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Incentives and Exit Behavior: An Examination of the Unemployment Insurance System in Turkey

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Abstract

We use microdata obtained from the Turkish Employment Agency (İŞKUR) to shed light on the functioning of the unemployment insurance (UI) system over the period 2010-16. We examine the individual, institutional and macroeconomic determinants of exit rates to employment using a variant of the Cox-PH model. We rely on stratification that permits arbitrary baseline hazard functions that vary by strata. Effects of the explanatory variables on the hazard are assumed to be constant across strata and are estimated using the Stratified Partial Likelihood Estimator (Ridder and Tunalı, 1999). Subsequently we are able to obtain non-parametric estimates of the cumulative hazard rate by stratum, and examine how the exit rate varies across strata. We initially stratified by PBD and found striking violations of the proportional hazards assumption for indicators of gender and "type" of termination, a classification based on the reason provided by the employer. We argue that these could serve as markers for differences in the re-employability of the unemployed individuals and stratify further, by PBD × gender × type of termination. We then exploit various features of the institutional set-up and use quasi-experiments – a DD formulation and two RD designs – that allow us to tease out causal effects of changes in UI benefits and statutory benefit duration (PBD). We conclude that the UI system - one of the least generous among comparator countries - does not suffer from major incentive problems.

Keywords: unemployment insurance, job search, unemployment duration, unobserved heterogeneity

JEL: J64, J65

1 Introduction

The intended purpose of unemployment insurance (UI) is to provide protection against income losses associated with involuntary unemployment. Generous benefits can create reemployment disincentives and encourage longer unemployment spells. In a well-functioning UI program benefits have to be high enough to sustain workers while unemployed, and last long enough to allow them to find a job that matches their skills. At the same time neither the benefits nor their duration should be too generous to dissuade the recipient from active search activity.

Starting from the 1970s job search models emerged as a major theoretical framework for analyzing labor market dynamics (McCall, 1970; Mortensen, 1970; Gronau, 1971). Predictions obtained from search models on the effects of UI benefit provision inspired a large empirical literature. The simplest stationary job search model predicts that more generous UI benefits increase the reservation wage and reduce the search effort of workers, leading to longer unemployment spells. This UI induced distortion in search behavior is viewed as a "moral hazard" effect. Mortensen (1977) incorporated some institutional features of UI systems – such as the fixed duration of benefit receipts and the need to qualify for UI benefits via previous work history – into a dynamic sequential search model. He concluded that search behavior is not stationary over the spell of insured unemployment. As one gets closer to benefit exhaustion date, value of unemployment falls. This leads to a drop in the reservation wage while search intensity steadily increases until the lapse of benefits and stays constant thereafter. Consequently the hazard rate rises as the remaining window of benefit collection shrinks.

Most early empirical studies documented time-dependence in the hazard. Typically exit rates initially decline (or remain steady for a while) but eventually rise with a spike near benefit exhaustion and decline again after benefits lapse (Moffitt, 1985; Ham and Rea, 1987; Meyer, 1990; Katz and Meyer, 1990). The rise in the exit rate prior to benefit exhaustion has been interpreted as the prominent example of distortions created by UI. [1] Still, non-stationary search models (Mortensen, 1977; Van den Berg, 1990) continue to

[1] These findings only partially confirm the predictions of the non-stationary search model as this model does not explain the drop in the hazard rate after benefit exhaustion. Several studies proposed

be used as the main theoretical framework in empirical investigations.

While the early literature relied on cross-section variation, more recent studies have turned to examinations of policy driven changes in UI benefit levels or potential benefit durations for evidence on moral hazard (Card and Levine, 2000; Carling et al., 2001; Lalive et al., 2006). Others exploited some design features of the UI systems such as differences in benefit levels or length tied to observables such as age or pre-unemployment employment history (Card et al., 2007a; Schmieder et al., 2012; Le Barbanchon, 2016). These studies confirmed the disincentive effects of UI, though in varying shades.[2]

Although Turkey introduced an UI program in 1999, little is known about its impact on job search behaviors of unemployed workers. The fraction of unemployed individuals who collect UI is low, arguably because of the demanding qualification stipulations. Furthermore the replacement rate (RR) is low. Given the design parameters, it is clear that the architects of the UI system in Turkey were worried about the sustainability of a generous system. In light of the experiences in other countries, they may also have been concerned about creating disincentives for extending the period without work. Nevertheless a first glance at the data shows that more than half the individuals on UI benefits use them fully, and a significant fraction of those who transit to employment do so on the last day of benefit collection.[3] Does this mean that the disincentives are there? In this paper we aim to answer this question. We use microdata obtained from the Turkish Employment Agency, better known by its Turkish acronym, İŞKUR. We first examine the individual, institutional and macroeconomic determinants of exit rates to employment from the UI system using a reduced form duration model. We exploit the information in the administrative data to obtain markers that are likely to differentiate the experiences of different individuals. We then exploit the cross-section variation in our rich data set to tease out evidence of incentive problems. Subsequently, we engage in quasi-experimental analyses

modifications to search models in order to explain the fall in hazard rates after the expiration of benefits. DellaVigna et al. (2017) explain the fall in search effort after the benefit exhaustion by reference-dependent preferences as workers adapt to lower income levels by time. In addition, Card et al. (2007b) show that magnitude of the spike is much smaller when the spells are measured by the time to the next job instead of by the time spent in unemployment system indicating a serious measurement error.

[2]See Tatsiramos and Van Ours (2014) for a recent survey.

[3]Boone and van Ours (2012) propose a model of storeable job offers where workers delay the starting date of the new job until the end of benefits.

that shed further light on causal links between key system parameters and exit hazards.

To help motivate our methodological choices, it is useful to spell out the salient design features of the UI system in Turkey. Firstly, the eligibility conditions are quite stringent. To qualify for benefits, individuals (i) need to have registered with the Social Security Administration (SSA), (ii) accumulated 600 days of premium payments to the UI system in the past three years, and (iii) had a four month long continuous employment spell prior to separation. Consequently new entrants to the labor force who do not have any employment record and workers who do but are not registered with the SSA are left outside the UI system. Secondly, the duration of UI payments is tied to workers' premium payment record via three sharp thresholds. The UI system reserves the longest potential benefit duration(PBD) of 300 days for those who have not experienced any unemployment spell in the last three years that preceded termination (1080 days of employment in the last three years). Workers who have accumulated at least 900 (but less than 1080 days), and those with at least 600 (but less than 900) days of premium payments in the last three years qualify for 240, and 180 days of PBD, respectively.

In theory increases in PBD can affect search intensity adversely and stretch the unemployment spell. At the same time PBD differences can serve as a signal of re-employability potential. Individuals entitled to the highest PBD probably differ in various ways from those who are qualified for shorter PBDs. If there is demand for their skills, a perfect employment record might serve as a positive signal. By the same logic individuals who had the most interruptions and could only qualify for the shortest PBD should have more difficulty to find a new job. On the other hand, an older worker whose skills are no longer sought after, might have lower chances of returning to work despite a stellar employment record. Observables in micro data sets can provide important leads, but the list cannot capture the behavioral differences fully. Accordingly it is important to sort out the roles of observed and unobserved heterogeneity.

To achieve this, we use a variant of the Cox-PH model, which exploits stratification that permits arbitrary baseline hazard functions at the level of strata. Since misspecification of the baseline hazard is a major concern in duration models, this flexibility can be rewarding. This model has been popularized by Ridder and Tunalı (1999). Effects of the explanatory variables on the exit rate are assumed to remain the same over time and across strata, and are estimated using the Cox Partial Likelihood Estimator.[4] Subsequently it is possible to obtain non-parametric estimates of the baseline hazards by stratum. This proves to be a very handy form of flexibility that helps to circumvent specification problems.

In our substantive context an obvious dimension of stratification is the statutory length of the UI benefit payment period (PBD). After all the supports of the hazards of exit to employment vary by PBD. Gender is another obvious dimension. There is ample evidence of gender differences in labor market outcomes almost everywhere one looks, and Turkey is no exception. Predictably non-parametric data analysis and preliminary specification tests revealed that gender influenced the hazard of exit in a complicated (that is, non-proportional) manner. Our efforts to understand the subtleties of the labor code that the UI system latches on to, exposed another potentially important determinant: the "type" of termination. Labor code obliges employers to identify the reason for separation, which are grouped under six headings spelled out in Law no. 4957 and recorded in the administrative files. Actually, displacement is sometimes related to the ability of the worker: firms retain the most effective workers and lay off the unproductive ones. In some other cases separation stems from an exogenous reason unconnected to the performance of the worker such as plant closing or termination of a fixed term contract.[5] Accordingly, we surmised that type of separation might have signaling value about the re-employability of the worker, and this was supported by our empirical work.

Our empirical strategy stands on four legs. The first is non-parametric data analysis which reveals patterns that need explanations. The second is a reduced form investigation that aims to establish associations between key observables – such as pre-unemployment wages, unemployment benefits and/or the replacement rate – and exit rates, allowing for unobserved heterogeneity brought about by the differences in benefit duration (PBD). The administrative data set we use allows us to control for demographic markers (age, gender,

[4]Kalbfleisch and Prentice (1980) suggested stratification along observable dimensions as a way of relaxing the PH assumption and established the suitability of Cox's Partial Likelihood estimator for this setup.

[5]For instance, Gibbons and Katz (1991) have proposed a signaling model and showed that layoffs reveal a negative signal about the productivity of the worker. They provided evidence that workers displaced by layoffs have longer unemployment spells and lower postdisplacement wages compared to workers displaced by plant closings.

marital status and education), location of residence (province) and İŞKUR office handling the case, plus sector of previous employment. It also records the date of termination and the date of exit from the UI system. This information allows us to capture a horde of calendar time effects, and serve as controls for the effect of macroeconomic conditions. Since the model allows time-varying variables, we are able to study the exit decision as an experiment conducted among equals defined by a remarkably high dimensional vector. Exits from the UI system before the exhaustion of benefits can take the form of return to employment, or termination of UI benefits because of violation of administrative stipulations, or due to health failure. We focus on exits to employment and treat the other forms of exit as independent censoring events.

The third and fourth legs of our empirical strategy involve quasi-experiments that seek causal connections between some key UI system parameters and exit rates. There was no policy change affecting the UI system during the period we study.[6] In the third leg of our empirical investigation we exploited the link between UI benefits and the minimum wage, and set up a difference-in-differences (DD) experiment around statutory changes in the minimum. Our strategy is similar to Carling et al. (2001), where a policy change altered the replacement rate (RR) directly. In our case the RR change induced by the minimum wage adjustment.

In the fourth and final leg of our investigation we exploit a regression discontinuity (RD) design to determine if exit hazards changed around the APP thresholds of 900 and 1080 which determine PBD lengths. This is similar to the RD designs in Card et al. (2007a) and Le Barbanchon (2016), which examine the impact of discontinuities in PBD on the job finding rates in Austria and France, respectively. In Austria benefit entitlement changes from twenty weeks to thirty around a threshold of 36 months of employment in the past five years. The discontinuity in France is sharper. From 2000 to 2002, workers with an employment record between 6 to 8 months in the last 12 months were eligible to 7 months of unemployment benefits. PBD more than doubled to 15 months when employment period exceeded 8 months. Both studies found a significant negative impact

[6] In 2008 the method for calculating UI benefits was changed. Küçükbayrak (2012a) exploits this change using data from 1 January 2007 to 31 October 2010. She found mild evidence in favor of moral hazard.

of extended benefits on job finding rates.[7] Filiz (2017) was the first to apply this design to the Turkish context using local linear regression. Unfortunately her examination of the discontinuity around APP = 900 is deeply flawed, because of failure to recognize the implication of the endogenous change in the hazard support. We are more careful, because our semi-parametric approach (SPLE) allows us to estimate the (cumulative) baseline hazards separately and non-parametrically, over their different supports. Filiz did not examine the discontinuity at APP = 1080. We do, even though it poses methodological challenges.

Filiz (2017) used data for the period 2002-2012 from the same İŞKUR UI database we use. We are aware of three other papers that study the UI system in Turkey. Sahin and Kizilirmak (2007) use data from the İŞKUR UI database on workers who were employed in the private sector as of 19 September 2004. They fit a Weibull model to the entire sample, and do not control for calendar time effects. Küçükbayrak (2012a) exploits the policy change in 2008 that increased the replacement rate using a regression discontinuity design. She specifies the logit of the exit hazard as a linear function of covariates that include step functions or polynomials in time. Her investigation is based İŞKUR UI data from the period 1 June 2007 to 31 October 2010. In another paper Küçükbayrak (2012b) uses İŞKUR's unemployment registration data from the month of April 2008 and investigates the role of having UI benefit coverage on job finding. She uses the Cox-PH model and does not stratify on PBD. She finds that men receiving UI benefits quit unemployment more quickly compared to non-recipients while the opposite is true for women. Moreover, among UI beneficiaries unemployment duration increases with PBD and benefit level.

The plan of our paper is as follows: The next section contains a detailed exposition of the institutional background of the UI system in Turkey. In Section 3 we describe our data and undertake preliminary analyses that expose the stylized facts. We introduce our statistical model in Section 4 and discuss the details of our multi-pronged econometric strategy. Model based empirical results are collected in Section 5. The concluding section

[7] Both studies also analyzed the impact of UI on match quality of the subsequent job and found no effect. Moreover, Card et al. (2007a) found a significant negative impact of lump-sum severance payments on the job finding rate.

includes a discussion of what has been achieved, and some questions that remain.

2 Unemployment Insurance system in Turkey

Introduced in 1999 (with Law no. 4447), the program was designed as a self-sustaining group insurance system for workers who are registered with the Social Security Administration (SSA), often referred to as "formally employed" workers. While some formally employed workers have fixed-term contracts, most do not. In the eye of the Labor Law the latter are assumed to have indefinite contracts. The UI system is financed by contributions from the worker (1%), the employer (2%), and the government (1%), stipulated as a percentage of the gross wage, which are held in the worker's account.[8] Premium collection commenced in June 2000 and first payments were made in March 2002. The administration of the UI system is implemented by the national employment agency, İŞKUR.

To qualify for the UI, a minimum of 600 days of premium payments over a period of three consecutive years, as well as 120 days of continuous employment and premium contributions prior to layoff are needed.[9] Potential benefit duration (PBD) is a step function of accumulated premium payments (APP): 180 days (6 months) for APP $\in$ [600, 900), 240 days (8 months) for APP $\in$ [900, 1080), and 300 days (10 months) for APP = 1080 (see Figure 1). For the purposes of the UI system a month is defined as 30 days, and a year as 360 days. Hence an APP of 1080 days signals at least 3 years of continuous employment.

Figure 1 about here

[8] Originally shares were higher: respectively 2%, 3% and 2% Employers argued that they effectively paid the worker's share and that the combined 5% tax was a disincentive for employment. The reduction was stipulated as a temporary measure in 2001, in response to a major economic crisis that doubled the unemployment rate between 2000Q4 and 2002Q1 (Tunalı et al., 2003). It has remained in effect since then.

[9] The law recognized many exceptions to the 120 day continuous premium payment requirement, including: illness, unpaid leaves, disciplinary lay-offs, arrests, cessation of regular employment because of natural disasters, strikes, lock-outs or economic hardship experienced by the firm. However, determining whether a legitimate exception occurred took time and resulted in unwarranted delays in UI benefit collection. The second stipulation was removed altogether by a legislative change in early 2019.

Eligibility conditions of the UI system in Turkey are quite stringent. The length of the qualification period is one of the highest in the world. In almost all other countries, an employment history of 4 to 12 months in the last 1 to 3 years is sufficient for qualifying for UI benefits. The PBD is more in line with OECD average. In most UI systems PBD is linked to the contribution history or age of the workers. Industrialized countries of continental Europe are usually characterized by long periods of UI payments (up to 24 months in Germany, 36 months in France, no limit in Belgium) whereas other developed economies such as the UK and the USA provide shorter durations (26 weeks).[10]

The UI stipend is calculated as 40 percent of the average gross pay during the last 120 days (four months) of employment, and is capped at 80 percent of the gross minimum wage (see Figure 2). The upper bound of payments results in a constant replacement rate of 40 percent up to the ceiling, and a strictly decreasing rate beyond that. [11] In many countries UI payments are more generous compared to those in Turkey. Replacement rates vary between 50 percent (Estonia, Korea, Slovak Republic, United States) and 90 percent (Denmark).

In what follows we will exploit the design features reflected in Figure 1 and 2 to tease out the effect of benefits on the rate at which UI recipients leave the system. It is important recognize that these parameters operate within the context a broader set of labor market regulations. In the remainder of this section we review these and comment on their implications.

Figure 2 about here

Article 51 of the UI Law establishes links with the labor law and spells out the responsibilities of the parties (employer, worker and İŞKUR). A worker who is involuntarily terminated and is deemed not at fault in the eye of the law is able to collect benefits with minimal delay. In case of a voluntary separation, a worker can still qualify for UI payments if the employer behaves in ways that violates worker rights. This can create

[10]See Tatsiramos and Van Ours (2014) for a more detailed comparison.

[11]Between 2002-2008 the UI benefit was calculated as 50 percent of average net pay and was capped at 100 percent of the net minimum wage.

further delays in benefit payment. [12] The firm bears the responsibility for reporting the dismissal (along with the reason) to İŞKUR within 15 days of termination. The administrative data set includes the reason classified under one of six main headings listed in the UI Law. We scrutinize the potential information content of this classification in the next section.

The dismissed worker has to file the requisite documents with İŞKUR within 30 days of separation. Failure to do so can result in a shortened benefit duration.[13] Benefits are payable starting with the day after dismissal. The application is reviewed by İŞKUR and if the worker qualifies, accumulated benefits are paid at the end of the month of dismissal. If the beneficiary returns to work before the end of the month, a partial payment is made. In sum, while actual benefit payments follow a monthly clock, total payments equal the daily UI benefit times days of unemployment, up to and including the PBD, or PBD minus the penalty days if claim is filed after the 30 day window. Our sense is that the UI application, approval and compensation system in Turkey is streamlined compared to many others in Europe. (give citations)

According to the Labor Law, workers with an employment record of six or months with the same employer are entitled to severance pay. The payment amount is roughly one month's gross pay per year of tenure. Obviously an individual who qualifies for the maximum PBD of 300 days gets to collect at least three months of severance payment. Individuals who qualify for less than the maximum PBD might still be able to collect severance pay, depending on the length of their spell with the last employer. Unfortunately our data base does not contain information about the amount of severance pay entitlement or length of the last employment spell. This creates heterogeneity in the amount of liquidity that UI beneficiaries will have, above and beyond their private and family resources. Procedural delays mentioned earlier can exacerbate the heterogeneity.

[12] Labor Law considers the worker liable when termination results from violation of an unwritten goodwill clause. Behaviors that constitute violations are described by examples. Special Labor Courts are charged with resolving disputes over who is at fault (Sözer, 2001). An English translation of Labor Law no. 4857 is available on the web: Datassist Human Resources http://turkishlaborlaw.com/turkish-labor-law-no-4857/19-4857-labor-law-english-by-article

[13] In case of late applications, benefit duration is reduced by the number of days of delay. If the delay results from extraordinary circumstances outside the control of the worker (force majeur) the late filing penalty is not imposed.

The point of this discussion is that unemployed individuals will often start search without any UI benefits in hand, and as econometricians we know less than what they do. We return to this point in the context of the preliminary data analysis reported in Section 3, and adjust our empirical strategy accordingly.

The UI Law has two clauses that incentivize return to work. On the worker side if a UI recipient who exited to employment loses his/her job before fulfilling the eligibility conditions, he/she can collect the unused portion of benefits (PBD) earned earlier. On the firm side if a firm hires someone collecting UI benefits and in doing so augments its workforce, both the worker's and firm's share of the UI premium (totaling 2 percent of the gross wage) as well the general health insurance premium (12.5 percent of the gross wage up to a ceiling subject to annual adjustments) is paid by İŞKUR for a period that equals the unused portion of PBD.

In addition to the monthly stipend, all UI beneficiaries get health and maternity insurance coverage, plus institutional support for job search and active labor market programs (vocational training, skill development and retraining services) provided at İŞKUR offices. Since UI recipients may be required to participate in certain active labor market programs (ALMP), timing of the exit may be influenced by program participation status. Since we do not have participation information, we ignore this factor. Many of the controls we have – such as demographics, education, geographic location – are correlates of participation status, so omitted variable bias is not likely to be a problem. In a related development, over time İŞKUR's geographic reach and capacity to deliver services increased. We control for this using year and month of termination, and branch location fixed effects.

İŞKUR oversees two other programs: Job Loss Compensation (JLC) paid to former employees of State owned enterprises subjected to privatization (in accordance with Law no. 4046 enacted in 1994), and Short-term Employment Allowance (SEA) paid to employees of distressed firms which have to cut back on regular operation schedules, even suspend them for a short period. SEA was first implemented in 2009 in response to the global crisis that spilled into Turkey. Under certain circumstances workers who collect JLC or SEA may subsequently also collect UI benefits. According to İŞKUR, over the 2010-16 period, there were a total of 55,724 JCL and SEA cases, a tiny fraction (about

1.6 percent) of all benefit recipients (about 3.4 million in total).[14]

3 Data and some stylized facts

3.1 Data

To implement our study, we requested a random sample drawn from İŞKUR records of UI recipients over the period 2010-16, stratified by year to assure accurate representation of differences in flows.[15] We were supplied with a data set with about 90 thousand individual records. A minority of UI recipients in our sample also collected JLC and SEA benefits. Unfortunately given the manner digital records were kept, it was not possible to disentangle days of UI payments from days of other types of payments. We therefore decided to exclude 213 records (0.24 percent of the sample) with PBDs not equaling the standard 180, 240 or 300.[16]

Since UI related PBD values overlap with possible values for JLC, we also excluded records with monetary benefits that exceeded the maximum calculated by the UI benefit formula, as well as those whose APP record did not match days of earned UI benefits. These two criteria together resulted in the exclusion of an additional 927 records (1.03 percent of the sample). Next, we excluded records liable to introduce endogeneity, such as separations involving force majeure clauses or court action (557), late applications that resulted in UI benefit duration cuts (4,930), and UI collection episodes that ended because

[14] A breakdown is given in the Appendix, Table A1. Remarkably share of successful UI applications went down from about 72 percent to 52 percent over the years. Our contacts at İŞKUR attribute this to an increased awareness of the existence of the UI program thanks to the expansion of their geographical reach, and imperfect knowledge of the eligibility requirements.

[15] Although benefit payments started in March 2002, our contacts at İŞKUR informed us that data management capacity and hence quality improved over time and advised us not to go back further in time.

[16] JLC is paid for a certain number of days (90, 120, 180 or 240). SEA support can last anywhere from 1 to 90 days. In some cases affected individuals are able to collect UI benefits on top of the JCL and SEA. It is also possible for the granted UI benefit duration to differ from the statutory value. To qualify for the full duration of the entitlement, the worker has to apply for UI benefits within 30 days of termination. Failure to do so may results in a reduction of benefit duration. As a result, it is impossible to distinguish days of legitimate UI payments from other types of payments (JLC and SEA). Finally, individuals who did not use their UI benefits fully in an earlier episode are able to collect the remainder when they become unemployed again, without fulfilling the premium contribution requirement. Since we focus on the first episode in an individual record, this does not create additional problems.

of retirement (663) or conscription (1601). Finally we dropped observations with missing information on pre-unemployment wages (51) or type of separation (161).

Our working sample contains 81,172 records (about 90 percent of those in the full data set). Our intended and actual annual working sample sizes and the number of individuals who qualified for UI benefits in a given year can be seen in the Appendix, Table A2. The results we present in the paper are from a working sample that represents about 2.5 percent of the population of all beneficiaries over the 2010-16 period.

In Table 1 the breakdown of our annual working samples by days of earned UI benefits is given. The shares are remarkably stable. Those who qualify for 240 days of benefits constitute the largest group (about 42-45 percent). Given the stringent requirement for maximum benefits, those who qualify for 300 days have the smallest share (about 19-22 percent). Those with the shortest potential benefit periods account for a little more than a third of the annual samples. Linkage between PBD to PPD is a common design feature of many UI systems (Tatsiramos and van Ours, 2014). Mechanically speaking this reflects actuarial concerns: those who made more payments to the insurance pool get to collect more. It also reflects the recommendations of theoretical papers on incentive compatible design under asymmetric information (see for instance Hopenhayn and Nicolini, 2009).

Table 1 about here

3.2 Stylized facts

Determining whether the Turkish system indeed gets around the incentive problems is a key concern of our paper. Towards that end additional information about benefit use is given in Tables 2 and 3. In Table 2 we see that about 59 percent of those collecting UI benefits used them fully. This fraction exceeds 64 percent among those who have the shortest benefit duration of 180 days. Although it drops substantially to 55 percent for those who have a PBD of 240 days, it is 57.6 percent when PBD is at its maximum value of 300. The non-linearity suggests that factors other than PBD, observed and unobserved, play a role in who gets to remain in the system until the very end.

Table 2 about here

In Table 3 the share of those who exhausted their benefits is given by year. We see that the fraction dropped by 2 percentage points (pp) between 2010 and 2011 but rose by 1-2 pp every year after that. The drop from 2010 to 2011 and the subsequent rise over time mimics the pattern in the headline unemployment rate, which is an estimate based on the monthly Household Labor Force Survey (HLFS) conducted by the Statistical Office of Turkey (Turkstat). When we dag further into the HLFS we discovered that the drop followed by the secular rise is also consistent with the changes in the fraction of individuals unemployed for 6 months or less, and 12 months or less. The link between labor market conditions and full benefit use suggests that behavior responds to economic conditions.

Table 3 about here

The administrative database has information on actual accumulated days of premium payments (APP), but the values are truncated at 1080 for those with PBD = 300. The raw data reveal some mild bunching at multiples of 30 which may be attributable to the practice of reporting to the SSA on a monthly basis. These are absent in the kernel smoothed density given in Figure 3. Note that the dips in the extreme tails of the figure are artifacts of truncation below 600 and above 1080. The distribution is remarkably uniform between (600, 900). The density increases after 900 and those who have 1000 days of employment or more account for nearly half the sample (48.4 percent). APP actually has a mass at 1080, where the value is truncated in the data set. Those who managed to get the full 300 days of benefits by virtue of being continuously employed during the three years that preceded termination account for about 20 percent. Unfortunately we do not know how much further their employment spells extend.

Figure 3 about here

Conveniently the data set includes the average monthly gross wage the worker earned during the last four months as recorded in the SSA database. Workers who end up using the UI system are drawn from the lower end of the wage distribution. This surely reflects differences in exposure to risk of termination. It could also be the case that given the cap on UI benefits, individuals whose earnings are in the upper deciles do not bother to apply when they lose their jobs.

Another advantage of using administrative data is the ability to pinpoint the timing of entry and exit from the UI system. Qualifying individuals start collecting UI benefits the day after termination. In Figure 4 the month and year of terminations are shown. Apart from capturing the secular rise in the use of the UI system, the histogram reveals that terminations are not evenly distributed over months. This is not surprising given what we know about seasonality of employment. What is striking is the apparent link between terminations and minimum wage hikes. Vertical lines in Figure 4 show the dates when minimum wage adjustments became effective during our observation window. In all 12 incidences shown the frequency of terminations before the hike exceeds the frequency after the hike, often by a very large margin. Since the magnitude of the minimum wage hike is announced in advance, employers are likely to react swiftly and make the extensive margin adjustments before the increases become effective, rather than later, when their severance pay obligations will be higher.

We thought the pattern of increased terminations in months 6 and 12 could be a consequence of the minimum wage hikes. Note, however, that terminations in June 2016 are also more frequent than those in July 2016, even though there was no midyear adjustment in that year. Also the difference between the peak in December 2015 and the reduced level in January 2016 is not nearly as extreme as what we would expect given the magnitude of the minimum wage hike (30 percent nominal, 22 percent real increase). Consultations with İŞKUR experts offered another explanations: Evidently employment contracts are more likely to end in June and December. Whether or not a connection with minimum wage hikes is there, potential calendar effects have to be taken into consideration. We know that the geographical reach and capacity of individual İŞKUR offices to deliver services improved over time. Nonetheless a sharp rise in benefit applications can still prove to be a challenge, and influence the rate of return to employment.

Figure 4 about here

The seasonality in the timing of returns to employment given in Figure 5 is also striking. Obviously the data are truncated at both ends, by virtue of our sampling design. The vertical lines once again mark the timing of minimum wage increases. Since maximum value of PBD is 300 days, the segment between November 2010 and October 2016 provides us with a non-problematic window. We see that returns to employment peak in the middle months between the lines: typically March and September. It is as if employers shy away from hiring soon after a minimum wage hike takes place, or before an anticipated hike. Note, however, that a similar seasonal pattern can be observed for year 2016, even though the minimum wage remained unchanged in the second half of the year. This and the similar pattern we saw in Figure 4 suggest that the seasonal patterns could be attributable to a horde of factors. From an economic perspective, controls for calendar time of exit capture differences in the economic environment. From a statistical perspective, they sharpen the statistical experiment used in identifying the covariate effects, and are likely to yield better estimates of the time-dependence in the hazard of exit to employment. The connection between minimum wage hikes and seasonality of exit from, and return to employment awaits further research.

Figure 5 about here

The distribution of the timing of exits over the days of the month shown in Figure 6 captures yet another dimension: Employment terminations typically come at the end of the month (left panel) and new spells of employment are most likely to begin on the first of the month (right panel). These patterns may be attributable to common practices used in hiring and firing, whether or not fixed-term contracts are used. In our hazard analyses we control for calendar effects in both entry to, and exit from the UI system via year, month and day effects.

Figure 6 about here

A well-known feature of data on UI benefit use is the concentration of exits near the exhaustion date. In the three panels of Figure 7 kernel density estimates of exit times are shown, conditional on PBD. We kept the axis scales the same to capture the differences realistically. The patterns corroborate the evidence from other contexts: benefit recipients wait until the bitter end before exiting. This feature is dubbed "the wake-up call" in the literature.[17] The wake-up call pattern is suggestive of moral hazard: when UI benefits are there, the incentive to search is lower.

Figure 7 about here

The kernel densities given in Figure 7 do not distinguish between exits to employment and censoring due to other forms of exit. The records of İŞKUR contain the reason for termination if exit takes place before benefits run out. The full list of reasons, and the distribution by reason are given in Table A.3 in the appendix. As described earlier, we already excluded individuals who were conscripted while employed, as well as those who exited to military service and retirement after qualifying for UI benefits. Payments of a little more than one percent of benefit recipients were terminated because they had taken up employment without informing İŞKUR. Since these terminations were triggered by the start of a new employment spell in the SSA records, we treated these cases as exits to employment.[18] The other types of exit observed in the data are mostly due to various sanctions imposed by İŞKUR (a total of 921 cases, about 1 percent of the sample), because the benefit holder did not report to a consultation meeting, refused or dropped out from training, refused a proposed job, or claimed not be ready to start a new job. A tiny minority exited due to temporary disability (68 cases) or death (13 cases).

Table 4 about here

In Table 4 we show the breakdown of the working sample after grouping the reasons for exit under four main headings. In our hazard analysis we focus on timing of returns to employment and treat the other types of exit as independent censoring mechanisms. Among those who are in our working sample, 48.6 percent exited to employment, and 50.1 percent failed to find a job before exhausting their UI benefits fully. Interestingly the share of job finders is highest (51.3 percent) among those with PBD = 240, and about

[17]By now it is well established that the exit rate from unemployment sharply increase near benefit termination. See, for instance, Meyer (1990) and Katz and Meyer (1990) for the U.S, Ham and Rea (1987) for Canada, Carling et al. (1996) for Sweden, Dormont et al. (2000) for France, Røed and Zhang (2002) for Norway, Lalive et al. (2006) for Austria, Van Ours and Vodopivec (2006) for Slovenia.

[18]It is well-known that some UI recipients try to trick the system by working informally. Sanctions are designed to prevent such action.

the same for UI recipients facing the shortest (PBD = 180) and the longest (PBD = 300) benefit horizons.

In Figure 8 we redraw the kernel densities of the timing of exits on the subsample of those who transited to employment. While the "wake-up call" feature is still present, it is not nearly as prominent as in Figure 7. In fact all three graphs display a bimodal shape, typical of behavior associated with the presence of heterogeneity: individuals who are considered to be most employable exit early, while others remain longer. An alternative explanation for the second peak near the truncation point is behavior noted by Boone and van Ours (2012) based on data from Slovenia: Some successful job searchers delay the start of the new spell of employment with the consent of the employer. The UI system in Turkey has a built in disincentive against such behavior: If a beneficiary exits to employment before exhausting the UI benefits, the unused portion will be available for use during a future unemployment spell, even if premia accumulated on the new job are below 600 days. Nonetheless the behavioral pattern is still there.

Figure 8 about here

3.3 Examination of the exit hazard to employment

In the remainder of this paper we study exits to employment (conditional on collecting UI benefits). We begin our investigation by graphing the Kaplan-Meier estimates of the survival function, $S(t)$. Using subscripts to denote the strata, a naive model that expresses exit behavior solely as a function of search effort which is assumed to decrease with PBD would suggest $S_{180}(t) < S_{240}(t) < S_{300}(t)$ when supports overlap.[19] On the other hand since PBD depends on the worker's premium payment record, it may signal worker quality. After all individuals who qualified for 300 days of benefits did not experience any unemployment spell in the three years that preceded termination, and should be in the best position to return to work. By similar reasoning individuals who had the most interruptions and could only qualify for 180 days of benefits, should face the hardest

[19] Although Mortensen (1977) comes to mind, he does not have a model that studies the behavior of individuals with different PBDs. However his Proposition 3 offers a relevant comparative static result: "In the case of a newly laid-off worker, the escape rate decreases with the maximum benefit period." (p. 512).

time. A simple model which makes job arrival rates an increasing function of PBD would suggest the reverse ordering: $S_{180}(t) > S_{240}(t) > S_{300}(t)$.

Figure 9 about here

Figure 9 plots the KM-estimates of survival functions obtained from samples stratified by PBD along with 95 percent confidence intervals. All three display curvature consistent with a declining hazard of exit. Vertical portions capture exits that take place just as UI benefits expire. In each stratum a significant fraction exhausts their benefits without a successful transition. We find that $S_{240}(t)$ is below the others where supports overlap, while $S_{180}(t) \approx S_{300}(t)$ for $t < 50$ (approximately), and $S_{180}(t) < S_{300}(t)$ for $t > 50$. The fact that $S_{240}(t) < S_{180}(t)$ for $t < 180$ and $S_{240}(t) < S_{300}(t)$ for $t < 240$ suggests that heterogeneity of the worker subpopulations and the incentives created by the UI system are simultaneously at work. A deeper understanding of exit behavior requires further analysis, surely one that takes observed heterogeneity into account, and preferably one that takes heed of unobserved heterogeneity created by sorting into the benefit subsamples as well.

Gender gaps constitute a salient feature of the labor market in Turkey. This being the case we examined survival functions by PBD and gender. Since the confidence intervals were extremely narrow, we excluded them from Figure 10. Predictably exit rates of women are lower than that for men. Arguably more remarkable is the fact that the slopes of the survival functions are indicative of interaction effects. As we discuss in section 5 below, we explored this possibility in our econometric analysis and found corroborating evidence.

Figure 10 about here

Separations are never easy. Some end up in court. In some circumstances use of UI benefits is delayed by events beyond the control of the individual. These complications are captured by a variable called case type, which classifies each case as normal, litigated, and force majeure. As pointed out in Section 3.1, we excluded cases that involved litigation and force majeur from our working sample to avoid possible biases.

In anticipation of the complications that can arise, the Labor code requires the firm to report the reason for dismissal. Termination types are listed in Appendix B along with some preliminary data analysis. We investigated whether the reason for separation had any bearing on exit rates using KM-estimates of survival functions by type of separation, conditional on PBD and gender. The graphs provide evidence that exit rates vary by termination type, and that interactions with PBD and gender are present (Figure B.1 in Appendix B). Simply put, in most of the panels employer initiated dismissals bring about the slowest exit rates. Insofar as the layoffs are connected to worker productivity, this finding is not unexpected. Less able workers lose their jobs more easily and have more difficulty to find a new one. Workers who lost their jobs because of external causes that are not related to individual worker productivity such as plant closing, downsizing or organizational changes, or workers displaced at the end of a fixed-term contract have better chances of finding a job. Besides potential differences in their ability, these last groups arguably have better information about the date of job termination and hence have a head start in job search.[20]

As we discuss in full detail in the results section, we initially included gender and termination type as explanatory variables in our hazard model, and tested the proportionality assumption. Since the assumption was rejected, the results from semi-parametric duration analyses reported below have been carried out under three-way stratification, by PBD, gender and termination type.

4 Model and econometric strategy

4.1 Statistical model of exits to employment

We measure waiting time (t) with respect to the start of UI benefit payments ($t = 0$). Let $Z_i(t)$ denote a finite dimensional *covariate process* that records the evolution of individual i's covariates. $Z_i(t)$ consist of a vector of labor market indicators $M_i(t)$ with time and location specific components, a time-invariant vector of personal characteristics

[20] Addison and Portugal (1987) provide evidence that advanced notification before displacement significantly reduces the unemployment duration. In our sample, for the vast majority of employer initiated separations, workers were terminated with an advanced notice. In Turkey this typically means that the employer paid a compensation, "payment in lieu of notice," for their advanced notice obligation, at the time of dismissal.

X_i (recorded at the time of the UI application), individual's health status $h_i(t)$ (= 1 if the individual died or became disabled, = 0 otherwise), and UI benefit parameters. The latter include a_i = maximum days of benefit payments the individual qualified for, b_i = monthly UI benefits, and sanction status $c_i(t)$(= 1 if the individual has been subjected to a sanction as of time t, = 0 otherwise).

Consider a short time segment dt and let $D_i(t) = 1$ if the individual is observed to exit the UI system during this interval, and $D_i(t) = 0$ otherwise. Let $H_i(t) = \{Z_i(s), D_i(s); 0 \leq s \leq t\}$ denote the individual's *history* until time t and assume that conditional on $H_i(t^-)$, the history up to time $t^- = t - dt$, observed and unobserved factors determine the exit probability through

$$\begin{aligned} Pr\{D_i(t) = 1|H_i(t^-)\} &= \lambda_i(t)dt \\ &= Y_i(t|h_i(t), c_i(t))\lambda_0(t|s_i)exp\left\{\alpha' M_i(t) + \beta' X_i + \gamma b_i\right\} dt \end{aligned} \tag{1}$$

where $Y_i(t|.)$ is the observation indicator that determines whether the individual is under observation (=1) or not (=0), $\lambda_0(t|s_i)$ denotes the baseline hazard conditional on being in stratum s_i, and α, β and γ denote the parameters to be estimated. In our empirical work we break $M_i(t)$ into two components, a time-constant component $M_{1i} \equiv M_{1i}(0)$ that records calendar time and location information at the time of termination ($t = 0$), and a time-varying component $M_{2i}(t)$ that evolves with calendar time.

The separability assumptions present in equation (1) resemble Cox's Proportional Hazard model. In particular covariates other than those that define the strata (s_i) enter the model multiplicatively, through a positive function, $exp(.)$ as in Cox (1972). However a major distinction is that the baseline hazard – which is an arbitrary function of time in Cox (1972) – is allowed to differ across strata as in Ridder and Tunalı (1999). Our stratum specific baseline hazard $\lambda_0(t|s_i)$ captures the time-dependence of exits from the UI system for the reference individual, who is characterized by the covariate vector $Z_{0i}(t) = \{M_i(t) = 0, X_i = 0, h_i(t), a_i, b_i, c_i(t)\}$. The time dependent observation indicator is related to the observables according to:

$$Y_i(t|h_i(t), c_i(t)) = \begin{cases} 1, & \text{if } h_i(t) = c_i(t) = 0 \\ \\ 0, & \text{else} \end{cases} \tag{2}$$

The censoring processes $h_i(t)$ and $c_i(t)$ are assumed to operate independently of $D_i(t)$ and are otherwise arbitrary.

Let $\bar{D}(t) = \sum_1^n D_i(t)$ and $H(t) = \{H_i(t), i = 1, 2, ..., n\}$ where n denotes the sample size. Assuming that the exit probabilities defined by equation (1) are independent across individuals, and the form of the conditional probability is not affected when we condition on the histories of all individuals in the sample, the conditional probability that individual i from stratum defined by s_i is observed to exit from the UI system, given that exactly one person is observed to exit at time t is given by:

$$\begin{aligned} Pr\{D_i(t) = 1|H(t^-), \bar{D}(t) = 1, s_i\} &= \frac{\lambda_i(t|s_i)dt}{\sum_j \lambda_j(t|a_i)dt} \\ &= \frac{Y_i(t|h_i(t), c_i(t)) \exp\{\alpha' M_i(t) + \beta' X_i + \gamma b_i\}}{\sum_j Y_j(t|h_j(t), c_j(t)) \exp\{\alpha' M_j(t) + \beta' X_j + \gamma b_j\}} \\ &= \frac{Y_i(t|h_i(t), c_i(t)) \exp\{\alpha' M_i(t) + \beta' X_i + \gamma b_i\}}{\sum_{j \in \mathcal{R}_s(t)} \exp\{\alpha' M_j(t) + \beta' X_j + \gamma b_j\}} \end{aligned} \tag{3}$$

where $\mathcal{R}_s(t)$ denotes the risk set that consists of the collection of individuals in stratum s who are under observation at time t. As mentioned in the data analysis section, we initially took s = PBD and did some specification testing. In light of our preliminary findings, we decided to stratify the data along three dimensions of observed heterogeneity: PBD $\times$ gender $\times$ termination type. Under our independence assumption we may assemble terms in the final line of (3) for all individuals in all strata and form the log-likelihood function

$$\mathcal{L}(\alpha, \beta, \gamma) = \sum_s \sum_{i=1}^{n_s} \left(\frac{exp\left\{\alpha' M_i(t) + \beta' X_i + \gamma b_i\right\}}{\sum_{j \in \mathcal{R}_s(t)} exp\left\{\alpha' M_j(t) + \beta' X_j + \gamma b_j\right\}} \right) \quad (4)$$

where s denotes the strata, and n_s denotes the number of individuals in stratum a.

This log-likelihood function closely resembles the partial likelihood function introduced by Cox (1975) and can be estimated by conventional maximum likelihood methods. The only difference is that the conditional probabilities of exit are calculated over members of a given stratum, rather than the whole sample. Ridder and Tunalı (1999) dubbed the estimator that maximizes (4) the Stratified Partial Likelihood Estimator (SPLE) of the parameter vector $\theta = (\alpha', \beta', \gamma)'$ and showed that a Hausman-Dubin-Wu type specification test can be used to test if the baseline hazards are the same across the strata. They also showed that the generalized residuals can be exploited as in Breslow (1974) to estimate the stratum specific cumulative baseline hazards nonparametrically. Conveniently all the computational steps can be achieved using STATA.

In our case multiple exits can occur during the limited time window that benefits apply to, something that is ruled out in (3). Kalbfleich and Prentice (1980: 76-8) discuss the problem and argue that when the number of multiple exits is small relative to the size of the risk set, terms such as (3) serve as good approximations to the true likelihood that uses permutations. In fact better approximations suitable for our data configuration have been introduced by Breslow and Effron, and are part of STATA.

The first part of our empirical work is devoted to the examination of the SPL estimates of the parameters and the cross-strata differences in the non-parametric estimates of the stratum specific cumulative baseline hazards. As we establish in the results section, there is much to be gained from this exercise. However the estimates do not lend themselves for causal interpretations. In the second part we turn to quasi-experimental analyses that help us assess concerns about moral hazard more convincingly. In the next two subsections we discuss our identification strategies.

4.2 Dif-in-dif on minimum wage changes

Turkey has a national minimum wage (MW) policy which sets the floor for wages payable to workers registered with the social security administration. The MW is set by a commission that consists of representatives from the Government bureaucracy, the largest confederation of worker unions (Türk-İş) and the largest confederation of employer unions (TİSK). The commission meets in December of each year and determines the frequency and timing of MW increases. During our time window rises took place twice (on January 1st and July 1st) in years 2010-15 and only once (on January 1st) in 2016.

Our experimental design exploits the timing of MW changes and the link between the MW and the benefit level illustrated in Figure 2. We confine the test to the subsample of UI beneficiaries who were dismissed in the month before, or after the MW increase. Individuals who are dismissed in the month before the adjustment constitute the control group. Those dismissed in the month following the adjustment make up the treatment group. The treatment group is broken down further by treatment intensity, as illustrated in Figure 11. The new figure resembles Figure 2, except the positively sloped segment is extended and the horizontal segment is shifted to reflect the impact of the MW increase on the benefit level. By denoting the old and new levels of the gross MW respectively by MW_0 and MW_1, we are able to quantify how benefits adjust as a function of the (pre-unemployment) wage (calculated as the average gross monthly wage over the four months that preceded termination).

Figure 11 about here

The benefit levels of individuals whose wages are below two times the old gross minimum wage ($W < 2MW_0$) are not affected by the MW adjustment. Those with wages above the first threshold and below the second ($2MW_0 < W < 2MW_1$) experience a benefit gain of $b_1(W, MW_0) = 0.8(W - MW_0)$. Those with wages above the second threshold ($W \geq 2MW_1$) capture the largest absolute benefit increase, $b_2(MW_0, MW_1) = 0.8(MW_1 - MW_0)$. In what follows we refer to the three treatment groups generated by the adjustment by $T0, T1$ and $T2$ respectively. We use the same scheme to break the control group into three and denote them by $C0, C1$ and $C2$. Since the benefit gain for group $T0$ is $b_0 = 0$, there can be no treatment effect in this group. This group allows us to tease out time trends. Our approach is similar in spirit to that in Carling et al. (2001), where policy induced changes in the replacement rate motivate the dif-in-dif analysis.

The hazard specification is similar to that used in (1):

$$\lambda_i(t|s_i)dt = \lambda_0(t|s_i)exp\{\alpha' M_i(t) + \beta' X_i + \gamma b_i + \Sigma_g \delta_g D(g)\} \tag{5}$$

In the empirical work reported in section 5 we initially ignored the heterogeneity in treatment captured by the term γb_i and used dummies to classify each individual into control or treatment groups, defined via:

$$D_i(g) = I(i \in g), g = C1, C2, T0, T1, T2; \tag{6}$$

where $I(.)$ denotes the indicator function. Control group $C0$ serves as the reference group. In our more elaborate specification we included the average pre-unemployment wage (W in Figure 11) to capture heterogenous treatment effects. As in the first part, we rely on the SPLE.

4.3 Regression discontinuity around APP thresholds that determine PBD

Here the relevant contrast is that between groups of individuals who are just below and just above the statutory thresholds for increased benefit duration. We engage in two experiments:

RD900: Focuses on the threshold of $APP = 900$ that separates individuals with 180 and 240 days of benefits. The treatment effect is defined as:

$$T900 = \begin{cases} 1, & \text{if} \quad 900 \leq APP \leq 900 + d_1 \\ 0, & \text{if} \quad 900 - d_0 \leq APP \leq 900 \end{cases} \tag{7}$$

The results reported in Section 5.2 are based on $d_0 = d_1 = 50$.

RD1080: Focuses on the threshold of $APP = 1080$ that separates individuals with 240 and 300 days of benefits. Since the data on APP is truncated at 1080, we are unable to preserve symmetry in our RD window. We use:

$$T1080 = \begin{cases} 1, & \text{if} \quad APP \geq 1080 \\ 0, & \text{if} \quad 1080 - d_0 \leq APP \leq 1080 \end{cases} \tag{8}$$

to identify the treated. To obtain the results reported in Section 5.3 we took $d_0 = 40$.

In the standard regression framework this contrast is a comparison of averages. Since we are in a duration context and supports for individuals with different PBD levels are different, we need a different strategy for teasing out the causal effects. Consider the first treatment. If the change in PBD has no effect on the exit hazard, for a given sex (male, female) and ttype (A or C, B, D and E) combination,

$$\lambda_0 \ (t|T900 = 0, \text{sex, ttype}) = \lambda_0(t|T900 = 1, \text{sex, ttype}) \text{ for all } 0 < t < 180$$

In other words, baseline hazards which capture the time dependence are the same. Under the null of no effect, the graphs of the cumulative baseline hazards for $PBD = 180$ and $PBD = 240$ conditional on sex and termination type pairs should be indistinguishable over their common support. Once again SPLE will be used. Graphs of the non-parametric estimates of the cumulative hazards will be used to conduct and informal test.[21]

[21] We will conduct a formal test following the logic of "step 3" in Ridder and Tunalı(1999) in time for the conference.

5 Results

5.1 Reduced form analysis of exit rates to employment

In the first part of our empirical investigation, we exploited the full cross-section variation in our data set in effort to understand the determinants of the hazard of exit to employment, keeping a search-theoretic model and the institutional framework in mind. In our specification search we entertained a sequence of nested models (see Table 5). We also examined the estimated cumulative baseline hazards to glean the residual effect of unobserved heterogeneity by stratum. Initially we stratified on PBD alone, to take into account the differences in support. As we established in Section 3.3, PBD can affect exit hazards via multiple routes. By using our rich set of covariates sequentially, we hoped to understand their roles as observables, and also how the residual unobservable heterogeneity is manifested at each iteration. In particular we wanted to discover whether a strict ordering in the time-dependence functions could be achieved by isolating additional variation using observables, so that the role played by PBD could be pinned down. This did not turn out to be the case.

We used two covariates (termed search variables below) to tease out incentive effects: Real UI benefit per month (100TL) and real average pre-unemployment wage (100TL). From a search perspective, holding the previous wage constant, if increases in UI benefits slow down rate of exit, we might be concerned with moral hazard. Contents of the other variable groups identified in Table 5 are straightforward. We used them to control for individual characteristics available in the administrative data set, variation in local labor market conditions and İŞKUR's ability to provide services.

Table 5 about here

In Table 6 we report various fit statistics for the models we estimated. Tests of joint significance of the newly included variables shown in the LR test column revealed that the groups identified in Table 5 all had a say on the outcome. Results under the Wald test column revealed that variables entered earlier continued to be jointly statistically significant. In each specification we tested the validity of the PH assumption.[22]

[22] We used STATA's phtest command which is based on Schoenfeld residuals. The last model we used

Table 6 about here

SPLE estimation results are given in Table A.4). Age turns out to be an important determinant of exit rates. Linear, quadratic and cubic terms are all statistically significant in all specifications. Figure (12) plots the age distribution of our sample (left) and age profile of exit hazard to employment for the Model 7 (right). Workers between 25 and 40 years constitute the bulk of UI recipients. Younger workers usually do not satisfy the eligibility conditions and older workers have lower job turnover rates. The exit rate - normalized to 1 for 25 year old workers - has also an expected hump shape with a peak at 31 years. Lack of experience and related training costs probably slow down the exit rate of younger workers. Several potential reasons can also be cited for the low job finding rates of older workers. For instance, after a certain age it is more difficult to change occupation or industry due to higher job specific human capital. Skill obsolescence stemming from technological changes is also more likely at older ages. Arguably, for workers close to retirement age, returns to search and accordingly the search intensity are lower because of the shorter expected job duration. By the same token, firms will be reluctant to offer a job or give training to workers above a certain age as they will hardly recoup their investment.

Figure 12 about here

In the interest of conserving space and reader patience, we refrain from a detailed discussion of our findings. Remarkably all specifications with the search variables yielded similar magnitudes of the coefficient estimates. Both had statistically significant, but small positive marginal impacts on exit hazards. This finding runs against the moral hazard concern.

In all our specifications the non-parametric estimates of the cumulative baseline hazard suggested differences in the rate of exit by PBD. In Figure 13 we report the findings from a rich model (Model 7) stratified only by with PBD. Remarkably individuals with PBD = 240 have the fastest rate of exit. Rates of exit for PBD = 180 and 300 groups are the

in our specification search included time-varying indicators of the calendar time of exit to employment. This model taxed our computational resources. We decided to forego the tests of the PH-assumption.

same until about 100 days but diverge afterwards. The fact that individuals with PBD = 300 have the slowest rate of exit offer some support for our moral hazard concern. This pattern held up when we stratified further, conditional on a given sex and termination type. To sort things out, we turn to quasi-experiments.

Figure 13 about here

Predictably global tests of the PH assumption resulted in rejections in all models. We observed that the male dummy and some of the termination type dummies had the largest individual PH-test statistics. From our data analytic examination of exit hazards (reported in Section 3.3), we already knew that gender could be another potential dimension of stratification. We also argued that termination type might signal differences in re-employment potential and found corroborating evidence in cross-tabulations of probability of exhaustion of UI benefits by PBD and type. The PH-test results convinced us to include termination type as the third dimension of stratification. There were several other coefficients – in particular some province and economic activity dummies – for which the PH-test statistic had a p-value of 0.01 or smaller. Inspection revealed that this finding was attributable to small cell sizes. Intuitively when cells contain few observations, unobserved heterogeneity is more likely to be manifested in the form of evidence against the PH assumption.

5.2 Dif-in-dif experiment on minimum wage changes

Once again we relied on the SPLE to obtain the estimates of the parameters of the hazard of exit to employment and the same general estimation strategy. To recapitulate, exits from the UI system due to sanctions or health reasons were treated as independent censoring events. Data were stratified three ways, by combinations of PBD, sex and termination type. We excluded individuals whose terminations resulted in a court case or administrative decision, and did not fall under the types A-E identified in the İŞKUR record.

Since the DD working sample is about one-third of the full working sample, we adopted a more conservative model specification strategy. We first estimated a model without any covariates (model (1)). We subsequently added demographic variables (model (2)), indicators for sector and economic activity (model (3)), for İŞKUR office (model (4)), for calendar time of termination (model (5)).[23] We also estimated the heterogenous treatment effect version of the last model, which included the average pre-unemployment wage. Since it had a coefficient that was statistically significant different from zero, we report the latter version in Table 7.[24]

The estimates used in the DD calculations are reported in the top panel of Table 7. The bottom panel identifies the indicators used in each model. To conserve space we excluded the parameter estimates. LR tests reveal that groups of added indicators and variables are jointly statistically significant. To provide some comparison between the findings on the DD sample and the full sample we included the parameter estimates for the demographic characteristics and previous job experience.

Comparison of the results in columns (1) and (2) reveal that heterogeneity within our experimental groups 0, 1 and 2 are important. Estimated magnitudes of the treatment effects T0, T1 and T2 are quite robust in models (2)-(5). They reveal much slower exit rates relative to the C0 group. Differences among control groups are not present in models (1)-(4) but emerge in model (5).

Table 7 about here

Before we examine the results from the dif-in-dif analysis (reported in Table 8), it's worth remembering that members of the $T0/C0$ contrast are unaffected by the minimum wage adjustment. This contrast reflects the effect of being terminated one month later, albeit for a group with the lowest wages ($MW \leq W \leq 2MW$). This effect captures the trend in our short window. Our DD approach assumes that individuals in the $T1/C1$ and

[23]We are yet to estimate the computationally demanding version with time-varying exit times. Hope to have them by the conference.

[24]The reference individual in model (1) is someone in the control group C0. Additional markers for the reference individual are respectively being unmarried, illiterate in model (2), having worked in a job classified under economic activity code A in model (3), İŞKUR office in province 1 (Adana) in model (4), termination in January 2010 in model (5).

$T2/C2$ contrasts have the same trend, the so-called common or parallel trend assumption. Adapting Abadie's (2005) terminology, it means that if it were not for the minimum wage increase, average outcomes in the $T1/C1$ and $T2/C2$ contrasts would have been the same as that in the $T0/C0$ contrast.

In our duration context average outcomes are captured by the baseline hazards which are constrained to be the same for individuals in the same stratum (defined by PBD, sex and termination type), but different across strata. Thus our common trend assumption is a conditional one. In our PH model, with $C0$ as the reference group, treatment and control indicators $T0 - T2$ and $C1 - C2$ move the hazard of exit up or down by a proportional amount, a magnitude that remains constant over the relevant time window, which varies by PBD. We control for differences in the local labor market conditions by including indicators of province (or İŞKUR office handling the case), and calendar-time of termination (or exit). We also account for individual level heterogeneity via human capital (education, age, previous wage, and length of previous employment spell) and marital status variables which may respectively impact offer arrival rates and search intensity.

Table 8 about here

Results from the dif-in-dif analysis are reported in Table 8. Hazard parameter estimates on the treatment dummy T0 serve as estimates of the common trend, shown in the row for D0. In models that have controls these are all negative, sizable, and of similar magnitude. First differences reported in the D1 and D2 rows are also negative, but smaller in absolute magnitude. Consequently the dif-in-dif estimators of the UI benefit surge, DD10 and DD20 are positive. Remarkably the latter are statistically significant in models with controls, and imply 13-14 percent faster exit. As mentioned earlier, we repeated the exercise with the more appealing but also computationally taxing time-varying calendar-time controls and found weaker positive effects. (We left these out in the interest of conserving space.) Taken at face value, the dif-in-dif analysis on the full sample is not indicative of moral hazard problems.

Results we reviewed rest on a strong parallel trends assumption. Relaxation of this assumption would be tantamount to allowing interactions between the indicators, year dummies and the baseline hazards, so that the effect will vary over time. Technically this can be done by breaking the time window into intervals (months, weeks), but there will be too many parameters to deal with. Another alternative is to interact treatment and control indicators with a low order polynomial in time. We follow a different strategy and restrict our working sample to individuals who were terminated during the month before, and after the minimum wage hike in 2016. This was the largest in history, a 30 percent increase in nominal terms. Since labor market conditions on either side are likely to be similar, save the increase in MW, the assumption that the trend captured by the C0/T1 contrast captures the common trend is a reasonable one.

Replacement rates calculated for individuals included in our subsample are plotted in Figure 14. Vertical distances of the nonlinear segments define the treatment effects. The magnitude at the kink is a whooping 0.1 increase in the RR, 25 percent higher than the original.

Figure 14 about here

As we assembled this version of our paper, we discovered that the dif-in-dif exercise on the 2015/2016 minimum wage hike was done on the wrong sample. Thus the results reported in the final columns of 7 and Table 8 are incorrect. We will have the correct versions ready by the conference.

5.3 Regression discontinuity experiments around APP thresholds that define PBD

In our RD regressions, we relied on SPLE and the same specification as that used in model 5 of the DD experiment, reported in Table 7. Building on lessons from our earlier work, we stratified the RD subsamples in three dimensions: PBD $\times$ gender $\times$ termination type. SPLE results are reported in Table A.5. As discussed in some detail in section 3.3, our identification strategy is novel, in that we look for evidence of discontinuities (differences by PBD) at all points of their common support. We achieve this by examining the non-parametric estimates of the cumulative baseline hazards for the PBD groups on either side of the APP thresholds, conditional on gender and termination type. We have a total of 16 graphs, which have been collected in appendix A, in groups of four. Tables A.6 and A.7 included in the appendix contain information on sample sizes in each stratum.

We begin by reviewing the graphs for RD900, staring with males who constitute the larger subsample (about 6,500 total observations). Starting with the top left panel in Figure A.1, we have the graph for termination type A or C, followed by termination type B. The next row contains the graphs for termination types D (left), and E (right). A first glance at the graphs suggest that the only subsample that contains strong evidence against the null of equality of baseline hazards is males of termination type B (216 observations). This group is peculiar in that the worker initiates the termination, because of what may be called humiliating conduct by the employer, described in the labor code via concrete examples. The fact that individuals in the higher PBD group have slower hazards of exits over the range where supports overlap is suggestive of moral hazard.

In the case of males, one case out of 4 provides strong (graphical) evidence of moral hazard. Turning to females (about 4000 in total), we see that three of the graphs assembled in Figure A.2 are quite noisy, by virtue of smaller subsample sizes. The only graph that offers strong evidence in favor of moral hazard is that in the lower left corner, obtained on the subsample for termination type D. The workers in this group have non-renewable fixed-term contracts. Again, evidence in favor of moral hazard comes from one out of 4 cases studied.

Our RD1080 experiments were conducted on larger subsamples, about 24,000 observations in the case of males and 9,000 in the case of females. The results for males collected in Figures A.3 offer the strongest evidence assembled so far, in favor of moral hazard. Cumulative baseline hazards for the PBD = 240 group is below that for the PBD = 180 group except for some partial overlap in two of the panels. Turning to the results for females in Figure A.4 and proceeding in similar manner, we may conclude that three of the panels contain evidence in favor of moral hazard. In sum, we have substantially stronger evidence that longer benefit duration causes slower exit rates to employment when the contrast is between individuals who have near perfect ($1039 < APP < 1080$) and perfect employment records (APP = 1080).

Before we seal the case, it helps to lean on our search theoretic motivation some more.

Moral hazard emerges when workers who face longer benefit durations lower their search intensity. This assumes that the arrival rate offers on either side of the discontinuity is the same. Can we confidently say this is the case? We think not. All we know about the PBD = 300 group is that they had a perfect employment record (APP = 1080) in the three years that preceded termination. In our RD1080 subsample this group has about 17,000 members, 17 times the number of observations in nearby cells (APP = 1078, 1079). In the absence of additional information on their employment histories, we might speculate that some of the individuals in the PBD = 300 group have reached the tail end of careers in the same company, holding positions that are no longer available elsewhere in the labor market. If this is the case, the likelihood of finding a similarly remunerative job is very low. Assuming that pre-unemployment wages serve as an anchor for the reservation wage, exit rates to employment will be substantially lower.

As a final piece of speculative evidence, it is worth mentioning that workers who are terminated collect severance pay which is proportional to tenure. The amount is substantial, equaling one month's salary per year served (but capped at some level, which is attainable at most by a handful of individuals who are in the UI system). This means that many of the individuals in the PBD = 300 group may not have liquidity problems and can finance longer periods of search. Since we do not have access to the social security records of the individuals in our UI sample, we are unable to pursue the leads.

6 Conclusion

The UI system in Turkey was established in 1999 just as the economy was sliding into a massive crisis, and huge government deficits were the order of the day. It is financed by contributions from employed workers, employers and the government to an Unemployment Insurance Fund, which is supervised by the national employment agency, İŞKUR. Compared to the older UI systems Europe, it has one of the lowest replacement rates as well as low benefit duration, and strict eligibility conditions. Remarkably the UI Fund has been in surplus every year and has accumulated a very healthy sum, which reached 151 billion TL (about 30 billion USD) as of the end of 2018. With the benefit of hindsight, it is possible to argue that concerns about maintaining the system raised at the time of founding, were far-fetched. In fact at the depth of the global crisis in 2008 when the non-agricultural unemployment rate reached 16.5 percent, those collecting UI benefits was barely twenty percent. This statistic and the accumulated surplus created some stir at the time, but there has been no talk about relaxing eligibility requirements, or increasing benefits since. Arguably the fact that fifty percent of workers on UI benefits end up using them fully may have quelled the appetite for a more generous system.

In this paper we use micro data in the form of random samples from flows into İŞKUR's UI data base and undertake a thorough evaluation of exit times to employment, under the guidance of search theory and a large body of empirical evidence accumulated from around the world. We exploit the design features of the UI system (namely variations in the duration and amount of the unemployment benefit) to create various statistical experiments. We fail to find consistent evidence that points at incentive problems. Where we find some support in favor of moral hazard, we argue that alternative explanations are equally (if not more) plausible.

A defining feature of our empirical investigation is our reliance on a variant of the Cox-Proportional Hazards model which allows stratification of the data along multiple observable dimensions. What makes our model attractive is our ability to define the baseline hazard as an arbitrary function of time at the stratum level. We are able to recover non-parametric estimates of the stratum specific baseline hazards after partial likelihood estimation of the covariate effects. In our simplest model we stratify by potential benefit duration (PBD), which enables us to detect differences in the time dependence functions of the exit hazards over common supports. Notably we find that increases in unemployment benefits is associated with faster rather than slower exits, holding a long list of individual and location specific covariates (including time-varying controls for calendar time). Individuals with a PBD of 240 days exit faster than the others, ahead of those with PBDs of 180 and 300. Although the evidence from the first part of our empirical work is inconclusive, it allows us to engage in specification checks. Based on these we relax the PH-assumption further, and stratify by gender and type of termination, observables that may signal differences in re-employability.

In the second part of our empirical work we exploit quasi-experimental designs that can be handled by the same statistical model used in the first part. We begin our search for causal effects with a DD analysis that exploits exogenous variation in benefits induced by changes in the minimum wage (MW). Monthly UI benefits increase with the pre-unemployment wage, but are capped at 80 percent of the gross monthly MW. In our time window the adjustments typically took place twice a year. Moreover some of the MW hikes were quite substantial. For instance, in January 2016 the MW increased by almost 30 percent. Accordingly, there was a noticeable difference between the benefit levels of observationally similar workers who lost their jobs a few days apart. The link between UI benefits and the MW allows us to define three ranges over which control and treatment groups can be defined. Since UI benefits of individuals in the first range are not affected by the MW increase, the time trend in exit rates can be identified. This allows us to compare the effects of treatment for individuals in the other two ranges with those found in the first. In our DD analysis increased benefits ushered in faster rather than slower exits, and indicated hat there was no moral hazard.

Next we turn to an RD design that exploits another feature of the UI system, the connection with potential benefit duration (PBD) and accumulated premium payments (APP). Two sharp thresholds map APP to PBD. As a result observationally similar workers who have small differences in their APP values can end up with different PBD values. We use the discontinuity at APP = 900 that increase PBD from 180 to 240 days, and the discontinuity at APP = 1080 that raises PBD from 240 to 300 days to seek evidence in favor of moral hazard. The novelty of our testing approach is our ability to conduct it at all points of the shared supports, at the same time allowing for differences in the supports. We achieve this by comparing the non-parametric estimates of the cumulative baseline hazard. Presently all we have are graphical tests, but we know how to formalize our procedure. Our RD analysis around APP = 900 revealed mild evidence in favor of moral hazard in two small subsamples among the eight we delineated. That around APP = 1080 revealed stronger evidence, in six out of eight subsamples. We looked for alternative explanations of the pattern of slower exits of the PBD = 300 group, who had a prefect employment record as of the time of termination. One plausible explanation is that many in this group are individuals who are fired because of technological changes that render their jobs redundant. We plan to pursue this explanation in future work.

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Tables

Table 1: Breakdown of the working samples by days of earned UI benefits

Year	Potential Benefit Days (PBD)			
	180	240	300	Total
2010	3,145	3,835	1,745	8,725
	36.0	44.0	20.0	100.0
2011	3,134	3,842	1,915	8,891
	35.3	43.2	21.5	100.0
2012	3,336	3,753	1,908	8,997
	37.1	41.7	21.2	100.0
2013	3,340	3,893	1,815	9,048
	36.9	43.0	20.1	100.0
2014	4,976	5,948	2,546	13,470
	36.9	44.2	18.9	100.0
2015	4,913	6,028	2,650	13,591
	36.1	44.4	19.5	100.0
2016	6,581	8,336	3,533	18,450
	35.7	45.2	19.1	100.0
Total	29,425	35,635	16,112	81,172
	36.3	43.9	19.8	100.0

Source: İŞKUR and our own calculations

Table 2: Number and fraction of UI recipients who exhausted their benefits broken down by PBD

	Exhausted		
PBD	0	1	Total
180	10,441	18,984	29,425
	35.5	64.5	100.0
240	16,017	19,618	35,635
	44.9	55.1	100.0
300	6,829	9,283	16,112
	42.4	57.6	100.0
Total	33,287	47,885	81,172
	41.0	59.0	100.0

Source: Own calculations

Table 3: Fraction of UI recipients who exhausted their benefits broken down by year

	Exhausted		
PBD	0	1	Total
2010	43.4	56.6	100.0
2011	45.5	54.5	100.0
2012	44.1	55.9	100.0
2013	42.4	57.6	100.0
2014	40.5	59.5	100.0
2015	38.9	61.1	100.0
2016	37.5	62.5	100.0
Total	41.0	59.0	100.0

Source: Own calculations

Table 4: Main recorded reason for exit from the UI system broken down by PBD, number (column share)

Exit reason	PBD = 180	PBD = 240	PBD = 300	Total
Employment	13,581	18,298	7,587	39,466
	(46.2)	(51.3)	(47.1)	(48.6)
Sanction	324	401	196	921
	(1.1)	(1.1)	(1.2)	(1.1)
Health	32	40	9	81
	(0.1)	(0.1)	(0.1)	(0.1)
Benefit exhaustion	15,488	16,896	8,320	40,704
	(52.6)	(47.4)	(51.6)	(50.1)
Total	29,425	35,635	16,112	81,172
	(100.0)	(100.0)	(100.0)	(100.0)

Source: İŞKUR and our own calculations

Table 5: Estimation Strategy

Model	Search variables	Demographic variables	Sector and economic activity	İŞKUR office dummies	Year, month and day of termination	Month/Year of exit to employment
1	Y	No	No	No	No	No
2	Y	Y	No	No	No	No
3	Y	Y	Y	No	No	No
4	Y	Y	Y	Y	No	No
5	Y	Y	Y	Y	Y	No
6	Y	Y	Y	Y	Y	No
7	Y	Y	Y	Y	Y	Y

Table 6: Model fit statistics

Model	Log-likelihood	Change	No. of variables	LR test Chi-sq (df)	PH test Chi-sq (df)	Wald test Chi-sq (df)
0	-393555,87	-	0	-		-
1	–393424,97	130.9	2	261.8 (2)	12.72 (2)	-
2	-390840.29	2584.68	15	5169.36 (13)	244.68 (15)	161.98*** (2)
3	-390314,83	525,46	34	1050.92 (19)	499.81 (34)	3936.73*** (15)
4	-389794,14	520,69	179	1041.38 (145)	739.88 (179)	5402.32*** (34)
5	-389339,91	454,23	226	908.46 (47)	988.38 (226)	6781.51*** (179)
6	-388792,7	547,21	229	1094.42 (3)	1057.31 (229)	6907.71*** (226)

Table 7: Dif-in-dif analysis, SPLE (PBD, sex, ttype)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6 2015-2016**
T0	-0.1220***	-0.1215***	-0.1090***	-0.0964***	-0.3974***	-1.8174***
	(0.0199)	(0.0200)	(0.0200)	(0.0202)	(0.0264)	(0.0921)
C1	-0.0610	-0.0653	-0.0806	-0.1133*	-0.1509**	-0.0807
	(0.0641)	(0.0642)	(0.0643)	(0.0650)	(0.0669)	(0.1210)
T1	-0.1671*	-0.1651*	-0.816**	-0.1909**	-0.5065***	-1.7937***
	(0.0880)	(0.0882)	(0.0882)	(0.0886)	(0.0924)	(0.1672)
C2	0.0113	0.0015	0.0011	0.0010	-0.1937***	-0.0689
	(0.0319)	(0.0327)	(0.0329)	(0.0335)	(0.0468)	(0.1634)
T2	-0.0230	-0.0265	-0.0104	-0.0032	-0.4622***	-1.9130***
	(0.0360)	(0.0369)	(0.0370)	(0.0377)	(0.0528)	(0.1584)
Demographics						
age		0.1940***	0.1786***	0.1851***	0.1867***	0.0474
		(0.0373)	(0.0374)	(0.0374)	(0.0382)	(0.1019)
agesq100		-0.4528***	-0.4140***	-0.4310***	-0.4357***	-0.1028
		(0.0963)	(0.0965)	(0.0965)	(0.0988)	(0.2673)
agecu10000		0.3208***	0.2883***	0.3019***	0.3075***	0.0528
		(0.0808)	(0.0810)	(0.0809)	(0.0831)	(0.2278)
married		0.0095	0.0084	0.0096	-0.0005	0.0079
		(0.0225)	(0.0225)	(0.0228)	(0.0229)	(0.0586)
divorced		0.1260**	0.1295***	0.1342***	0.1161**	0.2956**
		(0.0490)	(0.0490)	(0.0493)	(0.0494)	(0.1274)
widow		0.2392	0.1908	0.1726	0.1832	-0.5299
		(0.1592)	(0.1595)	(0.1606)	(0.1604)	(0.7269)
litnodip		-0.1004	-0.0671	-0.0502	-0.0633	0.0169
		(0.1521)	(0.1522)	(0.1535)	(0.1536)	(0.3461)
primary		0.1815	0.1866	0.1484	0.1429	0.1173
		(0.1141)	(0.1141)	(0.1148)	(0.1150)	(0.2308)
highsch		0.1265	0.1439	0.1035	0.0805	0.0754
		(0.1147)	(0.1147)	(0.1154)	(0.1156)	(0.2330)
univassoc		0.1071	0.1224	0.0761	0.0483	-0.0420
		(0.1194)	(0.1195)	(0.1202)	(0.1203)	(0.2463)
univ4yr		0.1477	0.1303	0.0976	0.0526	0.0004
		(0.1168)	(0.1173)	(0.1180)	(0.1183)	(0.2424)
msphd		0.2561	0.2145	0.1850	0.1148	0.0766
		(0.1662)	(0.1665)	(0.1673)	(0.1681)	(0.4314)
Previous wage						
Roldw100					0.0110***	0.0036
					(0.0021)	(0.0059)
Controls - Indicators for						
Sector and economic activity	No	No	Yes	Yes	Yes	Yes
İŞKUR office dummies	No	No	No	Yes	Yes	Yes
Year, month and day of termination	No	No	No	No	Yes	Yes
Observations	25,453	25,453	25,453	25,453	25,453	4,383

Standard errors in parentheses
p***<0.01, p**<0.05, p*<0.1

Table 8: Dif-in-Dif analysis continued:
The effect of boost in UI benefits via exogenous minimum wage chages
Estimation results are reported in Table 7

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6 2015-2016**
C0	0	0	0	0	0	0
T0	-0.12***	-0.12***	-0.11***	-0.10***	-0.40***	-1.81***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.09)
D0 = T0 - C0	-0.12***	-0.12***	-0.11***	-0.10***	-0.40***	-1.81***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.09)
C1	-0.06	-0.06	-0.08	-0.11*	-0.15**	-0.08
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(-0.12)
T1	-0.17*	-0.16*	-0.18**	-0.19**	-0.51***	-1.78***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.17)
D1 = T1 - C1	-0.11	-0.10	-0.10	-0.08	-0.36	-1.70***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.19)
DD10 = D1 - D0	0.01	0.02	-0.01	0.02	0.04	0.11
	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.18)
C2	0.01	0.001	0.0003	-0.0007	-0.20***	-0.06
	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.16)
T2	-0.02	-0.03	-0.01	-0.004	-0.46***	-1.90***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.16)
D2 = T2 - C2	–0.03	-0.03	-0.01	-0.005	-0.26***	-1.84***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.15)
DD20 = D2 - D0	0.09*	0.09*	0.10**	0.10**	0.14**	-0.03
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.15)
Observations	25,453	25,453	25,453	25,453	25,453	4,383

Standard errors in parentheses
p***<0.01, p**<0.05, p*<0.1

Figures

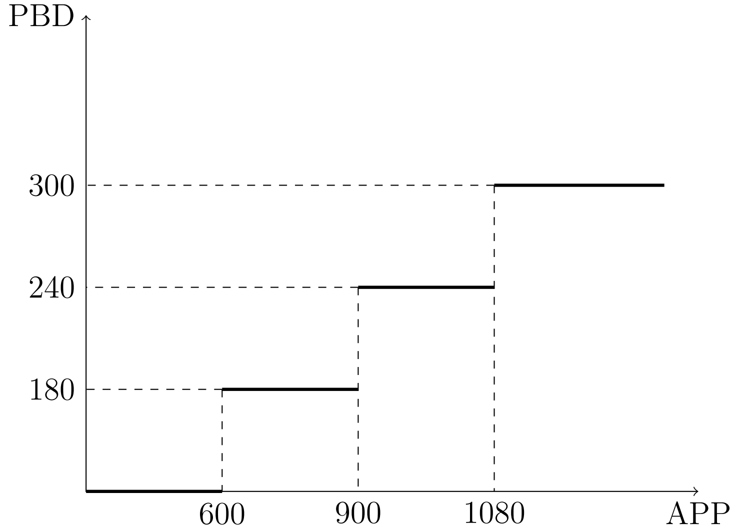


Figure 1: Accumulated Premium Payments (APP) and Potential Benefit Duration (PBD)

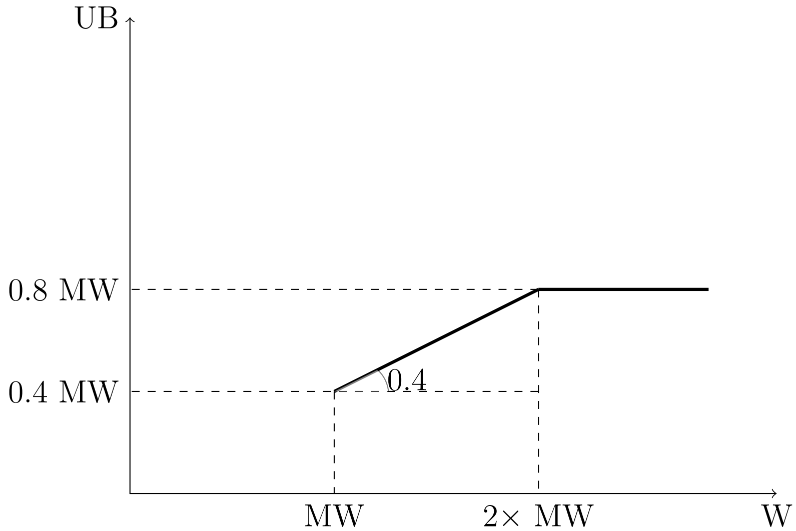


Figure 2: Gross Monthly Wage (W), Gross Minimum Wage (MW) and Unemployment Benefits (UB)

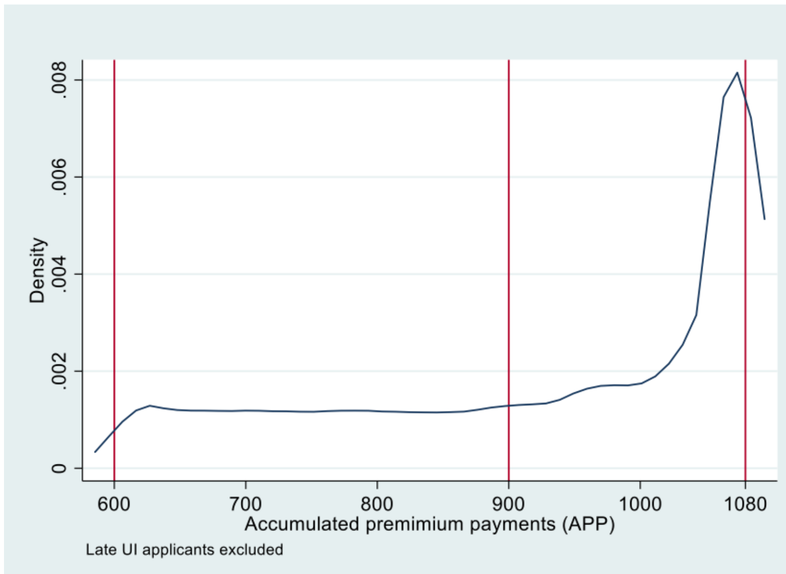


Figure 3: Kernel density estimate of accumulated premium payments (APP)

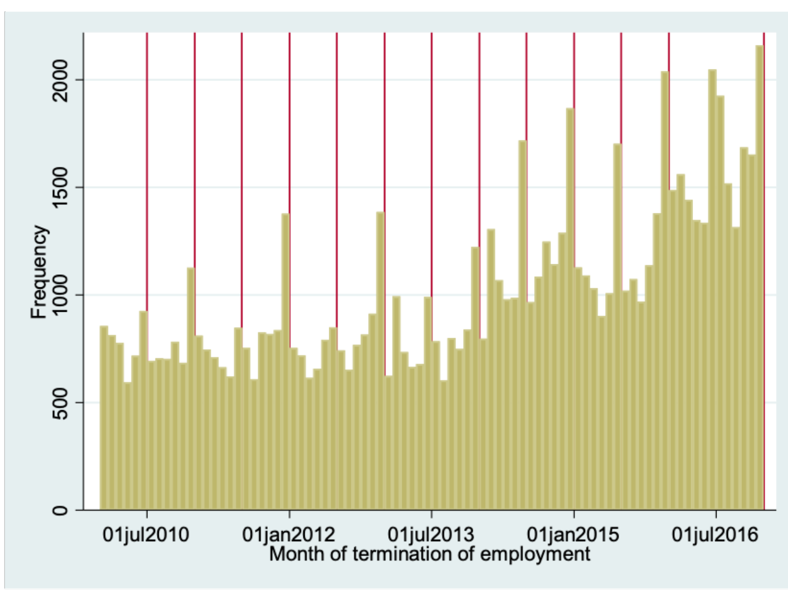


Figure 4: Distribution of the month and year of employment termination

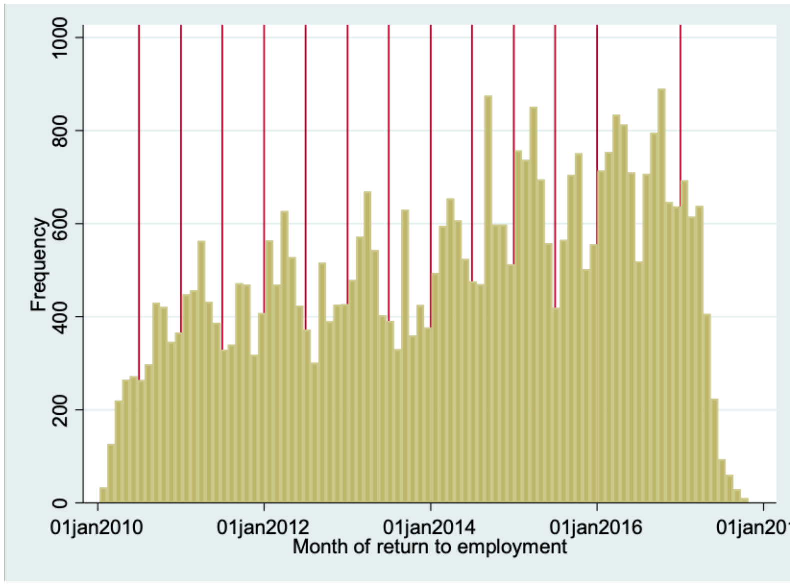


Figure 5: Distribution of the month and year of exit from UI system, to employment

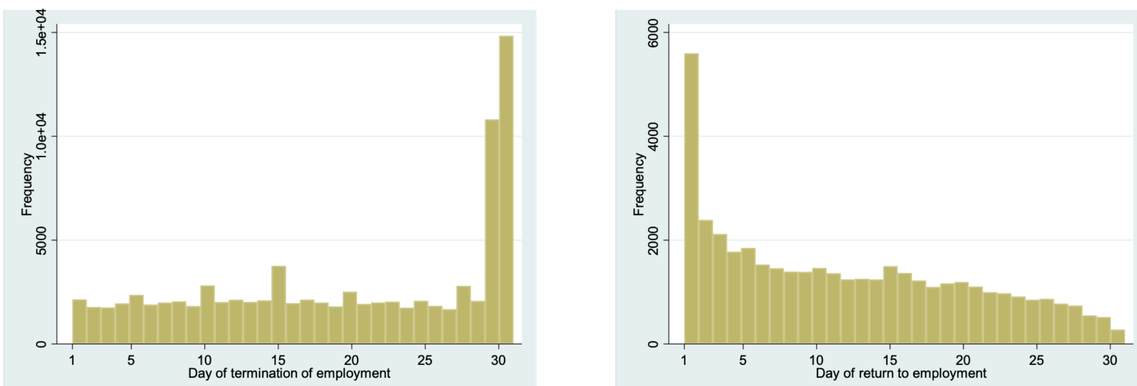


Figure 6: Distribution of the day of termination of employment (left) and day of termination of UI benefit payments (right)

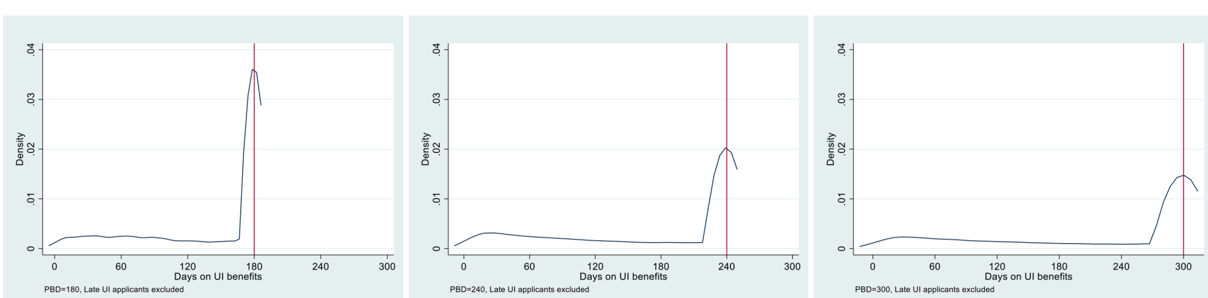


Figure 7: Days spent collecting UI benefits, conditional on PBD

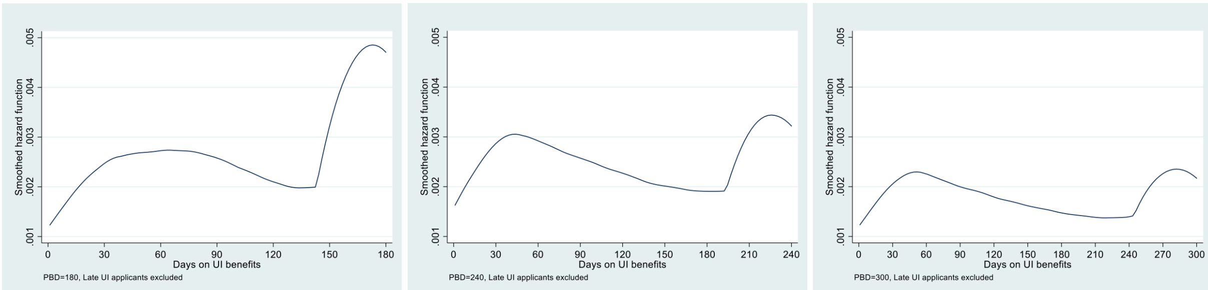


Figure 8: Days spent collecting UI benefits, conditional on PBD

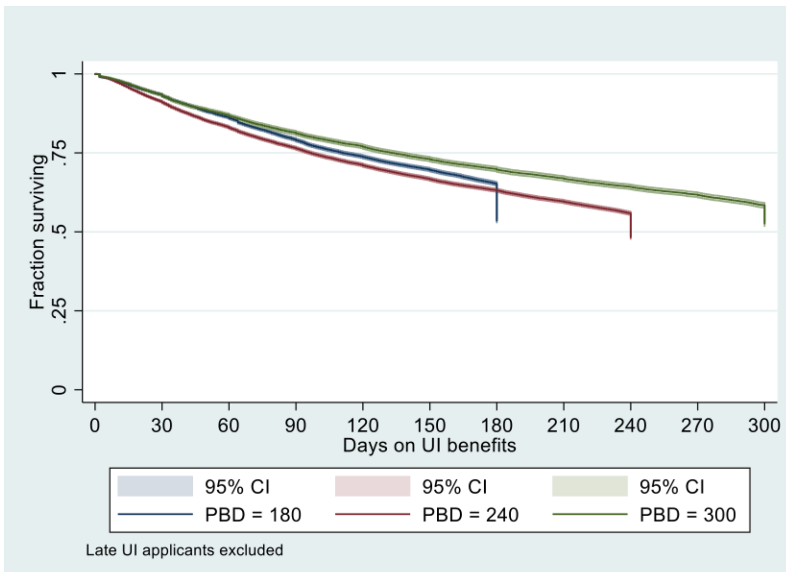


Figure 9: Kaplan-Meier estimate of the survival function for exits to employment

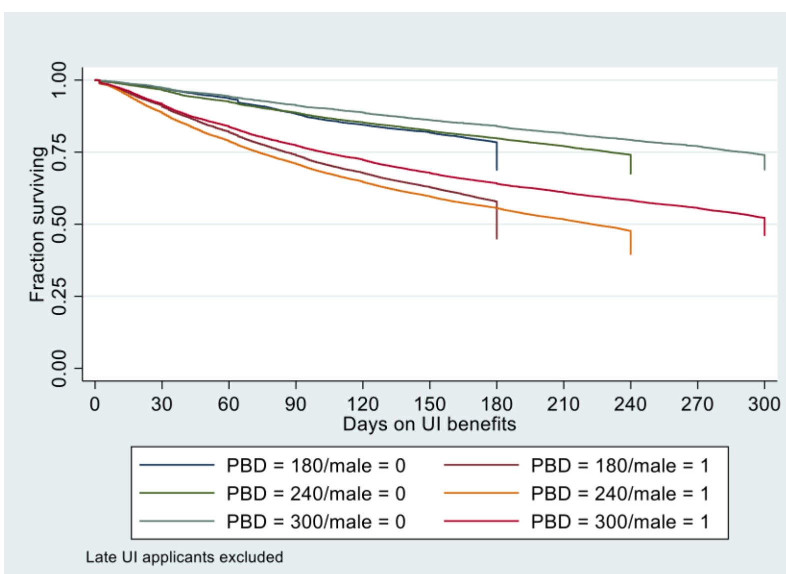


Figure 10: Kaplan-Meier estimates of the survival functions for exits to employment by gender and PBD

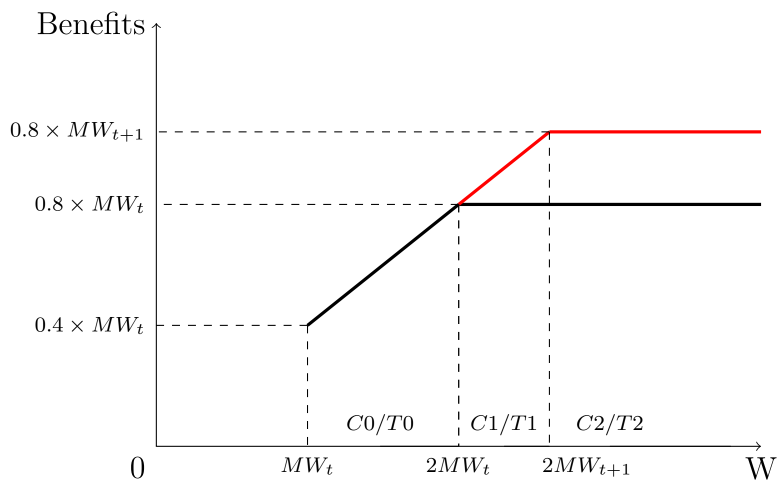


Figure 11: Minimum wage hikes and benefit changes

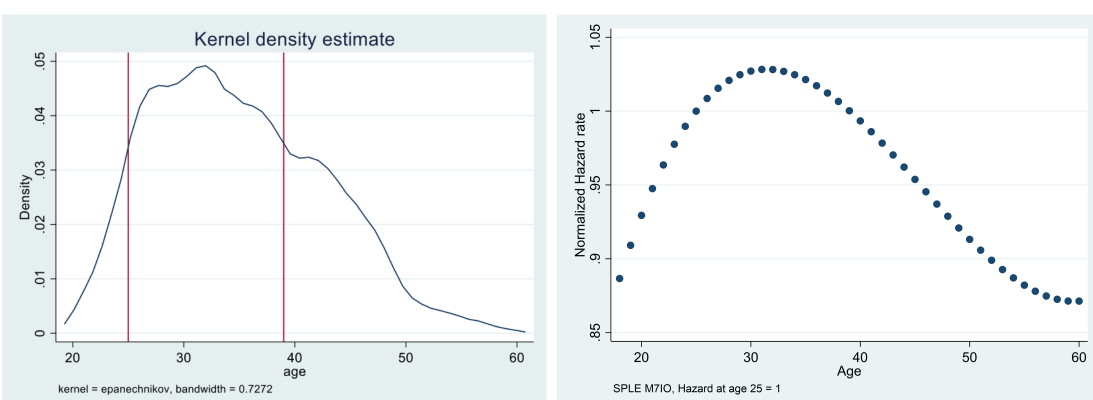


Figure 12: Sample age distribution (left) and age profile of exit hazard to employment, SPLE (PBD) Model 7 (right): (normalized to 1 for age 25)

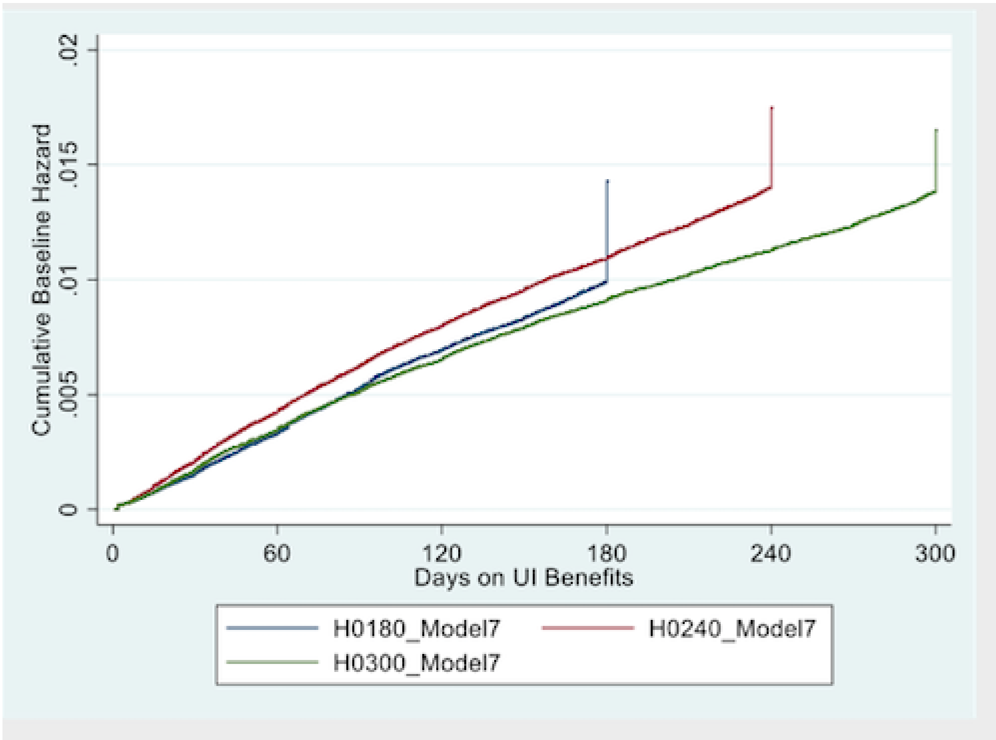


Figure 13: Non-parametric estimates of the cumulative baseline hazards by PBD

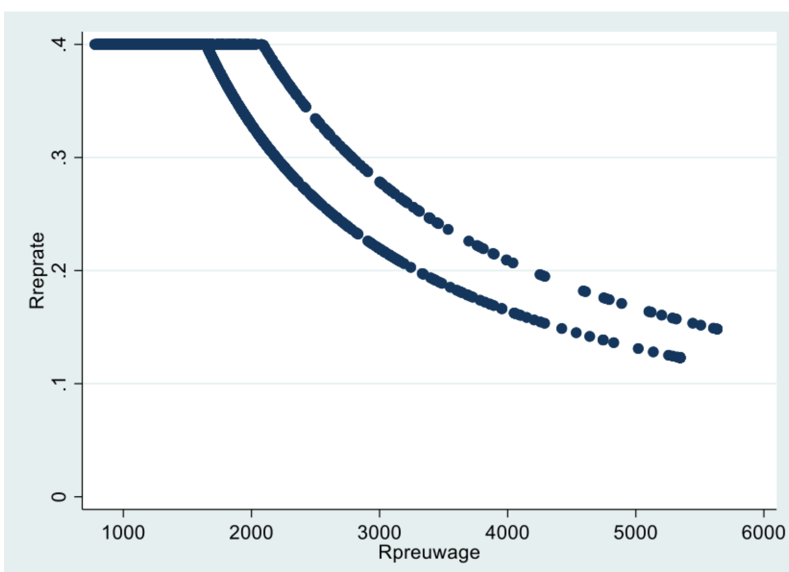


Figure 14: Replacement rates on the 2015/16 RD subsample

A Appendix

Table A.1: Passive labor market programs administered by İŞKUR, 2010-16

Year	SEA	JLC	UI applications	UI benefit granted	UI collection ratio	Benefitiary Total
2010	27,158	9,485	459,426	331,740	0.722	368,383
2011	5,814	1,855	499,234	322,980	0.647	330,649
2012	2,855	532	609,537	372,077	0.610	375,464
2013	969	3,353	733,032	431,820	0.589	436,142
2014	66	1,214	901,892	514,028	0.570	515,308
2015	115	879	1,086,848	592,682	0.545	593,676
2016	733	300	1,521,054	801,878	0.527	802,911

Source: İŞKUR and own calculations

Table A.2: Administrative records and working sample size

Year	(1) Qualified for UI benefits	(2) Intended sample size	(3) Working sample size	(4) (3) as % of Total Working Sample	Share (%) (3)/(1)
2010	331,745	10,000	8,725	10,7	2,63
2011	322,987	10,000	8,891	11,0	2,75
2012	372,093	10,000	8,997	11,1	2,42
2013	431,85	10,000	9,048	11,1	2,10
2014	514,082	15,000	13,470	16,6	2,62
2015	592,835	15,000	13,591	16,7	2,29
2016	802,113	20,000	18,450	22,7	2,30
Total	3,367,705	90,000	81,172	100,0	2,41

Source: İŞKUR and our own calculations

Table A.3: Reason for cessation of unemployment insurance payments

Started a new job	38,570	47.52
Already working in a remunerated job	882	1.09
Found a job abroad	6	0.01
By law 5921	8	0.01
Did not report to consultation	402	0.50
Refused Training	63	0.08
Temporary disability	68	0.08
Dropped from training	56	0.07
Death	13	0.02
Refused proposed job	51	0.06
Not ready to start a new job	349	0.43
Total	81,172	100.00

Source: İŞKUR and our own calculations

Table A.4: Stratified Partial Likelihood Results

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Search Variables							
Roldw100	0.0012	0.0047***	0.0055***	0.0066***	0.0029***	0.0033***	0.0032***
	(0.0010)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)
Rruib100	0.0523***	0.0251***	0.0130**	0.0034	0.0437***	0.0287***	0.0254***
	(0.0056)	(0.0057)	(0.0058)	(0.0059)	(0.0063)	(0.0064)	(0.0069)
Demographics							
age		0.2399***	0.2292***	0.2332***	0.2169***	0.2186***	0.2428***
		(0.0222)	(0.0225)	(0.0225)	(0.0226)	(0.0227)	(0.0250)
agesq100		-0.5794***	-0.5533***	-0.5606***	-0.5168***	-0.5218***	-0.5903***
		(0.0577)	(0.0585)	(0.0586)	(0.0587)	(0.0591)	(0.0650)
agecu10000		0.4284***	0.4045***	0.4079***	0.3731***	0.3764***	0.4327***
		(0.0488)	(0.0496)	(0.0496)	(0.0497)	(0.0500)	(0.0551)
male		0.7744***	0.7338***	0.7292***	0.7179***	0.7102***	0.7576***
		(0.0131)	(0.0134)	(0.0136)	(0.0136)	(0.0136)	(0.0151)
married		0.0002	0.0033	-0.0047	-0.0255*	-0.0178	-0.0139
		(0.0131)	(0.0131)	(0.0132)	(0.0133)	(0.0133)	(0.0144)
divorced		0.0792***	0.0860***	0.0796***	0.0576**	0.0711**	0.0628*
		(0.0292)	(0.0292)	(0.0293)	(0.0293)	(0.0293)	(0.0325)
widow		0.1689*	0.1621	0.1469	0.1146	0.1077	0.1039
		(0.1000)	(0.1000)	(0.1001)	(0.1002)	(0.1002)	(0.1129)
litnodip		0.1420	0.1036	0.1443	0.1068	0.1119	0.0241
		(0.0938)	(0.0939)	(0.0942)	(0.0943)	(0.0943)	(0.1050)
primary		0.3393***	0.3285***	0.3042***	0.2633***	0.2613***	0.2059***
		(0.0688)	(0.0688)	(0.0689)	(0.0690)	(0.0690)	(0.0744)
highsch		0.2534***	0.2629***	0.2310***	0.1820***	0.1862***	0.1529**
		(0.0691)	(0.0691)	(0.0692)	(0.0693)	(0.0693)	(0.0748)
univassoc		0.2050***	0.2181***	0.1812**	0.1366*	0.1531**	0.1131
		(0.0716)	(0.0716)	(0.0717)	(0.0718)	(0.0718)	(0.0775)
univ4yr		0.1373*	0.1613**	0.1416**	0.0940	0.1245*	0.1007
		(0.0705)	(0.0707)	(0.0708)	(0.0709)	(0.0709)	(0.0765)
msphd		0.1131	0.1253	0.1235	0.1057	0.1310	0.1183
		(0.0982)	(0.0985)	(0.0986)	(0.0987)	(0.0987)	(0.1064)
Termination Type							
Type B						0.0203	0.0068
						(0.0271)	(0.0293)
Type D						0.5147***	0.4372***
						(0.0199)	(0.0222)
Type E						0.4085***	0.3888***
						(0.0151)	(0.0165)
Controls - Indicators for							
Sector and economic activity	No	No	Yes	Yes	Yes	Yes	Yes
İŞKUR office	No	No	No	Yes	Yes	Yes	Yes
Day/Month/Year of termination	No	No	No	No	Yes	Yes	Yes
Month/Year of exit to employment	No	No	No	No	No	No	Yes
Observations	81,172	81,172	81,172	81,172	81,172	81,172	14,107,407

Standard errors in parentheses
p***<0.01, p**<0.05, p*<0.1

Table A.5: RD Results

Variables	RD900	RD1080
Demographics		
age	0.0704	0.3120***
	(0.0686)	(0.0433)
agesq100	-0.1279	-0.7825***
	(0.1811)	(0.1111)
agecu10000	0.0530	0.5833***
	(0.1552)	(0.0934)
married	-0.0527	0.0228
	(0.0382)	(0.0207)
divorced	-0.0151	0.1053**
	(0.0901)	(0.0461
widow	-0.2347	-0.0112
	(0.3469)	(0.1695)
litnodip	0.1621	0.0472
	(0.2778)	(0.1563)
primary	0.3869*	0.1674*
	(0.2038)	(0.0999)
highsch	0.2861	0.1143
	(0.2048)	(0.1003)
univassoc	0.2857	0.1323
	(0.2118)	(0.1044)
univ4yr	0.3160	0.0872
	(0.2091)	(0.1027)
msphd	0.6633**	0.1074
	(0.2888)	(0.1405)
Previous wage		
Roldw100	0.0060***	0.0073***
	(0.0023)	(0.0010)
Controls - Indicators for		
Sector and economic activity	Yes	Yes
İŞKUR office	Yes	Yes
Day/Month/Year of termination	Yes	Yes
Month/Year of exit to employment	Yes	Yes
Observations	10,167	32,835

Standard errors in parentheses
p***<0.01, p**<0.05, p*<0.1

Table A.6: RD Male Sample Size

	RD 900		RD 1080	
Male	PBD=180	PBD=240	PBD=180	PBD=240
Type A or C	2,352	2,635	9,554	9,602
Type B	90	105	774	354
Type D	247	214	432	250
Type E	419	428	1,554	1,337
Total	3,108	3,382	12,314	11,453

Table A.7: RD Female Sample Size

	RD 900		RD 1080	
Male	PBD=180	PBD=240	PBD=180	PBD=240
Type A or C	1,414	1,682	3,636	4,020
Type B	62	84	236	126
Type D	104	69	93	68
Type E	128	134	444	355
Total	1,708	1,969	4,409	4,469

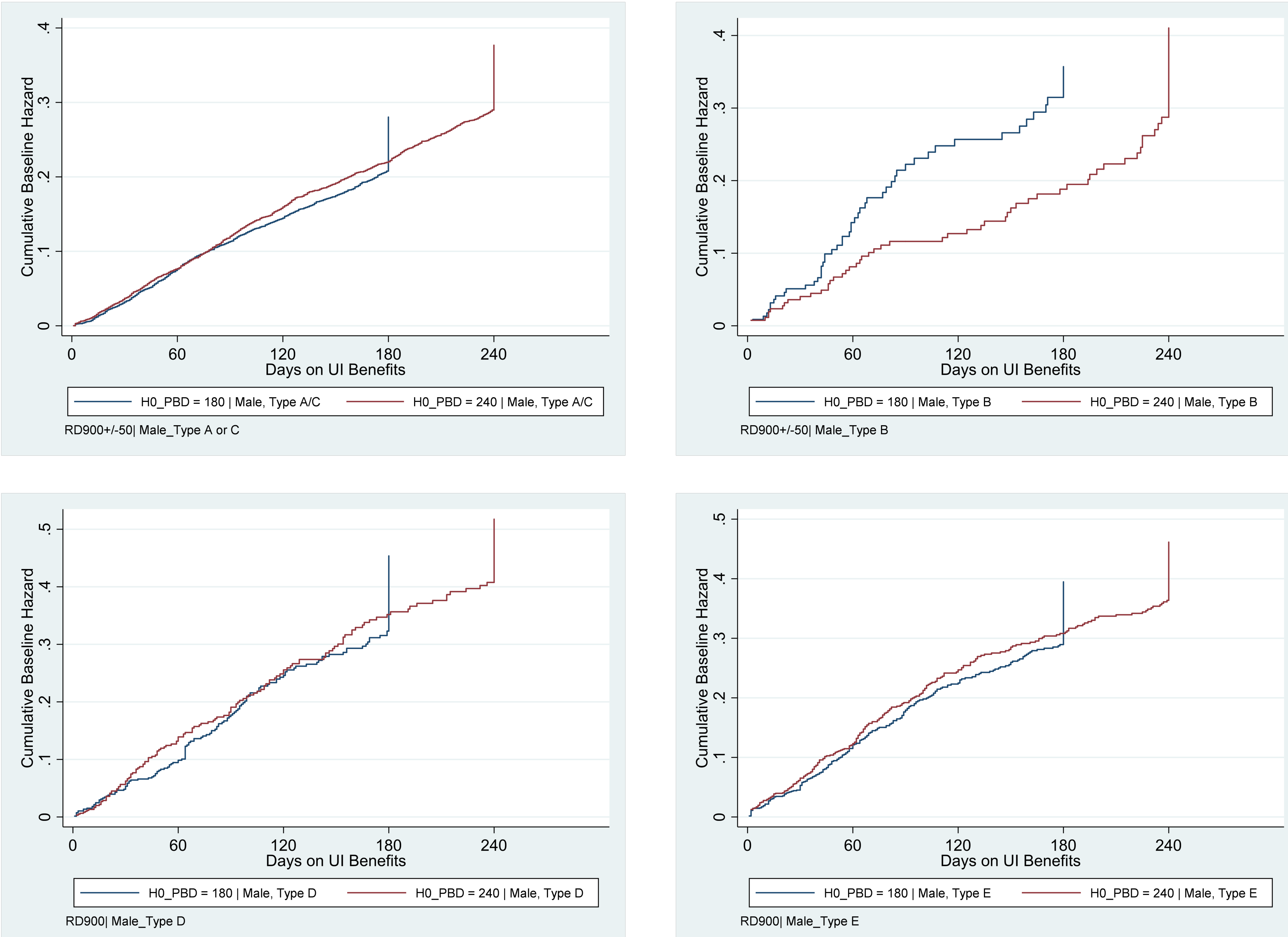


Figure A.1: Non-parametric estimates of the cumulative baseline hazard by PBD and termination type (men)

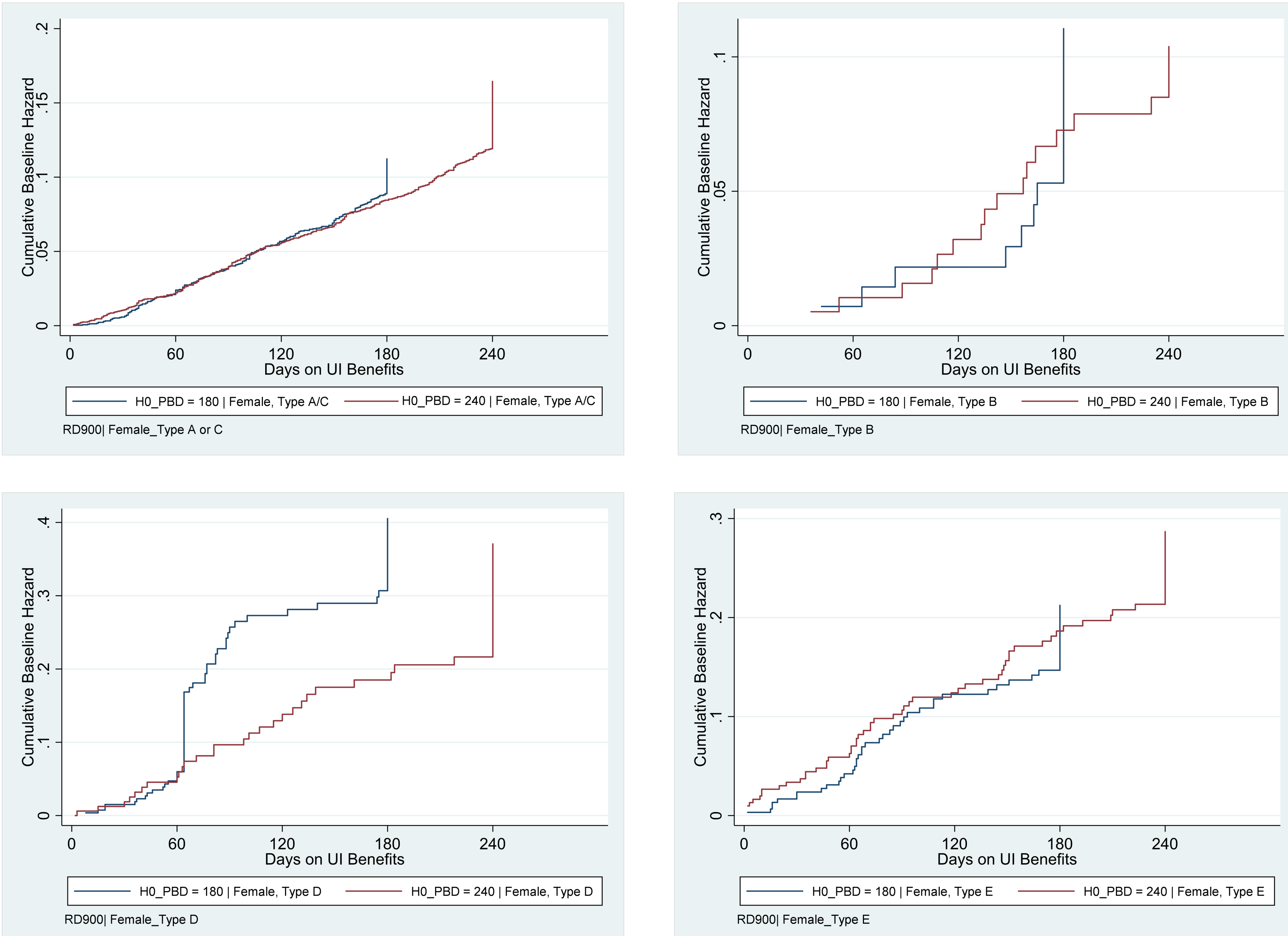


Figure A.2: Non-parametric estimates of the cumulative baseline hazard by PBD and termination type (women)

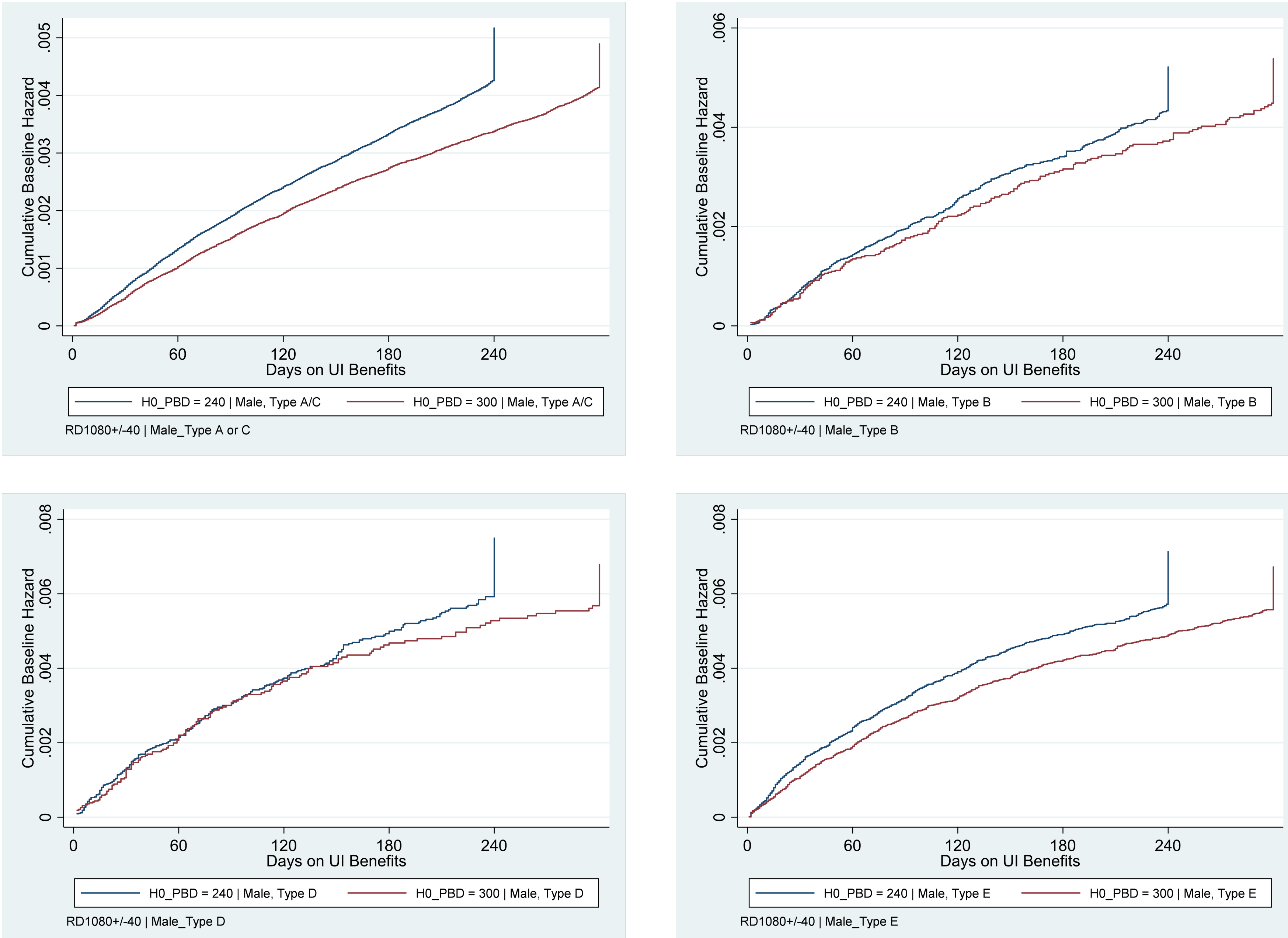


Figure A.3: Non-parametric estimates of the cumulative baseline hazard by PBD and termination type (men)

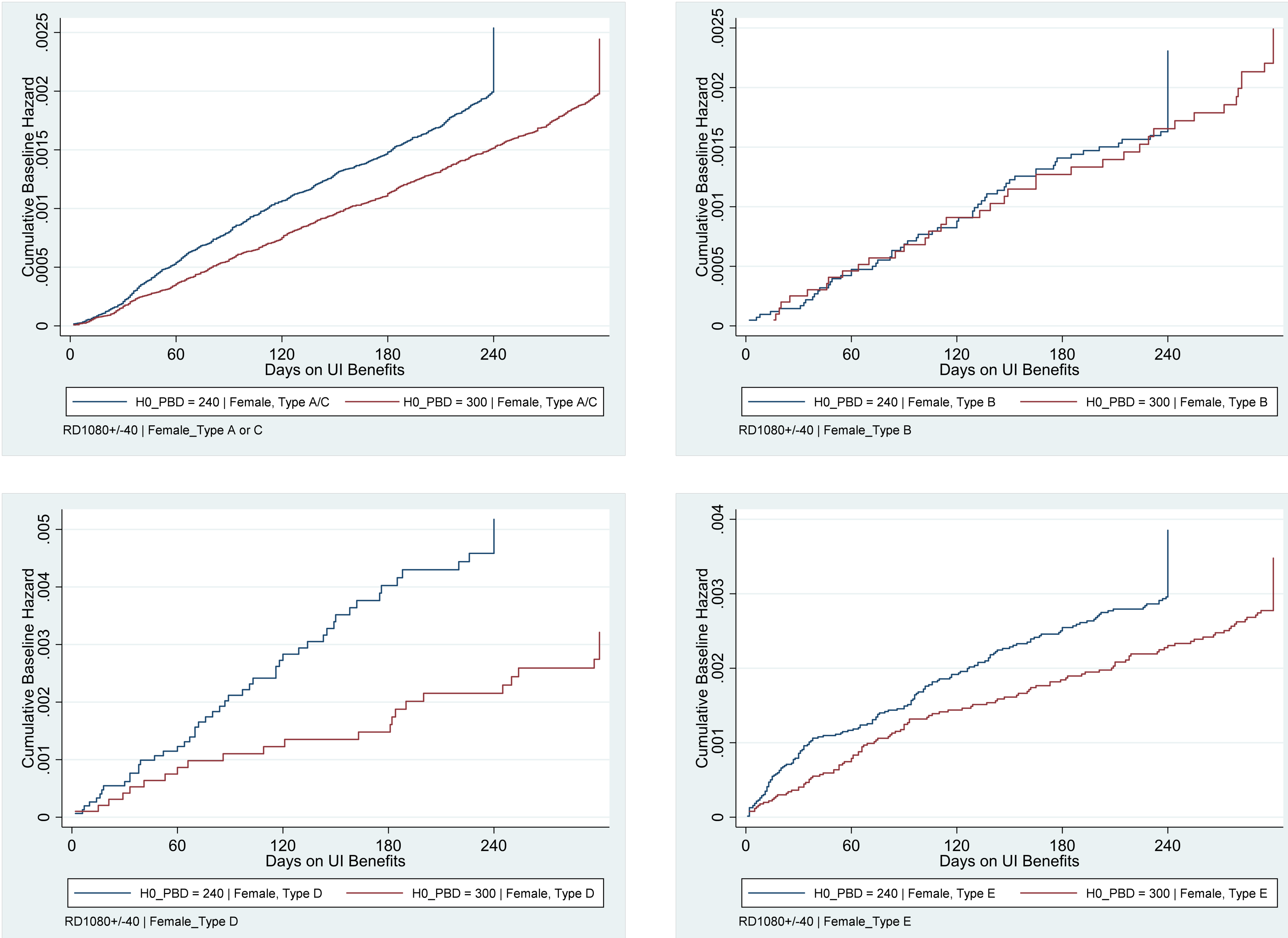


Figure A.4: Non-parametric estimates of the cumulative baseline hazard by PBD and termination type (women)

B Appendix

Unemployment insurance system is regulated by Law no. 4447. Public sector employees whose tenure and job security are secured by special laws – such as civil servants, faculty at public universities and military personnel – are not covered by this law. The law classifies eligible individuals under six groups, depending on the reason of termination:

A = Employer initiated; advanced notice given.

B = Employee initiated.

C = Employer initiated; advanced notice not given.

D = Fixed–term contract ended.

E = Establishment closure, downsizing, change of ownership, or redundancy of position due to change in the needs of the establishment, including change in job qualifications.

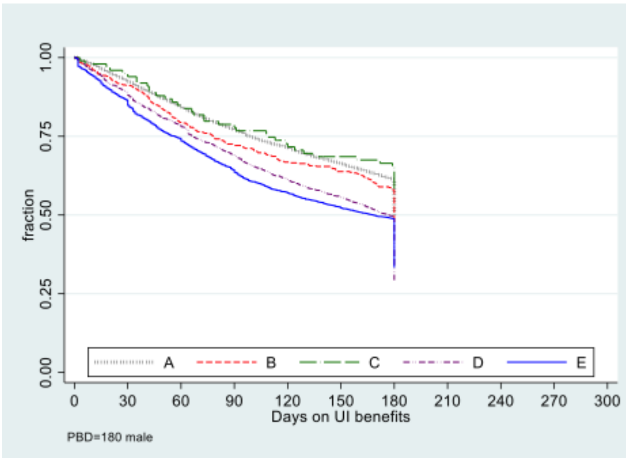
F = Privatization related.

In the full sample A is most common (77 percent), followed by E (12.6 percent), and D (6.1 percent). Nonstandard terminations (force majeure, court cases) account for 0.64 percent and those which are not classified under A-E account for 0.34 percent. Both were excluded from the working sample. F is a tiny group (10 people). Workers who lost their jobs because of privatization collect additional benefits on top of UI benefits. They were excluded from our working sample. Breakdown of our working sample of 81,172 observations by PBD, gender and termination type can be seen in Table B.1.

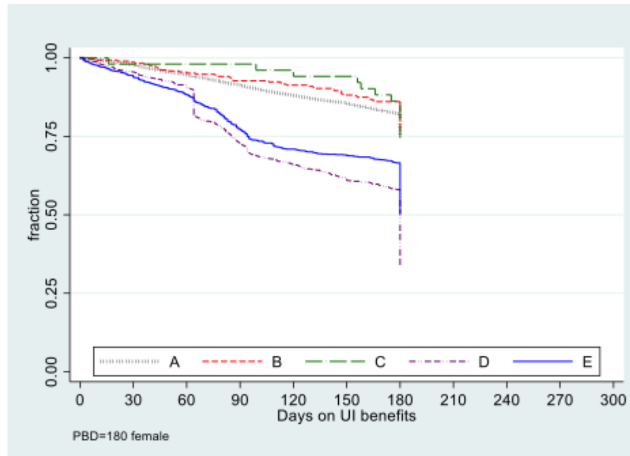
Kaplan-Meier estimates of survivor functions by termination type, obtained conditional on PBD and gender on our working sample, are shown in Figure B.1. Differences by type are discussed in the text. In our estimations we combined the smallest group in our working sample (type C, 0.61 percent) with the largest group (type A) because confidence intervals of the KM estimates of the survivor functions overlapped.

Table B.1: Number of job terminations and fraction of exits to employment broken down by Termination Type, PBD and Gender

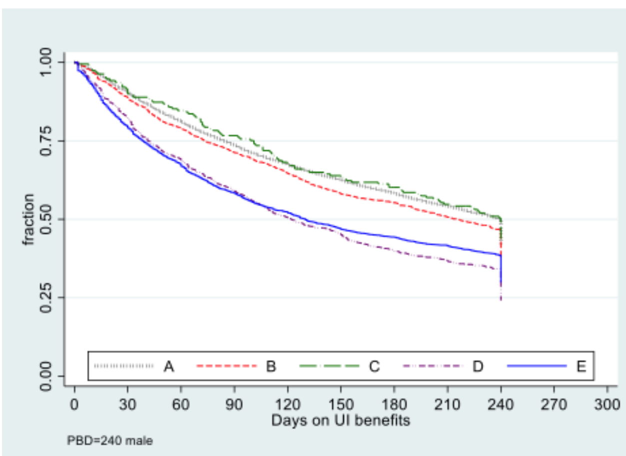
	Female				Male			
	PBD				PBD			
Termination Type	180	240	300	Total	180	240	300	Total
Type A or C	8,249	9,269	4,020	21,538	13,235	19,111	9,602	41,948
	24.9	30.2	30.0	28.2	49.5	57.4	51.6	53.5
Type B	289	506	126	921	439	1,300	354	2,093
	23.5	33.0	32.5	30.0	51.9	61.5	58.8	59.0
Type D	975	308	68	1,351	2,236	1,077	250	3,563
	65.3	53.2	36.8	61.1	70.1	75.3	66.0	71.4
Type E	1,033	961	355	2,349	2,969	3,103	1,337	7,409
	49.3	45.3	38.9	46.1	66.4	69.4	63.8	67.2
Total	10,546	11,044	4,569	26,159	18,879	24,591	11,543	55,013
	31.0	32.3	30.9	31.5	54.6	59.9	53.5	56.7



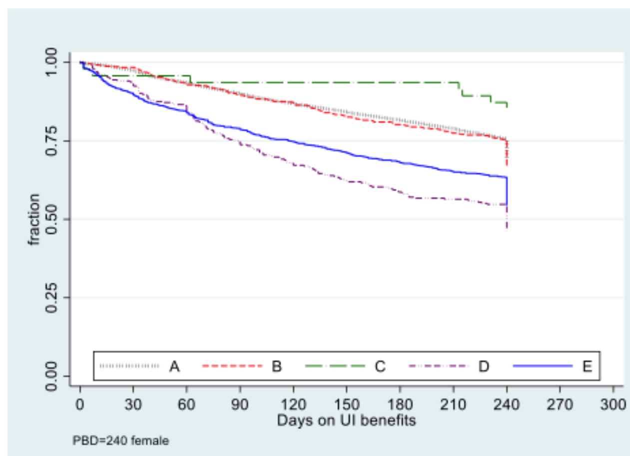
(a) Male, PBD=180



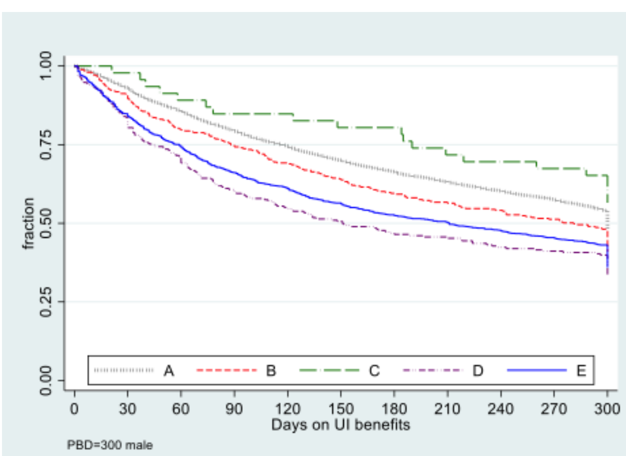
(b) Female, PBD=180



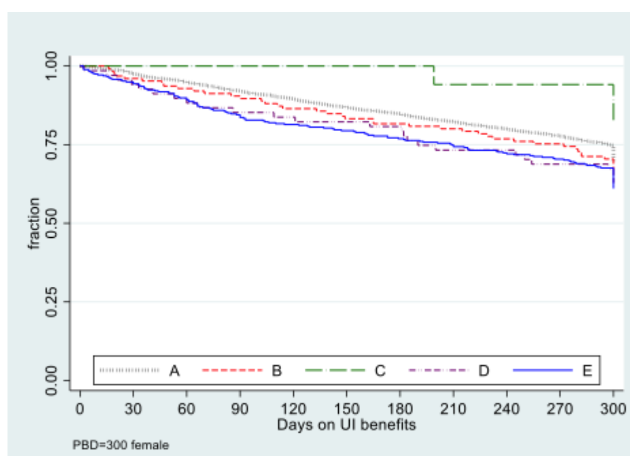
(c) Male, PBD=2400



(d) Female, PBD=240



(e) Male, PBD=300



(f) Female, PBD=300

Figure B.1: KM survival functions - by gender, PDB and termination type