utility is logarithmic in income, implying the absence of savings as in Frijters and van der Klaauw [2006]. Individuals employed at wage w derive logarithmic utility from their net wage, $\tau(w)$: $u(w) = log(\tau(w))$. The conversion of gross wages into net terms follows the procedure described in Appendix 3.A. When unemployed with benefits b_t, individuals have utility $u(b) = log(b_t)$. Unemployed agents receive wage offers from a log-normal distribution, $w_t \sim \mathcal{N}(\mu_t^w, \sigma_w)$, where the level of wage offers μ_0 is allowed to depend on individual characteristics X. The dependence on X is parameterized by the vector β^μ, which also includes a constant term. We suppress individual subscripts to ease notation. Over time, the mean of the wage offer distribution depreciates at rate θ^{obj},

$$\mu_t^w = \mu_0 - \theta^{obj} t, \tag{3.11}$$

$$\mu_0 = \beta^\mu X. \tag{3.12}$$

As in Paserman [2008] and DellaVigna et al. [2017], we assume the search cost function to be of power form:

$$c_t(s) = e_t \frac{s^{1+\gamma}}{1+\gamma}, \tag{3.13}$$

$$e_t = \exp(\beta^e X - \theta^e t). \tag{3.14}$$

The search cost component e_t is allowed to vary with individual characteristics X, which is parametrized by β^e (including a constant term). e_t can evolve geometrically with time, as measured by the cost-depreciation factor θ^e. For instance, search can become more costly over the unemployment spell, because easily available offers become exhausted or because motivation decreases. Other elements of duration dependence, not contained in the other model parameters, may also enter θ^e.

As noted by DellaVigna et al. [2017], the search cost parameter γ is the inverse elasticity of the search intensity to the net value of unemployment, $(\mathsf{E}_{F_t^{sub}} V(w) - U_t)/e_t$. Both for wage offers and for search costs, the vector of observable characteristics X includes the last wage received before entrance into unemployment (in addition to gender, education, as well as prior work and unemployment experience). These control for differences in ability or productivity, which may cause selection into prolonged unemployment. We discuss the role of unobserved heterogeneity below, in Section 3.4.3.

Subjective Wage Expectations

The survey data report subjective net wage expectations w_t^{exp} at different points early in the unemployment spell (between week 5 and 12). Some individuals also report a second subjective wage expectation after about 12 months of unemployment. Formally, we interpret the underlying subjective net wage expectation as a weighted average of future subjective wage offers:

$$\widetilde{w}_t^{exp}(\phi) = \sum_{\eta=0}^{\infty} \text{Prob}(d = t + \eta | \phi) \mathsf{E}_{F_{t+\eta}^{sub}} \tau(w) \tag{3.15}$$

$$= \sum_{\eta=0}^{\infty} S_{t,t+\eta}(\phi) s_{t+\eta}(\phi) \mathsf{E}_{F_{t+\eta}^{sub}} \tau(w), \tag{3.16}$$

where d is the duration of unemployment and $S_{t,t+\eta}(\phi) = \text{Prob}(d \geq t + \eta | d \geq= t, \phi)$ is the survival probability from t to $t + \eta$, given the model parameters ϕ. F_t^{sub} denotes the subjective wage offer distribution at time t characterized by $\mathcal{N}(\mu_t^{w,sub}, \sigma_w)$, where

$$\mu_t^{w,sub} = \mu_0 - \theta^{sub} t + \alpha^{sub}. \tag{3.17}$$

In this specification, an individual's subjective wage distribution may differ from the true wage offer distribution in two regards. First, there may be a different perception of the *rate* at which mean wage offers depreciate during the unemployment spell, i.e., $\theta^{sub} \neq \theta^{obj}$. Second, there may be a misperception of the overall *level* of wage offers, such that $\alpha^{sub} \neq 0$. Thus, wage optimism may be characterized by $\theta^{sub} < \theta^{obj}$, or $\alpha^{sub} > 0$, or both.

We assume that the measurement error of the wage expectation is normally distributed, i.e., $\varepsilon_{exp,t} \sim \mathcal{N}(0, \sigma_{exp})$.

3.4.3 Identification

The central parameters in our job search model are the rate of wage depreciation θ^{obj} and its subjective counterpart θ^{sub}, as well as the level parameter of wage optimism α^{sub}. Since the model abstracts from reservation wage choices,[14] we identify the full path of wage offer distributions F_t^{obj}, hence θ^{obj} and σ_w, from accepted wages at different job search durations t. This naturally also holds for all combinations of the vector X, such that β^{μ} is identified as well. The parameters of the subjective counterparts of the wage

[14] Cf. Section 3.1 for a discussion of this modeling choice.

distribution, denoted by θ^{sub} and α^{sub}, are identified by the (repeated) observations of the subjective wage expectations for different duration outcomes.

In the model, the job finding effort depends on the net value of employment, $(V_t - U_t)/e_t$, and the costs of search, $c_t(s_t)$. The optimal level of search given the net value of unemployment is defined by $s_t = ((V_t - U_t)/e_t)^{1/\gamma}$. We identify β^e from the scale of the hazard function and the differences between subgroups defined by X. Furthermore, γ determines how sensitive the hazard function is to time-varying unemployment benefits. It follows that for groups of individuals with the same benefit path and observable characteristics, duration dependence in the job finding hazard identifies the parameter of search cost dynamics θ^e.

We include past wages as a component of the vector of covariates X to control for heterogeneity between individuals in the average wage offer μ_w and in the cost of effort parameter e. In the context of job search, controls for the labor market history have been shown to be a powerful tool to control for (usually unobserved) heterogeneity between unemployed individuals [see, e.g., Caliendo et al., 2017, who used the same data as this paper]. We, however, acknowledge that we cannot fully exclude the possibility of remaining unobserved heterogeneity. Such heterogeneity would mostly lead to an over-estimation of θ^e, which is identified from duration dependence conditional on X.

Following the estimates obtained by Frijters and van der Klaauw [2006] for German individuals, set the discount rate to 20 % p.a., which is equivalent to a monthly discount rate of $r = 1.53\%$. In our setting, it is difficult to disentangle the parameter values of γ and r, since both respond to variation in individual benefit and wage and benefit paths over the spell. As in Frijters and van der Klaauw [2006], we assume that job finding is an absorbing state, motivating the relatively high baseline discount rate of 20 %. To assess the sensitivity of our policy effects with respect to the chosen discount rate, we provide results based on estimations with r = 0.01 and r = 0.02, as lower and upper bounds, respectively, in Section 3.5.3.

3.5 Estimation Results

We first report parameter estimates and the fit of the job search model with subjective wage expectations. We then use the estimates of the subjective expectations model to simulate a scenario in which individuals are perfectly informed about their wage prospects. On this basis, we discuss the effect of wage optimism on the duration to re-employment, re-employment wages, and UI benefit payments.

3.5.1 Parameter Estimates

Table 3.1 shows parameter estimates based on the likelihood specified by (3.9) and (3.10), where the discount rate is set to r = 1.53 % per month. The mean subjective wage expectation for period t, $\mu_t^{w,sub}$, is composed of the average initial wage level, μ_0, the level difference between expected and actual wage offers, α^{sub}, and the subjective wage depreciation factor, θ^{sub} (cf. (3.17)). Results show that, as expected, the average re-employment wage μ_0 increases in the pre-unemployment wage and education, and is lower for females. Conditional on these variables, work experience and unemployment experience have no significant influence. The level parameter of wage optimism, α^{sub}, indicates that job seekers over-estimate their future re-employment wage level by 7 % on average. The estimated subjective wage offer depreciation rate, θ^{sub}, is not different from zero, implying that individuals do not anticipate their wage offers to fall. The actual wage depreciation factor, θ^{obj}, is estimated to be 1.2 % per month of unemployment. Therefore, individuals are on average wage optimistic both with respect to the wage offer level, and with respect to its depreciation.

Search costs increase in pre-unemployment wages and are about 35 % higher for female job seekers. The estimate of θ^e suggests that search costs increase by about 37 % per month of unemployment. This is in line with the intuition that job seekers have increasing difficulties in generating job offers.

3.5.2 Model Fit

Figures 3.1 to 3.3 illustrate how the model fits the data. They plot model predictions based on 1,000 independent random draws for each of the 4,723 individuals in the sample, using the parameter estimates reported in Table 3.1.

As shown by Figure 3.1, job finding exhibits strong negative duration dependence in the data. The job finding hazard starts out from about 15 to 17 % and declines to as little as 3 % after 20 months. This pattern is well captured by the model. Figures 3.2 to 3.3 show histograms for the fit of gross re-entry wages and net wage expectations, respectively. Both wage measures are well predicted by the model.

3.5.3 The Effects of Wage Optimism on Job Finding

We now quantify the impact of wage optimism on job finding. To this end, we used the parameter estimates to simulate a scenario in which individuals are perfectly informed about future wage offers. We first report baseline results and then assess how sensitive the results are with respect to the choice of the discount factor. All simulations are based on 1,000 independent random draws for each of the 4,723 individuals, using the parameter estimates reported in Table 3.1.

Baseline Results

To understand how wage optimism affects job finding, we simulated a counter-factual scenario in which job seekers are fully aware of the path of wage offers over the progres-

	Estimate	S.E.
Wage Offers		
μ_0 :		
Constant	3.008	0.037
Log Pre-UE Wage	0.599	0.005
Education: Medium	0.023	0.007
Education: High	0.178	0.008
Female	-0.101	0.006
Work Experience $>$ Median	-0.012	0.006
UE in Prev. 10 Yrs (Yes/No)	-0.001	0.006
θ^{obj}	0.012	0.001
θ^{sub}	0.001	0.002
α^{sub}	0.073	0.021
Inverse Elasticity of Search		
γ	3.401	0.494
Search Costs		
e_0 :		
Constant	3.836	0.840
Log Pre-UE Wage	0.696	0.212
Education: Medium	-0.102	0.157
Education: High	0.251	0.208
Female	0.353	0.173
Work Experience $>$ Median	-0.179	0.152
UE in Prev. 10 Yrs (Yes/No)	-0.124	0.151
θ^e	0.369	0.053
Variance Parameters		
SD of Log Wage Offers σ_w	0.305	0.003
SD of Log Wage Expectations σ_ϵ	0.245	0.001
Average Log L	-2.678	
N	4,723	

Table 3.1: Parameter Estimates

Estimates are based on the likelihood specified by equations 3.9 and 3.10. The discount rate is set to $r = 0.0153$. "Education: Medium" takes the value one if the individual has finished the German Realschule or Fachoberschule. "Education: High" takes the value one if the individual holds the German Abitur. Prior work and unemployment experience both refer to the 10 years prior to entry into the current unemployment spell. The median work experience level over this period is 5 years.

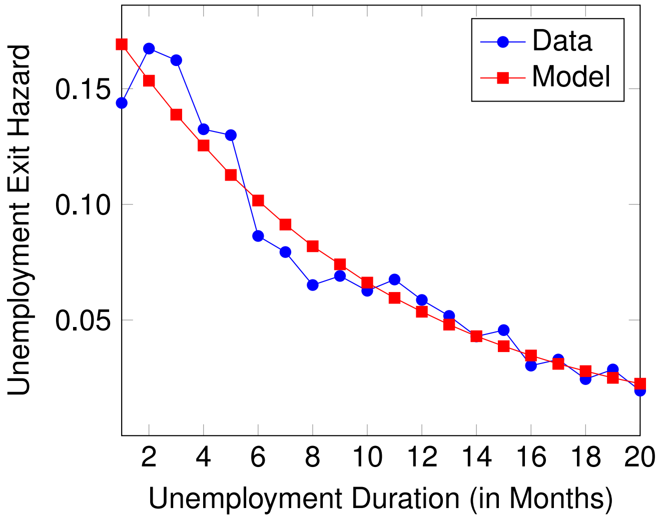


Figure 3.1: Fit of Job Finding Hazard

Predictions are made based on the parameter estimates reported in Table 3.1.

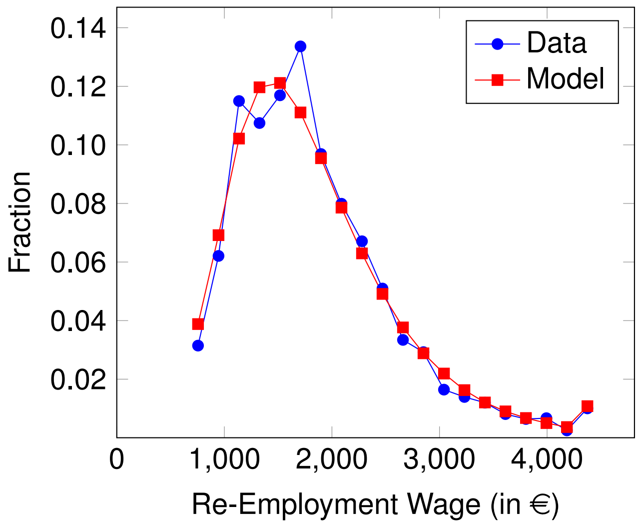


Figure 3.2: Fit of Re-Employment Wages

Predictions are based on 1,000 independent random draws for each of the 4,723 individuals in the sample, using the parameter estimates reported in Table 3.1.

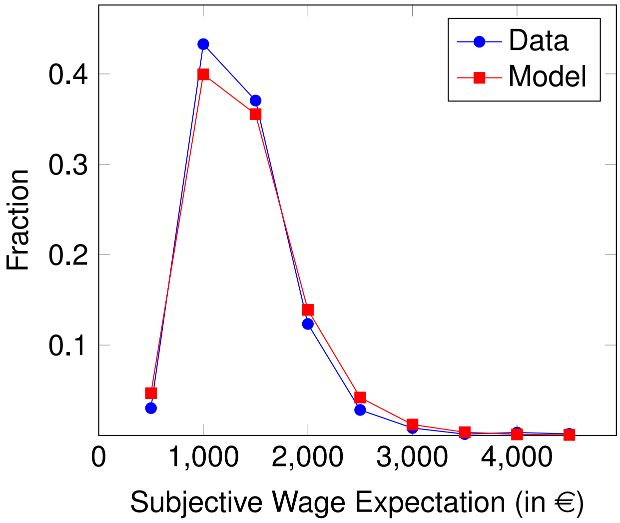


Figure 3.3: Fit of Subjective Wage Expectations

Predictions are based on 1,000 independent random draws for each of the 4,723 individuals in the sample, using the parameter estimates reported in Table 3.1.

sion of unemployment. To this end, we estimated the subjective expectations model while imposing $\alpha^{sub} = 0$ and $\theta^{sub} = \theta^{obj}$. In terms of policy, we predicted the effects of an intervention in which the average job seeker is provided with perfect information about their wage profiles. We simulated a policy that leads to a full adjustment of individual wage expectations to actual wage offer distributions. This is, of course, an ideal that is unlikely reached in practice. However, well-designed counseling, or an "information treatment" will likely lead to a partial adjustment of subjective wage expectations. Therefore, we use our simulation results to understand the dynamic reactions of job search to optimism, and to measure an upper bound on the potential effect of information provision.

We contrast the effect of information provision with the effect of a 10 % reduction in search costs e_t in each month t of the spell. From a policy perspective, search costs can for instance be reduced by offering support with application writing or by referring suitable vacancies.

Figure 3.4 plots predicted percentage changes in the job finding hazard over the unemployment spell. In line with intuition, the search cost reduction has unambiguously positive effects on job finding. Given that search costs increase over the spell (due to a positive estimate of θ^e), the benefits of a 10 % cost reduction also follow a slightly increasing pattern. Overall, job-finding increases by around 2-3 %.

In contrast, the information treatment shows highly dynamic effects over the course of the unemployment spell. As wage losses can be avoided by exiting at an earlier stage, perfectly informed individuals are around 8 % more likely to find a job during the first month of unemployment. This effect sharply decreases over the spell and reaches a point estimate of zero in month seven. From then onward, perfect information reduces incentives to search and the job finding probability decreases by up to 15 % in month 20.

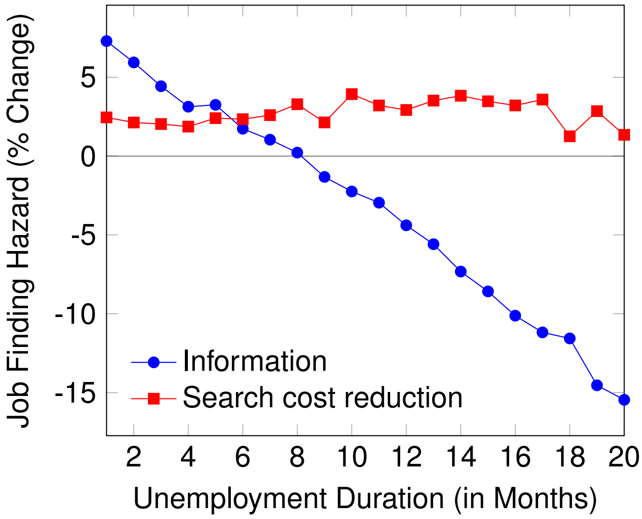


Figure 3.4: Simulation: Effect of Information Provision and Search Cost Reduction

The counter-factual simulations are based on 1,000 independent random draws for each of the 4,723 individuals in the sample. The information treatment imposes perfect information about wage offers by setting $\alpha^{sub} = 0$ and $\theta^{sub} = \theta^{obj}$. The simulated search cost reduction reduces e_t by 10 % at each month of the spell.

This simulated pattern sheds light on the qualitative predictions discussed in Section 3.1: at the beginning of the unemployment spell, the prospect of falling wage offers creates an incentive to search more today. Under wage optimism, this incentive is absent, which explains that the counter-factual with perfect information predicts more individuals finding a job very early on. For individuals who remain unemployed, rational expectations reduce the motivation to search: informed individuals now realize that they have lower returns from searching, since the quality of their wage offers has depreciated.

In Table 3.2, we report how the change to perfect information affects the average duration of unemployment, the amount of benefit payments and wages. Given that a large share of individuals exits unemployment at early stages, the average duration to re-employment reduces substantially in response to the provision of information, by about 0.7 months ($\approx$ 6.5 %). As a consequence, benefit payments per person fall by around 452 € ($\approx$ 6 %) per person. As the average individual avoids nearly one month of wage depreciation, the average re-employment wage increases by about 1 %. The 10 % search cost reduction reduces unemployment and benefit payments by about 2 % and increases wages by about 0.1 %.

Taken together, the simulation illustrates an economically significant potential to increase early job finding by raising the awareness about falling wage offers. This benefit, however, comes at the price of discouragement among long-term unemployed workers, rendering overall policy implications ambiguous.

	Information Provision		Search Cost Reduction	
	Simulated Effect	% Change	Simulated Effect	% Change
Duration of UE in Months	-0.7	-6.5%	-0.2	-1.7%
UI Benefit Payment in Euros	-452.8	-5.9%	-118.9	-1.5%
Monthly Gross Wage in Euros	12.2	0.7%	1.6	0.1%

Table 3.2: Simulated Average Effects of Information Provision and Search Cost Reduction

The counter-factual simulations are based on 1,000 random independent draws for each of the 4,723 individuals in the sample. The information provision imposes perfect information about wage offers by setting $\alpha^{sub} = 0$ and $\theta^{sub} = \theta^{obj}$. The search cost reduction decreases e_t by 10 % at each month of the spell.

Sensitivity to the Chosen Discount Factor

As evoked in Section 3.4.3, the estimated returns to information may be influenced by the chosen discount factor r. Setting r too low may lead us to over-estimate the effect of information provision on job finding: more patient job seekers find a decrease in future wage offers more salient, such that initial job search shows stronger reactions to future wage offer reductions. Setting the discount rate too high has the opposite effect of under-estimating the role of information provision. By contrast, the estimated effect on search at later stages of the spell is unlikely to be affected, as it is mostly driven by changes in current payoffs.

To provide evidence on the sensitivity of predicted effects to the discount factor, we estimate the effect of optimism for a low value of r = 1 %, and for a high value of r = 2 %. The corresponding parameter estimates are reported in tables 3.C.1 and 3.C.2 of Appendix 3.C. Figure 3.5 shows that the qualitative pattern of the policy effect looks very similar across discount factors. However, the initial effect sizes vary: for the lower bound of r = 1 %, the initial increase in the job finding hazard due to information starts off at around 12 % and becomes zero only in month 11. This reflects that patient individuals initially perceive future wage losses as being more salient. In turn, the effects simulated with the upper bound of 2 % are only slightly more negative than those from the baseline with $r \approx 1.5\%$. The effect of the information treatment for longer-term unemployed (12+ months) does not depend on the chosen discount rate. This is expected, as the decision to search is less influenced by future payoffs when the stationary period approaches.

Given that job finding predominantly occurs at the beginning of a spell, the size of average effects reacts to the choice of r. As reported in Table 3.3, the duration in unemployment is predicted to decrease by 10 % for r =1 %, compared to an increase by 6.5 % in the baseline case with r = 1.53 % and an increase by 5 % for r = 2 %.

We conclude that the exact initial effect sizes are sensitive to the choice of the discount factor. However, we can confirm the robustness of the following findings. First, the potential effect of information about wage opportunities on job finding is economically significant. Second, the effect is initially positive and switches signs later in the spell. It is in our setting unambiguously positive in the first six months, and unambiguously negative for spells lasting longer than a year.

	r=1%		r=1.53% (Baseline)		r=2%	
	Effect	% Change	Effect	% Change	Effect	% Change
Duration of UE in Months	-1.1	-10.3%	-0.7	-6.5%	-0.5	-4.8%
UI Benefit Payment in Euros	-728.7	-9.5%	-452.8	-5.9%	-334.3	-4.3%
Monthly Gross Wage in Euros	14.5	0.8%	12.1	0.7%	10.4	0.6%

Table 3.3: Simulated Average Effects of Information Provision, for Different Discount Factors

The counter-factual simulations are based on 1,000 random independent draws for each of the 4,723 individuals in the sample. The information provision imposes perfect information about wage offers by setting $\alpha^{sub} = 0$ and $\theta^{sub} = \theta^{obj}$. The search cost reduction decreases e_t by 10 % at each month of the spell.

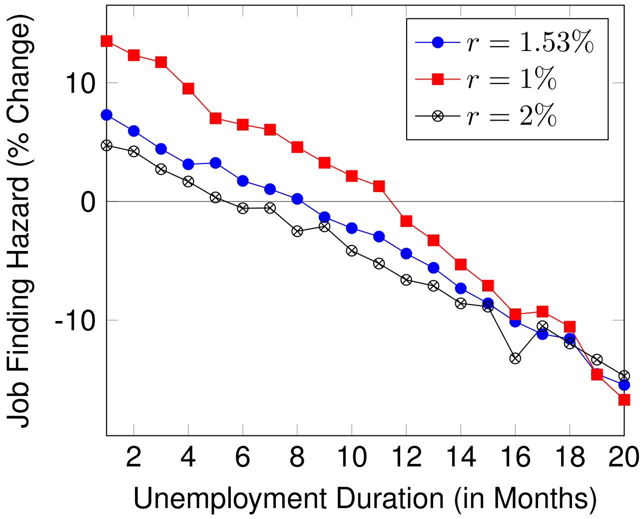


Figure 3.5: Simulation: Effect of Information Provision for Different Discount Factors

The counter-factual simulations are based on 1,000 independent random draws for each of the 4,723 individuals in the sample. The information treatment imposes perfect information about wage offers by setting $\alpha^{sub} = 0$ and $\theta^{sub} = \theta^{obj}$.

3.6 Conclusion

We combine data on subjective expectations with data on realized job search outcomes. We show that job seekers significantly over-estimate their future wage outcomes, by 10 % on average.

We build a structural job search model that accounts for the divergence of subjective beliefs from the true wage offer distribution. Based on simulations of a counter-factual with perfect information, we find that wage optimism increases the average unemployment duration by around 0.7 months (6.5 %). However, this average effect masks important dynamics: more information leads individuals to increase their search effort over the first few months of unemployment. During this time, the information about future reductions in job offer quality raises the incentive to search for a job. For longer-term unemployed individuals, who are already affected by deteriorated wage offers, information lowers the search incentive and therefore reduces job finding. This implies a cautionary note for efforts aimed at informing job seekers better about the dynamics of their job search environment: care needs to be taken not to discourage the long-term unemployed.

Finally, our study suggests an easy-to-implement test for potential mis-specification in dynamic job-search models: combining the use of actually observed declines in wage offers with the assumption of a static subjective wage offer distribution, to account for the fact that individuals do not anticipate the depreciation of wages. This procedure can serve as a useful robustness check for policy simulations based on search models whenever data on subjective wage expectations is not available.

Appendix

3.A Gross-Net Conversion

To convert gross re-employment wages into net terms, we exploit two main sources: (i) the theoretical tax schedule for 2008 and (ii) the fact that we observe pre-unemployment wages both in gross terms (administrative data) and in net terms (survey data).

We use a functional form similar to the ones by Heathcote et al. [2014] and Blundell et al. [2016b] to approximate the theoretical relationship between gross pre-unemployment wages pre_i and net pre-unemployment wages $\tau(pre)_i$:

$$\widehat{\tau(pre)_i} = \hat{\beta}^* pre_i^{1-\mu}, \tag{3.18}$$

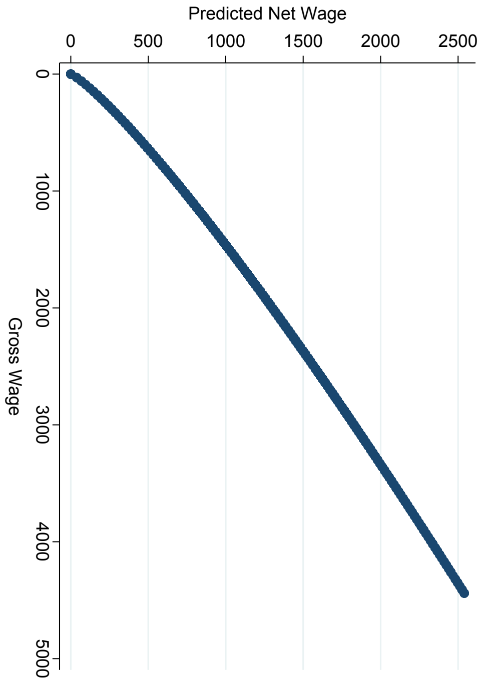
where $1 - \mu$ describes the curvature of the tax function, i.e., its progressivity. We proceed in two steps. We first obtain μ = 0.16 from the theoretical schedule governing the income taxation of a single individual in 2008. We then relate net to gross pre-unemployment wages using (3.18). The function fits the data remarkably well, with an R^2 of 0.97. Figure 3.A.1a presents the relationship between pre_i and $\widehat{\tau(pre)_i}$, and Figure 3.A.1b the relationship between the predicted $\widehat{\tau(pre)_i}$ and the $\tau(pre)_i$ observed in the survey data. We interpret the %-deviation of $\tau(pre)_i$ from $\widehat{\tau(pre)_i}$ as a result of taxation rules applying to the individual's situation (e.g., marriage and family status etc.): $Dev_i = \dfrac{\tau(pre)_i - \widehat{\tau(pre)_i}}{\widehat{\tau(pre)_i}}$.

We assume that the individual-specific rules still apply after the unemployment spell, and measure individual i's net re-employment wage $\tau(w)_i$ as:

$$\tau(w)_i = \widehat{\tau(w)_i} + Dev_i \times \widehat{\tau(w)_i}, \tag{3.19}$$

where $\widehat{\tau(w)_i} = \hat{\beta}^* w_i^{1-\mu}$ is the theoretical net gross re-employment wage, with $\hat{\beta}$ estimated from equation 3.18.

(a) Gross and Predicted Net Pre-UE Wages



(b) Predicted Net and Net Pre-UE Wages

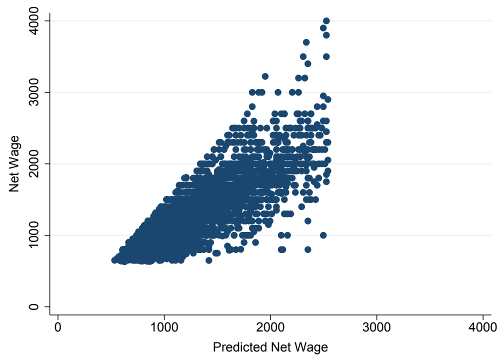


Figure 3.A.1: Pre-Unemployment Wages: Gross, Predicted Net and Net

3.B Additional Descriptive Evidence

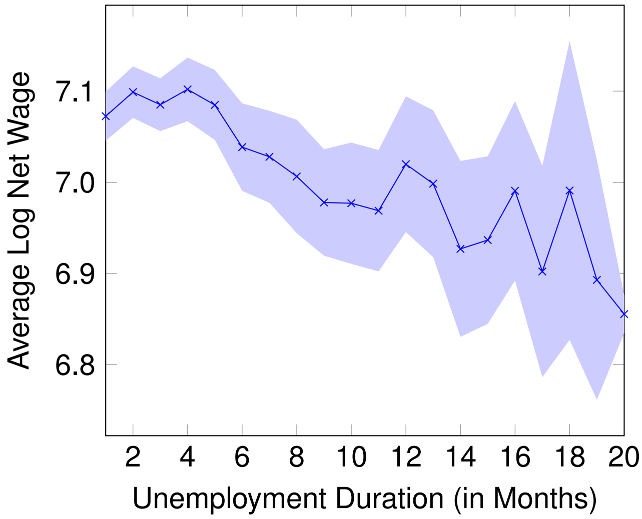


Figure 3.B.1: Re-Employment Log Wage (Net)

Source: IAB Employment Biographies. Gross wages are converted into net terms according to the procedure described in Appendix 3.A. The shaded area shows 95 % confidence bands. The graph includes individuals who enter re-employment within 20 months (N=3,642).

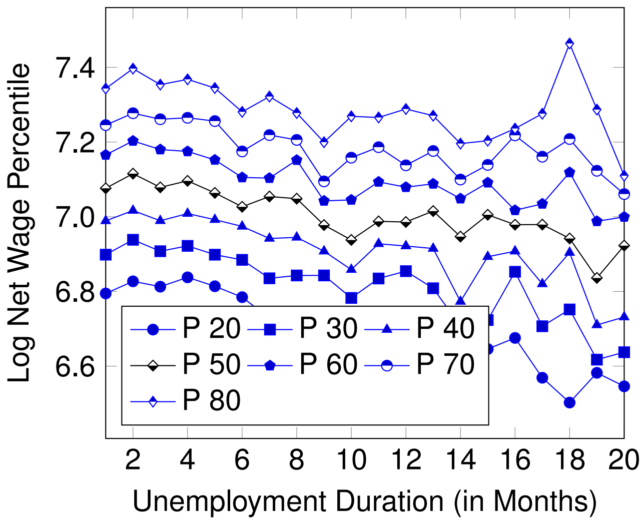


Figure 3.B.2: Deciles of Re-Employment Log Wage (Net)

Source: IAB Employment Biographies. Gross wages are converted into net terms according to the procedure described in Appendix 3.A. The graph includes individuals who enter re-employment within 20 months (N=3,642).

	Ratio Re-Employment/Expected Wage	$\mathbb{1}$(Ratio $<$ Median)
	(1)	(2)
Log Pre-UE Wage	-0.065***	0.023
	(0.015)	(0.028)
Female	-0.014	0.022
	(0.010)	(0.020)
Education: Medium	0.017*	-0.033
	(0.010)	(0.021)
Education: High	0.039**	-0.067**
	(0.015)	(0.029)
Work Experience $>$ Median	0.036***	-0.038*
	(0.011)	(0.020)
UE in Prev. 10 Yrs (Yes/No)	0.025**	-0.061***
	(0.011)	(0.022)
Outcome Mean	0.906	0.476
N	2874	2874

Table 3.B.1: Wage Optimism and Individual Characteristics

The sample includes individuals with an observed wage expectation, re-entering employment within the observation period (20 months). “Education: Medium” takes the value one if the individual has finished the German Realschule or Fachoberschule. “Education: High” takes the value one if the individual holds the German Abitur. Individuals in the baseline category hold a lower level of education. Prior unemployment and work experience both refer to the 10 years prior to entry into the current unemployment spell. The median work experience level over this period is 5 years. Robust standard errors. $^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$.

Figure 3.B.3: Re-Employment Minus Pre-Unemployment Log Wage (Net)

Source: IAB Employment Biographies. Gross wages are converted into net terms according to the procedure described in Appendix 3.A. The shaded area shows 95 % confidence bands. The graph includes individuals who enter re-employment within 20 months (N=3,642).

3.C Additional Parameter Estimates

	Estimate	S.E.
Wage Offers		
μ_0 :		
Constant	3.059	0.059
Log Pre-UE Wage	0.592	0.008
Education: Medium	0.027	0.007
Education: High	0.184	0.008
Female	-0.099	0.006
Work Experience $>$ Median	-0.011	0.007
UE in Prev. 10 Yrs (Yes/No)	-0.002	0.006
θ^{obj}	0.012	0.001
θ^{sub}	0.000	0.002
α^{sub}	0.063	0.020
Inverse Elasticity of Search		
γ	3.319	1.042
Search Costs		
e_0 :		
Constant	3.840	1.975
Log Pre-UE Wage	0.690	0.216
Education: Medium	-0.093	0.162
Education: High	0.255	0.212
Female	0.396	0.218
Work Experience $>$ Median	-0.181	0.155
UE in Prev. 10 Yrs (Yes/No)	-0.143	0.156
θ^e	0.367	0.107
Variance Parameters		
SD of Log Wage Offers σ_w	0.305	0.003
SD of Log Wage Expectations σ_ϵ	0.246	0.001
Average Log L	-2.677	
N	4,723	

Table 3.C.1: Parameter Estimates: Lower Bound Discount Factor (r=0.01)

Estimates are based on the likelihood specified by (3.9) and (3.10). “Education: Medium” takes the value one if the individual has finished the German Realschule or Fachoberschule. “Education: High” takes the value one if the individual holds the German Abitur. Prior work and unemployment experience both refer to the 10 years prior to entry into the current unemployment spell. The median work experience level over this period is 5 years.

	Estimate	S.E.
Wage Offers		
μ_0 :		
Constant	2.991	0.035
Log Pre-UE Wage	0.601	0.005
Education: Medium	0.025	0.007
Education: High	0.183	0.008
Female	-0.097	0.006
Work Experience $>$ Median	-0.012	0.006
UE in Prev. 10 Yrs (Yes/No)	-0.003	0.006
θ^{obj}	0.012	0.001
θ^{sub}	0.001	0.002
α^{sub}	0.079	0.021
Inverse Elasticity of Search		
γ	3.446	0.561
Search Costs		
e_0 :		
Constant	3.834	0.687
Log Pre-UE Wage	0.690	0.206
Education: Medium	-0.106	0.157
Education: High	0.248	0.204
Female	0.338	0.171
Work Experience $>$ Median	-0.177	0.149
UE in Prev. 10 Yrs (Yes/No)	-0.118	0.149
θ^e	0.368	0.058
Variance Parameters		
SD of Log Wage Offers σ_w	0.306	0.003
SD of Log Wage Expectations σ_ϵ	0.246	0.001
Average Log L	-2.678	
N	4,723	

Table 3.C.2: Parameter Estimates: Upper Bound Discount Factor (r=0.02)

Estimates are based on the likelihood specified by (3.9) and (3.10). “Education: Medium” takes the value one if the individual has finished the German Realschule or Fachoberschule. “Education: High” takes the value one if the individual holds the German Abitur. Prior work and unemployment experience both refer to the 10 years prior to entry into the current unemployment spell. The median work experience level over this period is 5 years.

General Conclusion

In this doctoral thesis, I have provided an empirical assessment of three aspects of individual labor supply: the trade-off between fertility and a work career for women (Chapter 1), the time conflicts that women face at the workplace (Chapter 2), and the information frictions faced by the unemployed (Chapter 3).

I conclude from the first chapter that the risk of unemployment is in fact an important determinant for female work and fertility careers. As explained in the main text, recent empirical findings point to a complementary relationship between female career opportunities and fertility choices. My analysis builds on these findings and derives the policy options arising from this relationship: parental leave policies such as parental leave job protection and parental leave benefits increase fertility by (a) reducing the risk of prolonged involuntary non-employment following parental leave, and (b) improving the income situation of working women who decide to take care of a newborn for a limited time period. The life-cycle employment response to changes in the maximum duration of parental leave job protection of benefit receipt is quite low according to my simulations.

Of course, the structural approach taken in the first chapter has its limitations. First and foremost, the identification of fertility and life-cycle employment effects relies on some strong assumptions, such as perfect foresight or the invariance of labor market frictions to changes in parental leave policies. However, the advantage of this approach is to provide a counter-factual assessment of hypothetical policy options where credible (quasi-) experimental evidence is not available. This makes structural estimates the best guess that can be obtained on this specific question.

In the second chapter, I followed a different route to identify the causal effect of the introduction the Part-Time and Limited-Term Employment Act (Part-Time Law) in Germany in 2001 on subsequent employment and work hours of affected employees. The hypothesis here was that average employment responses in affected firms say little about the actual potential of the Part-Time Law to decrease hours constraints, because these constraints are innately heterogeneous. Focusing on the age dimension, I found that the group of female full-time employees above the age of 50 responded to the legal right to reduce their work hours by switching to part-time work hours. Moreover, subsequent employment increased. This suggests that hours constraints at the workplace may force women out of the labor force when personal circumstances tighten the time budget.

Moreover, a legal claim seems to have solved this problem for some women.

Such a legal claim to part-time work is currently subject to a debate in Germany. Specifically, the new government announced in their coalition agreement from 2018 to establish a legal right to return to previous work hours after a time-limited reduction of work hours. In view of my results, it is conceivable that such a reform would even induce younger women to temporarily reduce their work hours.

The third part of the thesis evaluates the scope for a less often debated policy tool: information provision to the unemployed. In structural modeling, perfect information of decision makers is often assumed for convenience. My coauthors and I provide new descriptive evidence on biased wage expectations among job seekers: comparing the wage expectations of job seekers to their actual realizations shows that the former are heavily upward biased. Moreover, job seekers do not anticipate that their job offers will fall the longer they remain unemployed. In the context of a dynamic job search model, we show that correcting these false beliefs would increase initial job finding, decrease average non-employment durations and reduce the costs to the unemployment insurance system.

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Summary

English Summary

This doctoral thesis comprises three chapters dealing with individual labor supply, each from a different perspective. In the first chapter, I estimated a dynamic structural life-cycle model of female labor supply and fertility to evaluate the effect of parental leave policies on these outcomes. Chapter 2 is an evaluation study of the 2001 introduction of the Part-Time and Limited-Term Employment Act in Germany, which I exploit to obtain a causal estimate of the effects on hours constraints on hours of work and labor market participation. In Chapter 3, my coauthors Amelie Schiprowski, Luke Haywood and I investigate the subjective wage expectations of the unemployed. We estimate a structural job search model to estimate the causal effect of biased expectations on non-employment durations. In all three chapters, I applied microeconomic reasoning to individual labor supply decisions, and used microeconometric estimation techniques to draw policy conclusions on empirical grounds.

In Chapter 1, I develop a dynamic discrete choice model of female labor supply and fertility to evaluate parental leave policies based on the German Socio-economic Panel [Wagner et al., 2007]. Building on recent empirical evidence on the connection between fertility and unemployment risk, I emphasize the importance of labor market frictions and job security for dynamic fertility and labor supply decisions of women. To quantify the effect of parental leave job protection and parental leave benefits, I simulated counterfactual remaining life-cycles for synthetic samples of women affected by the reforms at different ages. I find that a reduction in the maximum job protection period from 3 to 2 years would decrease remaining fertility by 4.1 % for the sample affected at age 20, and an extension of the benefit period from 1 to two years would increase fertility by 4.7 %. Life-cycle employment effects are rather small. Effects on the employment rate are not persistent but effects on the part-time share among female employees are. I conclude that reform effects on parental leave durations tend to overestimate the employment effects of parental leave reforms. On the other hand, usually unobserved effects on total remaining fertility rates seem to be positive for both considered policies.

In Chapter 2, I evaluate the 2001 introduction of the Part-Time and Limited-Term Employment Act (Part-Time Law) in Germany. This reform granted a legal claim to reduce

work hours for employees in establishments more than 15 employees. Using employees of establishments with up to 15 employees as a control group, I estimate the causal effect of the reform on transitions to part-time work and subsequent employment in a difference-in-differences setting. The analysis is innovative in two important respects. First, previous studies exploiting the reform effect did not account for important employee-level heterogeneity in hours constraints. However, I show using highly accurate employee-level administrative data from the SIAB [Antoni et al., 2016] that the individual incidence and transitions to part-time are highly heterogeneous, especially with respect to employee age. Second, focusing on transitions to part-time work and non-employment for full-time employees, I am able to identify the effect of hours constraints on labor force participation. I find that the Part-Time Law significantly increased transitions to part-time work for female employees above the age of 50 (by 1-2.5 percentage points). Moreover, I find evidence of increased subsequent employment in this age group (1 percentage point).

In Chapter 3, my coauthors and I analyze how subjective expectations about wage opportunities influence the job search decision. We match data on subjective wage expectations with administrative employment records. The data reveal that unemployed individuals overestimate their future net re-employment wage by 10 % on average. In particular, the average individual does not anticipate that wage offers decline in value with their elapsed time out of employment. How does this optimism affect job finding? We analyze this question using a structural job search framework in which subjective expectations about future wage offers are not constrained to be consistent with reality. Results show that wage optimism has highly dynamic effects: upon unemployment entry, optimism decreases job finding by about 8 %. This effect weakens over the unemployment spell and eventually switches sign after about 8 months of unemployment. From then onward, optimism prevents unemployed individuals from becoming discouraged and thus increases search. On average, optimism increases the duration of unemployment by about 6.5 %.

German Summary

Diese Doktorarbeit besteht aus drei Kapiteln, die sich mit dem individuellen Arbeitsangebot befassen, dabei jeweils aus einer anderen Perspektive. Im ersten Kapitel schätzte ich ein dynamisches strukturelles Lebenszyklusmodell der Arbeitsangebots- und Fertilitätsentscheidungen von Frauen. Ziel ist es, die Auswirkungen von Familienpolitiken (Elterngeld und Elternzeit) auf diese Ergebnisgrößen zu schätzen. Bei Kapitel 2 handelt es sich um eine Evaluationsstudie der Einführung des Teilzeit- und Befristungsgesetzes (TzBefrG) in Deutschland im Jahr 2001. Im Rahmen eines quasi-experimentellen Forschungsdesigns nutze ich diese Politikreform, um den kausalen Effekt von Arbeitsstundenbeschränkungen auf die Erwerbstätigkeit sowie den Erwerbsumfang von Frauen zu messen. Im Kapitel 3 untersuchen meine Koautoren Amelie Schiprowski, Luke Haywood und ich die subjektiven Lohnerwartungen von Arbeitslosen. Hierfür schätzen wir ein strukturelles Arbeitssuchmodell, um den kausalen Effekt von verzerrten Erwartungen auf die Dauer der Arbeitslosigkeit zu schätzen. In allen drei Kapiteln verfolge ich einen mikroökonomischen Ansatz, um individuelle Arbeitsangebotsentscheidungen zu analysieren. Zudem wende ich mikroökonometrische Schätztechniken an, um empirisch fundierte politische Schlussfolgerungen zu gewinnen.

In Kapitel 1 entwickle ich ein dynamisches Modell der diskreten Wahl des weiblichen Arbeitskräfteangebots und der Geburtenrate, um Elternzeitregelungen auf der Grundlage des Sozio-oekonomischen Panels zu evaluieren [Wagner et al., 2007]. Aufbauend auf neueren empirischen Belegen zum Zusammenhang zwischen Fertilität und Arbeitslosigkeitsrisiko betone ich die Bedeutung von Arbeitsmarktfriktionen und Arbeitsplatzsicherheit für dynamische Fertilitäts- und Arbeitsangebotsentscheidungen von Frauen. Um die Auswirkungen von Elternzeit und Elterngeld zu quantifizieren, simuliere ich kontrafaktische Lebenszyklen für die verschiedenen Politikszenarien. Es zeigt sich, dass eine Verringerung der maximalen Elternzeitdauer von 3 auf 2 Jahre die weitere Fertilität für FRauen im Alter von 20 Jahren um 4,1 Prozent verringern würde. Eine Verlängerung des Bezugszeitraums des Elterngeldes von einem auf zwei Jahre würde die Fertilität um 4,7 Prozent erhöhen. Die Beschäftigungseffekte über den gesamten Lebenszyklus sind eher gering. Die Auswirkungen auf die Beschäftigungsquote sind nicht persistent, die Auswirkungen auf Teilzeitquote bei weiblichen Arbeitnehmern hingegen schon. Ich komme zu dem Schluss, dass die unmittelbaren bei einer Veränderung von Elterngeld und Elternzeit gemessenen Reformeffekte tendenziell die gesamten Beschäftigungswirkungen dieser Reformen überschätzen. Auf der anderen Seite scheinen normalerweise unbeobachtete Auswirkungen auf die weitere zusammengefasste Geburtenziffer für beide betrachteten Politiken positiv sind.

In Kapitel 2 evaluiere ich die Einführung des Teilzeit- und Befristungsgesetzes (TzBefrG) in Deutschland im Jahr 2001. Diese Reform gewährte einen Rechtsanspruch auf Arbeitszeitverkürzung für Arbeitnehmer in Betrieben mit mehr als 15 Beschäftigten. Ich betrachte Arbeitnehmerinnen in Betrieben mit bis zu 15 Mitarbeitern als Kontrollgruppe, um die Wirkung der Reform auf (a) Übergänge in Teilzeitarbeit und (b) die anschließenden Beschäftigungsraten weiblicher Beschäftigter im Rahmen eines Difference-in-Differences-Ansatzes zu schätzen. Der wissenschaftliche Beitrag der Analyse besteht im Wesentlichen in zwei Punkten. Erstens berücksichtigten frühere Evaluationen des TzBefrG nicht die wichtige Heterogenität auf der Beobachtungsebene des einzelnen Beschäftigten. Ich zeige allerdings mit qualitativ hochwertigen administrativen Individualdaten auf Basis des SIAB [Antoni et al., 2016], dass die individuelle Inzidenz sowie die Übergänge in Teilzeit sehr heterogen sind, insbesondere im Hinblick auf das Alter der Arbeitnehmerinnen. Zweitens bin ich in der Lage, die Auswirkungen von Arbeitszeitbeschränkungen auf die Erwerbsbeteiligung zu ermitteln, indem ich mich auf Übergänge in Teilzeitarbeit und Nichtbeschäftigung von Vollzeitbeschäftigten konzentriere. Ich stelle fest, dass das Teilzeitgesetz die Übergänge in Teilzeitarbeit für weibliche Beschäftigte im Alter von über über 50 Jahren deutlich erhöht hat (1-2,5 Prozentpunkte). Darüber hinaus finde ich in dieser Altersgruppe Hinweise auf eine erhöhte Wahrscheinlichkeit einer zukünftigen Erwerbstätigkeit (1 Prozentpunkt).

In Kapitel 3 analysieren meine Koautoren und ich, wie subjektive Erwartungen über Wiedereinstiegslöhne die Arbeitssuchentscheidung beeinflussen. Wir vergleichen Daten über subjektive Lohnerwartungen mit administrativen Beschäftigungsdaten auf Basis des IZA Evaluationsdatensatzes (IAB Merge, Eberle et al., 2017). Unsere Ergebnisse zeigen, dass Arbeitslose ihren zukünftigen Netto-Wiedereinstiegslohn im Durchschnitt um 10 % überschätzen. Insbesondere erwartet der durchschnittliche Arbeitsuchende nicht, dass sich Lohnangebote mit fortlaufender Dauer der eigenen Arebitslosigkeit verschlechtern. Wie wirkt sich dieser Optimismus auf die Jobsuche aus? Wir analysieren diese Frage anhand eines strukturellen Arbeitssuchmodells, in welchem die subjektiven Erwartungen über zukünftige Lohnangebote nicht der Realität entsprechen müssen. Wir finden, dass Lohnoptimismus hochdynamische Effekte hat: Zu Beginn der Arbeitslosigkeit verringert Lohnoptimismus die Wiedereinstiegsrate um etwa 8 Prozent. Der Effekt verringert sich jedoch mit fortschreitender Arbeitslosigkeit und kehrt sich nach etwa 8 Monaten sogar um: Ab einer Dauer der Arbeitslosigkeit von länger als 8 Monaten, verhindert der Optimismus, dass Arbeitsuchende entmutigt werden und erhöht so auch die Wiedereinstiegschancen. Im Durchschnitt erhöht Optimismus die Dauer der Arbeitslosigkeit um etwa 6,5 %.

Erklärung gemäß § 4 Abs. 2 der Promotionsordnung

Hiermit erkläre ich, dass ich mich noch keinem Promotionsverfahren unterzogen oder um Zulassung zu einem solchen beworben habe und die Dissertation in der gleichen oder einer anderen Fassung bzw. Überarbeitung einer anderen Fakultät, einem Prüfungsausschuss oder einem Fachvertreter an einer anderen Hochschule nicht bereits zur Überprüfung vorgelegen hat.

Ich erkläre außerdem, dass ich meine Dissertation selbstständig verfasst habe.

Berlin, den 30. April 2018,

Sascha Drahs

Erklärung gemäß § 10 Abs. 3 der Promotionsordnung

Hiermit erkläre ich, dass ich für die Dissertation folgende Hilfsmittel verwendet habe:

Das Statistikprogramm Stata für die Datenaufbereitung und statistische Analysen, die Software Matlab für numerische Berechnungen sowie das Tabellenkalkulationsprogramm MS Excel.

Berlin, den 30. April 2018,

Sascha Drahs