Do Unemployment Benefits Affect Workers' Job Search? Evidence from Establishment Closures in West Germany*

Job Market Paper

Italo A. Gutierrez†

University of Michigan

Abstract

The effect of unemployment benefits (UB) on the behavior of unemployed individuals has been extensively studied in the literature. In contrast, we still know little about how UB affect the behavior of employed workers. This paper aims at filling this gap, using job-to-job (JTJ) transitions as the main outcome of analysis. The theoretical framework developed in the paper indicates that UB should only affect the behavior of workers who are at risk of job loss. Therefore, I focus the analysis on workers at establishments that subsequently closed down. The data come from administrative records for West Germany. I exploit changes in the rules for the duration of unemployment benefits in the 1980s and 1990s to test the prediction from the model that workers with longer benefits would be less likely to take a new job before their establishments close down. This can be explained because workers entitled to longer benefits have incentives to exert less effort in searching for a new job and also have higher reservation wages. I find that the empirical evidence strongly supports this prediction. In other words, I find that workers entitled to longer benefits are more likely to remain with the establishments until their closure.

Keywords: Unemployment benefits, establishment closures, job-to-job transitions, duration analysis, competing risks, difference-in-difference methods.

*I thank Jeffrey Smith, Charles Brown, Melvin Stephens and Brian McCall for comments on earlier drafts of this paper. I also thank seminar participants at the University of Michigan and at the Workshop on the Analysis of Administrative Data (WAAD) in Nuremberg for helpful suggestions. I am also grateful to the Sweetland/Rackham Dissertation Institute and to the Rackham Graduate School for providing funding for this research. Finally, I want to acknowledge my appreciation to Stefan Bender, Jörg Heining and Daniela Hochfellner at the German Institute for Employment Research (IAB) for their help and continuous assistance throughout this project. All errors are my own.

†Email: italo@umich.edu

1 Introduction

The behavioral effects of unemployment insurance benefits (UB) have been extensively studied in the economics literature. However, the focus has been on unemployed individuals, especially on the duration of unemployment spells and, to a lesser extent, on re-employment outcomes. In contrast, much less research has been done on the effects of UB on the behavior of employed workers. This paper aims at filling this gap and is motivated by a reappraisal of the reasons for on-the-job search (OTJS) and job-to-job (JTJ) transitions. Traditionally, OTJS and JTJ transitions have been explained by a job ladder motivation. In other words, the standard economic analysis explains OTJS as an action to improve worker utility, usually in the form of higher wages.[1] However, another motivation for OTJS is job insecurity. Workers who are at risk of job loss are likely to engage in OTJS to find a job that can be used as a fallback in case they are laid off. In fact, evidence from survey data confirms that a non-trivial fraction of workers who search while employed do so because of job insecurity. For example, Fujita (2011) documents that the primary reason for on-the-job search for 12% of job seekers in the UK (2002-2009) was the fear of losing their jobs.[2] Rosal (2003) documents that 27% of on-the-job seekers in Spain (2000) engage in job search because of their job instability.[3] Since UB reduce the financial costs of unemployment, they may also reduce the importance of the job insecurity motivation for OTJS and JTJ transitions.

Only few papers have previously studied the relationship between UB and job search behavior of employed workers (Burgess and Low, 1998; Light and Omori, 2004; Gutierrez, 2012). This paper complements and improves upon the previous empirical analysis in four main aspects. First, the theoretical framework developed in this paper indicates that UB should only affect the behavior of workers who are job insecure. Although some of the previous studies have focused on workers at risk of displacement, their estimates may be subject to sample composition bias because either they have examined only workers who ultimately entered unemployment (Burgess and Low, 1998) or only workers who have survived reductions in personnel (Gutierrez, 2012). In this paper, I focus on establishment closures in Germany, as a way to study the effect of UB on workers who are at (imminent) risk of layoff, which is arguably known to them and exogenous to their own characteristics.[4] Second, I use a rich administrative data set that allows me to distinguish whether the

[1] Even JTJ transitions with wage cuts that are commonly observed in the labor markets have been explained as the worker accepting a reduction in earnings in exchange for a faster growth of wages (e.g. better promotion opportunities) or for better job amenities (e.g. health insurance, retirement plans, etc.).

[2] The source is the United Kingdom Labour Force Survey and the sample period is from the first quarter of 2002 to the first quarter of 2009.

[3] The source is the Spanish Survey of Economically Active Population (Encuesta de Poblacion Activa) from the second quarter of 2000.

[4] The institutional settings in Germany, regarding mandatory advance dismissal notifications (in written form) and mandatory consultations with work councils and local employment agencies prior to a closure, ensures that establishment closures are not a surprise to workers. Thus, workers at an establishment that is near its demise are likely to be

worker separated from the closing establishment to start a new job without an intervening nonemployment spell, i.e. a JTJ transition, or whether he separated by entering nonemployment, i.e. a job-to-nonemployment (JTN) transition. Previous papers have only relied on self-reported employment history and reasons for employment termination to classify a separation of a worker from his employer as a JTJ or a JTN transition. Third, I use a more credible identification strategy based on difference-in-difference methods that exploits changes in the rules for the potential duration of unemployment benefits (PDB) in Germany in the mid-1980s and mid-1990s. Previous papers have used the non-linearity on the UB formula in the US (Burgess and Low, 1998) or cross-state differences in UB rules (Light and Omori, 2004; Gutierrez, 2012) as a source of identification. Thus, their results are subject to bias coming from omitted variables that could be potentially correlated with earnings history or state-specific characteristics. Fourth, and related to the last point, this paper is the first one to explore the effects of changes in the duration of UB rather than changes on their levels (or in the replacement rates).

The theoretical prediction I test in this paper, as suggested by the model, is that workers entitled to longer PDB have incentives to exert less effort in searching for a new job and have higher reservation wages, as well. As a result, they have a lower probability of experiencing a JTJ transition before the establishment closes. I find empirical evidence in support of this prediction. In particular, I find that the large expansion in the PDB in the 1980s reduced the probability that workers left their establishments before their closure to take on new jobs. I also find that the reduction in the PDB in the mid-1990s increased the probability that workers moved to a new job before their establishments closed, although the size of the effect per month of change in the PDB is smaller (and non-statistically significant) than that found for the 1980s. This can be explained because the moderate reductions in the PDB in the 1990s are likely to have affected the search behavior a smaller fraction of workers, as opposed to the large increase in the the 1980s.

Thus, the findings in this paper support the theoretical claim that UB affect the job search behavior of employed workers at risk of layoff and should warrant further research on this topic. Furthermore, they have two important implications. First, studies regarding the optimal design of UB should include their potential effect on employed workers, particularly those at risk of job loss, in their analysis. Second, studies that use establishment closures to study the effect of job loss should be aware of the potential sample composition bias arising from the fact that workers present at the moment of closure are likely to be entitled to more generous UB.

The rest of the paper is organized as follows: Section 2 describes the related literature; Section 3 describes the institutional background in Germany, specifically the unemployment insurance system and the procedures for dismissing workers; Section 4 describes the data set; Section 5 presents the theoretical framework that guides the empirical analysis; Section 6 discusses the econometric

aware of their impending layoff, providing an ideal setting to test the effects of UB on workers' search behavior.

strategy; Section 7 presents the empirical results; and Section 8 concludes by summarizing the findings and suggesting avenues for future research.

2 Related literature

The literature on the effects of UB on employed workers is relatively rare in comparison to the extensive research done on the effects of UB on unemployment durations and re-employment outcomes. Nevertheless, an important strand of the literature has analyzed the effect of UB on firms' layoff policies, in particular temporary layoffs. Feldstein (1976) proposed that employers and workers have implicit contracts that include temporary layoffs, which are subsidized by imperfect experience rating, as a mechanism to deal with temporary decreases in product demand. Empirical studies of experience rating have supported Feldstein's analysis (Feldstein, 1978; Topel, 1983; Anderson and Meyer, 1993; Card and Levine, 1994). More recently, Jurajda (2003) developed a dynamic model where firm's layoff and recall decisions are related to UB. He showed that, assuming that firms are aware that unemployed workers with generous UB will search less intensively, the optimal strategy for the firms is to lay off workers with high benefit entitlements and recall those approaching the expiration of their benefits.

The evidence that UB affect the probability of entering unemployment is not limited to the case of temporary layoffs. Empirical research has also found that the risk of permanent layoff increases when workers qualify for UB. Christofides and McKenna (1995, 1996), Green and Riddell (1997) and Green and Sargent (1998) find that the exit rate from employment to unemployment in Canada increases substantially as soon as the workers satisfy the number of weeks worked in order to qualify for UB. More recently, Jurajda (2002) and Rebollo-Sanz (2012) also find for the cases of US and Spain, respectively, a spike in the risk of layoff at the moment that a worker qualifies for benefits. Moreover, Green and Riddell (1997), Jurajda (2002) and Rebollo-Sanz (2012) explicitly show that qualifying for UB increases the risk of separation due to layoffs but does not affect workers' voluntary quits into unemployment, highlighting the role of employers in the separation decision.

A different strand of the literature has studied the effect of increasing the PDB, rather than qualifying for them, on the probability of exiting employment. Winter-Ebmer (2003) finds strong unemployment inflow effects of the Austrian regional extended benefit program which granted very long benefits for older workers in certain regions. Similarly, Lalive, van Ours, and Zweimüller (2011) show that an extension in the PDB in Austria led to a decrease in the outflow from unemployment but also increased the inflow into unemployment. Moreover, although the second effect was more modest, it had the largest impact on the equilibrium unemployment rate because there are many more employed workers than unemployed workers. For the case of Germany, Fitzenberger and Wilke (2009) analyzed the increase in the PDB in the 1980s and found that it led to an increase in separations, especially for older workers for whom it facilitated the transition into retirement. Haan and Prowse (2010) reached similar conclusions by studying the changes in the PDB in the mid-1990s. They concluded that unemployment insurance is used as a stepping stone into retirement. In contrast, Schmieder, von Wachter, and Bender (2010) find that an increase in PDB only has a small impact on the inflow into unemployment.

All of the previously cited papers have either studied the effect of UB on the probability of entering unemployment alone or have distinguished between layoffs and voluntary quits into nonemployment. However, they have omitted the fact that UB can also affect workers' behavior through their OTJS effort and their reservation wages, and thus affect their JTJ transitions. In fact, workers engage in OTJS not only to find better paying jobs but also to insure themselves against the possibility of nonemployment. Tudela and Smith (2012) formalize this idea in an equilibrium model in which past search experiences becomes capital that (partially) insures workers against displacement. In other words, if a worker gets displaced, he can use his network of contacts as a fallback to avoid unemployment.[5] Light and Omori (2004) and Gutierrez (2012) postulate similar models, in which although workers cannot store information from prior contacts, they react to higher risks of layoff with increased job search efforts in order to have a job offer lined-up in case they get displaced. Since UB provide temporary financial assistance to unemployed workers and reduce the economic burden of unemployment, it also reduces the value of the insurance motivation for OTJS.

Among the very few papers that have directly studied the effect of UB on workers OTJS behavior or JTJ mobility, Burgess and Low (1998) found, using data from displaced workers in Arizona, that UB strongly discouraged OTJS for workers who received advanced layoff notification and did not expect to be recalled by their employers. Conversely, they found no statistically significant effect of UB on search behavior for non-notified workers or for notified workers who expected to be recalled. In other words, UB only changed the behavior of workers who knew they were going to be laid off permanently. This conforms to the theoretical prediction that the effects of UB depend on the level of job insecurity, as discussed in Section 5. Although the results of Burgess and Low (1998) are coherent, two limitations threaten their validity, as acknowledged by the authors. First, there is a sample selection problem because the study was comprised of workers with at least five weeks of unemployment. Therefore, workers who perform more OTJS were less likely to be part of the sample. Second, since all respondents were unemployed workers in Arizona in the years 1975-1976, there is no variation in UB other than that due to the workers' earnings histories that could be used to identify the effects. This could have led to potential biases in the estimated effects

[5] This mechanism helps to explain JTJ transitions with wage cuts or the immediate re-accessions that are commonly observed in labor market data for OECD countries (Jolivet, Postel-Vinay, and Robin, 2006).

of UB.

Another paper that studies the effect of UB on workers' behavior is Light and Omori (2004). In their model UB reduce the insurance value of OTJS because they increase the reservation wage, or the minimum wage offer the worker would be willing to accept in case he is displaced. Thus, more generous UB would be associated with lower OTJS effort, higher reservation wages and lower JTJ transitions. Light and Omori (2004) looked for evidence of this latter effect using the 1979 National Longitudinal Survey of Youth (NLSY79).[6] They found that JTJ transitions decline as UB increase, although the estimated effect is very small. A drawback of this paper is that it lacks a good measure of the workers' risk of job loss. As discussed in detail in Section 5, UB should have a very small effect if the worker does not feel vulnerable to job loss. Thus, without focusing on a sub-population that has a relatively high level of job insecurity, the estimated effects may be small given that the risk of job loss is also small for the average worker.

The last paper in the literature that studies the effect of UB on workers' behavior is Gutierrez (2012). In that study, I use information on older (50+) American workers from the Health and Retirement Study (HRS) to test the hypothesis that an increase in the replacement rate (i.e. in the fraction of earnings that UB replace when the job is lost) reduces the incentives to engage in OTJS.[7] I run separate analysis for workers in downsizing firms, or firms that have experienced a permanent reduction in employment, and for workers in non-downsizing firms. I find that workers in downsizing firms are more job-insecure and more likely to be searching for another job. I also find that an increase in the replacement rate results in a decrease in the probability of workers engaging in OTJS, a decrease in the probability of experiencing a JTJ transition, and an increase in the probability of transitioning into a jobless spell, but only for workers in downsizing firms. The sizes of the effects are substantial for the probability of OTJS, but very moderate for employment transition probabilities. A potential explanation for the small effects on transition probabilities is that the sample of workers who are still with an employer after it has experienced (or during) a downsizing process may be a non-random selection of the workers who were present when the downsizing just started. For instance, they may be more productive and have lower risk of layoff than the workers who were dismissed first. Since the HRS is an individual survey and not an employer survey it is not possible to identify the set of workers who were displaced earlier in the downsizing process.

[6] The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and are currently interviewed on a biennial basis. The study is conducted by the US Bureau of Labor Statistics (BLS). Further information available at http://www.bls.gov/nls/nlsy79.htm .

[7] The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and the Social Security Administration. It is conducted by the University of Michigan, Ann Arbor, Michigan. The HRS consists of a national sample of adults over the age of 50. It has been conducted every two years since 1992. Further information is available at http://hrsonline.isr.umich.edu/.

The present paper aims at expanding the evidence on the effect that UB have on employed workers' behavior, using establishment closures to focus on workers who are at high risk of job loss. Therefore, this paper also touches on the literature about the non-random selection of workers who are ultimately displaced by a plant closure. In an early work, Pfann and Hamermesh (2001) studied the demise of Fokker Aircraft, a large Dutch corporation, and concluded that the firm learned about each worker's probability of quitting and adjusted its layoff policy accordingly. Thus, workers who remained in the firm until its closure were selected non-randomly from the group of workers present at the firm when the negative shocks initially arrived. For the US, Lengermann and Vilhuber (2002) find evidence that the pattern of workers' separations prior to a plant closure is consistent with both highly qualified workers leaving distressed firms and with management actions to lay off low skilled workers. In Austria, Schwerdt (2011) finds evidence that a significant fraction of all separations happening up to two quarters before a plant closure are directly related to "early leavers", or workers who decided to "abandon the sinking ship". These early leavers are distinct in terms of higher productivity than ultimately displaced workers, even after controlling for observed characteristics. This paper analyzes whether UB have a role in altering the timing of separation from establishments that are approaching their demise or, put differently, whether they make workers more likely to stay until the establishment closes. Studying these potential effects is important for understanding sample composition bias in previous studies that have used plants closings as a natural experiment to study the effects of job loss on distinct outcomes.

3 Institutional background

3.1 The German unemployment insurance system

There are two types of benefits for the unemployed in Germany: unemployment benefits (UB) and unemployment assistance (UA). The former is funded by contributions of employers and job holders and is granted for a certain number of months depending of an individual's previous contribution period and age. During the period of my study (1982-2004) eligibility for UB was achieved after 12 months of work in the last three years.[8] If an individual exhausts the maximum number of months of UB, then he is eligible for UA. This benefit is funded from government revenue and is not time-limited. It is granted for a year and re-approved every year if a means test is passed and the claimant is younger than 65 (Schmitz and Steiner, 2007). The amount received under UB depends on prior income. Until 2005, the amount of benefits from UA also depended on prior

[8] A person who voluntarily quits his job is subject to a waiting period sanction of 12 weeks before collecting benefits. In case of hardship the sanction could be limited to six weeks and if the job would have ended within four weeks anyway, the sanction could be limited to three weeks only (Hofmann, 2008). If a person is sanctioned with 12 weeks, the duration of his entitlement is also shortened by 25% or at least twelve weeks.

income.[9] However the benefits from UA could be reduced considerably by spousal earnings and other sources of income.[10] Individuals who were not entitled to UB/UA or whose net income after receiving benefits was sufficiently low, received social assistance. Social assistance payments are non-time-limited transfers which raise the individual's net income up to the social minimum income.[11]

As shown in Table 1, the formula determining the PDB for each age changed considerably in the 1980s and 1990s, which provides two quasi-natural experiments for the identification of the effects of interest. Before 1985, unemployed workers were only entitled to a maximum duration of 12 months of UB, regardless of age, as long as they were eligible for benefits. Starting in 1985, older workers were entitled to longer potential durations of UB, depending on the number of months they have worked in the last seven years prior to the start of the unemployment spell. Subsequent increases in the PDB were phased in between 1985 and 1987. Since July 1987, the PDB formula included increases in potential duration of benefits for workers age 42 or older, depending on their working history. The longest potential duration was 32 months for workers age 54 or older.[12] The rules determining PDB remained stable in Germany for over a decade. In April 1997, a new reform (the Employment Promotion Act) was introduced to reduce potential disincentive effects of unemployment insurance. The PDB were lowered by increasing the age requirements to qualify for longer UB durations by 3 years. The reform was phased in gradually, so that for most people it only took effect in April 1999 (Schmieder, von Wachter, and Bender, 2012; Schmitz and Steiner, 2007).[13] The fourth Hartz reform, which was introduced in 2005 but became effective in February 2006, further reduced PDB. The PDB was set back to 12 months

[9] Until December 1983 the replacement rate for UB was 68% and for UA was 58% of the previous *net* wages, irrespective of whether the recipient had children. Since the UB and UA benefits are calculated from net earnings, they are not taxed. However, they can push total income into a higher tax bracket (Schmieder, von Wachter, and Bender, 2012). Starting in 1984, the replacement rate of UB and UA was lowered for workers without dependents to 63% and 53%, respectively. The replacement rates were further lowered slightly in January 1994, to 60% for UB if the worker had no dependents and to 67% in case of dependents; and to 50% for UA if no dependents and to 57% in case of dependents. The replacement rates for UB have remained constant since then and were changed for UA in 2005 with the fourth Hartz Reform.

[10] Although the nominal replacement rate is above 50%, after taking in consideration deductions due to other sources of income, the effective replacement rate for older workers is around 35% for men and 10% for women (Schmieder, von Wachter, and Bender, 2012).

[11] In January 2005, with the introduction of the fourth Hartz reforms, UA was integrated with social assistance to become Unemployment Benefit II (UBII), which is still means-tested and, in principal, granted indefinitely. However, the amount does not depend on the former net income of the unemployed individual anymore, but on the legally defined social minimum of the household which depends on the number and age of the household members and includes costs for renting and heating up to certain amounts.

[12] For unemployed people who already received UB in the last 7 years the period between the last and the new unemployment spell is used to determine the entitlement length. The remaining months of UB from the last unemployment spell are then added. The total duration is still capped by the maximum PDB determined by age.

[13] Those who became unemployed after April 1997 but had worked at least 12 months out of the last three years prior to the spell before April 1997 were entitled to UB according to the old regulation (Schmitz and Steiner, 2007).

for all workers younger than 55 years old, and was reduced to 18 months for workers age 55 or older.[14] Furthermore, the reform also tightened the criteria for eligibility for UB. After the reform, a person has to have worked for at least 12 months in the last two years (instead of three) to qualify for UB (Schmitz and Steiner, 2007).

This paper studies the effects of the first two changes in the determination of the PDB. The last reform is not included in the analysis because the data covers only the period 1982-2004. Future work will expand the analysis to incorporate the Hartz reforms.

3.2 Dismissal procedures

The German labor market is highly regulated and employers have to follow many procedures before dismissing their workers. For permanent (or open-ended contracts) dismissal protection sets in after a probationary period of six months during which only minimum requirements and a short notice period of two weeks apply. Legal dismissal protection currently does not apply to firms with fewer than ten employees. However, this threshold has changed over time. It was increased from five to ten in 1996, lowered to five in 1999, and then increased again to ten in 2004. In order to avoid complications from these changes in the empirical analysis, I work only with establishments that had more than ten workers in the year prior to their closure.[15]

The legal minimum notice period is four weeks for both the employer (layoffs) and the employee (voluntary quit). Minimum notice periods for employers increase with tenure: 1 month after 1 year of service, 2 months after 5 years of service, 3 months after 8 years of service, 4 months after 10 years of service, 5 months after 12 years of service, 6 months after 15 years of service and 7 months after 20 years of service. Longer notice periods and additional employment protections can be introduced through collective agreements, particularly for older or long-tenured workers, or by individual contracts. Every dismissal needs to be consulted with the works council, which is an organization that represents the workers of a firm or establishment.[16] In case of collective (mass) dismissals or closures, both the works council and the local employment agency need be informed in advance. Moreover, the employer has the obligation to check all options for continuing employment, e.g. through reorganization or employment at other organizations. Also, for collective dismissals in plants with more than 20 workers, the works council can request a social plan to mitigate the effects of the layoffs. They include agreements on severance payments and other provisions for promoting re-employment. Also, the selection of workers to be dismissed

[14] Also, after the reform, the PDB is calculated on the number of months worked in the last three years, instead of seven.

[15] They account for over 75% of workers in Germany (Schmitz and Steiner, 2007).

[16] Works Councils are authorized, but are not automatic, in all establishments with five or more employees (Addison, Bellman, and Kölling, 2002).

needs to consider some priority rules or social criteria, such as years of service, age, and family obligations, among others.

4 Establishment closures data

This paper uses a matched establishment-worker data set prepared by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).[17] The data set was constructed by sampling establishments that closed in West Germany during the period 1982-2004.[18] Establishment closures are in principle identified by the disappearance of the identification number from the administrative records, which would happen if there are no more workers (liable to social security) at that establishment. However, there are many reasons why an establishment identification number may disappear that are not related to real closures. For example, if a firm is taken over, the establishments belonging to the firm may change identification number, but they clearly continue to operate. In order to identify real closures, the FDZ have classified establishment closures in four categories following the work of Hethey and Schmieder (2010). I focus on the analysis of establishments closures classified as atomized deaths, meaning that workers from these establishments do not appear together (at least in a great proportion) at a subsequent establishment.[19] Atomized deaths are more likely to correspond to true closures. Also, working with atomized deaths minimizes the risk that the employers implemented a restructuring of its labor force, for example by relocating workers at other locations.[20] These relocation would complicate the interpretation of JTJ transitions as resulting from workers' behavior.

Among establishments classified as atomized deaths, I further limited the sample to those with at least 10 workers in the year before closure, as mentioned in Section 3.2. Overall, my sample represents about 2.6% of the atomized closures (with more than 10 employees) in West Germany during the period 1982-2004. The sampling design was stratified by establishment size in the year

[17] More information available online at http://fdz.iab.de/en.aspx

[18] Establishments are defined by their identification numbers, which are allocated to organizational units consisting of at least one worker liable to social security. Thus an establishment can be a plant, a restaurant, a gas station, a bank branch, etc. In other words, this definition of an establishment does not necessarily correspond of that of a firm, which may be comprised of many establishments. Instead, it is more accurate to think of an establishment as a local economic unit consisting of workers and capital, operating under a joint legal framework (such as being part of a firm), and producing some sorts of goods or services (Hethey and Schmieder 2010).

[19] All closing establishments with fewer than four workers are classified by FDZ as small establishment deaths. The FDZ defines a cluster of workers as a group of workers from the closing establishment that after the closure appear together in a new establishment. Closing establishments with more than four workers and for which the largest cluster of workers represented less than 30% of the employment in the last year before closure (at the exiting establishment) are classified as atomized deaths. Closing establishments where that percentage is between 30%-80% are classified as chunky deaths; and establishments where that ratio is above 80% are classified as not true closures. In this latter case, they are more likely to correspond to changes of identification numbers or to establishment take-overs.

[20] See Section 3.2 about requirements of social plans in case of collective dismissal of workers.

prior to the closure, with larger establishments being oversampled.[21]

The data set also contains the full working biography of all workers who were present at the sampled establishments at any moment within the last five years of their existence. Access to the workers' complete biography allows me to estimate their potential entitlement to UB, based upon their work history. It also allows me to follow the worker after he separates from the establishment. Therefore, I can determine whether he moved to another establishment without any intervening nonemployment spell, i.e. a job-to-job (JTJ) transition, or whether he separated by entering nonemployment, i.e. a job-to-nonemployment transition (JTN).

Some caveats in interpreting and measuring these transitions are worth mentioning. First, a JTN transition can be initiated by the employer (layoff) or by the worker (voluntary quit or resignation). It is not possible to distinguish in the data between these two.[22] Second, the data set only includes employment that is within the social security system. This covers about 80% of all jobs (Schmieder, von Wachter, and Bender, 2012). The main categories that are not included are the self-employed and government employees. Thus, all coded JTJ transitions are correct, whereas coded JTN transitions may be partly contaminated.

The main econometric analysis is restricted to workers aged 38 to 56 years who have worked (in a position covered by social security) at least 64 months in the last seven years at the beginning of the last year of existence of an establishment. The latter restriction allows me to include only workers with long labor force attachment who would have been eligible for the maximum changes in the PDB that are studied in this paper (see Table 1). Workers age 38 to 41 are included to act as the control group since their entitlement to UB was not modified.[23]. Workers age 57 years or older are excluded to avoid confounding the effects of PDB with incentives for early retirement. Although the legal retirement age in Germany is 65 years old, earlier retirement at age 60 is possible.[24] Thus, workers age 57 or older can potentially use long entitlements of UB as a means to step into early retirement, as suggested by Haan and Prowse (2010). In fact, during the 1980s and

[21] Establishments with 11-50 workers were sampled with a probability of 0.025; establishments with 51-500 workers were sampled with a probability of 0.25; and establishments with more than 500 workers were sampled with a probability of 1.

[22] Since workers who voluntarily quit their jobs are subject to a waiting period sanction, it should be possible to look at gaps between the last employment and the first benefit receipt spell to identify voluntary quits. However, these gaps can also occur if the worker voluntarily (or involuntarily) delays notifying the local employment agency that he is unemployed, or if the worker experiences a short period of self-employment. Moreover, the waiting period sanction is not clearly defined, since it can range from three weeks to twelve weeks (see footnote 8).

[23] I tried alternative cutoff points at 35 and 40 and the results were qualitatively similar.

[24] The legal retirement age in Germany is 65 years old. Retirement at age 60 was possible after 180 contribution months if unemployed at the commencement of the pension and if unemployed for 52 weeks after completion of the age of 58.5 years. Alternatively, retirement at age 63 was possible after 35 years of insurance (Ebbinghaus and Eichhorst, 2006; Tatsiramos, 2010). Recent changes in early 2000s increased this age limits up to 65, but retirement at ages 60 and 63 are still possible with the acceptance of pension reductions, which amounts to 0.3% of the pension for each month during which the pension is claimed earlier (Tatsiramos, 2010).

1990s, the government promoted UB as a bridge between employment and early retirement.[25]

Empirical evidence suggests that most of the workers' reaction in OTJS behavior happens when the firm is relatively close to its closure and thus the impending risk of layoff is well known. For example, Schwerdt (2011) finds, for the Austrian labor market, that workers who decide to leave distressed employers (or "abandon the sinking ship") can be traced only up to two quarters before closure. Earlier separations are indistinguishable from normal turnover.[26] Schwerdt (2011) argues that the fact that selective turnover sets in only up to two quarters before closure and not earlier is because the maximum notice period is five months.[27] Thus, information of impending layoffs may not be available for workers earlier. Given that the length of the notice period in Austria is similar to that in Germany, it should be expected that most of the workers who strategically leave the exiting establishment (to another employer) in my analysis sample do so during the last year of its existence. Additional evidence is also provided by Kahn (2012), who studied job search behavior of workers under temporary contracts using the European Community Household Panel (ECHP) data.[28] He finds that workers in temporary jobs search harder than workers on permanent jobs and that the search intensity increases as the remaining duration of the contract falls. However, most of this increase (84%) happens in the last 6 months before the termination of the contract. Thus, the focus of this paper will be on the analysis of workers' separations during the last year of existence of an establishment.

5 Theoretical framework

There are at least three mechanisms through which UB could affect firms' layoffs decisions. First, UB, if it is imperfectly experience rated, promote and facilitate the use of temporary layoffs. Second, in highly regulated labor environments such as the German one, firms cannot easily separate employees, especially older ones with long tenure, due to the social criteria that must be considered for separations (see Section 3.2). Employers usually have to provide severance payments and other

[25] Since January 1986 unemployed workers aged 58 or older who formally agreed to retire at the age of 60 years old could receive UB without being registered as searching for work (Fitzenberger and Wilke, 2009; Hunt, 1995; Schmitz and Steiner, 2007). However, the recent Hartz reforms introduced a break in this incentive. Not only the PDB for older workers were reduced (since 2006), but also the exemption for search requirements for workers aged 58 or older was abolished in December 2007.

[26] Schwerdt (2011) compares employment and earnings outcomes of workers separated from exiting establishments (plants) with those of workers separated from non-exiting establishment (i.e. the control group reflecting normal turnover). He finds that workers at exiting establishments who separated up to two quarters before closure, but not earlier, had on average better employment prospects than workers who separated from non-exiting establishments. Thus, these workers are considered "early leavers" or workers who strategically decided to leave the establishment in distress.

[27] In Austria, the maximum notice period for blue collar workers is two weeks before dismissal. White collar workers have a notice period of 1.5 months that can increase up to five months with tenure Schwerdt (2011).

[28] The data covers the period 1995-2011 and 11 countries: Austria, Belgium, Denmark, Finland, France, Greece, Ireland, Italy, the Netherlands, Portugal and Spain.

benefits to dismiss workers. In this case, UB can be used as a subsidy to reach a mutual agreement between employers and workers (Dlugosz, Stephan, and Wilke, 2009). Third, an increase in UB decreases the employer-employee match surplus, by increasing the employee's outside option. Thus, more generous UB should result in an increase in the rate of job destruction as was shown in Pissarides (2000). However, the potential effect of UB on firms' layoff decisions would be arguably small or negligible for the case of establishments near their demise, regardless of the mechanism behind. Thus, establishment closures are not ideal to study these effects.

In contrast, establishment closures provide an interesting framework to study how UB affect the behavior of employed workers who are at risk of layoff. In this section I model the search effort and reservation wages of an employed worker to study how they are affected by changes in the PDB, denoted by T. I also explore how those effects vary depending upon the level of job insecurity. In order to capture the institutional settings in Germany, I assume that if an employer wants to lay off a worker he has to give him a notification N periods in advance. A worker can leave his employer for another job at any time if a suitable offer is available.[29] If a worker is ultimately displaced he can collect UB, denoted by b for a total of T periods. Upon exhaustion of the UB, the worker can collect UA, which is denoted by a (and $b > a$). The worker is entitled to UA indefinitely.

I assume that any new job that the worker takes on lasts forever. This assumption rules out that the value of future employment spells can be affected by changes in UB. In a dynamic job search model, changes in UB will affect not only the value of current unemployment spells but also of possible future ones. Thus, more generous UB (either higher levels or longer duration) also increase the value of future jobs by increasing their termination value.[30] This effect creates incentives for workers to increase job search efforts in response to more generous UB. In my model, I let UB affect the value of the current job by affecting the value of the next possible unemployment spell, but UB do not affect the value of any following job because they last forever. This eliminates some analytical indeterminacy in the comparative statics in the model. Nevertheless, as long as these effects are small or dominated by the effect of UB on the value of the next possible unemployment spell (as suggested by evidence from the effects of UB on unemployment duration) the results discussed here remain valid.

The insights of the model are built up by small steps, or propositions. I start by analyzing the effect of changes in PDB on an unemployed worker. Then I study their effects for a worker who is

[29] In the model all quits are related to moving to a new employer. There are no voluntary quits into nonemployment or self-employment. I also abstract from modeling retirement.

[30] This is similar to the "entitlement effect" described in Mortensen (1977) by which an increase in UB generosity increases job search efforts by the unemployed who are not eligible to receive them. This is because an employment spell is a port of entry into eligibility for UB (the "entitlement") and thus more generous UB increases the value of finding a job.

still employed but has already received a layoff notification. Finally, I study the effects of changes in the PDB for a worker who has not yet received a layoff notification. I use these comparative statics results to predict the patterns of JTJ transitions in the data and how it is modified by the changes in the PDB.

5.1 Modeling the value of unemployment

I start by assuming that the worker has become unemployed. Let $V(t)$ denote the continuation value of unemployment when there are t remaining periods of entitlement to unemployment benefits b, counting the current period. Workers can choose search effort intensity which is equivalent to choosing the probability of getting an offer s. The cost of search is given by $c(s)$, which for convenience is assumed to be $c(s) = 0.5s^2$. I assume that job offers come (if any) at the end of each period and only one offer per period can be received. If the worker has already exhausted this UB entitlement, the continuation value of unemployment is given by $V(0)$, as described by equation (5.1):

$$V(0) = \underset{s}{Max}\left\{z + a + \beta\left\{sE\left[Max(W(x), V(0)\right] + (1-s)V(0)\right\} - 0.5s^2\right\} \tag{5.1}$$

The term z denotes the value of leisure, β denotes the time discount factor, and $W(x)$ is the continuation value of a job which pays a wage of x. Since any new job lasts forever, we have $W(x) = \frac{x}{1-\beta}$. Let x_t^U denote the minimum (reservation) wage offer that an unemployed individual with t remaining periods of UB would be willing to accept. Thus, $V(0) = W(x_0^U)$ and the worker will take any offer with $x > x_0^U$. I assume that wage offers follow a distribution function $F(x)$, which is constant over time and equal for employed and unemployed workers. The continuation value of unemployment during the last period of entitlement for UB, denoted by $V(1)$, is described by equation (5.2). Note that $V(1) = V(0) + (b-a) > V(0)$.

$$V(1) = \underset{s}{Max}\left\{z + b + \beta\left\{sE\left[Max(W(x), V(0)\right] + (1-s)V(0)\right\} - 0.5s^2\right\} \tag{5.2}$$

Proposition 1. *The value of unemployment and the reservation wage increase with longer (remaining) entitlement to UB.*

Proof. See section A.1 in the Appendix □

Proposition 1 is intuitive. Since $b > a$, i.e. $UB > UA$, an individual who has a longer remaining entitlement to UB will have a higher expected utility from remaining unemployed or, to put it differently, a larger opportunity cost of accepting a job. Proposition 1 also implies that an increase in the maximum PDB, denoted by T, leads to an increase in the initial value of unemployment $V(T)$.

5.2 Modeling the value of employment for a notified worker

Now I model the search decision of an employed worker who has received a layoff notification. Let $B^L(w,n,T)$ denote the worker's continuation value in his current employment given that he has received a layoff notification, has a maximum of n periods remaining (including the current one) before he is separated from his employer, earns a wage of w, and can collect UB benefits for a total of T periods if unemployed. I assume that $w > b+z$, so that the flow utility if employed is larger than that if unemployed. Let $x^L(w,n,T)$ denote the reservation wage for a notified individual, i.e. the minimum outside wage offer that the individual is willing to accept. Equations (5.3) and (5.4) provide expressions for $B^L(w,n,T)$ when $n=1$ and when $n>1$, respectively:

$$B^L(w,1,T) = \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),V(T)\right]+(1-s)V(T)\right\}-0.5s^2\right\} \tag{5.3}$$

$$B^L(w,n,T) = \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),B^L(w,n-1,T)\right]+(1-s)B^L(w,n-1,T)\right\}-0.5s^2\right\} \tag{5.4}$$

Proposition 2. *The value of employment and the reservation wage are smaller the closer is the separation date.*

Proof. See section A.2 in the Appendix. □

Proposition 2 is also intuitive. Given that $w > b+z$ (and that the duration of benefits b is limited), the value of employment is smaller the shorter the worker can receive a certain flow utility of at least w.

Proposition 3. *As the separation date approaches, the search effort is intensified.*

Proof. Let's denote by $S^L(w,n,T)$ the optimal search effort when a worker has received a layoff notification. Assuming an interior solution, and after some manipulation, $S^L(w,n,T)$ is described by equation (5.5). Given the result from proposition 2, it can be easily shown from equation (5.5) that the optimal search effort increases as n goes to 1 because the lower bound of the integral gets smaller and the value of the integrand gets larger.

$$S^L(w,n,T) = \beta\left\{\int_{(1-\beta)B^L(w,n-1,T)}^{\infty}\left[W(x)-B^L(w,n-1,T)\right]dF(x)dx\right\} \tag{5.5}$$

□

The intuition for Proposition 3 follows from Proposition 2. As the separation date approaches, the reservation wage decreases and, thus, the marginal returns to searching for another job increases as it is more likely that the worker will find a suitable offer.

Proposition 4. *Longer PDB increases the value of current employment and the reservation wage, and reduces search effort. These effects are stronger the closer the worker is to the separation date.*

Proof. See section A.3 in the Appendix. $\square$

The first part of proposition 4 is intuitive. More generous UB duration increases the value of the current job by increasing the value of its termination (i.e. unemployment), and thus the returns to looking for another job are smaller. The intuition behind the second part of proposition 4 is less evident. The value of unemployment becomes more important for the search decision as the worker approaches the separation date from this employer. Thus, any change in the value of unemployment, in this case due to longer PDB, has a stronger impact on search effort the closer the separation date is.

5.3 Modeling the value of employment for a non-notified worker

Now, let $E(w,\phi,N,T)$ denote the continuation value of employment if the worker has not received (yet) a layoff notification, but expects to receive it with probability ϕ. I assume that notifications come at the end of each period but before the worker chooses whether to accept a job offer if he has received one. Thus, there are two reservation wages. Let $x^E(w,1,N,T)$ denote the minimum wage offer that a worker would be willing to accept if he received a notification at the end of the period, and let $x^E(w,\phi,N,T)$ denote the minimum wage offer he would accept if he did not received a layoff notification. Equation (5.6) below defines the continuation value for $E(w,\phi,n,T)$:

$$\begin{aligned} E(w,\phi,N,T) = & \underset{s}{Max}\Bigg\{ w+\beta\Bigg\{\phi sE\left[Max\left(W(x),B^L(w,N,T)\right)\right]+\phi\left(1-s\right)B^L(w,N,T) \\ & +\left(1-\phi\right)sE\left[Max\left(W(x),E(w,\phi,N,T)\right)\right]+\left(1-\phi\right)\left(1-s\right)E(w,\phi,N,T)\Bigg\} \\ & -0.5s^2\Bigg\} \end{aligned} \tag{5.6}$$

Notice that $E(w,\phi,N,T) > B^L(w,N,T)$ per Proposition 2 because a non-notified worker can continue his employment for a least one more period than if he had received a notification.

Proposition 5. *Longer PDB increases the value of the reservation wage for a worker who receives a notification at the end of the period (i.e. $x^E(w,1,N,T)$).*

Proof. A worker who receives a notification would be willing to take a new job that pays at least $x^E(w,1,N,T)$, where $x^E(w,1,N,T) = (1-\beta)B^L(w,N,T)$. Per proposition 4 we know that $\frac{\partial B^L(w,N,T)}{\partial T} > 0$. Thus, $\frac{\partial x^E(w,1,N,T)}{\partial T} > 0$. $\square$

Proposition 6. *Longer PDB increases the value of current employment. It also increases the reservation wage for a worker who did not receive a notification at the end of the period. However, all these effects are zero if the worker has a zero probability of receiving notification (i.e. $\phi = 0$).*

Proof. See section A.4 in the Appendix. □

Proposition 7. *Longer PDB decreases search effort but only if the worker has a positive probability of receiving a layoff notification ($\phi > 0$). Moreover, the effect is always lower than for workers who have already received a layoff notification.*

Proof. See section A.5 in the Appendix. □

The intuition behind the effects of changes in the PDB for a non-notified worker is similar to that for a notified worker. A longer entitlement to UB increases the value of employment by increasing the value of its termination. This leads to lower search effort because there is a lower probability of finding a job that the worker will take. The difference for non-notified workers arises when they are completely secure at their jobs, i.e. when the probability of receiving a notification is (or is perceived to be) zero. In this case, changes in the duration of UB do not affect the value of current unemployment and are irrelevant for the optimal search effort level.

5.4 Implications for JTJ transitions in the data

The probability of a JTJ transition at the end of a period is given by $P(JTJ) = s \times (1 - F(x))$. As described above s is the probability of getting an offer, which is the measure of search effort in the model; $F()$ is the wage offer distribution; and x is reservation wage to take a new job. Following the discussion in the previous section, an increase in the PDB will reduce search effort and increase the reservation wage. Therefore, an increase in the PDB will decrease the probability that a worker takes a new job. Moreover, according to propositions 4- 7 the reduction in $P(JTJ)$ will be stronger for notified workers than for non-notified workers. Among notified workers, the effects will be larger the closer they are to the separation date. For non-notified workers, the effect will be zero if the worker has a zero probability of receiving a notification.

In the data I do not observe whether a worker has received a layoff notification or not. However, I expect that as the establishment's date of closure approaches, a larger proportion of workers should have received a layoff notification. Also, as the closure approaches, a higher fraction of notified workers should be reaching their effective date of separation. Thus, I expect to see two patterns in the data: First, the probability of observing a JTJ transition should increase as the date of the establishment closure approaches, both due to lower reservation wages (Proposition 2) and to larger search effort (Proposition 3). Second, the effect of a change in the PDB on the probability of a JTJ transition (in comparison to the counter-factual of no change) should be larger as the date of closure approaches, due again to larger effects on job search effort and reservation wages. The next section specifies the econometric approach employed to test these implications from the theoretical framework.

6 Econometric approach

This section develops the econometric approach to test whether changes in the PDB have any effect on the timing of separation of a worker from a closing establishment. Although the focus of the paper is on separations due to JTJ transitions during the last year of existence of an establishment, the analysis is repeated for total separations and separations due to JTN transitions.[31] The econometric approach relies on a difference-in-difference (DiD) design within a survival analysis framework. The DiD design arises from the changes in the PDB that took place in Germany during the 1980s and 1990s, which affected only workers aged 42 years or older. The survival analysis framework allows me to study whether these policy changes had any effect on the timing (and the type) of workers' separation from the closing establishments.

The next subsections describe each of the building blocks of the econometric approach. Subsection 6.1 specifies the measure of analysis time that will be used for the survival analysis in this paper; Subsection 6.2 defines the cause-specific hazard rates of separation; Subsection 6.3 reviews the policy changes under study and defines the concept of treatment dose; Subsection 6.4 introduces alternative measures of the treatment effects; Subsection 6.5 provides the identification assumptions required to estimate those treatment effects; finally, Subsection 6.6 discusses the estimation procedure and the advantages of the Cox Proportional Hazards Model (CPHM) as the estimation method.

6.1 Analysis time

In standard survival analysis researchers define the analysis time t as the time the individual has been at risk of failure since the onset of the risk. For example, when studying unemployment spells, the analysis time becomes the time that the individual has been looking for a job ("failure") since he became unemployed ("onset of the risk"). Researchers usually assign explanatory power to analysis time since it acts as a proxy for processes that are unobserved or difficult to measure. Going back to the example, the analysis time can proxy for the amount of information the individual has collected about the labor market, for potential changes in his reservation wages or in his expectations of finding a job, among other things (Cleves, Gould, Gutierrez, and Marchenko,

[31] Separations due to JTJ transitions can be directly linked to workers' behavior, whereas JTN transitions can be either initiated by the workers or by the employer (see the discussion in Section 4).

2010). Thus, in standard survival analysis, the analysis time is defined as $t = 0$ at the onset of the risk of failure and it accumulates as long as the individual has not failed, i.e. $t \in [0, \infty)$.

When studying worker separations from their employer, a natural candidate for analysis time would be the time elapsed since the worker was hired as one could argue that the risk of separation started at that moment. Denote that definition of analysis time as $\tilde{t}$. Thus, $\tilde{t} = 0$ at hiring and accumulates with tenure. In this case, $\tilde{t}$ conveys potential information on, for example, employers and employees learning about the match quality. However, since this paper focuses on establishments that close down, an alternative is to define the analysis time as the calendar distance until the closure. In this case the analysis time would proxy for (unobserved) information about the financial conditions of the employer, the workers' knowledge of the impending risk of layoff (for instance, the probability of having received a layoff notification), etc. Denote this definition of analysis time as $\bar{t}$. To make this definition operational I define $\bar{t} = 0$ as some moment in time, for example one year before the establishment closure, and study the risk of separation in the following months for all workers who were present at the establishment at $\bar{t} = 0$.

The implications of the different definitions of analysis time become more evident when thinking about the risk of separation. Let $h(t|X = x)$ be the hazard rate of separation (for any reason) at analysis time t of an individual with observed characteristics X, which is defined as the (limiting) probability that he separates in a given period, conditional on being present at the establishment at the beginning of that period. Thus, if T denotes the time of separation, the hazard rate of separation at analysis time t is defined as:

$$h(t|X = x) = \lim_{\triangle t \to 0} \frac{P\left(t + \triangle t > T > t \middle| \text{Worker is in the establishment at } t, X = x\right)}{\triangle t} \tag{6.1}$$

Ideally, the analysis time is chosen such that two individuals with the same value of t and of X must share the same risk of separating from their employer. If the analysis time is defined as $\tilde{t}$ (i.e. tenure), then it is assumed that two individuals with identical tenure and other observables have the same risk of separation. This will obviously fail if one of the individuals is observed in the last month of existence of an establishment, while the other individual is observed many years before the establishment's closure. Of course, calendar distance to closure can be introduced as an additional control in X. The empirical analysis will be based on a Cox Proportional Hazard Model (CPHM), which controls for the effect of the analysis time non-parametrically and for the effect of the covariates in X using a proportional hazard assumption. This assumption imposes some limitations to the flexibility with which I can control for calendar distance to closure. On the other hand, if the analysis time is defined as $\bar{t}$ (i.e. as the calendar distance to closure), then it is assumed that two individuals present at a firm at the same exact moment (say one year before closure) and with the same value of X have the same risk of separation. Here, the effect of calendar distance to closure is estimated non-parametrically and tenure can be included in X, but again the proportional hazards assumption imposes some restrictions on its effects. So, there is a trade-off about which information one believes it is more important to control for in a flexible way (i.e. non-parametrically): the information conveyed by tenure or the information conveyed by the proximity of establishment closure. The second approach is more sensible and more directly connected with the theoretical framework developed in Section 5. Thus, the CPHM specification in my analysis defines analysis time as the calendar distance to closure ($\bar{t}$).

6.2 Cause-specific separation analysis

The focus of this paper is to study how the PDB affects the behavior of workers who are at risk of layoffs. Thus, it is important to distinguish whether separations from an establishment occurred because the worker moved to another employer, i.e. a JTJ transition, or because he moved into nonemployment, a JTN transition.[32] Define the following cause-specific hazard rates of separation:

$$h_{jtj}(\bar{t}|X=x,D=d) = \lim_{\triangle\bar{t}\to 0} \frac{P\left(\bar{t}+\triangle\bar{t} > T > \bar{t},\ \text{JTJ transition}\middle|\text{Worker is at the establishment at } \bar{t}, X=x, D=d\right)}{\triangle\bar{t}} \tag{6.2}$$

$$h_{jtn}(\bar{t}|X=x,D=d) = \lim_{\triangle\bar{t}\to 0} \frac{P\left(\bar{t}+\triangle\bar{t} > T > \bar{t},\ \text{JTN transition}\middle|\text{Worker is at the establishment at } \bar{t}, X=x, D=d\right)}{\triangle\bar{t}} \tag{6.3}$$

Thus, $h_{jtj}(\bar{t}\big|X=x,D=d)$ and $h_{jtn}(\bar{t}\big|X=x,D=d)$ are the hazard rates of separation due to a JTJ transition and to a JTN transition, respectively, given that the worker is still at the establishment at the beginning of the period.

6.3 Policy changes and treatment dose

I define *treatment dose* (D) as the difference (in months) in the PDB that a person would be entitled to when comparing the rules determining UB duration between two periods. The dashed red bars in Figure 1b represents the maximum treatment dose by age calculated by comparing the set of rules in effect during the period July 1987-1991 as opposed to those in effect during 1982-1984.

[32] As discussed in Section 4, transitions into nonemployment include both layoffs and voluntary quits. It cannot be labeled as unemployment because some workers may not be looking for a job and others may have entered into retirement. Also, the data does not record self-employment and thus some transitions into self-employment may be miss-categorized as nonemployment.

Hereafter, I refer to this first comparison as Policy Change #1. Note that the period January 1985-June 1987 is left out of the comparison because this was a period of transitioning into the new unemployment insurance system (see Table 1). Also, although my sample includes establishments from West Germany only, I stop the first comparison shortly after the German reunification to avoid potential biases in the analysis coming from this institutional change.

Define also the index j as equal to one if the observation belongs to the treatment period (i.e. after the policy change), and equal to zero if it belongs to the pre-treatment period (i.e. before the policy change). Thus, for the analysis of Policy Change #1, j=*0* if the observation belongs to the period 1981-1984 and j=*1* if it belongs to the period July 1987-1991. As noted in Section 3.1 and depicted in Figure 1a and in Figure 1b, this policy change was characterized by a substantial increase in the PDB for workers aged 42 and older with long working history.

The solid blue bars in Figure 1b represents the maximum treatment dose when comparing the rules determining UB duration in the periods 1999-2004 and 1992-1997. Hereafter, I refer to this second comparison as Policy Change #2. In this case, the index j takes the value of zero if the observation belongs to the period 1992-1997 and of one if it belongs to the period 1999-2004. As discussed in Section 3.1, this second policy change was the result of increasing the age requirements to qualify for longer UB durations by 3 years, which resulted in a reduction in the PDB for many workers. However, the magnitude of the reduction was much smaller than the previous expansion, especially for older workers, as shown in Figure 1a and in Figure 1b.

Finally, I define *treatment status* as the treatment dose that a worker was actually subject to. In the DiD setup it is given by the combination of the treatment dose variable (D) and the index j, i.e. by $D \times j$. In other words, a worker was exposed to treatment status D if he was eligible for treatment dose D and his observation belonged to the treatment period (i.e. $j = 1$) for a particular policy change analysis. Otherwise, the treatment status is equal to zero.

6.4 Treatment effects

Define $h^{j,D}(\bar{t}|X = x, D = d)$ as the *potential* hazard rate of separation in period j and analysis time $\bar{t}$ if the treatment status were equal to D, for a worker with observed characteristics x and who was eligible for a treatment dose d. Thus, the *treatment effects (TE)* at analysis time $\bar{t}$, for a worker with observed characteristics x and a treatment dose of d can be defined in terms of the potential hazard rates of separation as:

$$TE_h(\bar{t},x,d) = h^{1,d}(\bar{t}|X = x, D = d) - h^{1,0}(\bar{t}|X = x, D = d) \tag{6.4}$$

In words, the TE is the difference between the (observed) factual hazard rates and the (unobserved) counter-factual hazard rates if the worker had not received any treatment. Following the same analysis for the cause-specific hazard rates of separations as, we obtain:

$$TE_{h_k}(\bar{t},x,d) = h_k^{1,d}(\bar{t}|X=x,D=d) - h_k^{1,0}(\bar{t}|X=x,D=d) \tag{6.5}$$

where $k \in K := \{jtj,\ jtn\}$.

The TE can also be defined in terms of any transformation of the hazard rates. One useful transformation is the *failure function*. The failure function is the probability that a worker has separated from his employer by analysis time $\bar{t}$. The expression for the potential failure function is given by $F^{j,D}(\bar{t},x,d) = 1 - exp\left\{-\int_0^{\bar{t}} h^{j,D}(u|X=x,D=d)du\right\}$. Thus, the TE in the failure function is given by:

$$\begin{aligned} TE_F(\bar{t},x,d) =& F^{1,d}(\bar{t},x,d) - F^{1,0}(\bar{t},x,d) \\ =& -exp\left\{-\int_0^{\bar{t}} h^{1,d}(u|X=x,D=d)du\right\} + exp\left\{-\int_0^{\bar{t}} h^{1,0}(u|X=x,D=d)du\right\} \end{aligned} \tag{6.6}$$

An equivalent of the failure function for JTJ and JTN transitions needs to account for the fact that separations can occur by either of the two competing risks. I work with the *cumulative incidence function* (CIF), which is defined as the cumulative probability of separating due to a specific cause before or up to time $\bar{t}$ (Cleves, Gould, Gutierrez, and Marchenko, 2010). Formally, the potential CIF of separation type k at analysis time $\bar{t}$ for workers with observed characteristics (x,d) is defined as:

$$CIF_k^{j,D}(\bar{t},x,d) = \int_0^{\bar{t}} h_k^{j,D}(u|X=xD=d) \times exp\left(-\int_0^u \left[\sum_K h_K^{j,D}(w|X=x,D=d)\right]dw\right)du \tag{6.7}$$

It can be seen from equation (6.7) that the CIF for any type of separation depends both on the hazard rates for that type of separation and on the hazard rate for the competing type of separation. Thus, although the expression for the TE in the cause-specific CIF is omitted here (see Appendix B.3 for details), it is straightforward that it depends on $h_{jtj}^{1,d}(\bar{t}|X=x,D=d)$, $h_{jtn}^{1,d}(\bar{t}|X=x,D=d)$ and on the counterfactuals $h_{jtj}^{1,0}(\bar{t}|X=x,D=d)$, $h_{jtn}^{1,0}(\bar{t}|X=x,D=d)$.

Therefore, in order to estimate the TE either for failure functions or for CIFs, it suffices to estimate the factual hazard rates and the non-treatment counter-factual hazard rates. The next section lays down the identifying assumptions to accomplish this.

6.5 Identifying assumptions

The first identifying assumption is that the true potential hazard rates $h^{j,d}(\bar{t}|X=x,D=d)$ and $h^{j,0}(\bar{t}|X=x,D=d)$ follow a proportional hazard functional form. More specifically, they can be specified as in equations (6.8) and (6.9) below. The term $h_0(\bar{t})$ is called baseline hazard function and measures the role of analysis time in the risk of separation. The terms $exp\,(\delta j+\gamma d+\beta x)$ and $exp\,(\delta j+\gamma d+\beta x+\theta d j)$ are called the relative hazards, and thus, $\delta j+\gamma d+\beta x$ and $\delta j+\gamma d+\beta x+\theta d j$ are known as log-relative hazards or risk scores (Cleves, Gould, Gutierrez, and Marchenko 2010).

$$h^{j,0}(\bar{t}|X=x,D=d)=h_0\,(\bar{t})\,exp\,(\delta j+\gamma d+\beta x) \tag{6.8}$$
$$h^{j,d}(\bar{t}|X=x,D=d)=h_0\,(\bar{t})\,exp\,(\delta j+\gamma d+\beta x+\theta d j) \tag{6.9}$$

Besides the proportional hazard functional form, three other important assumptions are embedded in equations (6.8) and (6.9) which are worth highlighting:

1. The only difference between equations (6.8) and (6.9) is given by the term $\theta d j$ that measures the change in the risk score in the treatment period for workers who are eligible for a treatment dose of d. Thus, treatment dose in the treatment period affects only the risk score, not the baseline hazard. Put differently, this assumes that, after conditioning on X, time period, and treatment dose, the role of non-modeled factors that are proxied for with the calendar distance to establishment closure remains the same regardless of actual treatment status. This is a standard assumption in DiD survival models.[33] I relax this assumption in the empirical analysis when I look at time-varying estimates of θ.

2. Equations (6.8) and (6.9) assume that the effect of the treatment dose d on the risk score, conditional on X, is linear. This assumption is less flexible than a non-parametric specification using a full set of dummies, one for each treatment dose value. However, it allows the efficient use of all of the variation in the PDB, which is important because the sample sizes for looking at each specific treatment dose value are relatively small.[34] Moreover, as shown by Schmieder, von Wachter, and Bender (2010, 2012), the increase in the duration of nonemployment spells per month of increase in the PDB is similar across age thresholds, even when the total increase in the PDB is different. This also supports the linearity of the specification of the effect of d.

3. Finally, the definitions of the risk scores in equations (6.8) and (6.9) implicitly assume a common trend in the potential non-treatment risk scores.[35]

[33] It is similar, for instance, to controlling for the role of time without interacting it with the treatment variable when working with discrete-time survival analysis models.

[34] A similar strategy is used in Haan and Prowse (2010) for identifying the effect of changes in entitlements periods on labor market status.

[35] To see this, define $RS^{j,0}(X=x,D=d)$ as the potential non-treatment risk score in period j for workers with observed characteristics x who were eligible for treatment dose d. The common trend assumption implies that the differences in the potential non-treatment risk scores between the pre-treatment period and the treatment period would have been the same regardless of treatment dose, conditional on having the same values of X. In other words, it assumes that $\{RS^{1,0}(X=x,D=d)-RS^{0,0}(X=x,D=d)\}=\{RS^{1,0}(X=x,D=0)-RS^{0,0}(X=x,D=0)\}\ \forall d$. The

Regarding the last point, assuming a common trend in the potential non-treatment risk scores actually precludes a common trend in potential non-treatment hazard rates, failure functions or CIFs. This is a common problem in DiD methods, namely the scale dependence of identifying assumptions (Lechner, 2010). In other words, a common trend on a given outcome (in this case the risk score) will not hold for non-linear transformations of that outcome (e.g. the hazard rate). However, this assumption is convenient because it allows me to build the TEs from the ground up. I first estimate the counter-factual non-treatment risk scores in the treatment period. Then I can recover the counter-factual non-treatment hazard rates. Using the counter-factual non-treatment hazard rates I estimate the counter-factual non-treatment failure function and CIFs. After having calculated all these objects I can easily estimate the TEs. Moreover, the common trend assumption in the potential non-treatment risk scores, joint with the proportional hazard functional form assumption, allows me to determine the direction of most of the TEs (with the exception of those for the CIFs) based solely on the sign of θ. To see this, plug equations (6.8) and (6.9) into equations (6.4) and (6.6). After a few manipulations, the following expressions can be obtained (see Appendix B for more details):

$$TE_h(\bar{t},x,d) = h^{1,0}(\bar{t}\,|X=x, D=d)\,[exp(\theta d)-1] \tag{6.10}$$

$$TE_F(\bar{t},x,d) = \left(1-F^{1,0}(\bar{t},x,d)\right)\left[1-\left(1-F^{1,0}(\bar{t},x,d)\right)^{exp(\theta d)-1}\right] \tag{6.11}$$

Equations (6.10) and (6.11) show that the direction of the two alternative measures of the TE are given by the sign of θ. Specifically, if $\theta = 0$, both TE equal zero; if $\theta > 0$, meaning that treatment dose increases the risk of separation in the treatment period, then $TE_h(\bar{t},x,d) > 0$ and $TE_F(\bar{t},x,d) > 0$; similarly, if $\theta < 0$, meaning that treatment dose reduces the risk of separation, then $TE_h(\bar{t},x,d) < 0$ and $TE_F(\bar{t},x,d) < 0$.

Notice also that for small values of θd, the expression $exp(\theta d)-1$ can be approximated by θd. Thus, it follows from equation (6.10) that if θ is sufficiently small, it can be directly interpreted as the percentage change in the hazard rate of separation resulting from a one-month expansion in the PDB.

The analysis of the TE on the hazard rates for each type of separation follows the same structure as in equations (6.4) and (6.10). Thus, the TE for the cause-specific hazard rates of separation is

definitions of the risk scores in equations (6.8) and (6.9) satisfy this assumption:

$$\begin{gathered}RS^{1,0}(X=x, D=d) - RS^{0,0}(X=x, D=d) = RS^{1,0}(X=x, D=0) - RS^{0,0}(X=x, D=0)\\ \delta + \gamma d + \beta x - (\gamma d + \beta x) = \delta + \beta x - (\beta x)\\ \delta = \delta\end{gathered}$$

given by equation (6.12):

$$TE_{h_k}(\bar{t},x,d) = h_k^{1,0}(\bar{t}|X=x, D=d)\,[exp(\theta_k d)-1] \tag{6.12}$$

The TE for a cause-specific CIF depends not only on the effects of the PDB on the cause-specific hazard rates of separation alone but on the alternative cause hazard rates as well. More formally, the TE for the cause-specific CIFs are given by equation (6.13) (see Appendix B for its derivation):

$$\begin{aligned} TE_{CIF_k}(\bar{t},x,d) = \int_0^{\bar{t}} & h_k^{1,0}(u|X=x, D=d) \times exp(-\int_0^u \sum_{i\in K} h_i^{1,0}(w|X=x, D=d)dw) \\ & \times \left\{ exp\left(\theta_k d - \int_0^u \sum_{i\in K} \left[h_i^{1,0}(w|X=x, D=d)\,(exp(\theta_i d)-1)\right] dw\right) - 1 \right\} du \end{aligned} \tag{6.13}$$

Thus, the TE will be zero only if both θ_{jtj} and θ_{jtn} are zero. For example, even if θ_{jtn} is zero we would have $TE_{CIF_{jtn}}(\bar{t},x,d) > 0$ if $\theta_{jtj} < 0$ and $d > 0$. In other words, even if the PDB does not directly affect the hazard risk of JTN transitions, the cumulative probability of separation due to a JTN transition increases when the increase in the PDB reduces the hazard risk of JTJ transitions.[36]

6.6 Parameters estimation

The coefficients in equations (6.8) and (6.9) are estimated using a Cox Proportional Hazard Model (CPHM).[37] The analysis includes all workers aged 38 to 56 years who are present in an establishment exactly one year before its closure and who have worked at least 64 months in the prior seven years. The date that marks exactly one year before plant closure is labeled $t = 0$, and all time-varying covariates, with the exception of age, are fixed at that moment. Age and treatment dose are measured using the year of closure of the establishment. Workers are followed until they separate from the establishment and the type of separation, i.e. a JTJ transition or a JTN transition,

[36] A similar situation arises in multinomial logit models, which are used to estimate discrete-time competing hazard models. In multinomial logit models, the marginal effect of a covariate z on the probability of a given outcome depends not only on the coefficient of z on that outcome equation, but also on its coefficients for the other (competing) outcomes. Cameron and Trivedi (2005, page 502) provides further details on computing marginal effects in a multinomial logit model.

[37] The CPHM leaves the baseline hazard unspecified and estimates the coefficients in the risk score by comparing individuals at failure times. If workers separate at $\bar{t}$, the CPHM compares the characteristics of that worker to the characteristics of other workers who were present at any establishment at $\bar{t}$ and did not separate, i.e. workers in the same risk set. By doing the comparison at every failure time, the coefficients of the risk scores in equations (6.8) and (6.9) are estimated by maximum likelihood in order to maximize the probability of having the observed order of separations. After estimating the coefficients of the risk score, the baseline hazard (and the functions related to it, such as the baseline failure function) can be recovered non-parametrically.

is recorded.

The CPHM has two characteristics that make it ideal for the empirical problem at hand. First, the non-parametric estimation of the baseline hazard is convenient when using $\bar{t}$, or the calendar distance to the establishment's closure date, as the definition for the analysis time. This is because the risk of separation increases faster as the establishment approaches its closure and it is unlikely that any parametrization of the baseline hazard will have enough flexibility to accommodate this pattern. Second, the CPHM does not attach any specific significance to the value of $\bar{t}$. The analysis time is only used to order the data and to define the risk sets for estimation purposes (Cleves, Gould, Gutierrez, and Marchenko, 2010). Thus, labeling $t = 0$ as one year before plant closure has no special meaning other than defining the risk sets for estimation of the coefficients of the risk score.

It can be shown that if, after conditioning on X and D, the hazard rates $h_{jtj}(\bar{t}|X = x, D = d)$ and $h_{jtn}(\bar{t}|X = x, D = d)$ are independent, then the (log) likelihood of observing the failure times for each type of transition can be factored into two parts, where each part depends only on the parameters for one type of transition. Thus, the estimation can proceed by maximizing the two components parts separately (Jenkins, 2005) and treating separations due to the other type of transition as randomly censored observations. In the CPHM, this is achieved just by keeping those observations in the risk sets until they have failed due to the competing risk and excluding them thereafter. However, if after conditioning on X and D, the cause-specific risks are not independent, then treating separations due to the competing risk as randomly censored observation may introduce bias in the results.

Identification of the parameters in the case of correlated risks is more difficult. It is usually done by introducing unobserved components in $h_{jtj}(\bar{t}|X = x, D = d)$ and in $h_{jtn}(\bar{t}|X = x, D = d)$ that are allowed to be correlated but are independent of X. I conducted several tests that have allowed me to conclude that the unobserved heterogeneity and its correlation between the competing risks can be safely ignored.[38] Thus, I treat each separation risk, after conditioning on X and D, as independent.

[38] This can be explained since, given that everybody will eventually leave the establishment within a year or less, there is less room for any unobserved heterogeneity to have an important role in explaining the observed separation patterns. Two different tests corroborate this empirically. First, I assume that each separation risk is independent and run my analysis specifying an unobserved component that follows either a gamma or a log-normal distribution (using the frailty option in Stata). For both risks I find that the variance of the unobserved component is minimal. Then, I allow the unobserved components to be correlated and to follow either a bivariate normal distribution or a discrete distribution with three points of support for each risk. Using maximum likelihood estimation I find that the variance of the unobserved components and their correlation are again small (and not statistically significant). Moreover, the coefficients on all the covariates are robust to the introduction of the unobserved components in the analysis.

7 Results

7.1 CPHM estimation results

Table 3 presents the CPHM estimation results for the analysis of the first policy change. As mentioned earlier the sample consists of workers aged from 38 to 56 years who were present at a closing establishment one year before its demise. Also, all workers in the sample had at least 64 months of prior working history in the last seven years. Estimations are weighted by the probability of observing each establishment and standard errors take into account the stratification of the sampling design (by establishment size) and the clustering of workers at the establishment level (see footnote 21).

The estimates of the parameters of interest θ are highlighted in Table 3. Following the interpretation of θ discussed in Section 6, I find that a one-month increase in the PDB resulted in a decrease of 0.4% in the hazard rate of any separation. This is a small and not statistically significant effect. However, it masks two opposing effects on the hazard rates for JTJ transitions and for JTN transitions. I find that a one-month expansion in the PDB decreased the hazard rate of JTJ transitions by 2.1%. This effect is significant at the 5% level. I also find that a one-month expansion in the PDB increased the hazard rate of a JTN transition by 1.2%, although this effect is not statistically significant (p-value of 0.154).

A potential concern with the analysis of the effects of the first policy change is that the treatment dose increases monotonically with age. Thus, one may argue that the estimated effects are coming only from the very large expansions in the PDB for the older workers, who would have less opportunities in the labor markets and also more incentives to look for earlier retirement (even though my sample only includes workers up to 56 years old). In order to investigate this issue, in Table 4 I re-estimate the CPHM allowing for differential effects for two age groups: workers who were 42-48 years old and workers who were 49-56 years old. Panel A presents the coefficients of the interactions between the corresponding age group dummy and the time dummy for being in the treatment period. Panel B linearizes those coefficients by dividing the effect from Panel A by the average in increase in the PDB for each age group. I find that the increase in the PDB reduced the hazard rates of JTJ transitions for all workers, not only the older ones. In fact, the linearized effects are larger (in absolute value) for workers in the 42-48 age group than for workers in the 49-56 age group, although the standard errors are sufficiently large to prevent concluding that the estimates are statistically different from each other.

Table 5 presents the CPHM estimation results for the analysis of the second policy change. The point estimate of θ for JTJ transitions is smaller than the one found for Policy Change #1. I find that a one month reduction in the PDB increased the hazard rate of JTJ transitions by 1.5%. However, this effect is not statistically significant at the conventional levels (p-value of 0.172).

The estimates of θ for any separations and for JTN transitions are very small and not statistically significant as well.

One possible explanation for why the estimates of θ are different in magnitude between both policy changes may be non-linearities in the effects of changing the PDB depending on the starting point: Policy Change #1 implied a change in the potential earnings profile starting at month 13 of unemployment for workers aged 42 or older. In contrast, Policy Change #2 implied a change in the potential earnings profile at month 13 for workers age 42-44; at month 19 for workers aged 45-46; at month 23 for workers aged 49-51 and at month 27 for workers aged 54-56. It is plausible that workers' search decisions are less responsive to changes in the right tail of potential future unemployment durations because they do not expect their actual income profile to be affected. This is more likely to be true for workers aged 45 and older for whom the maximum PDB was still very generous even after the reduction implied by the second policy change. For example, using data from my analysis sample for the period 1992-1997, I found that the average 50-year-old worker who separated from the closing establishment by entering unemployment had an UB spell duration of 13.2 months, while his maximum entitlement was 26 months. Thus, a reduction in the PDB to 22 months, as it happened after 1999, would likely have little effect on his pre-displacement search behavior. In fact, Figure 2a shows that the reduction to 22 months only "bites" 33% of the UB spells. These numbers are more dramatic if one excludes spells that are clustered at the exhaustion point (26 months), since these spells may belong to workers who are less likely to exert effort to search for a job or who are not capable of finding one. Excluding the spells that exhausted benefits, I find that reducing the PDB to 22 months would affect only 4% of the UB spells. Figure 2b presents similar analysis on the potential "bite" of the reduction in the PDB that happened after Policy Change #2 (excluding spells that exhausted benefits) for workers aged 42-56. It is clear from the graph that this "bite" for most ages is very small.

In order to further investigate the non-linearity of the effects depending on the strength of the potential "bite" of the policy change, I re-estimate the CPHM models using only workers aged 38 to 44 years. Workers aged 38 to 41 years act again as the control group, for whom there were no changes in their PDB. Workers aged 42 to 44 years are the treated group. Policy Change #2 had a larger "bite" on their potential UB durations as shown in Figure 2b. Moreover, for these group of workers, the treatment dose under Policy Change #1 and Policy Change #2 are exactly the same but with opposite sign (see Figure 1b). In other words, for workers aged 42 to 44 years Policy Change #2 just reversed the previous expansion in their PDB by setting it equal to 12 months. The new estimates of θ are presented in Table 6. The point estimate of θ for JTJ transitions is now larger than before. I find that a one-month decrease in the PDB led to a 2.6% increase in the hazard rate of JTJ transitions (p-value 0.053). Thus, results from the analysis of Policy Change #2 corroborates the previous evidence from Policy Change #1: longer (shorter) PDB decreases (increases) the probability that workers leave to a new employer before the establishment closes.

Although it is not the main focus of this paper, I discuss also some of the coefficients associated with other observed workers' characteristics. I find that men, shorter-tenured workers and white-collar workers are more likely to exit the closing establishments earlier, especially because of JTJ transitions. These are workers who may have better opportunities to find new employment. For example, for the case of white-collar workers the literature has provided evidence that they are less negatively affected by a separation from their employers since a smaller fraction of their acquired skills are job-specific. In contrast, blue-collar workers seem to have skills that are less transferable across jobs (Podgursky and Swaim, 1987; Kletzer, 1989). Therefore, it is plausible that white-collar workers have better opportunities for finding new jobs than blue-collar workers.

Regarding establishment size, I find strikingly opposite results between the time-periods covered by both policy changes, especially with respect to JTJ transitions. For the time period covered in the analysis of the first policy change (1982-1984 and 1987-1991), workers in larger establishment have lower hazard rates of JTJ transitions than those in smaller establishments. The converse is true for the time period covered in the analysis of the second policy change (1992-1997 and 1999-2004). The reasons why there is this difference in the effect of establishment size over time has yet to be more rigorous investigated.

7.2 Placebo tests

Before continuing the discussion of the empirical results, I present evidence from placebo tests that supports the validity of the causal nature of the previous findings. First, I test for common trends in the risk scores prior to the policy changes. In order to conduct these tests I use only information from the pre-treatment period and pretend that the change in the PDB happened at some earlier date in the pre-treatment period. In the case of Policy Change #1, I assume that the change in the PDB applied to establishments that closed in 1984 but not to establishments that closed in 1982-1983. In the case of Policy Change #2, I assume that the change in the PDB applied to establishments that closed in 1995 to 1997, but not to those that closed in 1992 to 1994. This artificial earlier change in the PDB is the placebo. Thus, it should not have any effect on the risk scores unless there were differential trends prior to the actual changes in the PDB between those who were affected by them and those who were not. The credibility of the common trend assumption (and of the identification strategy) would be enhanced if the coefficient of the interaction of the treatment dose (D) and the dummy marking the artificial change (placebo) is equal to zero. Table 7 presents the results of these tests. All the coefficients are not statistically different from zero at the conventional significance levels. Furthermore, the estimated coefficients for JTJ transitions are positive rather than negative. The point estimates are also particularly close to zero for Policy Change #1 (Panel

A) and for Policy Change #2 when I only include workers from ages 38-44 (Panel C). Thus, the tests shows no evidence of differential trends in the non-treatment risk scores between the treated and control groups prior to the changes in the maximum PDB.

The second placebo test is to falsely assume that the policy changes affected a group of workers who were actually not affected by them. In my analysis, I assume that the policy changes affected workers of age 37-40, and I use as control group individuals of age 32-36. I re-run the CPHM including a dummy variable for being in the age group 37-40, a dummy variable for being in the treatment period, and an interaction of both. Since the PDB for workers younger than 42 years old remained unchanged, the interaction term should not be significant unless there were a change in the age gradient for the risk scores between the pre-treatment period and the treatment period. Thus, the over-identifying assumption is that the age gradient for workers who were not affected by the changes in the PDB remained stable before and after the policy change. The results of these tests are shown in Table 8. I find that the interaction terms are not statistically significant. Moreover, the point estimates are very small in magnitude. For example, compare the estimate -0.030 for JTJ transitions in Panel A (Policy Change #1) with the estimate -0.278 obtained for workers age 42-48 years old in Panel A of Table 4. For the case of Policy Change #2, the placebo estimate for JTJ transitions is -0.022 (Table 8, Panel B), which is not only small but also implies that the risk scores of a JTJ transition for workers aged 37-40 decreased in the treatment period in comparison to the younger control group of workers aged 32-36. This finding is opposite to the results discussed earlier in Table 6, which indicated that workers aged 42-44, whose PDB were reduced in the treatment period, were finding new jobs faster than before in comparison to their younger control group (workers aged 38-41). In conclusion, the results from these tests support that the changes in the PDB were the cause for changes in the risk scores of JTJ transitions for workers aged 42 years or older, and not some underlying trends in the age gradients.

The last test relies in the insights provided by the theoretical discussion in Section 5. The changes in the PDB should only affect workers who have received a layoff notification or perceive that they will receive one. Thus, the effects of a change in the PDB should be stronger as the closure date approaches since more workers would have received a layoff notification or would be aware of the impending closure of the establishment. Figure 3 helps us understanding this argument. One year before closure, establishments have already reduced their personnel by about 20%. Thus workers are likely to be aware of the distressed situation of their employers. In contrast, three years before closure the size of the personnel is relatively stable. Thus workers who were present at the establishments three years before closures would be less likely to feel job insecure. Table 9 presents the CPHM estimation results for workers that were present at the establishments one, two and three years before their closure. The sample selection criteria is the same as before: workers aged 38 to 56 years who have worked at least 64 months in the last seven years. In each case, the worker is followed only up to 12 months. If at the end of that period the worker is still present at the establishment then his failure time (and type) is treated as censored. Notice that the exercise for workers present three years before closure can only be done for the second policy change since the administrative records start at 1975 and thus it is not possible to identify workers with sufficiently long working history. The estimated parameters are not very different for the last year of existence (discussed earlier) and when I redo the analysis for workers present two years before closure; although in the former case the coefficients are more precisely estimated. This may be explained because, as mentioned in Section 3, employers have to communicate in advance their decision of mass-layoffs to the works council and the local employment agency. Thus, workers present at the establishments two years before closure may become aware that, on average, their employers are going to downsize by about 20%. However, it is important to recall that the estimated parameters θ measures the proportional change in the hazard rates as a result of a one-month expansion in the PDB. The final effect in levels on the hazard rates, failure function and CIF would depend also on the counter-factual non-treatment hazard rates, which increase significantly as the closure dates approaches. Thus the changes in the PDB would have a much stronger effect in levels in the last year of existence of an establishment than two years before its closure, as predicted by the theoretical model. Panels B and C shows that for workers present three years before closure, the estimated parameters θ are much smaller, which is consistent with the previous annotation that the level of job insecurity should be smaller as well.

7.3 Time-varying effects

As mentioned above, the theoretical model in Section 5 predicted that the effects of changes in the PDB on the probability of JTJ transitions should get stronger as the closure approaches. However, the specification of the hazard rates in equations (6.8) and (6.9), and the empirical results in Tables 3, 5 and 6 implies that the treatment dose only delivers a constant proportional change in the hazard rates during the last year of existence of the establishment. Nevertheless, the TE in the hazard rates when measured in levels, as in equations (6.4) and (6.5), will increase with the proximity to closure as predicted by the theoretical model because the underlying counter-factual non-treatment hazard rates also increase with the proximity to closure. However, in order to investigate if I am imposing a strong restriction by the assuming a constant proportional change, I fit a more flexible specification of the hazard rates. I re-estimate my base CPHM for workers present one year before closure and allow θ to vary with the proximity to the establishment demise as measured in quarters (the fourth quarter being when the establishment closes). Table 10 presents the estimation results. In the case of Policy Change #1, I do not find a clear pattern of the estimates of θ for JTJ transitions as closure approaches. Moreover, I cannot reject the null hypothesis of equality of the coefficients of θ across quarters (the p-value of the F-test of joint equality of coefficients is given in parenthesis in Table 10). In the case of Policy Change #2, the quarterly coefficients of θ seems to get smaller as closure approaches, specially when I focus only on workers aged 38-44. Although, I again cannot reject the null hypothesis of equality of coefficients. Therefore, I will keep the original specification as the preferred one, which delivers a constant proportional change in the hazard rates of JTJ transitions and an effect that is increasing with the proximity to closure when measured in levels.

7.4 Treatment effects calculations for the average treated worker

The average treated worker in Policy Change #1 had an increase in his PDB of about 13.4 months, or 112%.[39] Therefore, using the estimates of θ from Table 3, I obtain that his hazard rates of all separations decreased by 5.6% (p-value 0.231), his hazard rates of JTJ transitions decreased by 24.6% (p-value of 0.008) and his hazard rates of JTN transitions increased by 19.5% (p-value 0.084).[40]

Using the formulas in equations (6.10), (6.11), (6.12) and (6.13), I also estimated the TE in levels on the hazard rates, failure function and cause-specific CIF. These are shown in Figure 4, Figure 5 and Figure 6, along with the point-wise 2nd and 98th percentiles of 500 bootstrap replications.[41]. I cannot reject (with 96% confidence) that the TE on the hazard rates for all separation and the failure function are equal to zero, which is not surprising given that the estimate of θ for all separation in Table 3 was not statistically significant. In the case of JTJ transitions, the TE on the hazard rates are negative and become stronger in the last two quarters up to establishment closure, as supported by the theoretical framework. I also find that the increase in the PDB led the average treated worker to be about 9.7 percentage points less likely to have moved to another establishment by the time of closure. I can reject the null hypothesis of a zero effect with 96% confidence, although the confidence intervals are still relatively wide. The policy change also led the average treated worker to be about 7.5 percentage points more likely to have separated due to a JTN transition by the time of closure (see Figure 6). Notice that this effect is statistically significant even though the estimate of θ in the hazard rates for JTN transitions is not. This is because although there is no statistically strong evidence that the expansion in the PDB affected directly the hazard rates of a JTN transition, there is strong evidence that it decreased the hazard rates of a JTJ transition. Thus, the expansion in the PDB made workers less likely to voluntarily abandon the closing establishment for a new job and therefore increased their probability of being effectively separated by entering nonemployment.

[39] I define the average treated worker as a worker whose observed characteristics are evaluated at the mean values among all workers affected by the change in the PDB.

[40] Standard errors were calculated using the delta method and p-values were obtained using the normal distribution.

[41] The hazard rates were smoothed using an Epanechnikov kernel with a bandwidth of 60 days.

For the analysis of Policy Change #2, I focus only on treated workers aged 42-44 years old, since they were the ones more affected by the policy change as discussed earlier. The average treated worker had a reduction of 6.9 months in his PDB. As a result, using the estimates of θ from Table 6, I find that his hazard rates of all separations increased by 9.5% (p-value 0.059), his hazard rates of JTJ transitions increased by 19.6% (p-value of 0.047) and his hazard rates of JTN transitions increased by 3.1% (p-value 0.391). I also find that the average treated worker was 4.0 percentage points more likely to have moved to a new job and 0.7 percentage points less likely to have entered nonemployment by the time of closure. However, these effects are not statistically significant, as can be seen in Figure 8 and in Figure 9.

To summarize, the TE calculations show that an increase (decrease) in the PDB reduces (increases) the hazard rates of JTJ transitions and the probability of having moved to a new job before the establishments closes down. The statistical evidence is stronger for the first policy change, that implied a large extension in the PDB, than for the second policy change, that implied a more moderate reduction in the benefits.

7.5 Estimates of θ by subgroups

Finally, in this section I analyze how the estimates of the parameter θ vary across different subgroups. I focus the discussion mainly on the estimates of θ in the JTJ transition equations. First, I distinguish between low-wage earners and non-low wage earners. Low earners are more likely to receive social assistance to bring their income to an established social minimum. Thus, as long as they are entitled to social assistance, changes in their PDB do not actually change their expected income profile. Non-low earners, in contrast, are more likely to have deductions in their UA payments and thus an expansion in the PDB would have a higher impact on their expected income profile. Therefore, I expect that changes in the PDB would have a smaller effect for low-wage workers than for non-low-wage workers. To implement this test, I define low-wage workers as those whose daily wage rate is less than two-thirds of the median wage, as it is defined in official statistics (Lo, Stephan, and Wilke, 2012). Panels A in Tables 11 and 12 present the estimates of θ for low-wage and non-low-wage workers for the analysis of both policy changes. For Policy Change #1, I find a larger negative coefficient θ for JTJ transitions for the case of non-low-wage workers, as expected. However, the point estimates between low-wage and non-low-wage workers are not statistically different as indicated by the p-value from the test of the null hypothesis of equality of coefficients (shown in parenthesis). For Policy Change #2, I found the opposite results: the point estimate for low-wage earners is more negative than for non-low-wage earners. However, again I cannot reject the null hypothesis of equality of coefficients.

I also estimate the coefficient θ by gender, occupation and tenure. In general, I find that in the analysis of Policy Change #1 the increase in the PDB had stronger negative effects on the hazard rates of JTJ transitions for those subgroups that were more likely to move earlier to new jobs. In other words, the increase in the PDB had stronger effects for males, white-collar workers and workers with shorter tenure. Two alternative explanations may account for this pattern. On the one hand, these groups of workers may exert more OTJS effort upon the imminent risk of job loss, which explains why they are more likely to separate earlier. Thus, increases in the PDB can have stronger incentives to discourage OTJS for them. On the other hand, it is possible that all workers exert comparable levels of OTJS but the subgroups mentioned above are on average more successful in finding new jobs. Then, everything else equal, increases in the PDB would result in larger observed effects in reducing JTJ transitions for them than for workers who are less likely to get job offers. Since I do not observe directly OTJS efforts (or reservation wages) but only JTJ transitions, I cannot discriminate which alternative explanation is more likely to be true. It is also important to mention that for all of these groups of workers, although the point estimates are in some cases very different, I cannot reject the null hypothesis of equality of coefficients. For the case of Policy Change #2, the difference in the coefficients' point-estimates are less dramatic and again I cannot reject the null hypothesis of equality of coefficients.

Two cases where I can reject the null hypothesis of equality of coefficients are the estimates of θ by educational level and establishment size for the case of Policy Change #1. Moreover, the estimates of θ for JTJ transitions are positive for workers with college or university degree and for workers at large establishments (501-1000 workers). These results go against the predictions from the model in Section 5. However, an implicit assumption in the model was that changes in the PDB have no effect on the probability of layoff. I found evidence that this assumption may not hold for workers with college degree or workers at large establishments. For these groups of workers the expansion in the PDB also increased their hazard rates of JTN transition, as can be shown by the positive and statistically significant estimates of θ. If I allow expansions in the PDB to increase the risk of layoff in the model, and also let workers to be aware of this effect, then the total effect on the probability of JTJ transition is ambiguous. On one hand, the increase in job insecurity due to the expansion in the PDB increases on-the-job search, reduces reservation wages and increases the probability of JTJ transitions. On the other hand, the expansion in the PDB increases the value of future unemployment, reduces on-the-job search, increases reservation wages, and reduces the probability of JTJ transitions. A priori it is not possible to determine which effect is larger. Further evidence that the increase in job insecurity may drive the positive estimates of θ in JTJ transition equations is given by the results in Policy Change #2. In this case, the reduction in the PDB did not have an effect on the hazard risks of JTN transitions for college graduates, and I find a negative estimate of θ on the hazard rates for JTJ transitions, as would be predicted by the model.

8 Conclusions

This paper aims at filling the gap in the literature on the effects of unemployment benefits (UB) on employed workers' behavior, particularly job-to-job (JTJ) transitions. The theoretical framework presented in this paper show that such effects should vary depending on workers' job insecurity, with larger effects for workers who have received a layoff notification and have a short period remaining before separation from their employers. Therefore, studying the effects of UB on workers' behavior can be empirically challenging because in general it is difficult to obtain measures of job insecurity that are uncorrelated with workers unobserved characteristics. In this paper, I overcome this problem by focusing on workers at establishment closures in West Germany. Using difference-in-difference methods within a competing risks survival analysis, I test whether changes in the potential duration of unemployment benefits (PDB) affect the timing of the workers' separation from the closing establishments, distinguishing between JTJ transitions and job-to-nonemployment (JTN) transitions. The identification strategy relies in exploiting changes in the PDB in the mid-1980s and mid-1990s for older workers in Germany.

In general, I do not find evidence that changes in the PDB affects the hazard rates for JTN transitions. This can be explained by the fact that I focus my analysis on workers present at the establishments one year before their closure. Thus, all of them will be layoff within a year and considerations other than UB, for example age and seniority, are likely to be the most important factors in the timing of the layoffs.

In contrast, I find evidence that changes in the PDB affect workers' probability of moving to another job before the closure of an establishment, i.e. the hazard rates of JTJ transitions. As mentioned above, I analyze two changes in the PDB in Germany. The first change, which occurred in the mid-1980s and is referred in the paper as Policy Change #1, brought an expansion in the maximum PDB for workers aged 42 or older. I find that the hazard rates of JTJ transitions decreased by approximately 2.1% per month of increase in the PDB. The second change, which occurred in the mid-1990s and is referred in the paper as Policy Change #2, brought a reduction in the maximum PDB for certain age-groups of workers aged 42 or older. I find that a one-month reduction in PDB increased workers' hazard rates of JTJ transitions by 1.5%, although this effect is not statistically significant. The smaller effects in Policy Change #2 in comparison to Policy Change #1 can be explained by the moderate reductions in the maximum PDB in the second policy change as opposed to the previous large expansions in the first policy change. In fact, even after the reductions in the maximum PDB, the average length of the entitlement to UB was still very generous. As a consequence, only for a small fraction of workers the second policy change would have had an effect in their expectations of potential future income.

To compare my results with those found in previous work, I calculate the implied elasticities.

For the reasons discussed in the previous paragraph I focus the analysis on the results from Policy Change #1. For the average treated worker, the elasticity of the hazard rates of JTJ transitions to the extension in the PDB was -0.23. The main difficulty in benchmarking this elasticity is that previous studies have analyzed the effects of changes in the level of benefits rather than changes in their duration. To make the comparisons as close as possible, I transformed the expansion in the PDB into a change in the discounted valued of potential UB receipt. I did this calculation for the average treated worker, who was entitled to 12 months of UB before the policy change and to 25 months of UB after the change. I assume that before the expansion in the PDB, the worker collects UB for 12 months at a replacement rate of 67% and then he collects Unemployment Assistance (UA) for 13 months at a replacement rate of 35% (see footnote 10). After the expansion in the PDB the worker collects UB for 25 months. The monthly discount rate is 0.99. Under these assumptions, I find an elasticity of the hazard rate of JTJ transitions to the potential increase in UB receipt of approximately -0.84.

Light and Omori (2004) found that the elasticity of the probability of a JTJ transition (over a period of 15 weeks) with respect to the level of UB was only -0.09. This small elasticity can be explained by the fact that the authors did not use a sample of workers at high risk of job loss, but a representative sample of the working population. As discussed in Section 5 the generosity of UB would only matter to workers who feel at risk of job loss. In contrast, in my work using older Americans workers (Gutierrez, 2012) at downsizing firms (i.e. firms that have recently reduced personnel), I find that the elasticity of the monthly probability of JTJ transitions with respect to the replacement rate provided by UB was -0.88. Thus, the elasticity I find in this paper for the analysis of Policy Change #1 is similar to the one I found in the US for older workers at downsizing employers. However, one need to be cautious about these comparisons because the generosity of the UB systems in the US and Germany are very different.[42]

Evidence presented in this paper should encourage further studies on this topic. One avenue of research would be the incorporation of UB effects on workers' search behavior in the analysis of optimal design of unemployment insurance systems. Previous studies have mostly focused on the effects that UB have on transitions from unemployment to employment. Thus, they have neglected the fact that UB can also affect the entry rate into unemployment by affecting the behavior of workers. One exception is Wang and Williamson (1996). The authors consider an environment where the worker's probability of remaining employed depends on his work effort. Higher UB creates incentives for the worker to shirk and thus makes job destruction endogenous. In their analysis,

[42] In Germany, the PDB in the pre-treatment period (before it was extended) was 12 months for the sample of workers under analysis (i.e. with long-labor force attachment). Moreover, the replacement rate of UB was above 60%. In the US the PDB is, under normal circumstances, about 26 weeks (or 6 months). Also, the group of workers studied in Gutierrez (2012) consisted of men aged 50 years or older for whom the average replacement rate, taking into consideration states' limits on weekly benefits, was effectively about 35%.

Wang and Williamson (1996) show that the optimal system involves a large penalty for a transition from employment to unemployment (to discourage shirking) and a large subsidy for a transition from unemployment to employment (to encourage search effort). Put differently, workers receive a large drop in consumption in the first period of unemployment and a large reemployment bonus. There is no empirical evidence in favor of the work effort-UB relationship in the literature (Fredriksson and Holmlund, 2006). However, this paper presents evidence that workers at risk of layoff may exert less search effort to find an alternative job when they are entitled to more generous UB. Thus the recommendations from Wang and Williamson (1996) analysis remain valid. In fact, many existing unemployment insurance systems involve (although Germany does not) a waiting period before benefits are paid out. The existence of such waiting period may be defended as a way to discourage entry into unemployment.[43] Another policy that could be considered is the introduction of search requirements for workers who have received a layoff notification, just as those requirements exist for unemployed workers. Both theoretical and empirical literature have provided support for the case of imposing penalties on less active job search for the unemployed (Fredriksson and Holmlund, 2006). A similar system could be implemented for employed workers who have received a layoff notification.

Another avenue for further research is the role that UB can play in managing human resources at distressed firms. Recent work by Brown and Matsa (2012) has shown that employers in the US who are experiencing financial distress receive less applications for open positions, both in comparison to the period before entering distress and to other employers who are not in financial problems. However, the authors also find that workers are more willing to apply to positions at distressed firms in states where the cost of unemployment are lower because of more generous UB. The evidence I present in this paper indicates that UB can not only help distressed employers to recruit personnel but also to retain them longer. For instance, according to Fallick (1994), one of the arguments provided by employers against the advance layoff notifications required by the 1988 Worker Adjustment and Retraining Notification Act (in the US) was that early departures of workers would hamper operations and could lead to shutting down before schedule (or else sustain losses in keeping the plant open). As shown in this paper, UB provides incentives for workers to stay longer with distressed employers, which may facilitate an orderly process of shutting down or downsizing.

Finally, the results of this paper also provide a cautionary note about using establishment closures to study the effects of job loss on different outcomes. Workers present at the moment of closure are likely to be entitled to more generous UB than those who left earlier. Thus, researchers

[43] Other considerations include for example potential benefits in reducing the administrative burden of the unemployment insurance system since many unemployment spells may end before the waiting period is over or it may discourage workers who expect to be reemployed soon to claim UB.

should be aware of the potential contamination of their estimates due to this source of selection bias, which has not been addressed in the literature before. Further research should address the effect of other institutional arrangements, such as notification periods, severance payments, seniority protections, among others, on the non-random selection of workers at establishment closures.

References

ADDISON, J. T., L. BELLMAN, AND A. KÖLLING (2002): “Unions, Works Councils and Plant Closings in Germany,” *IZA Discussion Paper Series*, No. 474.

ANDERSON, P. M., AND B. D. MEYER (1993): “Unemployment Insurance in the United States: Layoff Incentives and Cross Subsidies,” *Journal of Labor Economics*, 11, S70–S95.

BROWN, J., AND D. A. MATSA (2012): “Boarding a sinking ship? An investigation of job applications to distressed firms,” *NBER Working Paper Series*, No. 18208.

BURGESS, P. L., AND S. A. LOW (1998): “How do Unemployment Insurance and Recall Expectations Affect On-The-Job Search among workers who Receive Advance Notice of Layoff?,” *Industrial and Labor Relations Review*, 51(2), 241–252.

CAMERON, A. C., AND P. K. TRIVEDI (2005): *Microeconometrics. Methods and Applications*. Cambridge University Press.

CARD, D., AND P. B. LEVINE (1994): “Unemployment Insurance Taxes and the Cyclical and Seasonal Properties of Unemployment,” *Journal of Public Economics*, 53, 1–29.

CHRISTOFIDES, L. N., AND C. MCKENNA (1995): “Unemployment Insurance and moral hazard in employment,” *Economics Letters*, 49, 205–210.

——— (1996): “Unemployment Insurance and Job Duration in Canada,” *Journal of Labor Economics*, 14, 286–312.

CLEVES, M., W. GOULD, R. C. GUTIERREZ, AND Y. V. MARCHENKO (2010): *An Introduction to Survival Analysis Using Stata. Third Edition*. Stata Press.

DLUGOSZ, S., G. STEPHAN, AND R. A. WILKE (2009): “Fixing the leak: Unemployment incidence before and after the 2006 reform of unemployment benefits in Germany,” *Discussion Papers in Economics*, University of Nottingham, No. 09/10.

EBBINGHAUS, B., AND W. EICHHORST (2006): “Employment Regulation and Labor Market Policy in Germany, 1991-2005,” *IZA Discussion Paper Series*, No. 2505.

FALLICK, B. C. (1994): “The Endogeneity of Advance Notice and Fear of Destructive Attrition,” *The Review of Economics and Statistics*, 76, 378–384.

FELDSTEIN, M. (1976): “Temporary Layoffs in the Theory of Unemployment,” *Journal of Political Economy*, 84, 937–958.

——— (1978): "The Effect of Unemployment Insurance on Temporary Layoff Unemployment," *American Economic Review*, 68(5), 834–846.

FITZENBERGER, B., AND R. A. WILKE (2009): "Unemployment Durations in West Germany Before and After the Reform of the Unemployment Compensation System during the 1980s," *German Economic Review*, 11, 336–366.

FREDRIKSSON, P., AND B. HOLMLUND (2006): "Improving incentives in Unemployment Insurance: A review of recent research," *Journal of Economic Surveys*, 20, 357–386.

FUJITA, S. (2011): "Reality of on-the-Job Search," *Reserve Bank of Philadelphia*, Working Paper No.10-34/R.

GREEN, D. A., AND W. C. RIDDELL (1997): "Qualifying for Unemployment Insurance: An Empirical Analysis," *Economic Journal*, 107, 67–84.

GREEN, D. A., AND T. C. SARGENT (1998): "Unemployment Insurance and Job Durations: Seasonal and Non-Seasonal Jobs," *Canadian Journal of Economics*, 31, 247–278.

GUTIERREZ, I. A. (2012): "Does unemployment insurance discourage on-the-job search? Evidence from Older American Workers," *University of Michigan*, Working Paper.

HAAN, P., AND V. PROWSE (2010): "The Design of Unemployment Transfers: Evidence from a Dynamic Structural Life-Cycle Model," *IZA Discussion Paper Series*, No. 4792.

HETHEY, T., AND J. F. SCHMIEDER (2010): "Using Worker Flows in the Analysis of Establishment Turnover. Evidence from German Administrative Data," *FDZ-Methodenreport*, No. 06/2010.

HOFMANN, B. (2008): "Work Incentives? Ex Post Effects of Unemployment Insurance Sanctions-Evidence from West Germany," *CESifo Working Papers*, No. 2508.

HUNT, J. (1995): "The Effect of Unemployment Compensation on Unemployment Duration in Germany," *Journal of Labor Economics*, 13(1), 88–120.

JENKINS, S. P. (2005): "Survival Analysis. Online Manuscript," *University of Essex*.

JOLIVET, G., F. POSTEL-VINAY, AND J.-M. ROBIN (2006): "The Empirical Content of the Job Search Model: Labor Mobility and Wage Distributions in Europe and the US," *European Economic Review*, 50, 877–907.

JURAJDA, S. (2002): "Estimating the effect of unemployment insurance compensation on the labor market histories of displaced workers," *Journal of Econometrics*, 108(108), 227–252.

——— (2003): "Unemployment Insurance and the Timing of Layoffs and Recalls," *Labour*, 17(3), 383–389.

KAHN, L. M. (2012): "Temporary jobs and job search effort in Europe," *Labour Economics*, 19, 113–128.

KLETZER, L. G. (1989): "Returns to Seniority After Permanent Job Loss," *American Economic Review*, 79(3), 536–543.

LALIVE, R., J. C. VAN OURS, AND J. ZWEIMÜLLER (2011): "Equilibrium unemployment and the duration of unemployment benefits," *Journal of Population Economics*, 24, 1385–1409.

LECHNER, M. (2010): "The Estimation of Causal Effects by Difference-in-Difference Methods," *Foundations and Trends in Econometrics*, 4, 165–224.

LENGERMANN, P. A., AND L. VILHUBER (2002): "Abandoning the Sinking Ship. The Composition of Worker Flows Prior to Displacement," *U.S. Census Bureau*, Technical paper No. TP-2002-11.

LIGHT, A., AND Y. OMORI (2004): "Unemployment Insurance and Job Quits," *Journal of Labor Economics*, 22(1), 159–188.

LO, S. M. S., G. STEPHAN, AND R. WILKE (2012): "Estimating the Latent Effect of Unemployment Benefits on Unemployment Duration," *IZA Discussion Papers Series*, No. 6650.

PFANN, G. A., AND D. S. HAMERMESH (2001): "Two-sided learning, labor turnover and worker displacement," *NBER Working Paper*, No. 8273.

PISSARIDES, C. A. (2000): *Equilibrium Unemployment Theory*. Massachusetts Institute of Technology.

PODGURSKY, M., AND P. SWAIM (1987): "Job Displacement and Earnings Loss: Evidence from the Displaced Worker Survey," *Industrial and Labor Relations Review*, 41(1), 17–29.

REBOLLO-SANZ, Y. (2012): "Unemployment insurance and job turnover in Spain," *Labour Economics*, 19, 403–426.

ROSAL, O. D. (2003): "La Busqueda De Empleo De Los Ocupados. Intensidad Y Motivos," *Estudios de Economia Aplicada*, 21, 151–174.

SCHMIEDER, J. F., T. VON WACHTER, AND S. BENDER (2010): "The effects of unemployment insurance on labour supply and search outcomes. Regression discontinuiy estimates from Germany," *IAB Discussion Paper*, No. 4/2010.

——— (2012): "The Effects of Extended Unemployment Insurance Over the Business Cycle: Evidence from Regression Discontinuity Estimates over Twenty Years," *Quarterly Journal of Economics*, 127, 701–752.

SCHMITZ, H., AND V. STEINER (2007): "Benefit-Entitlement Effects and the Duration of Unemployment: An Ex-Ante Evaluation of Recent Labour Market Reforms in Germany," *IZA Discussion Paper Se*, No. 2681.

SCHWERDT, G. (2011): "Labor turnover before plant closure: Leaving the sinking ship vs. Captain throwing ballast overboard," *Labour Economics*, 18, 93–101.

TATSIRAMOS, K. (2010): "Job displacement and the transitions to re-employment and early retirement for non-employed older workers," *European Economic Review*, 54, 517–535.

TOPEL, R. H. (1983): "On Layoffs and Unemployment Insurance," *American Economic Review*, 73, 541–559.

TUDELA, C. C., AND E. SMITH (2012): "Search Capital," *CESifo Working Papers*, No. 3741.

WANG, C., AND S. WILLIAMSON (1996): "Unemployment insurance with moral hazard in a dynamic economy," *Carnegie Rochester Conference Series on Public Policy*, 44, 1–41.

WINTER-EBMER, R. (2003): "Benefit duration and unemployment entry: A quasi-experiment in Austria," *European Economic Review*, 47, 25–273.

Tab. 1: Potential Unemployment Benefits Duration by working history and age (in parenthesis)

Months worked in last seven years	Potential duration of Unemployment Benefits (months)				
	Period 1: Until Dec 1984	Period 2: Jan 1985 - Dec 1985	Period 3: Jan 1986 - Jun 1987	Period 4: Jul 1987 - Mar 1999	Period 5: Apr 1999 - Jan 2006 1/
12	4	4	4	6	6
16	4	4	4	8	8
18	6	6	6	8	8
20	6	6	6	10	10
24	8	8	8	12	12
28	8	8	8	14 (>=42)	14 (>=45)
30	10	10	10	14 (>=42)	14 (>=45)
32	10	10	10	16 (>=42)	16 (>=45)
36	12	12	12	18 (>=42)	18 (>=45)
40	12	12	12	20 (>=44)	20 (>=47)
42	12	14 (>=49)	14 (>=44)	20 (>=44)	20 (>=47)
44	12	14 (>=49)	14 (>=44)	22 (>=44)	22 (>=47)
48	12	16 (>=49)	16 (>=44)	24 (>=49)	24 (>=52)
52	12	16 (>=49)	16 (>=44)	26 (>=49)	26 (>=52)
54	12	18 (>=49)	18 (>=49)	26 (>=49)	26 (>=52)
56	12	18 (>=49)	18 (>=49)	28 (>=54)	28 (>=57)
60	12	18 (>=49)	20 (>=49)	30 (>=54)	30 (>=57)
64	12	18 (>=49)	20 (>=49)	32 (>=54)	32 (>=57)
66	12	18 (>=49)	22 (>=54)	32 (>=54)	32 (>=57)
72	12	18 (>=49)	24 (>=54)	32 (>=54)	32 (>=57)

1/ The reform was phased in gradually, so that for most people it only took effect in April 1999.

Tab. 2: Sample Means

	Policy Change #1		Policy Change #2	
	1982-1984	1987-1991	1992-1997	1999-2004
# Establishments	197	169	526	720
# Workers	6,669	6,822	14,456	15,123
Potential duration of UB	12.000	22.98197	22.744	18.51259
Age	46.494	47.849	47.552	46.517
Working history in last seven years (months)	82.349	82.474	82.465	82.367
Female	0.250	0.315	0.332	0.306
Daily wage (in 2005 euros)	77.150	86.830	86.928	87.261
Low wage earners	0.134	0.147	0.124	0.151
Tenure at establishment (years)				
$x < 5$ years	0.418	0.360	0.356	0.506
5 years $\leq x < 8$ years	0.344	0.129	0.170	0.139
$x \geq 8$ years (Policy Change #1)	0.238	0.511	—	—
8 years $\leq x < 10$ years	—	—	0.073	0.088
10 years $\leq x < 12$ years	—	—	0.062	0.064
12 years $\leq x < 15$ years	—	—	0.073	0.055
$x \geq 15$ years	—	—	0.266	0.149
Education				
Secondary/intermediate w/o vocational training	0.260	0.245	0.242	0.151
Secondary/intermediate w/ vocational training	0.600	0.619	0.634	0.625
Upper secondary school w/o vocational training	0.002	0.005	0.002	0.002
Upper secondary school w/ vocational training	0.004	0.005	0.012	0.024
Completion of a university of applied sciences	0.021	0.040	0.018	0.026
College / university degree	0.011	0.014	0.020	0.031
Missing	0.102	0.072	0.072	0.141
Occupation				
White-collar worker	0.294	0.409	0.322	0.373
Blue-collar worker	0.629	0.497	0.607	0.524
Part-time worker	0.077	0.095	0.071	0.103
Plant-size				
10-50 employees	0.662	0.543	0.608	0.656
51-100 employees	0.148	0.164	0.184	0.190
101-500 employees	0.170	0.135	0.168	0.119
501-1000 employees	0.020	0.028	0.023	0.011
1001+ employees	—	0.130	0.017	0.024

Industry				
Agriculture, energy, minning	0.027	0.146	0.005	0.046
Primary production	—	0.114	0.076	0.040
Structural metal products	0.112	0.042	0.095	0.076
Steel deformation, vehicle construction	0.282	0.049	0.179	0.061
Consumer goods	0.135	0.203	0.165	0.090
Food and luxury good industry	0.008	0.018	0.023	0.017
Main construction industry	0.134	0.058	0.068	0.090
Finishing trade	0.011	0.019	0.021	0.038
Wholesale trade	0.040	0.064	0.041	0.049
Retail industry	0.061	0.065	0.061	0.088
Transportation & comunication	0.031	0.044	0.021	0.051
Economic services	0.020	0.050	0.034	0.096
Household services	0.009	0.006	0.032	0.020
Education, social & health care services	0.011	0.013	0.010	0.025
(Street) cleaning organizations	—	—	0.005	0.018
Public administration, social security	—	—	0.024	0.005
Missing	0.120	0.110	0.140	0.192

Tab. 3: Policy Change #1: Full CPHM Estimation Results

	All Separations		JTJ Transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Treatment Dose (D)	-0.485***	0.134	-1.054***	0.201	5.471***	0.008
Treatment Period (j)	0.169	0.197	0.637**	0.307	-0.358	0.259
$D \times j$ (Coefficient θ)	**-0.004**	**0.006**	**-0.021****	**0.010**	**0.012**	**0.009**
Work history in last seven years (months)	0.000	0.006	0.017**	0.009	-0.015**	0.006
Female	-0.244***	0.075	-0.271***	0.091	-0.200*	0.096
Daily wage (in 2005 euros)	-0.002*	0.001	0.001	0.002	-0.005***	0.001
Tenure at establishment						
5 years $\leq x <$ 8 years	-0.178**	0.09	-0.267*	0.139	-0.095	0.096
$x \geq$ 8 years	-0.143	0.101	-0.141	0.137	-0.166	0.11
Education						
Secondary/intermediate w/ vocational training	-0.175***	0.066	-0.072	0.094	-0.284***	0.094
Upper secondary school w/o vocational training	0.249	0.184	0.05	0.277	0.363	0.469
Upper secondary school w/ vocational training	-0.158	0.32	-0.271	0.610	0.030	0.292
Completion of a university of applied sciences	-0.232	0.158	-0.224	0.174	-0.175	0.289
College / university degree	-0.06	0.229	-0.010	0.256	-0.258	0.245
Missing	-0.137	0.119	-0.327	0.208	-0.048	0.162
Occupation						
Blue-collar worker	-0.164**	0.068	-0.257**	0.102	-0.038	0.101
Part-time worker	-0.270**	0.111	-0.405**	0.193	-0.196	0.156
Plant-size						
51-100 employees	-0.335***	0.108	-0.493***	0.157	-0.186	0.137
101-500 employees	-0.447***	0.147	-0.648***	0.228	-0.174	0.166
501-1000 employees	0.120	0.239	-0.778**	0.369	0.999**	0.500
1001+ employees	-0.963***	0.233	-0.205	0.291	-2.197***	0.315
Industry						
Primary production	0.284	0.231	-0.06	0.270	0.621*	0.366
Structural metal products	0.046	0.222	-0.131	0.313	0.183	0.302
Steel deformation, vehicle construction	0.636***	0.212	0.852***	0.267	0.213	0.336
Consumer goods	0.272	0.230	0.036	0.323	0.414	0.298
Food and luxury good industry	-0.290	0.236	-0.847*	0.447	0.081	0.267

Main construction industry	-0.095	0.229	0.118	0.368	-0.248	0.310
Finishing trade	0.001	0.244	-0.294	0.364	0.355	0.338
Wholesale trade	0.395	0.268	0.434	0.340	0.360	0.322
Retail industry	-0.087	0.218	-0.658*	0.350	0.246	0.309
Transportation & comunication	-0.164	0.242	-0.069	0.327	-0.281	0.373
Economic services	0.600	0.479	0.855	0.634	0.355	0.327
Household services	-0.032	0.275	0.199	0.364	-0.229	0.379
Education, social & health care services	-0.251	0.342	-0.476	0.531	-0.074	0.401
Missing	-0.198	0.225	-0.218	0.277	-0.151	0.318
Age Dummies						
39	-0.066	0.11	0.016	0.133	-0.182	0.182
40	-0.015	0.109	-0.049	0.126	0.028	0.166
41	-0.246*	0.141	-0.392**	0.164	-0.047	0.157
42	2.758***	0.815	6.073***	1.199	-32.852***	0.127
43	2.84***	0.822	6.246***	1.255	-32.89***	0.131
44	4.801***	1.358	10.471***	2.026	-54.709***	0.115
45	4.696***	1.355	10.354***	2.013	-54.798***	0.137
46	4.806***	1.372	10.404***	2.035	-54.597***	0.125
47	4.797***	1.345	10.358***	2.014	-54.602***	0.114
48	4.706***	1.360	10.359***	2.011	-54.754***	0.103
49	6.658***	1.890	14.55***	2.813	-76.599***	0.130
50	6.647***	1.897	14.389***	2.816	-76.493***	0.112
51	6.679***	1.898	14.472***	2.826	-76.509***	0.125
52	6.615***	1.906	14.517***	2.835	-76.642***	0.12
53	6.723***	1.901	14.682***	2.82	-76.599***	0.123
54	9.62***	2.699	20.911***	3.981	-109.373	.
55	9.489***	2.684	20.504***	3.985	-109.284***	0.131
56	9.507***	2.688	20.761***	3.992	-109.456***	0.155
Year Dummies						
1982	0.259	0.163	0.202	0.319	0.302*	0.182
1983	0.151	0.161	0.353	0.281	-0.074	0.171
1984	0.668	0.413	0.231	0.604	0.836*	0.479
1987	-0.447*	0.244	-0.598*	0.358	-0.216	0.367
1988	0.096	0.211	-0.532**	0.238	0.591**	0.298
1989	0.049	0.241	0.052	0.338	0.089	0.256
# of Establishments	366		366		366	
# of Workers	13,491		13,491		13,491	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level.

Tab. 4: Policy Change #1: CPHM Estimates by Age Groups

	All separations		JTJ Transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Age Group*Time Coefficient						
42-48 years	-0.126	0.082	-0.278**	0.123	0.191	0.142
49-56 years	-0.093	0.100	-0.286*	0.150	0.175	0.150
B. Linearized Estimates						
42-48 years	-0.011	0.009	-0.031**	0.014	0.021	0.016
49-56 years	-0.006	0.006	-0.018*	0.009	0.011	0.009

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size. The linearized estimates were calculated dividing the estimates from panel A by the average treatment dose, which was 9.0 months for workers 42-48 years old and 16.1 months for workers 49-56 years old. The standard errors of the linearized estimates were calculated using the delta method.

Tab. 5: Policy Change #2: Full CPHM Estimation Results

	All Separations		JTJ transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Treatment Dose (D)	-0.037	0.086	-0.400	0.361	0.071	0.137
Treatment Period (j)	0.169	0.136	0.078	0.195	0.237	0.183
$D \times j$ (Coefficient θ)	**-0.002**	**0.007**	**-0.015**	**0.011**	**0.003**	**0.010**
Work history in last seven years (months)	-0.002	0.003	0.005	0.005	-0.006	0.004
Female	-0.07	0.046	-0.168**	0.069	-0.003	0.059
Daily wage (in 2005 euros)	-0.001	0.001	0.001	0.001	-0.002**	0.001
Tenure at establishment (years)						
5 years $\leq x < 8$ years	-0.093*	0.048	-0.139*	0.073	-0.056	0.063
8 years $\leq x < 10$ years	0.002	0.061	-0.047	0.086	0.046	0.085
10 years $\leq x < 12$ years	-0.065	0.057	-0.085	0.09	-0.039	0.086
12 years $\leq x < 15$ years	-0.144***	0.055	-0.202**	0.085	-0.091	0.08
$x \geq 15$ years	-0.118**	0.055	-0.153*	0.084	-0.087	0.067
Education						
Secondary/intermediate w/ vocational training	-0.101**	0.043	-0.09	0.061	-0.101*	0.057
Upper secondary school w/o vocational training	-0.323**	0.141	0.005	0.226	-0.814***	0.263

Upper secondary school w/ vocational training	-0.138	0.088	-0.025	0.115	-0.27*	0.139
Completion of a university of applied sciences	0.028	0.084	0.07	0.118	-0.039	0.125
College / university degree	0.032	0.101	0.023	0.13	0.019	0.148
Missing	0.02	0.088	-0.135	0.104	0.117	0.125
Occupation						
Blue-collar worker	0.061	0.042	-0.068	0.061	0.157***	0.056
Part-time worker	-0.045	0.061	0.102	0.087	-0.123	0.086
Plant-size						
51-100 employees	0.081	0.062	0.289***	0.094	-0.075	0.078
101-500 employees	0.075	0.091	0.267**	0.121	-0.054	0.119
501-1000 employees	0.332	0.229	0.938***	0.295	-0.541	0.437
1001+ employees	1.244***	0.216	1.898***	0.213	0.139	0.224
Industry						
Primary production	0.413**	0.21	-0.028	0.248	1.355***	0.457
Structural metal products	0.379*	0.203	-0.041	0.207	1.318***	0.458
Steel deformation, vehicle construction	0.484***	0.22	0.202	0.324	1.344***	0.458
Consumer goods	0.229	0.21	-0.139	0.206	1.127***	0.467
Food and luxury good industry	0.166	0.232	-0.003	0.24	0.935*	0.479
Main construction industry	0.326	0.234	-0.249	0.198	1.332***	0.484
Finishing trade	0.238	0.204	-0.296	0.249	1.243***	0.457
Wholesale trade	0.32	0.209	0.208	0.221	0.997*	0.464
Retail industry	0.266	0.219	0.01	0.206	1.096*	0.474
Transportation & comunication	0.268	0.211	0.208	0.218	0.932*	0.469
Economic services	0.396**	0.196	0.146	0.192	1.199***	0.453
Household services	0.069	0.229	-0.023	0.221	0.782	0.486
Education, social & health care services	0.335	0.212	0.065	0.228	1.196***	0.46
(Street) cleaning organizations	0.408*	0.247	0.098	<.306	1.302**	0.535
Public administration, social security	0.225	0.252	-0.888**	0.415	1.974***	0.423
Missing	0.193	0.192	-0.146	0.187	1.077**	0.451
Age Dummies						
39	0.004	0.059	-0.047	0.080	0.054	0.097
40	-0.033	0.058	-0.063	0.079	-0.002	0.093
41	-0.001	0.063	-0.088	0.084	0.08	0.093
42	-0.343	0.518	-2.688	2.169	0.429	0.816

43	-0.342	0.519	-2.57	2.169	0.325	0.817
44	-0.471	0.87	-4.316	.	0.75	1.365
45	-0.238	0.352	-1.859	1.45	0.323	0.548
46	-0.187	0.351	-1.915	1.449	0.447	0.549
47	-0.008	0.061	-0.238***	0.088	0.172*	0.093
48	-0.086	0.06	-0.279***	0.09	0.074	0.094
49	-0.317	0.354	-1.975	1.451	0.275	0.547
50	-0.241	0.351	-1.922	1.448	0.364	0.548
51	-0.251	0.351	-1.912	1.453	0.349	0.547
52	-0.093	0.06	-0.300***	0.088	0.077	0.092
53	-0.076	0.059	-0.345***	0.098	0.121	0.089
54	-0.377	0.509	-2.977	2.167	0.553	0.807
55	-0.348	0.515	-2.952	2.166	0.577	0.816
56	-0.351	0.52	-3.147	2.173	0.642	0.818
Year Dummies						
1992	0.122	0.129	0.058	0.205	0.171	0.184
1993	0.374**	0.159	0.039	0.251	0.554***	0.195
1994	0.354**	0.145	0.057	0.214	0.557***	0.186
1995	0.587***	0.192	0.602	0.366	0.582***	0.177
1996	0.401***	0.148	0.296	0.21	0.469**	0.199
1998	0.157	0.101	0.224*	0.13	0.092	0.155
1999	0.392***	0.144	0.475**	0.216	0.342*	0.186
2000	0.169*	0.088	0.304***	0.111	0.035	0.121
2001	0.208**	0.094	0.385***	0.118	0.074	0.132
# of Establishments	1,246		1,246		1,246	
# of Workers	29,579		29,579		29,579	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level.

Tab. 6: Policy Change #2: Full CPHM Estimation Results Using Only Workers 38-44 Years Old

	All Separations		JTJ transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Treatment Dose (D)	0.016**	0.007	0.038***	0.012	0.001	0.011
Treatment Period (j)	0.218	0.171	0.160	0.206	0.296	0.257
$D \times j$ (Coefficient θ)	**-0.012**	**0.008**	**-0.026***	**0.014**	**-0.003**	**0.013**
Work history in last seven years (months)	-0.004	0.004	0.008	0.007	-0.012*	0.006
Female	-0.058	0.051	-0.164**	0.078	0.032	0.075
Daily wage (in 2005 euros)	-0.002**	0.001	0.000	0.001	-0.003***	0.001
Tenure at establishment (years)						
5 years $\leq x <$ 8 years	-0.085	0.058	-0.085	0.097	-0.076	0.084
8 years $\leq x <$ 10 years	0.030	0.072	0.057	0.102	0.013	0.115
10 years $\leq x <$ 12 years	-0.016	0.073	-0.029	0.117	0.025	0.113
12 years $\leq x <$ 15 years	-0.092	0.073	-0.181	0.12	-0.003	0.108
$x \geq$ 15 years	-0.028	0.073	-0.042	0.122	-0.002	0.09
Education						
Secondary/intermediate w/ vocational training	-0.196***	0.057	-0.234***	0.085	-0.155**	0.081
Upper secondary school w/o vocational training	-0.085	0.237	0.000	0.354	-0.262	0.286
Upper secondary school w/ vocational training	-0.089	0.111	-0.098	0.145	-0.105	0.193
Completion of a university of applied sciences	0.006	0.13	-0.150	0.149	0.146	0.245
College / university degree	-0.035	0.112	-0.188	0.155	0.110	0.188
Missing	-0.082	0.089	-0.245*	0.129	0.049	0.123
Occupation						
Blue-collar worker	-0.017	0.051	-0.225***	0.074	0.178**	0.074
Part-time worker	-0.136	0.084	0.032	0.119	-0.261**	0.129
Plant-size						
51-100 employees	0.085	0.066	0.255***	0.096	-0.073	0.086
101-500 employees	0.075	0.097	0.282**	0.124	-0.105	0.135
501-1000 employees	0.100	0.223	0.669**	0.282	-0.819**	0.415
1001+ employees	1.407	0.229	2.08***	0.242	-0.009	0.241
Industry						
Primary production	0.382*	0.211	-0.006	0.266	1.359***	0.550
Structural metal products	0.399*	0.208	0.095	0.230	1.327***	0.558

Steel deformation, vehicle construction	0.557**	0.230	0.374	0.344	1.402***	0.556
Consumer goods	0.275	0.220	-0.021	0.221	1.178*	0.574
Food and luxury good industry	0.176	0.234	0.131	0.235	0.878	0.596
Main construction industry	0.339	0.228	-0.148	0.228	1.371*	0.566
Finishing trade	0.175	0.222	-0.129	0.286	1.101***	0.561
Wholesale trade	0.269	0.214	0.182	0.229	0.987*	0.580
Retail industry	0.214	0.219	0.059	0.229	1.018*	0.562
Transportation & comunication	0.296	0.211	0.374	0.245	0.841	0.561
Economic services	0.372*	0.200	0.126	0.210	1.26**	0.554
Household services	0.105	0.226	0.026	0.265	0.829	0.598
Education, social & health care services	0.537**	0.249	0.416	0.295	1.333**	0.565
(Street) cleaning organizations	0.420	0.300	-0.046	0.293	1.497**	0.685
Public administration, social security	0.124	0.263	-0.916**	0.396	2.137***	0.488
Missing	0.188	0.194	0.032	0.211	0.997**	0.549
Age Dummies						
39	0.009	0.058	-0.041	0.081	0.055	0.097
40	-0.040	0.057	-0.068	0.080	-0.012	0.093
41	0.000	0.063	-0.089	0.084	0.073	0.094
42	-0.072	0.047	-0.108	0.074	-0.033	0.075
43	-0.074	0.048	0.009	0.074	-0.142*	0.078
Year Dummies						
1992	0.128	0.162	0.179	0.209	0.101	0.255
1993	0.477**	0.192	0.180	0.252	0.696***	0.268
1994	0.368**	0.174	0.195	0.208	0.528**	0.255
1995	0.676***	0.212	0.724**	0.368	0.644***	0.250
1996	0.454**	0.181	0.52**	0.210	0.416	0.265
1998	0.208*	0.114	0.424***	0.150	-0.021	0.174
1999	0.318**	0.160	0.481**	0.231	0.178	0.216
2000	0.227**	0.099	0.358***	0.124	0.071	0.140
2001	0.215*	0.114	0.365***	0.134	0.078	0.166
# of Establishments	1,078		1,078		1,078	
# of Workers	11,341		11,341		11,341	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level.

Tab. 7: Placebo Test 1: Common Trends for Treated and Non-Treated Groups Prior to Policy Changes

	All separations		JTJ Transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Policy Change #1						
$\theta_{Placebo}$	0.001	0.006	0.002	0.012	0.013	0.010
# of Establishments	197		197		197	
# of Workers	6,669		6,669		6,669	
B. Policy Change #2						
$\theta_{Placebo}$	0.014	0.009	0.016	0.018	0.014	0.013
# of Establishments	526		526		526	
# of Workers	14,456		14,456		14,456	
C. Policy Change #2 (only workers 38-44 years old)						
$\theta_{Placebo}$	0.014	0.012	0.003	0.022	0.020	0.017
# of Establishments	453		453		453	
# of Workers	4,919		4,919		4,919	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size.

Tab. 8: Placebo Test 2: Common Trends for Non-Treated Groups After Policy Changes (workers aged 32-40 years)

	All separations		JTJ Transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Policy Change #1						
$\theta_{Placebo}$	-0.002	0.113	-0.030	0.159	-0.014	0.169
# of Establishments	339		339		339	
# of Workers	5,323		5,323		5,323	
B. Policy Change #2						
$\theta_{Placebo}$	-0.025	0.059	-0.022	0.090	-0.021	0.087
# of Establishments	1,119		1,119		1,119	
# of Workers	13,595		13,595		13,595	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size. The table compares the trends in the risk scores for workers aged 32-36 versus those aged 37-40 years old.

Tab. 9: Estimates of θ for up to three years before closure

	All separations		JTJ Transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Policy Change #1						
$\theta_{\text{last year}}$	-0.004	0.006	-0.021**	0.010	0.012	0.009
$\theta_{\text{2 years before closure}}$	-0.006	0.011	-0.025*	0.013	0.020	0.020
B. Policy Change #2						
$\theta_{\text{last year}}$	-0.002	0.007	-0.015	0.011	0.003	0.010
$\theta_{\text{2 years before closure}}$	-0.006	0.009	-0.021	0.015	0.001	0.012
$\theta_{\text{3 years before closure}}$	0.012	0.013	-0.005	0.022	0.020	0.018
C. Policy Change #2 (only workers 38-44 years old)						
$\theta_{\text{last year}}$	-0.012	0.008	-0.026*	0.014	-0.003	0.013
$\theta_{\text{2 years before closure}}$	-0.001	0.012	-0.031	0.019	0.023	0.017
$\theta_{\text{3 years before closure}}$	0.018	0.017	-0.007	0.026	0.034	0.024

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size.

Tab. 10: Time-Varying effects

	All separations		JTJ Transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Policy Change #1						
First quarter*	-0.025	0.020	-0.021	0.026	-0.002	0.024
Second quarter	0.006	0.016	-0.041*	0.024	0.032	0.022
Third quarter	-0.007	0.015	-0.011	0.018	-0.015	0.024
Fourth quarter	-0.001	0.007	-0.021*	0.013	0.019*	0.011
	(0.587)		*(0.785)*		*(0.506)*	
B. Policy Change #2						
First quarter*	0.037	0.023	-0.011	0.037	0.063**	0.032
Second quarter	-0.033	0.021	-0.055**	0.027	-0.02	0.027
Third quarter	-0.014	0.015	-0.022	0.021	-0.018	0.022
Fourth quarter	0.000	0.007	-0.003	0.014	0.001	0.012
	(0.120)		*(0.376)*		*(0.158)*	
C. Policy Change #2 (only workers 38-44 years old)						
First quarter*	0.003	0.030	-0.057	0.045	0.047	0.043
Second quarter	-0.051**	0.024	-0.077**	0.035	-0.038	0.034
Third quarter	-0.002	0.019	0.009	0.028	-0.016	0.026
Fourth quarter	-0.009	0.10	-0.020	0.017	0.002	0.016
	(0.378)		*(0.182)*		*(0.431)*	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size. The p-values from F-tests of the null hypothesis of joint equality of coefficients to the base case (marked with an asterisk) are presented in parenthesis.

Tab. 11: Policy Change #1: Estimates of θ by subgroups

	All Separations		JTJ transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Income						
Non-low wage earners*	-0.005	0.007	-0.021**	0.01	0.015	0.010
Low wage earners	-0.003	0.014	-0.016	0.029	0.003	0.018
	(0.938)		*(0.868)*		*(0.586)*	
B. Gender						
Male*	-0.005	0.008	-0.022**	0.011	0.017	0.012
Female	-0.004	0.010	-0.011	0.020	0.003	0.013
	(0.942)		*(0.592)*		*(0.411)*	
C. Occupation						
White-collar worker*	-0.011	0.013	-0.027*	0.014	0.018	0.022
Blue-collar worker	0.000	0.008	-0.016	0.014	0.013	0.010
Part-time Worker	0.013	0.016	0.016	0.036	0.007	0.023
	(0.511)		*(0.597)*		*(0.811)*	
D. Tenure						
$x < 5$ years*	-0.011	0.010	-0.035**	0.014	0.007	0.013
5 years $\leq x < 8$ years	-0.003	0.010	0.003	0.017	0.002	0.016
$x \geq 8$ years	0.001	0.010	-0.019	0.016	0.023*	0.014
	(0.706)		*(0.132)*		*(0.625)*	
E. Education						
Secondary/intermediate w/o vocational training*	-0.001	0.011	-0.016	0.020	0.004	0.016
Secondary/intermediate w/ vocational training	-0.009	0.008	-0.025**	0.012	0.013	0.011
Upper secondary school w/o vocational training	-0.027	0.056	0.085	0.121	-0.042	0.102
Upper secondary school w/ vocational training	0.040	0.045	-0.005	0.060	0.045	0.065
Completion of a university of applied sciences	-0.013	0.055	-0.007	0.049	0.078	0.084
College / university degree	0.143***	0.027	0.143***	0.046	0.143***	0.061
Missing	-0.003	0.019	-0.012	0.037	0.010	0.022
	(0.000)		*(0.001)*		*(0.773)*	
F. Establishment Size						
11-50 workers*	-0.013	0.010	-0.037***	0.014	0.007	0.012
51-100 workers	0.013*	0.007	0.021*	0.013	0.010	0.010
101-500 workers	-0.009	0.008	-0.019	0.016	0.003	0.010
501-1000 workers	0.038***	0.006	0.034***	0.007	0.050***	0.013
	(0.000)		*(0.000)*		*(0.000)*	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size. The p-values from F-tests of the null hypothesis of joint equality of coefficients to the base case (marked with an asterisk) are presented in parenthesis.

Tab. 12: Policy Change #2: Estimates of θ by subgroups

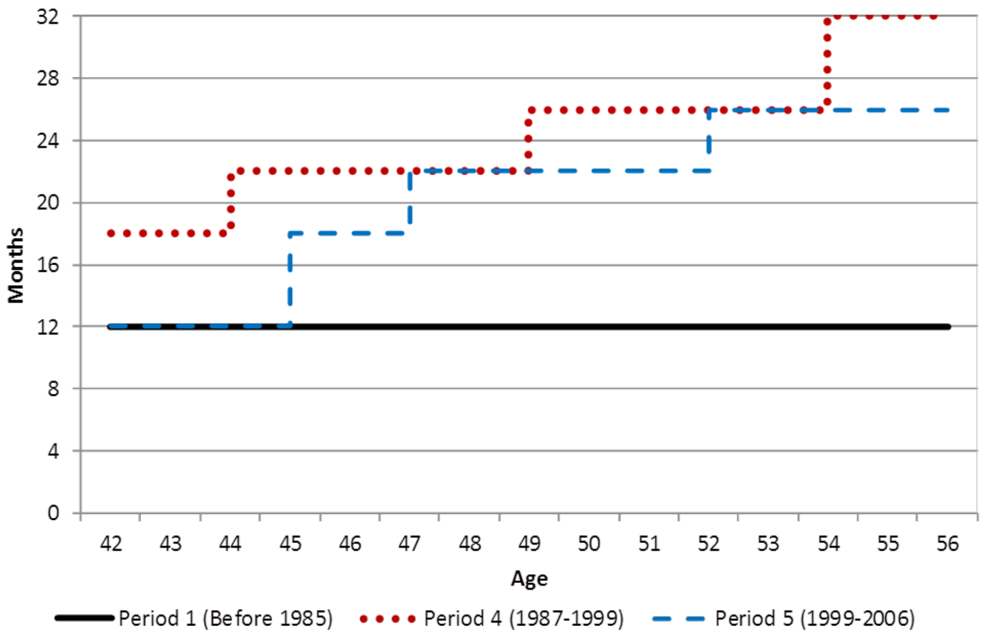
	All Separations		JTJ transitions		JTN Transitions	
	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
A. Income						
Non-low wage earners*	-0.001	0.007	-0.010	0.012	0.003	0.011
Low wage earners	-0.007	0.018	-0.049	0.034	0.005	0.023
	(0.769)		*(0.281)*		*(0.913)*	
B. Gender						
Male*	-0.001	0.008	-0.012	0.012	0.004	0.011
Female	-0.006	0.012	-0.022	0.025	-0.001	0.017
	(0.734)		*(0.714)*		*(0.758)*	
C. Occupation						
White-collar worker*	0.002	0.012	-0.015	0.019	0.014	0.017
Blue-collar worker	-0.004	0.008	-0.015	0.015	0.000	0.013
Part-time Worker	-0.011	0.021	-0.038	0.037	-0.009	0.031
	(0.674)		*(0.986)*		*(0.531)*	
D. Tenure						
$x < 5$ years*	-0.007	0.01	-0.009	0.017	-0.008	0.015
5 years $\leq x < 8$ years	-0.019	0.017	-0.017	0.028	-0.022	0.025
8 years $\leq x < 10$ years	-0.003	0.022	-0.039	0.037	0.018	0.032
10 years $\leq x < 12$ years	0.006	0.022	0.037	0.039	-0.013	0.037
12 years $\leq x < 15$ years	-0.036*	0.02	-0.083**	0.036	-0.012	0.033
$x \geq 15$ years	0.022	0.014	-0.018	0.024	0.046**	0.021
	(0.456)		*(0.632)*		*(0.486)*	
E. Education						
Secondary/intermediate w/o vocational training*	-0.013	0.016	-0.023	0.026	-0.019	0.022
Secondary/intermediate w/ vocational training	-0.002	0.008	-0.005	0.014	-0.003	0.012
Upper secondary school w/o vocational training	-0.072	0.056	-0.128	0.083	0.005	0.158
Upper secondary school w/ vocational training	-0.003	0.052	-0.148	0.128	0.118	0.105
Completion of a university of applied sciences	-0.004	0.063	0.071	0.053	-0.063	0.111
College / university degree	-0.035	0.03	-0.089*	0.048	0.015	0.054
Missing	0.010	0.021	-0.025	0.036	0.030	0.029
	(0.968)		*(0.099)*		*(0.936)*	
F. Establishment Size						
11-50 workers*	-0.005	0.01	-0.017	0.018	0.001	0.014
51-100 employees	-0.001	0.007	-0.012	0.010	0.005	0.009

101-500 employees	0.006	0.006	-0.005	0.009	0.014	0.011
501-1000 employees	0.005	0.012	-0.021	0.016	0.067	0.041
1001+ employees	0.000	0.007	-0.017	0.022	0.048	0.037
	(0.011)		(0.419)		(0.445)	

Note: *** denotes statistical significance at 1% level ; ** denotes statistical significance at 5% level; * denotes statistical significance at 10% level. Controls include gender, education, daily wage (in 2005 euros), occupation, industry, work experience in last seven years, tenure, and establishment size. The p-values from F-tests of the null hypothesis of joint equality of coefficients to the base case (marked with an asterisk) are presented in parenthesis.

Fig. 1: Maximum Potential Duration of Unemployment Benefits (PDB)

(a) Maximum PDB by age and period (in months)



(b) Changes in the maximum PDB by age (in months)

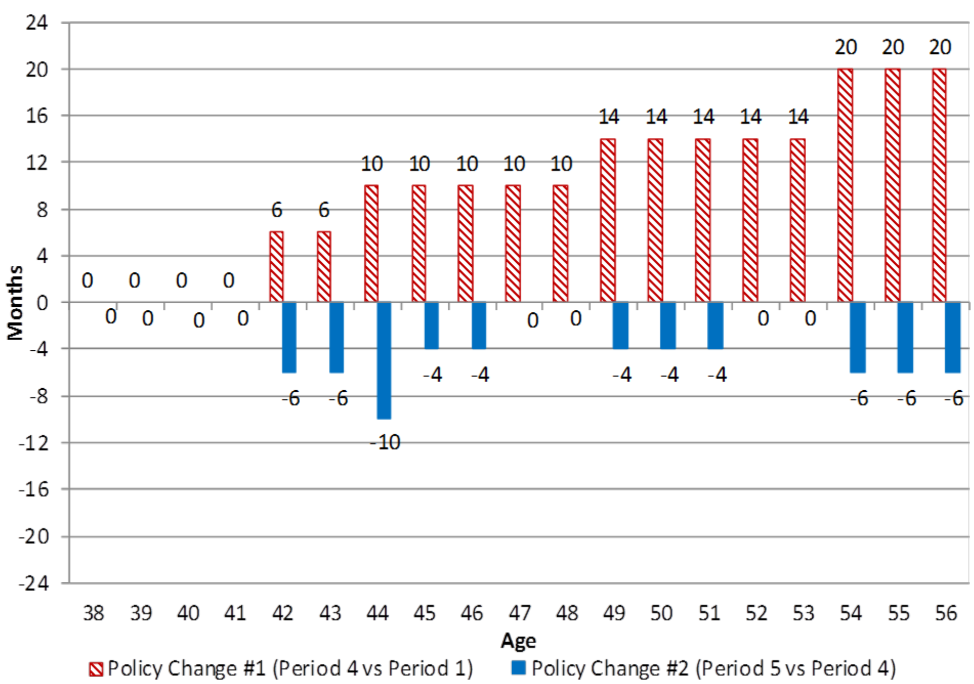
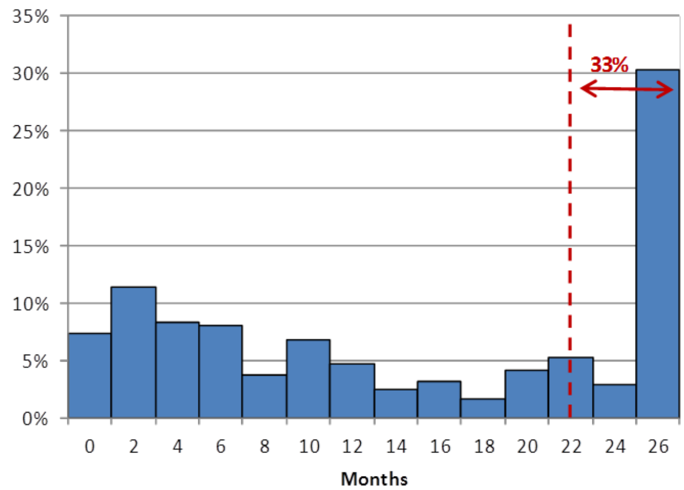


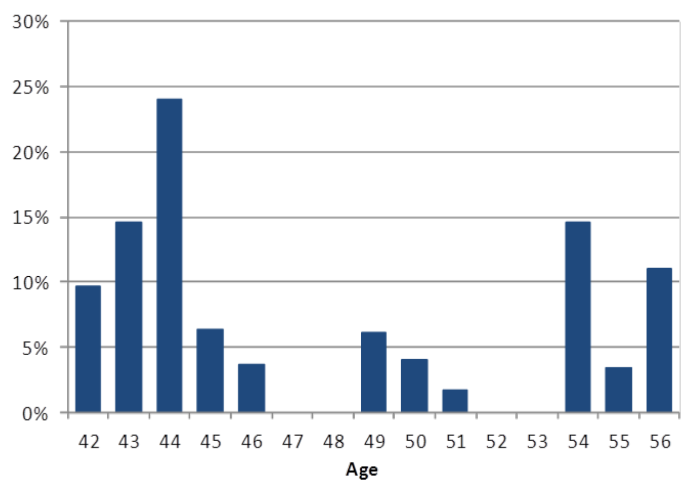
Fig. 2: Empirical analysis of the "bite" of Policy Change #2 on the distribution of UB durations

(a) Histogram of UB durations for 50 year olds workers (1992-1997)



Note: 33% of the UB spells of 50-years-old workers that separated from closing establishments by entering into unemployment (in 1992-1997) had a duration larger than 22 months.

(b) Percentage of UB spells in 1992-1997 potentially affected by Policy Change #2 (excluding spells that exhausted benefits)



Note: The figure shows the percentage of UB spells above the maximun PDB in 1999-2006 (Policy Change #2). The calculations include UB spells of workers that separated from closing establishments by entering unemployment during 1992-1997. Spells that exhausted UB benefits are excluded.

Fig. 3: Evolution of Establishment Size (Three years before closure = 100)

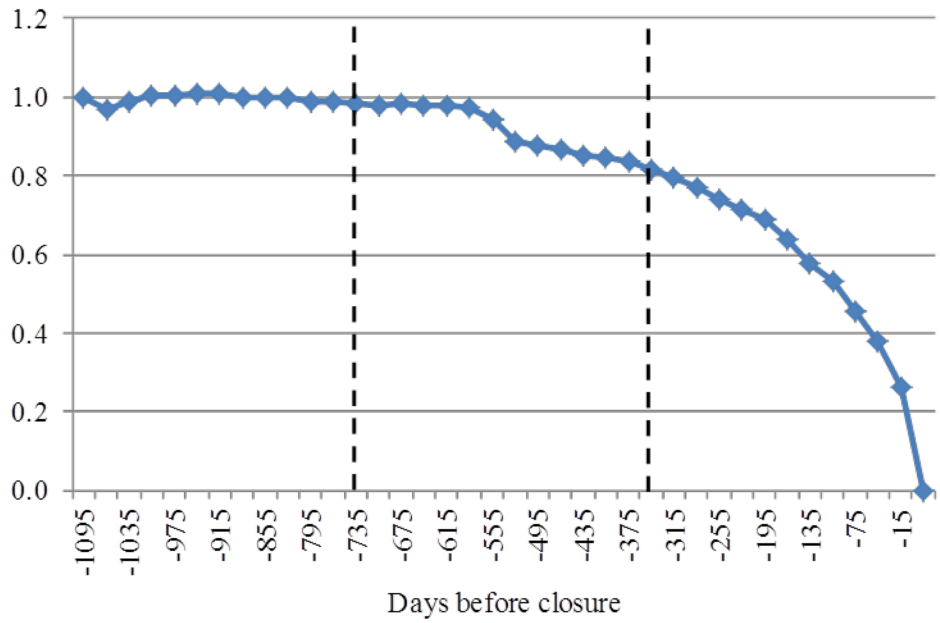
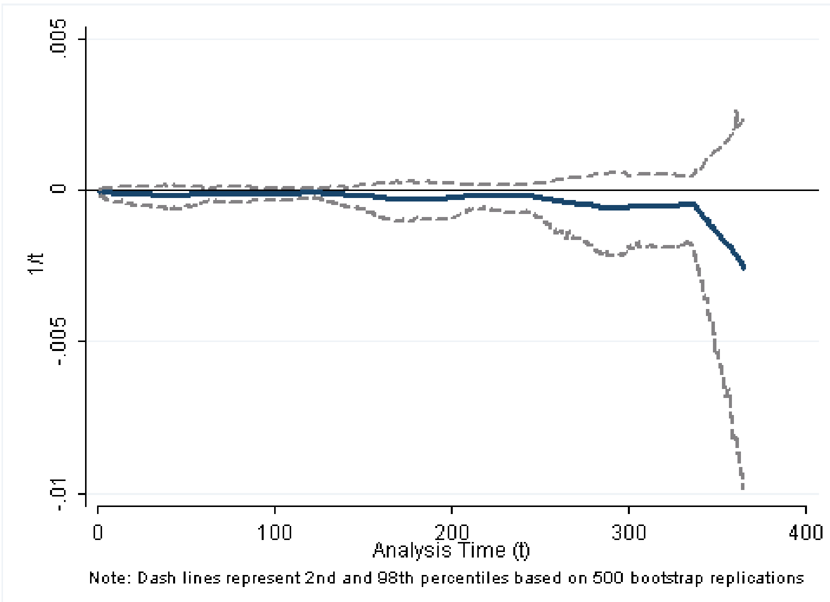


Fig. 4: Policy Change #1: Treatment effects on the hazard rates and failure function for all separation (for the average treated worker)

Treatment effects on the hazard rates



Treatment effects on the failure function

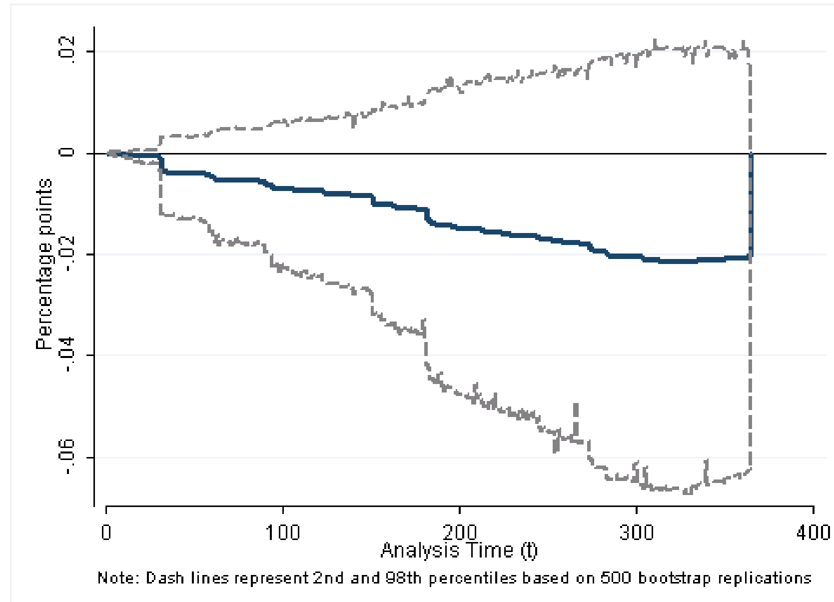
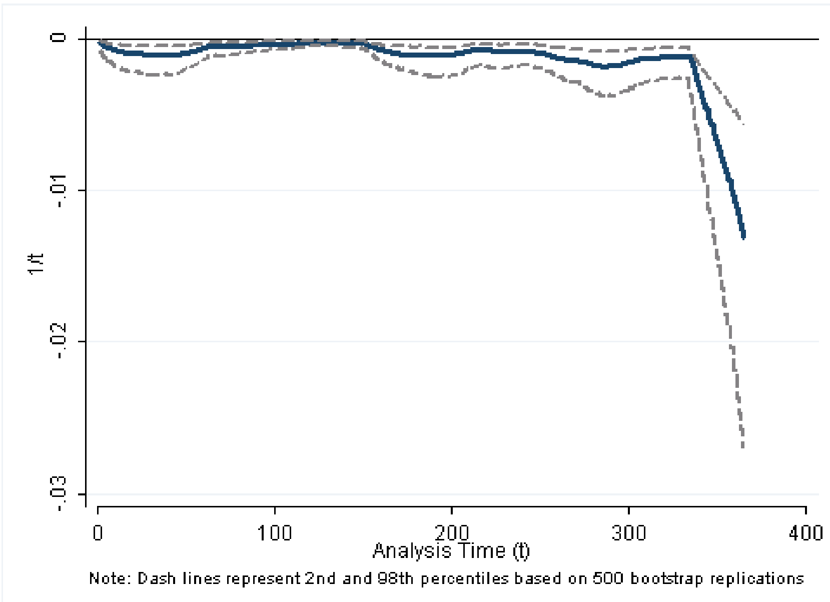


Fig. 5: Policy Change #1: Treatment effects on the hazard rates and CIF for JTJ transitions (for the average treated worker)

Treatment effects on the hazard rates



Treatment effects on the CIF

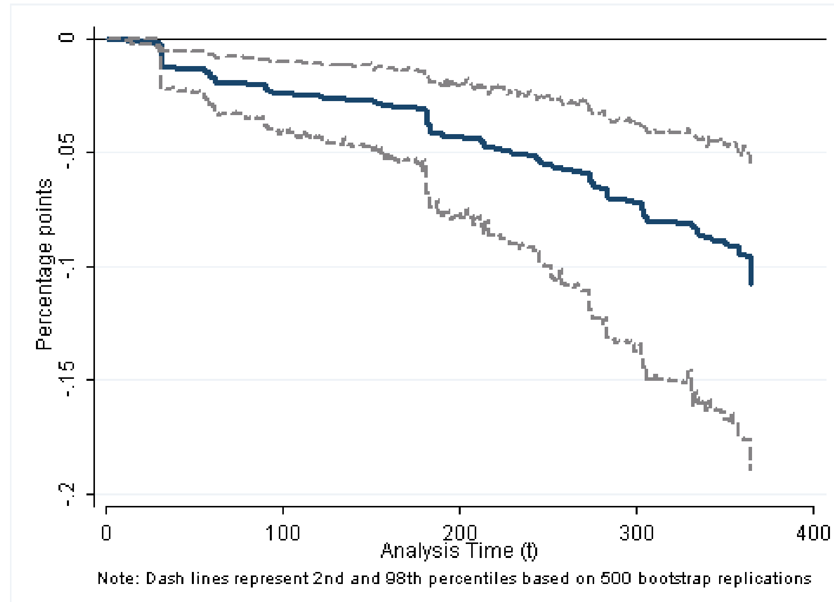
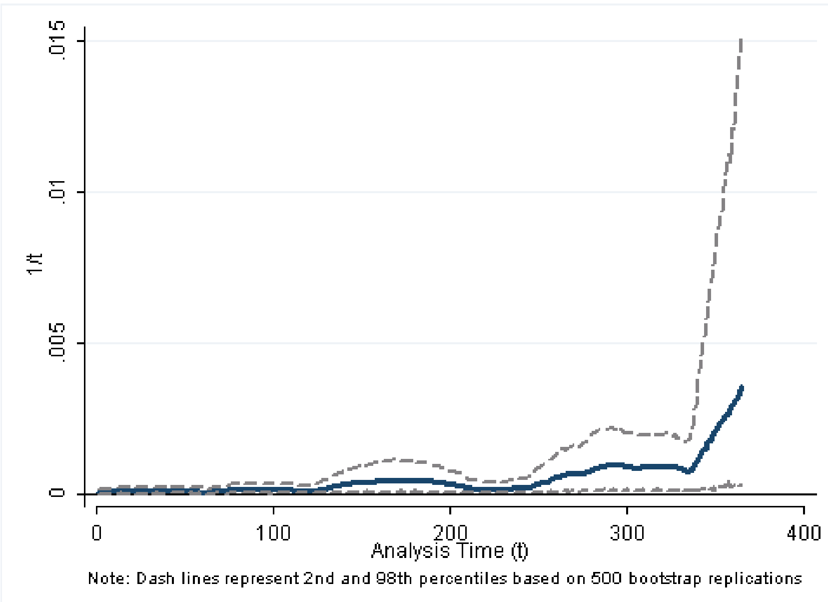


Fig. 6: Policy Change #1: Treatment effects on the hazard rates and CIF for JTN transitions (for the average treated worker)

Treatment effects on the hazard rates



Treatment effects on the CIF

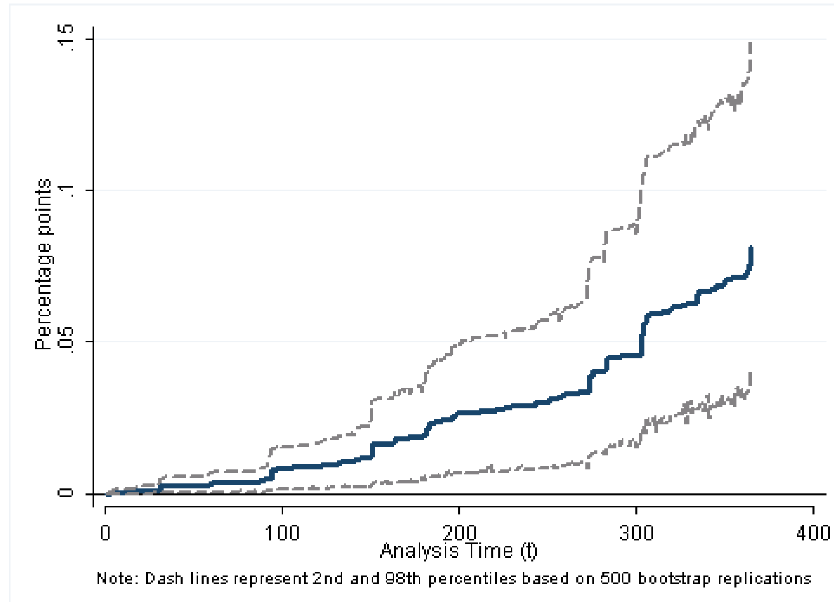
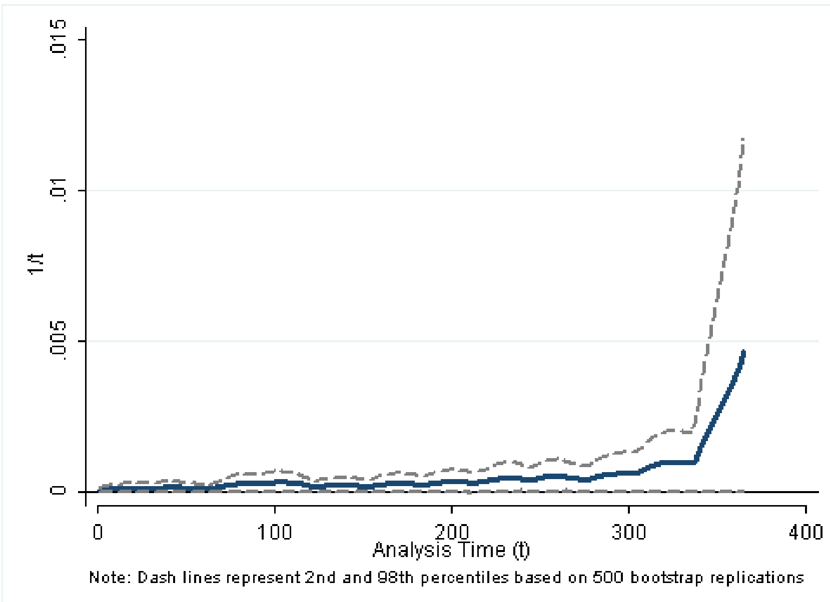


Fig. 7: Policy Change #2: Treatment effects on the hazard rates and failure function for all separation (for the average treated worker of age 42-44)

Treatment effects on the hazard rates



Treatment effects on the failure function

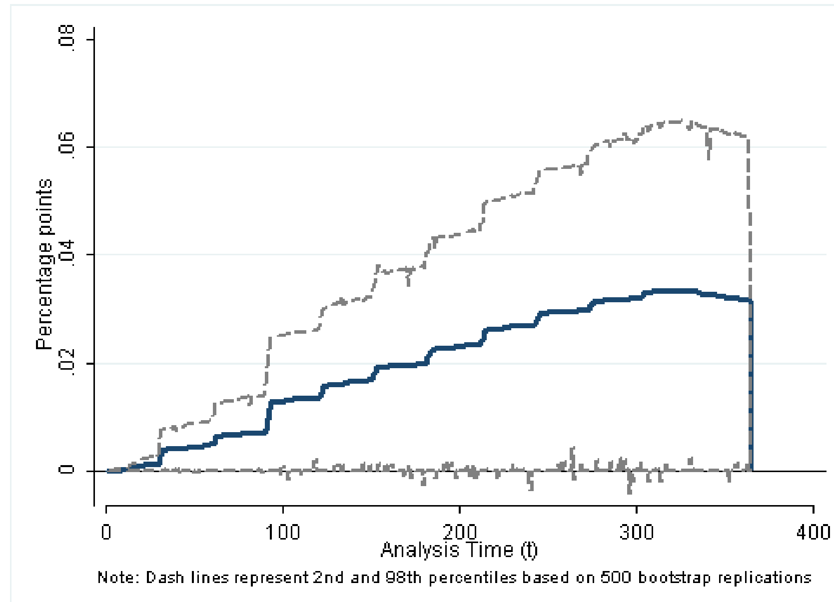
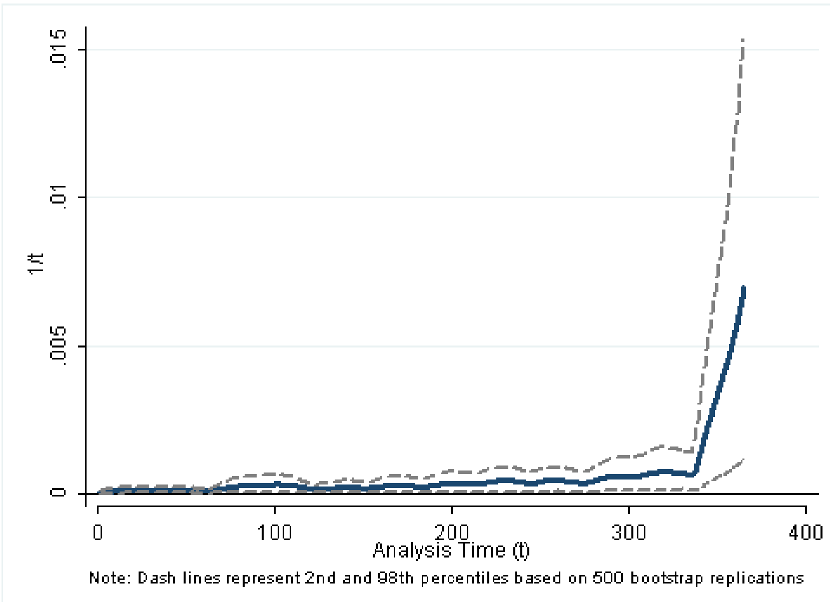


Fig. 8: Policy Change #2: Treatment effects on the hazard rates and CIF for JTJ transitions (for the average treated worker of age 42-44)

Treatment effects on the hazard rates



Treatment effects on the CIF

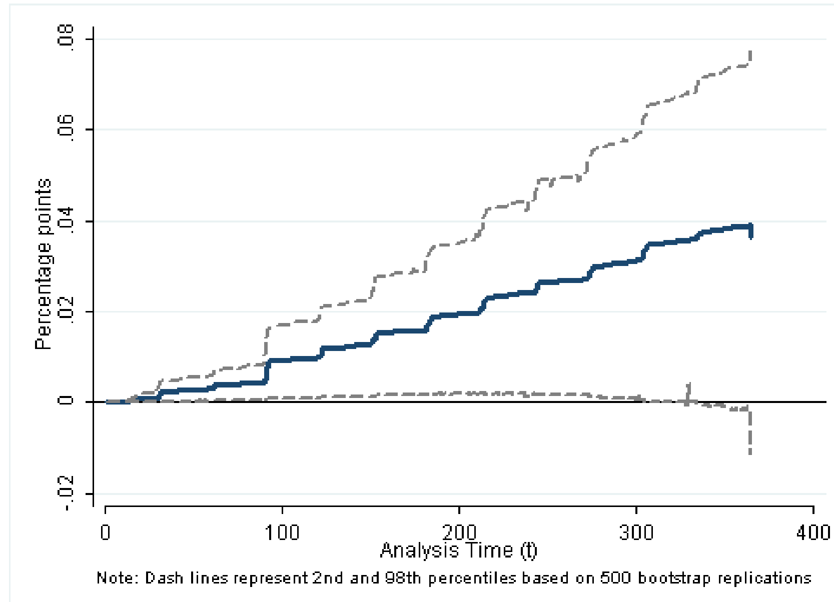
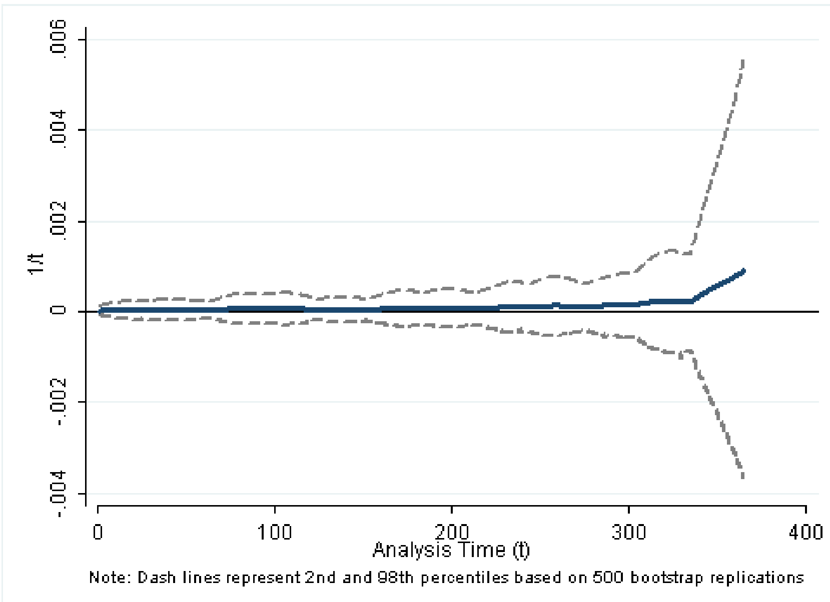
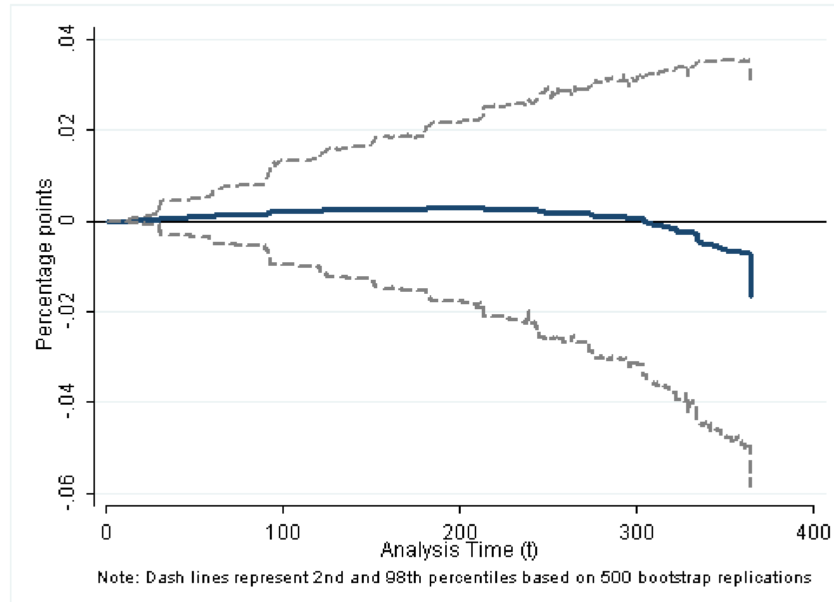


Fig. 9: Policy Change #2: Treatment effects on the hazard rates and CIF for JTN transitions (for the average treated worker of age 42-44)

Treatment effects on the hazard rates



Treatment effects on the CIF



A Proofs of Propositions

A.1 Proof of Proposition 1

I use proof by induction. The continuation value of unemployment when $t = 2$ is given by equation (A.1):

$$V(2) = \underset{s}{Max}\left\{b+z+\beta\left\{sE\left[Max(W(x),V(1)\right]+(1-s)V(1)\right\}-0.5s^2\right\} \tag{A.1}$$

It follows from equations (5.1) and (5.2) that $V(1) = b + V(0) > V(0)$. With a little manipulation the following inequalities are obtained:

$$V(2) > \underset{s}{Max}\left\{b+z+\beta\left\{sE\left[Max(W(x),V(0)\right]+(1-s)V(0)\right\}-0.5s^2\right\} \tag{A.2}$$

$$V(2) > V(1) \tag{A.3}$$

Now, if I assume that $V(t-1) > V(t-2)$, then:

$$V(t) = \underset{s}{Max}\left\{b+z+\beta\left\{\alpha E\left[Max(W(x),V(t-1)\right]+(1-\alpha)V(t-1)\right\}-0.5s^2\right\} \tag{A.4}$$

$$V(t) > \underset{s}{Max}\left\{b+z+\beta\left\{\alpha E\left[Max(W(x),V(t-2)\right]+(1-\alpha)V(t-2)\right\}-0.5s^2\right\} \tag{A.5}$$

$$V(t) > V(t-1) \tag{A.6}$$

which concludes the proof that the continuation value of unemployment increases with t or the length of the remaining length of entitlement to UB.

Regarding the reservation wages, it follows from inspection that $x_1^U = x_0^U$ because the expected value of declining a job offer at the end of the last period of entitlement is the same as the expected value of declining an offer at any period after that. Now, since $V(t) = W(x_t^U) = \frac{x_t^U}{1-\beta}$ and I have shown that $V(t) > V(t-1)$, then it follows that $x_t^U > x_{t-1}^U$ for $t > 1$.

A.2 Proof of Proposition 2

Again, I use proof by induction. Notice that:

$$B^L(w,1,T) = \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),V(T)\right]+(1-s)V(T)\right\}-0.5s^2\right\} \tag{A.7}$$

$$B^L(w,1,T) > \underset{s}{Max}\left\{b+z+\beta\left\{sE\left[Max(W(x),V(T-1)\right]+(1-s)V(T-1)\right\}-0.5s^2\right\} \tag{A.8}$$

$$B^L(w,1,T) > V(T) \tag{A.9}$$

Moving from the first to the second line is supported by the fact that $V(T) > V(T-1)$ (by Proposition 1) and that $w > b+z$ (by assumption). Similarly I show below that $B^L(w,2,T) > B^L(w,1,T)$:

$$B^L(w,2,T) = \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),B^L(w,1,T))\right]+(1-s)B^L(w,1,T)\right\}-0.5s^2\right\} \tag{A.10}$$

$$B^L(w,2,T) > \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),V(T)\right]+(1-s)V(T)\right\}-0.5s^2\right\} \tag{A.11}$$

$$B^L(w,2,T) > B^L(w,1,T) \tag{A.12}$$

Now if I assume that $B^L(w,n-1,T) > B^L(w,n-2,T)$, then:

$$B^L(w,n,T) = \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),B^L(w,n-1,T))\right]+(1-s)B^L(w,n-1,T)\right\}-0.5s^2\right\} \tag{A.13}$$

$$B^L(w,n,T) > \underset{s}{Max}\left\{w+\beta\left\{sE\left[Max(W(x),B^L(w,n-2,T)\right]+(1-s)B^L(w,n-2,T)\right\}-0.5s^2\right\} \tag{A.14}$$

$$B^L(w,n,T) > B^L(w,n-1,T) \tag{A.15}$$

which completes the proof that the value of employment decreases as the workers approaches the separation date.

Regarding the reservation wage, recall that $W(x^L(w,n,T)) = \frac{x^L(w,n,T)}{1-\beta} = B^L(w,n,T)$. Then, $x^L(w,n,T) = (1-\beta) * B^L(w,n,T)$. So given that $B^L(w,n,T)$ decreases as the separation date approaches (n gets smaller) so does the reservation wage.

A.3 Proof of Proposition 4

Let's start by analyzing how the value of employment $B^L(w,n,T)$ changes with changes in the PDB (denoted by T). The optimal value for $B^L(w,n,T)$, assuming an interior solution, is given by equation (A.16):

$$
\begin{aligned}
B^L(w,n,T) =& w+\beta\Big\{S^L(w,n,T)*E\left[Max(W(x),B^L(w,n-1,T)\right] \\
&+\left(1-S^L(w,n,T)\right)B^L(w,n-1,T)\Big\}-0.5\left(S^L(w,n,T)\right)^2
\end{aligned} \tag{A.16}
$$

I use the envelope theorem to show that:

$$
\frac{\partial B^L(w,n,T)}{\partial T} =\beta\left\{\frac{\partial B^L(w,n-1,T)}{\partial T}-S^L(w,n,T)*\int_{(1-\beta)B^L(w,n-1,T)}^{\infty}\frac{\partial B^L(w,n-1,T)}{\partial T}dF(x)dx\right\} \tag{A.17}
$$

$$
\frac{\partial B^L(w,n,T)}{\partial T} =\frac{\partial B^L(w,n-1,T)}{\partial T}\beta\left\{1-S^L(w,1n,T)*\left[1-F\left((1-\beta)B^L(w,n-1,T)\right)\right]\right\} \tag{A.18}
$$

And the corresponding expression when $n=1$ is given by:

$$
\frac{\partial B^L(w,1,T)}{\partial T}=\frac{\partial V(T)}{\partial T}\beta\left\{1-S^L(w,1,T)*\left[1-F\left((1-\beta)V(T)\right)\right]\right\} \tag{A.19}
$$

From Proposition 1, I know that $\frac{\partial V(T)}{\partial T}>0$. Then, I use the results from equations (A.18) and (A.19), to establish the following inequalities:

$$
0<\frac{\partial B^L(w,N,T)}{\partial T}<\frac{\partial B^L(w,N-1,T)}{\partial T}....<\frac{\partial B^L(w,1,T)}{\partial T}<\frac{\partial V(T)}{\partial T} \tag{A.20}
$$

By definition, the reservation wage is given by $x^L(w,n,T)=(1-\beta)*B^L(w,n,T)$. Using the result in equation (A.20), the inequalities below follow:

$$
0<\frac{\partial x^L(w,N,T)}{\partial T}<\frac{\partial x^L(w,N-1,T)}{\partial T}....<\frac{\partial x^L(w,1,T)}{\partial T} \tag{A.21}
$$

This completes the proof that and increase in the PDB increases the value of employment and the reservation wages and that the effect is stronger the closer the worker is to the separation date. Now, I analyze the effect of changes in the PDB on the the optimal search effort. In the last period of employment the optimal search effort and its derivative with respect to T are given by:

$$
S^L(w,1,T) =\beta\left\{\int_{(1-\beta)V(T)}^{\infty}\left[W(x)-V(T)\right]dF(x)dx\right\} \tag{A.22}
$$

$$
\frac{\partial S^L(w,1,T)}{\partial T} =-\beta\int_{(1-\beta)V(T)}^{\infty}\frac{\partial V(T)}{\partial T} \tag{A.23}
$$

I know that $\frac{\partial V(T)}{\partial T}>0$ from Proposition 1. Then, $\frac{\partial S^L(w,1,T)}{\partial T}<0$. A similar analysis can be done for $S^L(w,2,T)$:

$$S^L(w,2,T) = \beta\left\{\int_{(1-\beta)B^L(w,1,T)}^{\infty}\left[W(x)-B^L(w,1,T)\right]dF(x)dx\right\} \tag{A.24}$$

$$\frac{\partial S^L(w,2,T)}{\partial T} = -\beta\int_{(1-\beta)B^L(w,1,T)}^{\infty}\frac{\partial B^L(w,1,T)}{\partial T} \tag{A.25}$$

Given that $B^L(w,1,T) > V(T)$ per equation (A.9) and that $0 < \frac{\partial B^L(w,1,T)}{\partial T} < \frac{\partial V(T)}{\partial T}$ per equation (A.18), I obtain that $\frac{\partial S^L(w,1,T)}{\partial T} < \frac{\partial S^L(w,2,T)}{\partial T} < 0$. In general, for periods n and $n-1$ for $n \geqslant 2$ the comparative statics are given by:

$$\frac{\partial S^L(w,n,T)}{\partial T} = -\beta\int_{(1-\beta)B^L(w,n-1,T)}^{\infty}\frac{\partial B^L(w,n-1,T)}{\partial T} \tag{A.26}$$

$$\frac{\partial S^L(w,n-1,T)}{\partial T} = -\beta\int_{(1-\beta)B^L(w,n-2,T)}^{\infty}\frac{\partial B^L(w,n-2,T)}{\partial T} \tag{A.27}$$

Since $B^L(w,n-1,T) > B^L(w,n-2,T)$ per Proposition (2) and $\frac{\partial B^L(w,n-1,T)}{\partial T} < \frac{\partial B^L(w,n-2,T)}{\partial T}$ per equation (A.20), and using the previous result, I can establish that:

$$\frac{\partial S^L(w,1,T)}{\partial T} < \frac{\partial S^L(w,2,T)}{\partial T} .... < \frac{\partial S^L(w,N-1,T)}{\partial T} < \frac{\partial S^L(w,N,T)}{\partial T} < 0 \tag{A.28}$$

which concludes the proof that an increase in the PDB reduces search effort and the effect is larger the closer is the worker to the separation date.

A.4 Proof of Proposition 6

Let $S^E(w,\phi,N,T)$ denote optimal search effort decision for a non-notified worker. Then, using equation (5.6), the value of employment is given by:

$$\begin{aligned}E(w,\phi,N,T) = & w+\beta\Big\{\phi S^E(w,\phi,N,T) * E\left[Max\left(W(x),B^L(w,N,T)\right)\right] \\ & +\phi\left(1-S^E(w,\phi,N,T)\right)B^L(w,N,T) \\ & +(1-\phi)S^E(w,\phi,N,T) * E\left[Max\left(W(x),E(w,\phi,N,T)\right)\right] \\ & +(1-\phi)\left(1-S^E(w,\phi,N,T)\right)E(w,\phi,N,T)\Big\} \\ & -0.5(S^E(w,\phi,N,T))^2\end{aligned} \tag{A.29}$$

Invoking the envelop theorem and after some manipulation I obtain:

$$
\begin{aligned}
\frac{\partial E(w,\phi,N,T)}{\partial T} =& \beta\Bigg\{\phi\frac{B^{L}(w,N,T)}{\partial T}+\phi S^{E}(w,\phi,N,T)\int_{(1-\beta)B^{L}(w,N,T)}^{\infty} \\
&-\frac{\partial B^{L}(w,N,T)}{\partial T}dF(x)dx \\
&+(1-\phi)\frac{\partial E(w,\phi,N,T)}{\partial T} \\
&+(1-\phi)S^{E}(w,\phi,N,T)\int_{(1-\beta)E(w,\phi,N,T)}^{\infty}-\frac{\partial E(w,\phi,N,T)}{\partial T}dF(x)dx\Bigg\} \qquad \text{(A.30)}
\end{aligned}
$$

$$
\begin{aligned}
\frac{\partial E(w,\phi,N,T)}{\partial T} =& \beta\Bigg\{\phi\frac{B^{L}(w,N,T)}{\partial T}\left[1-S^{E}(w,\phi,N,T)\left(1-F\left((1-\beta)B^{L}(w,N,T)\right)\right)\right] \\
&+(1-\phi)\frac{\partial E(w,\phi,N,T)}{\partial T}\left[1-S^{E}(w,\phi,N,T)\left(1-F\left((1-\beta)E(w,\phi,N,T)\right)\right)\right]\Bigg\} \qquad \text{(A.31)}
\end{aligned}
$$

After some further manipulation I have:

$$
\frac{\partial E(w,\phi,N,T)}{\partial T} = \frac{\beta\phi\left[1-S^{E}(w,\phi,N,T)\left(1-F\left((1-\beta)B^{L}(w,N,T)\right)\right)\right]}{1-\beta(1-\phi)\left[1-S^{E}(w,\phi,N,T)\left(1-F\left((1-\beta)E(w,\phi,N,T)\right)\right)\right]}\times\frac{B^{L}(w,N,T)}{\partial T} \qquad \text{(A.32)}
$$

Notice that $\frac{\beta\phi\left[1-S^{E}(w,\phi,N,T)\left(1-F\left((1-\beta)B^{L}(w,N,T)\right)\right)\right]}{1-\beta(1-\phi)\left[1-S^{E}(w,\phi,N,T)\left(1-F\left(E(w,\phi,N,T)\right)\right)\right]} < 1$. Equation (A.18) shows that $\frac{B^{L}(w,N,T)}{\partial T} > 0$. Thus, I obtain the following results:

$$
\frac{\partial E(w,\phi,N,T)}{\partial T} = 0 \quad if \quad \phi = 0 \qquad \text{(A.33)}
$$

$$
0 < \frac{\partial E(w,\phi,N,T)}{\partial T} < \frac{B^{L}(w,N,T)}{\partial T} \quad if \quad \phi > 0 \qquad \text{(A.34)}
$$

which concludes the proof that an increase in the PDB increases the value of employment for non-notified workers $E(w,\phi,N,T)$ only if they have positive expectations of layoff ($\phi > 0$).

The reservation wage for taking a new job in case the worker did not receive a notification at the end of the period, denoted by $x^{E}(w,\phi,N,T)$, is such that $W(x^{E}(w,\phi,N,T)) = \frac{x^{E}(w,\phi,N,T)}{1-\beta} = E(w,\phi,N,T)$. Thus, using equations (A.33) and (A.34) I obtain the following results:

$$
\frac{\partial x^{E}(w,\phi,N,T)}{\partial T} = 0 \quad if \quad \phi = 0 \qquad \text{(A.35)}
$$

$$
\frac{\partial x^{E}(w,\phi,N,T)}{\partial T} = (1-\beta)\frac{\partial B^{L}(w,N,T)}{\partial T} > 0 \quad if \quad \phi > 0 \qquad \text{(A.36)}
$$

which concludes the proof that an increase in the PDB increases the reservation wage $x^{E}(w,\phi,N,T)$ for taking a new job if no notification is received, but only if the probability of receiving such notification is non-zero.

A.5 Proof of Proposition 7

Assuming an interior solution, the optimal search effort for a non-notified worker, denoted by $S^E(w,\phi,N,T)$, is given by:

$$\begin{aligned} S^E(w,\phi,N,T) =& \beta\left\{\phi\int_{B^L(w,N,T)(1-\beta)}^{\infty}\left(W(x)-B^L(w,N,T)\right)dF(x)dx\right. \\ &\left.+(1-\phi)\int_{E(w,\phi,N,T)(1-\beta)}^{\infty}\left(W(x)-E(w,\phi,N,T)\right)dF(x)dx\right\} \end{aligned} \tag{A.37}$$

Taking the partial derivative with respect to T:

$$\begin{aligned} \frac{\partial S^E(w,\phi,N,T)}{\partial T} =& -\beta\left\{\phi\int_{B^L(w,N,T)(1-\beta)}^{\infty}\frac{\partial B^L(w,N,T)}{\partial T}dF(x)dx\right. \\ &\left.+(1-\phi)\int_{E(w,\phi,N,T)(1-\beta)}^{\infty}\frac{\partial E(w,\phi,N,T)}{\partial T}dF(x)dx\right\} \end{aligned} \tag{A.38}$$

Given the results in equation (A.18), in equation (A.33) and in equation (A.34) I can establish the following results:

$$\frac{\partial S^E(w,\phi,N,T)}{\partial T} = 0 \quad if \quad \phi = 0 \tag{A.39}$$

$$\frac{\partial S^E(w,\phi,N,T)}{\partial T} < 0 \quad if \quad \phi > 0 \tag{A.40}$$

which concludes the proof that an increase in the PDB decreases search effort but only if workers have a positive probability of receiving a layoff notification.

Now, for $\phi > 0$, I know that $\frac{\partial E(w,\phi,N,T)}{\partial T} < \frac{B^L(w,N,T)}{\partial T}$ per equation A.34. And since $E(w,\phi,N,T) > B^L(w,N,T)$, I can then establish that:

$$\frac{\partial S^L(w,1,T)}{\partial T} < \frac{\partial S^L(w,2,T)}{\partial T} .... < \frac{\partial S^L(w,N-1,T)}{\partial T} < \frac{\partial S^L(w,N,T)}{\partial T} < \frac{\partial S^E(w,\phi,N,T)}{\partial T} < 0 \tag{A.41}$$

which concludes the proof that the effect of increasing the PDB on discouraging search effort is smaller for non-notified workers than for notified workers.

B Treatment effects formulas

B.1 Treatment effects on the hazard rate

Equation (6.4) specified the TE on the hazard rate of separation as:

$$TE_h(\bar{t},x,d) = h^{1,d}(\bar{t}|X=x,D=d) - h^{1,0}(\bar{t}|X=x,D=d) \tag{B.1}$$

Plugging in equations (6.8) and (6.9), I obtain:

$$\begin{aligned} TE_h(\bar{t},x,d) &= h_0(\bar{t})\,exp(\delta j + \gamma d + \beta x + \theta d) - h_0(\bar{t})\,exp(\delta + \gamma d + \beta x) \\ TE_h(\bar{t},x,d) &= h_0(\bar{t})\,exp(\delta + \gamma d + \beta x)\,[exp(\theta d) - 1] \\ TE_h(\bar{t},x,d) &= h^{1,0}(\bar{t}|X=x,D=d)\,[exp(\theta d) - 1] \end{aligned} \tag{B.2}$$

B.2 Treatment effects on the failure function

Equation (6.6) specified the TE on the failure function as:

$$\begin{aligned} TE_F(\bar{t},x,d) &= F^{1,d}(\bar{t},x,d) - F^{1,0}(\bar{t},x,d) \\ TE_F(\bar{t},x,d) &= -\,exp\left\{-\int_0^{\bar{t}} h^{1,d}(u|X=x,D=d)du\right\} + exp\left\{-\int_0^{\bar{t}} h^{1,0}(u|X=x,D=d)du\right\} \end{aligned} \tag{B.3}$$

Plugging in equations (6.8) and (6.9), I obtain:

$$\begin{aligned} TE_F(\bar{t},x,d) &= F^{1,d}(\bar{t},x,d) - F^{1,0}(\bar{t},x,d) \\ TE_F(\bar{t},x,d) &= -\,exp\left\{-exp(\theta d)\int_0^{\bar{t}} h_0(u)\,exp(\delta + \gamma d + \beta x)\,du\right\} \\ &\qquad + exp\left\{-\int_0^{\bar{t}} h_0(u)\,exp(\delta + \gamma d + \beta x)\,du\right\} \\ TE_F(\bar{t},x,d) &= -\,exp\left\{-\int_0^{\bar{t}} h^{1,0}(u|X=x,D=d)du\right\}^{exp(\theta d)} + exp\left\{-\int_0^{\bar{t}} h^{1,0}(u|X=x,D=d)du\right\} \\ TE_F(\bar{t},x,d) &= exp\left\{-\int_0^{\bar{t}} h^{1,0}(u|X=x,D=d)du\right\}\left[1 - exp\left\{-\int_0^{\bar{t}} h^{1,0}(u|X=x,D=d)du\right\}^{exp(\theta d)-1}\right] \\ TE_F(\bar{t},x,d) &= \left(1 - F^{1,0}(\bar{t},x,d)\right)\left[1 - \left(1 - F^{1,0}(\bar{t},x,d)\right)^{exp(\theta d)-1}\right] \end{aligned} \tag{B.4}$$

B.3 Treatment effects on the cumulative incidence function

The TE for the CIF is given by:

$$TE_{CIF_k}(\bar{t},x,d) = \int_0^t h_k^{1,d}(u \big| X = xD = d) \times exp\left(-\int_0^u \left[\sum_{i\in K} h_i^{1,d}(w \big| X = x, D = d)\right] dw\right) du$$
$$- \int_0^t h_k^{1,0}(u \big| X = xD = d) \times exp\left(-\int_0^u \left[\sum_{i\in K} h_i^{1,0}(w \big| X = x, D = d)\right] dw\right) du \qquad \text{(B.5)}$$

Using the fact that $h_i^{1,d}(u \big| X = x, D = d) = h_i^{1,0}(u \big| X = x, D = d) \times exp(\theta_i d)$, I can re-write equation (B.6) as:

$$TE_{CIF_k}(\bar{t},x,d) = \int_0^t h_k^{1,0}(u \big| X = x, D = d) \times exp(\theta_k d) \times exp\left(-\int_0^u \left[\sum_{i\in K} h_i^{1,0}(w \big| X = x, D = d) \times exp(\theta_i d)\right] dw\right) du$$
$$- \int_0^t h_k^{1,0}(u \big| X = xD = d) \times exp\left(-\int_0^u \left[\sum_{i\in K} h_i^{1,0}(w \big| X = x, D = d)\right] dw\right) du$$
$$TE_{CIF_k}(\bar{t},x,d) = \int_0^{\bar{t}} h_k^{1,0}(u \big| X = x, D = d) \times exp(-\int_0^u \sum_{i\in K} h_i^{1,0}(w \big| X = x, D = d) dw)$$
$$\times \left\{ exp(\theta_k d) \left(exp(-\int_0^u \sum_{i\in K} \left[h_i^{1,0}(w \big| X = x, D = d)\,(exp(\theta_i d) - 1)\right] dw) \right) - 1 \right\} du$$
$$TE_{CIF_k}(\bar{t},x,d) = \int_0^{\bar{t}} h_k^{1,0}(u \big| X = x, D = d) \times exp(-\int_0^u \sum_{i\in K} h_i^{1,0}(w \big| X = x, D = d) dw)$$
$$\times \left\{ exp\left(\theta_k d - \int_0^u \sum_{K} \left[h_{i\in K}^{1,0}(w \big| X = x, D = d)\,(exp(\theta_i d) - 1)\right] dw \right) - 1 \right\} du \qquad \text{(B.6)}$$