Private Information and Design of Unemployment Insurance

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Job Market Paper

November, 2018

Abstract

Unemployment insurance (UI) programs around the world are predominantly government-provided with universal coverage. One explanation for the dominant adoption of mandatory UI is that private knowledge about unemployment risks might lead to a selected pool of insured individuals and generate welfare losses. At the same time, mandates might have a detrimental effect on welfare because of fully restricted individual choices. This ambiguity motivates a need to consider alternative designs of UI that allow for the individual choice but restrict selection into insurance based on risks. I use institutional features of the Swedish voluntary UI system and detailed administrative data to study the optimal design of UI. To evaluate welfare under various alternative regulations, I estimate a structural model of insurance choice that captures heterogeneity in preferences and private information about future unemployment risks. The results suggest that mandating UI would unambiguously reduce welfare by on average 49% in terms of consumer surplus compared to a current system. In contrast, appropriate designs with voluntary enrollment generate large welfare gains. In particular, contracts with fixed enrollment timing and predetermined duration improve welfare by 58% - 95% in terms of the consumer surplus. A "two-part tariff" contract that fails to sufficiently restrict risk-based selection results in average consumer surplus loss of 3%.

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I thank Mikael Lindahl, Liran Einav and Aico van Vuuren for invaluable advice throughout the development of this project. This work has benefited from the comments of Natalie Bachas, Timothy Bresnahan, Raj Chetty, Mark Duggan, Randi Hjalmarsson, Arash Nekoei, Petra Persson, Emmanuel Saez, Måns Söderbom and seminar participants at the University of Gothenburg and Stanford University.

1 Introduction

Unemployment insurance (UI) is a part of a broader spectrum of social insurance programs in many countries. A typical UI program is state-provided and tax-financed with compulsory enrollment. At the same time, a few developed countries including Sweden have introduced a voluntary UI system.[1] On the one hand, the presence of adverse selection might lead to welfare losses in such a system. On the other hand, moral hazard and heterogeneity of preferences might rationalize the adoption of voluntary UI. This ambiguity and the absence of conclusive empirical evidence motivate a need to consider alternative regulations which preserve an individual choice but restrict selection into insurance based on risks. This paper attempts to comprehensively study the optimal design of UI.

The essence of adverse selection in the context of UI is that individuals tend to have private information about their unemployment risks (e.g. working in a risky occupation, an industry or a firm). Consequently, it might lead to an insurance pool of relatively high-risk individuals and even result in a classic example of the "market for lemons" unraveling (Akerlof, 1978). Alternatively, above-optimal prices might generate welfare losses and require large subsidies to sustain a program (Einav, Finkelstein, & Cullen, 2010).

At the same time, the presence of heterogeneity of preferences for insurance may serve as a rationale for a voluntary system. In this case, a mandate might impose the excess burden on low risk-aversion individuals who do not value insurance even in the presence of substantial risks. It also implies that a positive correlation between the likelihood of purchasing insurance and unemployment risks might not be sufficient to motivate the introduction of a mandate since it might be driven by a correlation between risks and risk preferences.[2]

Given these concerns regarding both voluntary and mandatory systems, it might be worth considering designs of UI contracts that address selection and at the same time allow for voluntary enrollment. For example, when adverse selection is primarily driven by unrestricted enrollment timing, alternative contracts that restrict time-selection might be welfare-improving.[3] In the context of UI, it means that individuals tend to buy insurance when they have higher unemployment risks, which vary over time. The presence of such selection was documented in, for example, dental (Cabral, 2016) and health insurance markets (Aron-Dine, Einav, Finkelstein, & Cullen,

[1]Similar voluntary UI exists in Finland, Norway, and Iceland.

[2]Another important part of the discussion about welfare in insurance is moral hazard. Moral hazard in UI means that the availability of insurance entails, for instance, a reduction in job search or on-the-job efforts, which raises probabilities or durations of unemployment. As a result, it might amplify the costs under a mandatory system and make such a policy suboptimal. Moral hazard is not a part of the focus of this paper.

[3]There is a membership eligibility condition that acts as a timing restriction but does not completely remove the possibility of time-selection.

2015; Einav, Finkelstein, & Schrimpf, 2015). Therefore, I study potential consequences of two contracts that restrict the selection of enrollment timing. First, I consider an "open enrollment" contract with fixed timing of enrollment and predetermined duration. Another alternative is an "entry costs" or "two-part tariff" contract which in addition to monthly premiums charges entry fees upon enrollment of previously uninsured (Cabral, 2016). In contrast to the open enrollment contract, this design affects time-selection indirectly by discouraging unenrollment when unemployment risks are low to possibly enroll later when risks are high.[4]

The context of Swedish voluntary unemployment insurance provides an appropriate set-up to understand the interaction between risks, private information, and individual preferences that should guide the choice of policy measures. This paper uses detailed individual-level administrative data, which allow observing dates of unemployment and insurance spells together with a variety of demographic and labor market characteristics. I start by augmenting the existing evidence of a positive correlation between insurance and unemployment probabilities by showing the presence of time-selection patterns. Using the eligibility condition for the income-based coverage that requires paying insurance premiums for at least twelve consecutive months, I demonstrate that individuals are more likely to start unemployment spells with exactly twelve months of UI enrollment. This evidence is robust and shows the presence of private information about unemployment timing.

To study welfare consequences of various designs of UI, I estimate a dynamic insurance choice model that exploits the variation in insurance premiums and benefits generosity as well as time-selection patterns. It enables recovering distributions of risk preferences and private information about future unemployment risks, which jointly determine insurance decisions. To identify risk preferences, I leverage two sources of variation. The first one is a result of differences in premiums and the generosity of benefits over time primarily due to a UI reform in 2007. Another source of variation stems from cross-sectional differences in premiums across industry-specific UI funds and replacement rates due to a benefits cap and differences in premiums across UI funds. The identification of individual information exploits patterns of timing of insurance purchase relative to the timing of future unemployment or changes in unemployment risks. To separately identify risk preferences and information about unemployment, I assume that changes in the attractiveness of UI do not affect the structure of private information about unemployment conditionally on the observed determinants of this information. The assumption is in line with the evidence from the data.[5] The results show considerable variation in risk preferences and

[4]In other words, if an individual interrupts the sequence by leaving the insurance pool even for one month, new entry requires paying entry fees again. As a result, this design discourages exits to re-enter the insurance pool later when needed.

[5]For example, I assume that although the UI reform in 2007 changed the generosity of benefits and premiums,

quality of information about future employment perspectives. I also estimate inertia parameters that suggest considerable choice persistence. It means that the insurance status in a previous period impacts future decisions. In the main specification, to identify the inertia parameters I assume that individuals who are aware of the forthcoming unemployment make inertia-free decisions.[6]

The efficiency of insurance programs is determined by an interplay between individual risk preferences, risks and private information about those risks. This complexity rationalizes a use of such a model that combines those parts to provide policy recommendations. Some of the existing works provide policy conclusions about UI based on a "reduced form" association between realized risks and insurance probabilities using observable characteristics, survey responses or arguably exogenous institutional variation (e.g. Hendren, 2017; Landais, Nekoei, Nilsson, Seim, & Spinnewijn, 2017). Instead, the approach in this paper allows not only studying a broader spectrum of alternative regulations but also exploring richer variation and behavioral patterns in the data to understand the consequences of various policies at the expense of imposing a number of theory-based assumptions.

To evaluate welfare under current and alternative structures of UI, I use the model estimates to recover UI demand functions and distributions of willingness-to-pay (WTP) for corresponding insurance contracts. The findings suggest that mandates would generate considerable welfare losses amounting to 243 SEK/month ($27 or 49%) per individual compared to the current system.[7] The intuition is that a mandate restricts selection not only on risks but also on preferences, which generates a consumer surplus loss.[8]

In contrast, appropriate contract design regulations are predicted to generate large welfare gains. I find that an alternative two-part tariff contract that charges extra fixed costs upon the payment of the first premium would perform slightly worse than the status quo. The reason is that the changes in the contract structure do not sufficiently restrict selection on risks but imposes additional fixed costs burden on individuals. However, an open enrollment contract with 18 months duration is predicted to generate welfare improvement of 545 SEK/month per individual ($61 or 95%) on average. In comparison with the entry costs design, it virtually

it did not affect the labor market itself such that individuals did not become more or less informed about their future employment perspectives. I show that time-selection patterns did not change as a result of the reform in 2007.

[6]I investigate the sensitivity of welfare analysis to this assumption. I find that welfare conclusions are robust to various formulations of inertia.

[7]This number applies to the range of subsidy levels considered in the welfare analysis.

[8]However, as I discuss in the section dedicated to the welfare analysis, a mandatory system in the absence of a moral hazard response allows achieving any reasonable budget balance. In contrast, the voluntary system is very limited in terms of which subsidy levels are feasible because of behavioral responses to price changes.

removes time-selection without imposing large additional costs on consumers. In contrast to mandates, it restricts undesirable selection without severe choice restrictions. A similar design of the open-enrollment contract but with 24 months duration lead to smaller welfare gains of 337 SEK/month ($36 or 58%) per individual on average. Smaller welfare gains stem from higher risk-exposure in the case of longer contracts.

This paper contributes to a large literature on private information in insurance programs and markets. Most attention to the importance of private information in insurance has been dedicated in health insurance, annuity, and long-term care markets. In particular, a large literature documents the presence,[9] discusses sources[10], analyses consequences of asymmetric information[11] as well as studies policies aimed at addressing inefficiencies in insurance markets.[12] The literature related to unemployment insurance has been primarily focused on the optimal UI theory[13] and on estimating labor supply responses to insurance benefits.[14] However, to the best of my knowledge, only a few empirical papers focus on the canonical private information problem in UI. Hendren (2017) shows that the absence of private UI markets is a result of the excess mass of private information. In this paper, I do not focus on the existence of private information and an effect on private markets but primarily attempt to look at how contract design can be used to address the problem.

Another paper studying private information in UI using the Swedish setup is Landais et al. (2017). The authors document that insured individuals on average have higher unemployment risks. It is argued that adverse selection must be an important component of the observed positive correlation between unemployment risks and insurance take-up. The paper concludes that mandating the system would not be an optimal policy because individuals who are not covered under the current system value insurance less than expected costs of covering them.[15] Instead, the combination of subsidies and a minimum basic insurance mandate is suggested to

[9]See e.g. Chiappori and Salanie (2000); Finkelstein and Poterba (2004).

[10]See e.g. Abbring, Chiappori, and Pinquet (2003); Abbring, Heckman, Chiappori, and Pinquet (2003); Barsky, Juster, Kimball, and Shapiro (1997); Fang, Keane, and Silverman (2008); Finkelstein and McGarry (2006); Cutler, Finkelstein, and McGarry (2008).

[11]See e.g. Einav, Finkelstein, and Cullen (2010); Hendren (2013); Spence (1978).

[12]See e.g. Einav, Finkelstein, and Schrimpf (2010); Handel, Hendel, and Whinston (2015); Handel, Kolstad, and Spinnewijn (2015).

[13]See e.g. Autor and Duggan (2003); Baily (1978); Card and Levine (2000); Chetty (2006, 2008); Fredriksson and Holmlund (2001); Holmlund (1998); Hopenhayn and Nicolini (1997); Landais, Michaillat, and Saez (2018b, 2018a); Kolsrud, Landais, Nilsson, and Spinnewijn (2018); Kroft (2008); Shimer and Werning (2008); Spinnewijn (2015).

[14]See e.g. Card, Johnston, Leung, Mas, and Pei (2015); DellaVigna, Lindner, Reizer, and Schmieder (2017); Lalive, Van Ours, and Zweimüller (2006); Landais (2015); Meyer (1990); Moffitt (1985); Schmieder, Von Wachter, and Bender (2012).

[15]The findings are based on the estimates of WTP and expected costs from extrapolation of points observed before and after a reform in 2007, which changed insurance premiums and generosity of benefits.

be a welfare-improving policy. In this paper, I attempt to look deeper into insurance decision-making by imposing a structure of the model. It allows examining a broader set of counterfactual policies that are difficult to study using the approach in Landais et al. (2017). The reason is that to analyze alternative insurance designs, one needs to take into account preferences, risks and private information about these risk. However, these parameters are difficult to recover without theoretical assumptions. Furthermore, such a structural model is necessary to study policies that have not been observed in this context before. Finally, the empirical approach in this paper allows for more comprehensive exploration of detailed data and rich variation not limited to price changes to understand complex insurance choices.

The model used in the empirical analysis is in the spirit of Einav, Finkelstein, and Schrimpf (2010) who evaluate the costs associated with private information and corresponding gains of mandates in an annuity market. The authors also use a comprehensive dynamic structural model of choice under uncertainty to recover policy-relevant dimensions of individual heterogeneity.

Finally, the paper is related to a strand of the literature studying the optimal design of insurance contracts.[16] Previous works emphasize the importance of a contract structure beyond pricing, which was a dominant focus of the literature. This paper contributes by adding a piece of evidence of the importance of a dynamic component of adverse selection. Similar time-selection evidence was documented in healthcare (Aron-Dine et al., 2015; Einav, Finkelstein, & Schrimpf, 2017; Einav et al., 2015) and dental care markets (Cabral, 2016). There are a number of papers that study the role of a non-linear benefits schedule on the dynamics of unemployment. For instance, Kolsrud et al. (2018) study the role of duration-dependent UI benefits but this work is more related to the literature on labor supply responses. Similarly, DellaVigna et al. (2017) analyze the role of a benefits structure in the presence of non-classical behavioral responses. Instead, I consider non-linear time-based insurance eligibility and additional dimensions of adverse selection that it creates instead of looking at how UI benefits affect the duration of unemployment.

The paper is organized as follows. Section 2 introduces institutional details of UI in Sweden and describes the data. Section 3 presents descriptive evidence that motivates the empirical analysis and modeling choices. Section 4 describes a structural model and an estimation approach. Section 5 analyzes welfare under current and counterfactual policies. Section 6 concludes.

[16]Azevedo and Gottlieb (2017) studies perfect competition in selection markets with the endogenous contract formation. They show that mandates may cause distortions associated with lower prices for low-coverage policies, which results in adverse selection on the intensive margin.

2 Institutional Setting and Data

2.1 UI in Sweden

A vast majority of developed countries have adopted centrally provided and mandatory unemployment insurance systems. Such systems are typically funded through taxes and cover all eligible individuals. In contrast, unemployment insurance in Sweden is divided into basic and voluntary income-based programs. The basic compulsory insurance similarly to mandatory systems grants a fixed daily amount of 320 SEK ($35) conditionally on meeting basic and work requirements.[17] Individuals are required to be registered at the Public Enrollment Service (PES), carry out a job-seeking plan and work at least 80 hours per month over six uninterrupted months during the preceding year.

Eligibility for voluntary income-based insurance also requires paying monthly fees to UI funds for at least 12 consecutive months.[18,19] Before 2007, fees for employed and unemployed individuals coincided. As a result of a labor market reform, fees for employed individuals more than tripled on average. Figure 1 demonstrates average fees for employed and unemployed individuals over time.

Benefits recipiency is limited to the period of 300 days (60 weeks or 14 months) of interrupted or uninterrupted unemployment after which eligibility requires fulfilling the working conditions from the beginning.[20] Unemployment without a valid reason results in an uncompensated period of up to 45 days. The reform in 2007 also reduced the generosity of benefits displayed in Figure 2.

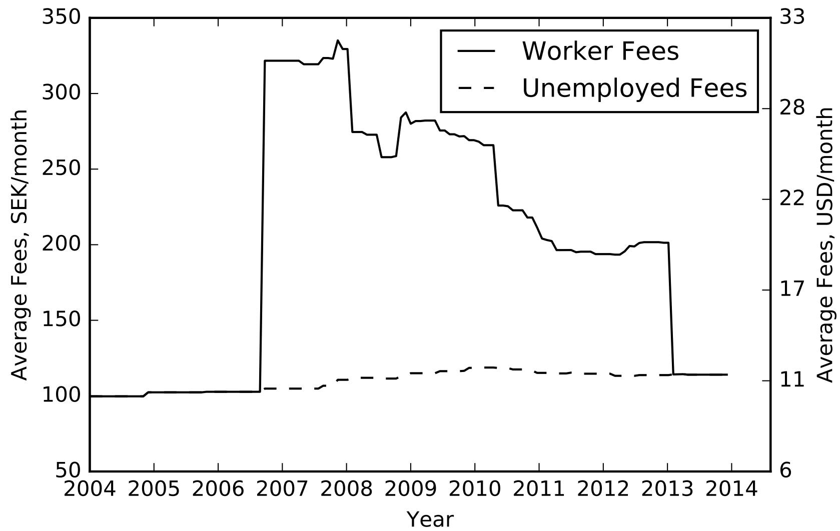
[17] The amount was raised to 365 SEK ($40) in September 2015. For more details regarding changes in 2015 see http://www.fackligtforsakringar.n.nu/a-kassan or http://www.regeringen.se/artiklar/2016/09/en-battre-arbetsloshetsforsakring/ .

[18] There are 29 UI funds that were active during the period under consideration. Individuals are often enrolled in a UI fund based on an industry or a type of employment since funds are linked to labor unions. Therefore, there is virtually no competition among funds.

[19] Enrollment requires working for 1 month.

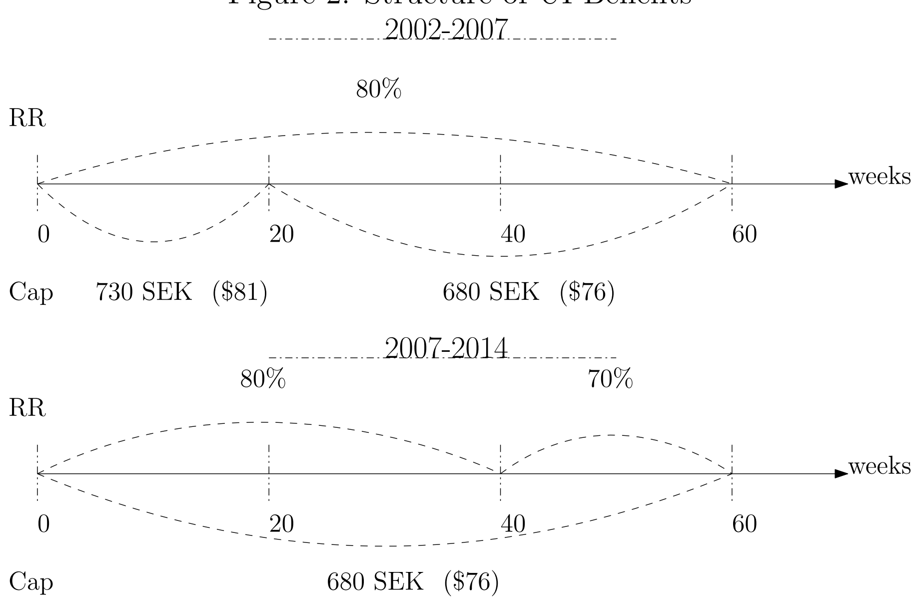
[20] If the accumulated unemployment duration exceeds 300 days, an individual is assigned to an intensified counseling program or can be granted with an extension of 300 days if the counseling is deemed to be unnecessary (but only once). This option disappeared after the reform in July 2007. For more information see https://handels.se/akassan/arbetslos1/regler1/forandringar-i-a-kassan-sedan-2007/ .

Figure 1: Voluntary Insurance Fees, SEK/month



Notes: The Figure demonstrates changes in monthly insurance fees during the period 2004 - 2014. The lines represent average over insurance funds premiums, which vary slightly. Two lines correspond to fees paid by employed and unemployed individuals, correspondingly. Those lines coincide during 2004 - 2007 and after 2013. Fees for employed individuals were considerably higher during 2007 - 2014.

Figure 2: Structure of UI Benefits



Notes: The Figure presents the structure of UI benefits before and after the reform in 2007. The lines with arrow represent schedules of benefits for a maximum of 60 weeks of accumulated unemployment covered by UI. Replacement rate (RR) is presented above the corresponding line. The cap is displayed below the corresponding line.

Before the reform in 2007, voluntary UI provided an 80% replacement rate subject to a cap, which depends on a number of accumulated unemployment weeks. For individuals who accumulated less than 20 weeks of unemployment, the cap was 730 SEK ($81) and 680 SEK ($76) for those with more accumulated weeks. To put this into perspective, the insurance caps correspond to approximately 16 060 SEK ($1 784) and 14 960 SEK ($1 662) of monthly income, respectively. Basic mandatory insurance benefits amount to 7 040 SEK ($782) of monthly income. Average income in the sample used in the analysis, which I discuss in the next section, is approximately 24 834 ($2 759) SEK in 2008. It is almost 54% higher than the first cap and 66% higher than the second cap. A labor market reform introduced changes in both a replacement rate and the cap structure in January 2007. The replacement rate for the first 40 weeks remained 80% and was reduced to 70% for the following 20 weeks.[21] The cap became constant for an entire 60 weeks period and amounted to 680 SEK ($76).[22]

2.2 Data

The empirical analysis in this paper is based on Swedish administrative data from a number of sources. A core dataset comes from a public authority that administers unemployment insurance funds (Inspektionen för arbetslöshetsförsäkringen - IAF). It contains monthly membership records including insurance fund affiliations and premiums. The dataset contains 2 167 287 unique individuals[23] over the period 1999 - 2014. It is not representative of the population since it does not contain individuals who have not claimed UI benefits.[24]

I match the IAF dataset to the data from the Public Employment Service (PES), which provides information on all registered unemployment spells including dates and unemployment categories.[25] A rich set of annually observed individual characteristics comes from the Longitudinal Integration Database for Health Insurance and Labour Market Studies (LISA) including a

[21] Parents with children, younger than 18 are eligible for additional 150 days of 70% replacement rate benefits. Those who are not eligible for additional benefits and continue under the job and activity guarantee program have 65% replacement rate.

[22] Eligibility for income-based insurance is a prerequisite for even higher income compensation from a union that removes the cap. The analysis in this paper does not take it into account. Although the presence of additional fund-based insurance affects parameter estimates, it should not affect the comparative analysis of various UI designs.

[23] In fact, the dataset contains 2 199 941 unique individuals but 32 654 individuals were missing in the longitudinal dataset, which provides individual labor market characteristics. Therefore, those individuals, which are a negligible share of the dataset, are excluded.

[24] Legal restrictions do not allow disclosing membership information about individuals who have not claimed unemployment benefits.

[25] The structural model presented later in this paper has monthly dynamics. I aggregate daily employment and insurance data to monthly. For the cases when, for instance, unemployment duration covers only a part of a month, I code this month as unemployment. Another option would be to round months off.

wide range of demographic characteristics, education, income from various sources (e.g. wage, profit, capital income, social security payment), unemployment, social insurance participation and many others.[26]

Although the data span a period 1999 - 2014, I limit attention to 2002 - 2014 to present the evidence in the next section while using the data for 1999 - 2001 to construct state variables that affect eligibility (e.g. previous enrollment, basic insurance eligibility, a number of accumulated unemployment weeks). The descriptive evidence in the next section is based on this sample to which I refer as "full sample".

A baseline sample used in the estimation differs from the full sample due to a number of restrictions that primarily exclude individuals who might not make active unemployment insurance decisions. For computational reasons, I restrict the data used in the estimation to 2005 - 2009 to capture a period containing the reform at the beginning of 2007, which provides important identifying variations for model parameters. I exclude individuals who at least once during 2005 - 2009 were registered at PES with categories that are unrelated to unemployment and usually not administered by the UI authority (e.g. training and educational programs, programs for people with disabilities). It reduces the sample by 672 890 individuals. I also exclude part-time unemployed since they have different budget sets not captured within the scopes of the empirical model. Accounting for part-time unemployment would introduce complications in the estimation since those individuals face an income stream which is a mix of wage and benefits. Therefore, to preserve a model tractability, I omit those individuals. It reduces the sample further by 185 321 individuals. I exclude individuals who were constantly either older than 64 or younger than 24 years old during the estimation period 2005 - 2009. A final restriction affects individuals who were always receiving social insurance benefits (e.g. disability, unemployment, sickness) during 2005-2009. It results in a baseline estimation sample that contains 865 363 individuals.[27] Table 1 presents key descriptive statistics of the full sample and the selected baseline estimation sample in comparison with the full economically active population of 16 - 64 years old.

[26] Wage data comes from annual records. I divide yearly wage by a number of employment months in a given year to calculate monthly wages.

[27] I use 5% random sample of the baseline sample in estimation and welfare analysis for computational reasons.

Table 1: Descriptive Statistics and Unemployment Patterns

	(1) Full Sample	(2) Baseline Estimation Sample	(3) Swedish population 16 - 64 years old
Descriptive Statistics, 2008			
Employment Income, *SEK/month*			
Mean	24 754	24 834	28 623
Median	23 233	23 308	25 317
Married	87%	87%	88%
With Children	54%	54%	54%
Nr. of Children, *median*	1	1	1
Age, *median*	40	40	40
Female	53%	51%	49%
With Higher Education	28%	27%	25%
Number of Unemployment Months per Individual, 2002 - 2014			
Mean	12.72	12.68	8.69
P1	1	1	1
P10	3	3	2
P25	5	5	3
P50	9	9	5
P75	16	16	11
P90	27	27	19
P99	64	64	49
Always Employed	83.9%	83.8%	89.5%
N	2 167 287	865 363	7 811 784

Notes: Column (1) shows descriptive statistics and unemployment patterns for the full sample. Column (2) represents the sample used in the empirical analysis. Column (3) describes the full Swedish population for the comparison purposes. The upper part of the Table shows descriptive statistics for 2008, which is one of the years used in estimation. The lower part describes a distribution of a number of unemployment months that individuals accumulated during 2002 - 2014.

Table 1 shows that full and baseline samples are very similar in terms of observables. Slight differences are observed in a share of female, which is 51% in a baseline sample compared to 53% in a full sample. Also, a baseline sample contains 27% of individuals with higher education, whereas 28% of individuals in the full sample have higher education. Both of these samples differ slightly from a full population. The main selection margin is the recipiency of UI benefits. Consequently, individuals who are omitted from the full sample on average have higher employment income not adjusted for work intensity. This difference is mechanical since unemployed individuals should have less wage income. The selected sample contains slightly more individuals with higher education, which is also mechanical since it contains less relatively young individuals who are most likely have not finished higher education. Finally, a full sample is represented by a 4% smaller share of female individuals.

Although full and baseline samples are very similar in terms of unemployment patterns, they, as expected, differ from a full population. Selected samples contain a 6% larger share of those who at least once during 2002 - 2014 were unemployed. Similarly, conditionally on being unemployed at least once, a distribution of a number of accumulated unemployment months is shifted to the right for the selected samples.

3 Descriptive Evidence

Unemployment insurance is at risk of private information problem, which might have non-negligible welfare costs. The term private information typically includes adverse selection and moral hazard. The essence of adverse selection in UI is that individuals tend to have more information about their overall unemployment risks. It usually leads to a positive correlation between insurance probabilities and unemployment risks. However, such a positive correlation might not only be driven by adverse selection.

Another alternative theoretical explanation, which is unrelated to private information, is a correlation between risk-preferences and risks (e.g. more risk-averse individuals have higher risks).[28] It would generate a qualitatively similar selection pattern but have different policy implications. The reason is that the absence of choice imposes the excess burden on individuals who do not value insurance. In addition, the potential presence of moral hazard, which might generate a similar positive correlation pattern. Moral hazard or ex-post selection is a behavioral response to being insured that increases unemployment probabilities. The intuition is that a lack of incentives due to lower financial stakes leads to less job-search or on-the-job efforts.

It implies that there are many scenarios arising from the complexity of insurance decisions that fundamentally hinges on risk perceptions and preferences for risks exposure. This ambiguity might result in a need of the opposite policy measures while generating same "reduced form"

[28]De Meza and Webb (2001) show that multiple levels of heterogeneity might also result in advantageous selection.

patterns in the data. This section does not attempt to disentangle those forces since it might have a limited use for the welfare analysis. For a discussion and an attempt to separate those scenarios using institutional variation, one should consult Landais et al. (2017). The main point of this discussion is that policy conclusions aimed at maximizing welfare rely on being able to disentangle risk preferences and information about risks, which often requires a theoretical structure. More importantly, in order to study alternative contract designs regulations, it is required to identify the sources of selection to be targeted by the contract features.

In this section, I present a number of descriptives patterns in the data that motivate modeling choices in the next section. There are several sources of variation that play a key role in the empirical analysis. Firstly, I leverage cross-sectional variation in incentives to be insured. This variation stems from differences in insurance premiums across occupation-specific UI funds and in a replacement rate due to a cap, which varies with unemployment duration. Another dimension of the variation is a result of a reform in 2007 which raised insurance premiums primarily for employed individuals and weakly reduced the generosity of benefits. These changes caused behavioral responses illustrated in Figure 3.

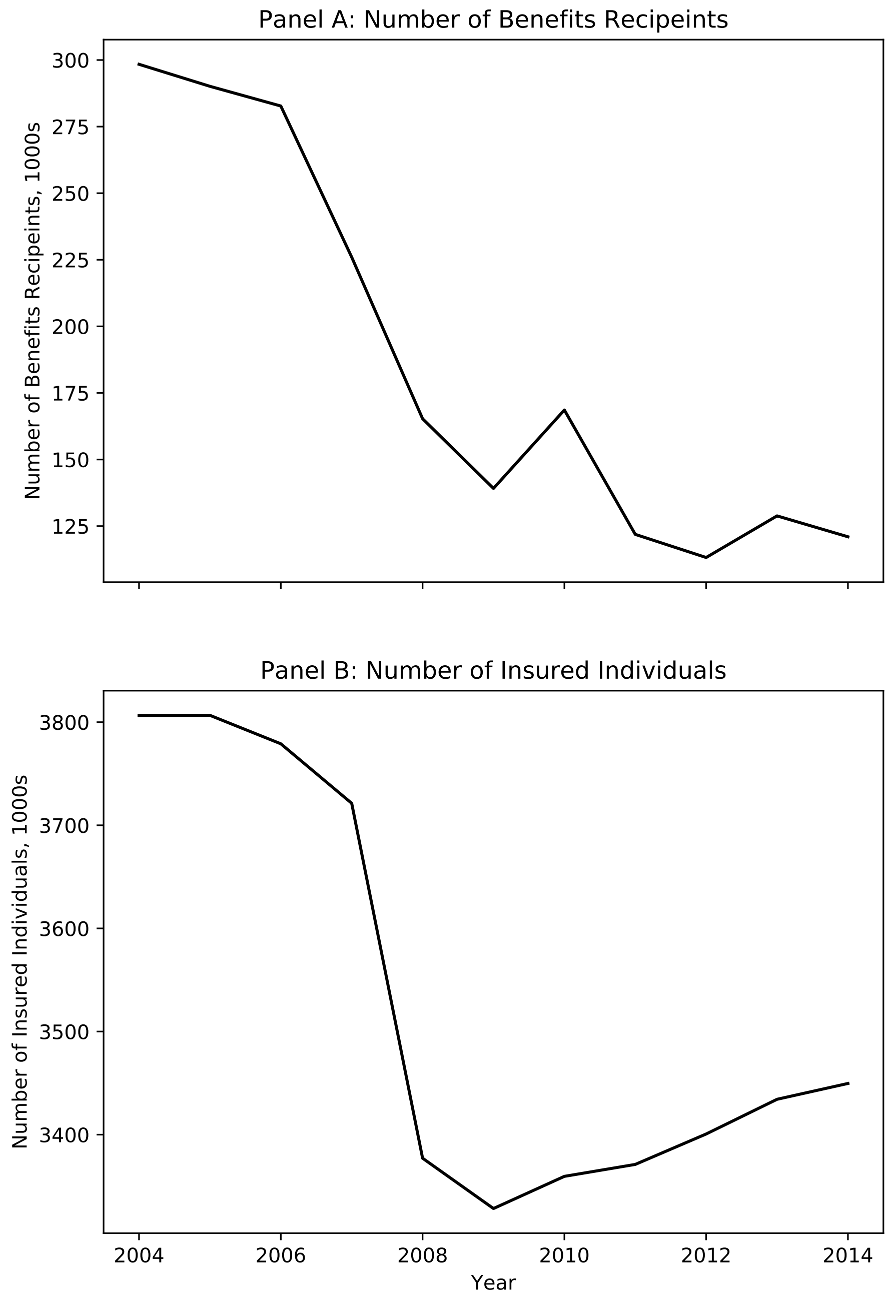
The Figure shows that a reform is associated with changes in a number of aggregate indicators, which might be driven by individual responses to the reform. More precisely, a number of benefits recipients and insured dropped in 2007 (Panels A and B, correspondingly).[29] However, this aggregate evidence cannot be solely attributed to changes in the structure of UI. The reason is that insurance decisions and aggregate outcomes are jointly determined by individual preferences, insurance structure, and labor market conditions.

Apart from an important role of adverse selection and moral hazard discussed in Landais et al. (2017), another dimension of private information might stem from the specific structure of insurance contracts. One of the eligibility conditions for voluntary UI requires being insured for at least twelve consecutive months. In this case, individuals with superior information about employment outcomes should start paying insurance fees exactly twelve months before the unemployment date. It implies that a dynamic nature of insurance eligibility introduces time-selection. The literature has documented similar behavioral patterns in, for example, health insurance (Aron-Dine et al., 2015; Einav et al., 2015, 2017) and dental markets (Cabral, 2016). The presence of this phenomenon also contributes to a positive correlation between unemployment risks and the likelihood of being insured. Although, it can be argued that time-selection is a part of adverse selection and can be resolved by mandates, alternative contracts that specifically restrict time-selection might be welfare-improving. The presence of time-selection can

[29] Note that a number of insured and a number of benefits recipients are not directly linked since one can receive basic insurance even without being a fund member.

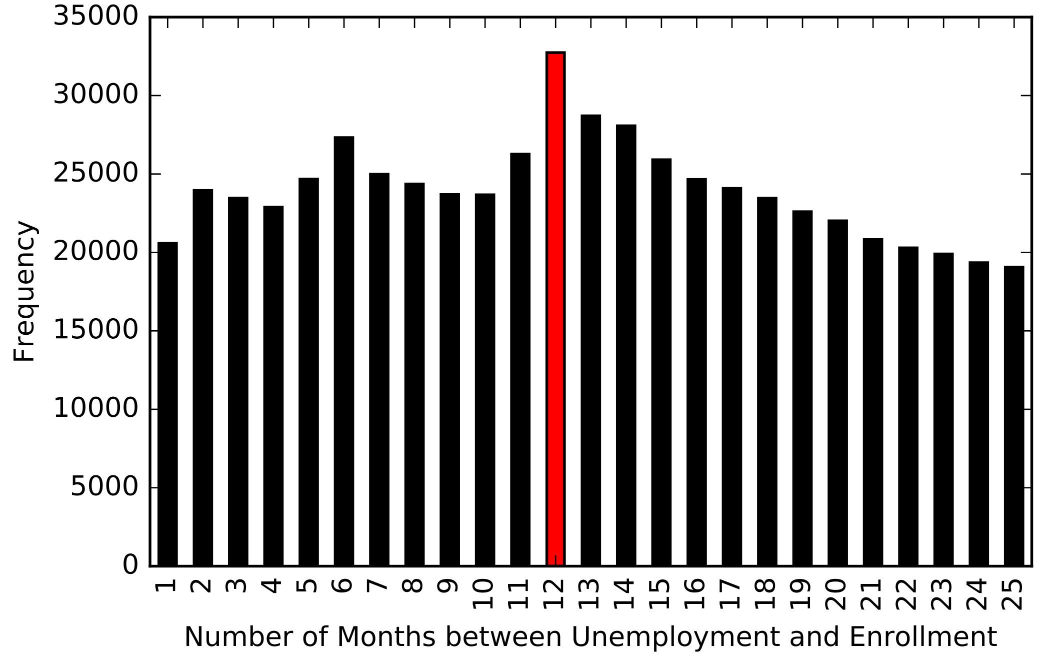
be shown with a distribution of a number of enrollment periods with which individuals start unemployment spells in the data displayed in Figure 4.

Figure 3: Unemployment Insurance and Benefits Recipiency, 2004 - 2014



Notes: The Figure presents aggregate indicators over time. The source is *Inspektionen för arbetslöshetsförsäkringen*.

Figure 4: Distribution of Accumulated Enrollment Months at the Beginning of Unemployment



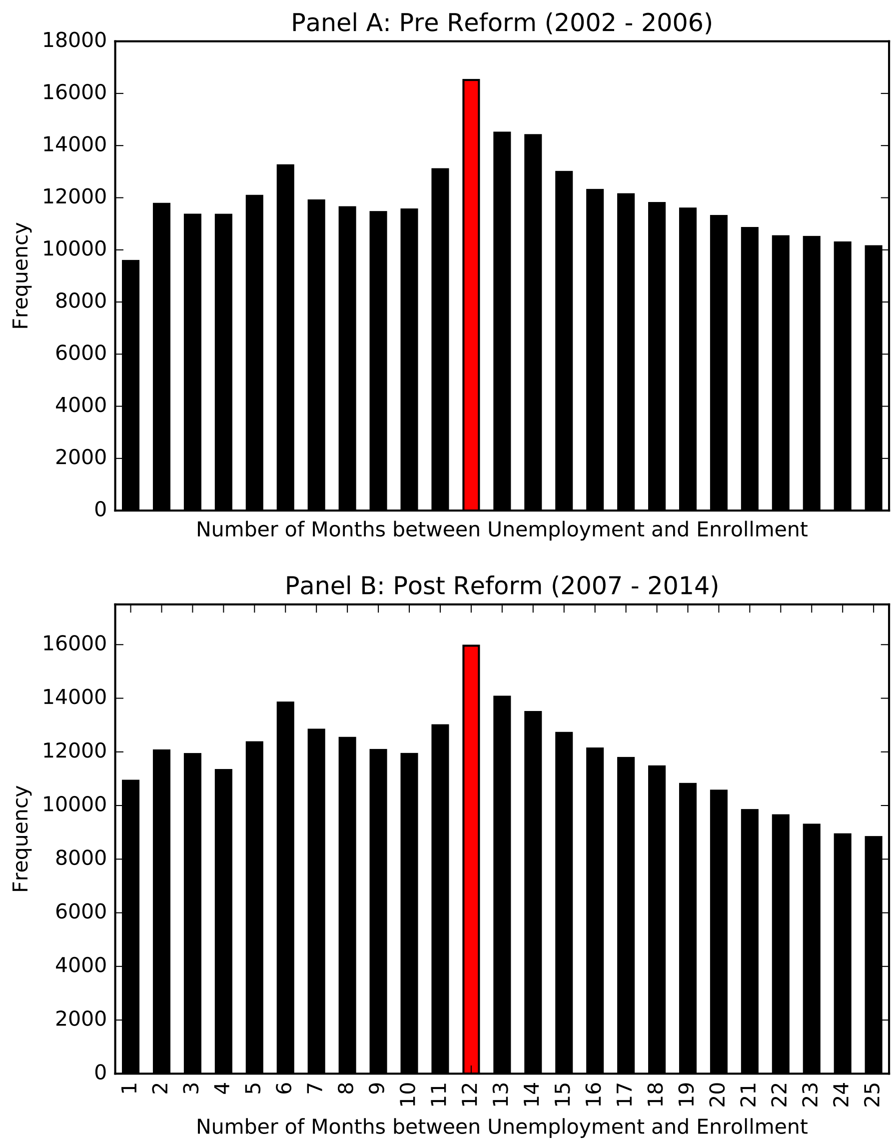
Notes: The Figure presents a discrete histogram of a distribution of a number of accumulated enrollment months before the commencements of unemployment spells. The red bar denotes twelve consecutive months of enrollment required for eligibility. The histogram contains a clear spike exactly at the red bar implying that individuals are more likely to start unemployment spells with twelve months of enrollment.

The distribution in the Figure has a spike (red) at exactly twelve months of enrollment, which suggests that individuals are more likely to start paying insurance premiums twelve months before unemployment. It allows being eligible for benefits exactly at the commencement of an unemployment spell, which minimizes the total amount of premiums to get eligibility. An area of the distribution to the left of the red spike is non-uniform and non-monotonic, which stems from differences in private information about future employment perspectives. These differences are a result of various layoff notices specified in employment contracts, differences in individuals informal knowledge about unemployment or the presence of probation contracts that often last for 6 months. The model in the next section systematically exploits those patterns and attributes them to the differences in the information structure about future employment outcomes. It is important to note that the model is agnostic about the source of this private information since only the fact of its existence is welfare-relevant. The additional evidence for various subgroups is presented in the Appendix B (Figures 13, 14 and 15) and shows identical patterns.

The key identification assumption that will allow using changes in the generosity of benefits and premiums to separately identify distributions of risk preferences and information about risks is that differences in insurance conditions are unrelated to the differences in information about unemployment beyond relevant labor market characteristics. The example of the violation of this assumption would be, for example, if reform in 2007 not only changed the attractiveness of insurance but also information about future unemployment. It would imply that changes in insurance decisions as a result of changes in are not only driven by attractiveness of insurance but also by changes private information structure. To investigate a potential violation of the identification assumption, I look at the time-selection evidence but separately before and after the reform in 2007 presented in Figure 5. As can be seen, the patterns are similar for both periods. However, this evidence should be viewed as neither necessary nor sufficient to ensure the validity of the assumption. The presence of considerable differences on those figures could alert about both changes in information and time-selection accompanied with a moral hazard response. The latter means that individuals not only select the timing of insurance but also choose if and when to become unemployed. The intuition is that the reform in 2007 weakly reduced the generosity of benefits and raised premiums, which implies that it costs more to qualify for less generous benefits. In the absence of the changes in information about future unemployment, the reform did not change bunching incentives for individuals who just knew about forthcoming unemployment. Those individuals should still prefer being covered even for one month compared to not paying fees and being ineligible. However, individuals who decide to facilitate a layoff and choose enrollment timing are affected since insurance becomes less generous. It might encourage them to keep being employed or switch a job without relying on benefits. Those individuals would exclude themselves from the bunching area and reduce the spike. The fact that it is difficult to graphically see considerable differences in bunching patterns can be also explained by a relatively small scale of the reform, which did not induce such institutional changes and behavioral responses.

Another important pattern of insurance decisions is that many individuals tend to have only one insurance spell, which often covers the whole observed period. A maximum number of insurance sequences in the course of observed period 1999 - 2014 amount to eleven. A median duration of an insurance sequence is 99 months. It might suggest that individuals display a considerable amount of inertia in fairly frequent monthly choices.

Figure 5: Distribution of Accumulated Enrollment Months: Before and After the Reform



Notes: The Figure presents a discrete histogram of a distribution of a number of accumulated enrollment months before the commencement of unemployment spells. It replicates the evidence in Figure 4 but separately for periods before (Panel A) and after the reform in 2007 (Panel B).

This section described the main behavioral patterns observed in the data. Firstly, it has shown that individuals seem to react to changes in premiums and benefits generosity. Secondly, the fact that many individuals have long insurance sequences might suggest a presence of choice inertia. Finally, the data display the signs of time selection. The model presented in the next section attempts to incorporate those elements in a framework that enables addressing the question of optimal regulations in UI.

4 Empirical Model

4.1 Overview of the Model

This section describes a model of an individual decision to pay monthly insurance premiums. The model has a purpose of recovering risk preferences, inertia, and private information about future employment outcomes, which jointly determine insurance choices. The estimates are used to obtain individual willingness to pay for insurance contracts, demand and cost functions. These elements are necessary for the welfare analysis and counterfactual policy experiments.

The structure of the model is motivated by a number of institutional features and descriptive patterns. The decision is a dynamic choice under uncertainty since individuals face unemployment risks and choose whether to pay premiums to become or keep being eligible for income-based coverage in the future. Such a forward-looking nature of the decision and presented time-selection evidence imply that private information primarily stems from the superior knowledge about time-varying risks and realization of shocks. The amount of private information is to a large extent determined by labor market observable characteristics such as tenure, industry affiliation and occupation type. The model is agnostic about the sources of this information being it due to employment contract conditions, negotiations with an employer to delay the layoff or any other alternative explanations. Therefore, an individual seeks to maximize gains from insurance and minimize total paid premiums based on preferences for risk exposure and available information about future employment outcomes and risks. Finally, individuals show the signs of inertia which implies that an individual is more likely to make the same decision as in the previous period ceteris paribus.

More formally, I assume that at each period when an individual makes a decision to start or keep paying monthly premiums, she plans for next T month in the future and has perfect information about unemployment outcomes for a part of this planning sequence. To be more precise, I model private information as the presence of a number of individual types in the population. An individual observes her type, which is unobserved to econometrician or insurer. It makes this information private. Each type denotes how many months of future employment outcomes are observed with certainty. As discussed above, it is motivated by temporary contracts with a fixed termination date, legally enforced layoff notice requirements and informal arrangements within firms that are often determined by labor market characteristics. It implies that within this planning horizon of length T, an individual knows the outcomes of $s < T$ periods and face uncertainty over the remaining part of the planning window, which creates uncertainty in this dynamic model. Then based on the preferences for risk exposure, an individual maximizes expected utility of an income stream over the planning horizon to decide whether to pay fees at the current period. This decision-making process is repeated every time the individual is observed to make such an insurance choice.

In summary, the estimation approach developed in this paper allows recovering three groups of fundamental policy-invariant parameters that affect individual decisions: parametrized distributions of risk preferences and information types as well as inertia parameters. Loosely speaking, to recover a distribution of risk preferences, I leverage variation in the generosity of benefits and fees across individuals and over time. To identify a distribution of discrete types separately from risk preferences, I assume that changes in the conditions of UI do not affect private information structure. It means that private information is assumed to be fixed conditionally on relevant labor market characteristics. Finally, the identification of inertia is challenging and often requires observing a group of individuals who make inertia-free decisions. Otherwise, inertia and a level of risk preferences are not separately identifiable without strong functional form assumptions. I assume that a group of individuals who face such inertia-free choices are those who at the time of a decision have observed forthcoming unemployment or have just exited the unemployment spell, which removes inertia and stimulates an active decision. It implies that whether a given individual decision is partly affected by inertia depends on her current type. Although inertia is important to explain the persistence of choices in the data, it is less relevant for the welfare analysis. The reason is that I do not take into account welfare losses of suboptimal choices. Therefore, since the focus of this paper is on properties of insurance contracts, it is important to analyze contract in the inertia-free environment to make them directly comparable.

The remainder of this section formally describes the model and identification, discusses an estimation approach and presents the results.

4.2 Model

I model an insurance choice as a forward-looking decision to maximize the expected utility of income over a fixed planning horizon of length T. I refer to this action as ”to be insured” from now on, which means paying insurance fees but not necessarily being eligible for benefits yet. All dynamics in the model is monthly. Each period an individual observes information about future employment, wages, insurance benefits and prices, and makes a decision to pay insurance fees to gain or keep the eligibility for income-based insurance in the future. A current insurance decision impacts future conditions and decisions through an eligibility condition that requires being insured for at least 12 consecutive months.

More formally, each individual i makes a decision each month t conditionally on observing the following information:

1. *A current number of accumulated enrollment periods* $\kappa_{it} \geq 0$.

2. *Private information in the form of known with certainty employment statuses for* $s > 0$ *periods or up to forthcoming unemployment.*[30] More formally, $\hat{s} = \min\{s, s_u\}$ where $\hat{s}$ denotes a number of periods that can actually be foreseen in the future, s_u is a number of periods until next unemployment and s is a number of periods that can be observed in the future in the absence of earlier unemployment. This formulation means that an individual can perfectly know future employment outcomes for s periods unless there is forthcoming foreseen unemployment. It reflects the fact that individuals cannot observe the end of unemployment spell. In this case, the information is limited to only one period ahead in unemployment spell. I assume that individuals can be one of twelve types $s \in \{1, ..., 12\}$. Own type is observed by an individual but unobserved to an econometrician. I limit the attention to twelve discrete types since it is required to capture the behavior stemming from the enrollment eligibility requirement. At the same time, being a type $s > 12$ does not provide much more beneficial information.

3. *Probability of unemployment outside of private type-specific information.* I assume that individuals have rational state-dependent expectations about unemployment probabilities about employment probabilities outside of the private information interval (from s to T). It implies that the expectations about unemployment probabilities are conditional on the preceding employment status. In other words, there are two state-dependent probabilities of employment: p_t^0 - probability of employment at time t conditionally on being unemployed at $t-1$; and p_t^1 - probability of employment conditionally on being employed at time $t-1$. It implies that individuals form expectations regarding n^{th} unknown period using Markov-type updating conditionally on a currently observed employment outcome.

   Example 1. *Imagine an individual who is employed at period t with certainty. She believes that a probability of employment in the next period is* p_{t+1}^0 *if unemployed at period* t *and* p_{t+1}^1 *otherwise. Since an individual knows that she is employed at period* t*, a probability of being employed at time* $t+1$ *is* p_{t+1}^1*. Consequently, beliefs about the probability of being employed at* $t+2$ *are formed as* $E[p_{t+2}] = p_{t+1}^1 \cdot p_{t+2}^1 + (1 - p_{t+1}^1) \cdot p_{t+2}^0$*. Similarly, the probability of*

[30] I exclude $s = 0$ since it is unlikely that individuals do not observe employment outcomes for the current month.

being employed further at period $t+3$ is $E[p_{t+3}] = E[p_{t+2}] \cdot p^1_{t+3} + (1 - E[p_{t+2}]) \cdot p^0_{t+3}$. An individual would roll such a probability chain for any unknown period in the future.

More generally, the expected probability of employment at period $t+n$ is constructed as follows:

$$E\left[p_{t+n}\right] = E\left[p_{t+n-1}\right] p^1_{t+n} + (1 - E\left[p_{t+n-1}\right])p^0_{t+n} \qquad \forall n > t+s \tag{1}$$

The assumption that individuals have rational expectations about unemployment risks allows inferring those probabilities from the data using a prediction model based on detailed data about labor market affiliations, demographic characteristics and preceding employment statuses.

4. *Expected wage, insurance fees and replacement rate for the entire planning horizon.* I assume that individuals observe those variables over the planning horizon $t = \{0, ..., T\}$. As discussed later, I focus on not very long planning windows primarily due to computations reasons but also because this assumption is less credible for high T.

An individual chooses whether to be insured or not $l_t \in \{0, 1\}$:

$$l_t = \begin{cases} 0, & \text{if uninsured} \\ 1, & \text{if insured} \end{cases}$$

The only state variable affected by a current insurance choice is a number of accumulated enrollment periods at $t+1$ (κ_{t+1}), which determines the eligibility status Λ_{t+1}:

$$\kappa_{t+1} = \begin{cases} \kappa_t + 1, & \text{if} \quad l_t = 1 \\ 0 \quad , & \text{if} \quad l_t = 0 \end{cases}$$

$$\Lambda_{t+1} = \begin{cases} 1, & \text{if} \quad \kappa_{t+1} >= 12 \\ 0, & \text{if} \quad \kappa_{t+1} < 12 \end{cases}$$

If an individual decides to continue or start paying insurance fees at time t, a number of accumulated enrollment periods increases by one in the next period and drops to or remains zero if fees are not paid. The eligibility comes after at least twelve periods are accumulated and lasts until a payment is missed.

A one-period payoff is:

$$\pi_{it} = \underbrace{(1-e_{it}) \cdot \left(\overbrace{(1-\Lambda_{it}) \cdot \underline{b}_{it}}^{\text{ineligible}} + \overbrace{(\Lambda_{it} \cdot \min\{b_{it} \cdot \bar{w}_{it}, B_{it}\}}^{\text{eligible}} \right)}_{\text{unemployed}} + \underbrace{e_{it} \cdot w_{it}}_{\text{employed}} - \underbrace{l_{it} \cdot \tau_{it}}_{\substack{\text{pay}\\ \text{premiums}}}$$

where e_{it} is employment status, which equals to one if an individual is employed; $\underline{b}_{it}$ - basic insurance amount that individuals would get if ineligible; b_{it} - wage replacement rate under voluntary insurance, B_{it} - voluntary insurance cap; $\bar{w}_{it}$ - mean income during twelve months preceding the current period based on which insurance value is constructed; w_{it} - actual wage received if employed.

The payoff of an insurance decision $l_{it} \in \{0, 1\}$ is a sum of monthly payoffs over the optimization horizon T conditionally on optimally planning future insurance decisions and on the specific expected sequence of employment outcomes j $(\{e_n^j\}_{n=t+1}^{t+T})$:

$$\Pi_t(l_t; \{e_t^j\}_{n=t+1}^{t+T}) = \overbrace{\pi_t(l_t)}^{\text{current}} + \overbrace{\sum_{n=t+1}^{T} \pi_n(l_n^*(l_t, \{e_n^j\}_{n=t+1}^{t+T}))}^{\text{planned}} \tag{2}$$

where $\pi_t(l_t)$ is a payoff from a current period when the actual decision about insurance is made; $\pi_n(l_n^*(l_t, \{e_k\}_{t=1}^T))$ is a payoff at some future period n conditionally on optimally choosing all l_n^* in the planning horizon T and conditionally on the expected employment sequence $\{e_k\}_{t=1}^T$.

There are three important clarifications about the model. Firstly, the intuition of equation (2) is that a current decision to pay insurance fees has an effect on future periods directly by affecting eligibility statuses and indirectly through an effect on forthcoming insurance decisions. Therefore, to decide whether to pay premiums now, an individual needs to solve a dynamic programming problem. She starts from a terminal period T and rolls back to select the optimal sequence of insurance decisions to choose a current insurance choice l_t. This decision-making process is repeated each period when actual decisions are made but planning window of size T shifts by one period. Secondly, the formulation of the equation (2) is loose for exposition purposes. I omit the notation that an optimal planned insurance sequence, a current decision, and payoffs are affected by time-varying state variables including a replacement rate, cap, fees, and wages. Finally, $\{e_k\}_{t=1}^T$ denotes a particular sequence that an individual expects while planning. Recall that the information structure consists of a private information about employment outcomes for s periods in the future and uncertainty about the remainder of the planning horizon (from s to T). If an individual does not have any uncertainty, $\{e_k\}_{t=1}^T$ would be a unique known sequence. The lack of information introduces a multiplicity of potential sequences. As a result, each potential sequence implies a different optimal planning rule and a payoff. The following example is intended to clarify the logic.

Example 2. *Imagine an individual who plans over T (from t to $t+T$) periods in the future to decide whether to pay an insurance premium now at t. The individual knows employment outcomes for all periods in the planning horizon except two final periods. For those periods, she forms beliefs that at the penultimate period she will be employed with probability 0.94 and with probability 0.95 in the last period of the planning horizon. Note that this is a simplified example in which probabilities of unemployment are independent across periods for simplicity. The model instead, as discussed earlier, imposes more realistic Markov structure but this example suffices for the illustrative purposes. Table 2 summarizes the information structure faced by the individual.*

Table 2: An Example of Various Employment Sequences under Uncertainty

	Planning Horizon (T)													Sequence Probability
Probability	-	-	-	-	-	-	-	-	-	-	...	0.94	0.95	ξ_j
Sequence	1	1	1	1	1	1	1	1	1	1	...	0	0	$0.06 \cdot 0.05 = 0.003$
												0	1	$0.06 \cdot 0.95 = 0.057$
												1	0	$0.94 \cdot 0.05 = 0.047$
												1	1	$0.94 \cdot 0.95 = 0.893$

***Notes**: The Table demonstrates an example of possible employment sequences, which generates uncertainty in the model. An individual knows true future outcomes but for the last two periods. It results in 4 possible sequences that might be realized. Note that each of those sequences might result in a completely different optimal insurance sequence. Using the probabilities of unknown periods, it is possible to calculate the probabilities of each sequence as in column ξ_j.*

Therefore, an individual has to solve a dynamic programming problem separately for each of those sequences.

The example demonstrates that each individual i at time t solves dynamic programming problems for all possible employment sequences. I solve a dynamic programming problem using backward induction from a terminal period T. Note that a number of sequences at each choice is 2^{T-s}, which can become an extremely large number. I discuss how I address those complications in Appendix A. Each sequence apart from generating a different payoff also occurs with a different probability as shown in the example and can be more formally defined:

$$\xi_{jt} = \prod_{q=t+s+1}^{T} m_{qt} \tag{3}$$

where m_q is a probability of a specific outcome in the sequence at time q as demonstrated in the example. Each m_q is constructed as in (1).

The expected utility of a decision to pay a premium now at time t is:

$$EV(l_t) = \sum_{j=1}^{2^{(T-s)}} \xi_{jt} \cdot u\left(\Pi_{jt}(l_t)\right) \tag{4}$$

where u - utility function; $\Pi_{jt}(l_t)$ is a simplified notation for $\Pi(l_t; \{e_n^j\}_{n=t+1}^{t+T})$ from (2), which is the payoff under a sequence j at a decision period t conditionally on choosing $l = \{0, 1\}$.

The individual i chooses to be insured at time t if $EV(l_{it} = 1) \geq EV(l_{it} = 0)$.

4.3 Estimation Approach and Parametrization

To proceed to the estimation of a model, I make a number of parametric and functional form assumptions. Firstly, I limit the length of a planning problem to $T = 18$. A chosen T must be larger than 12 in order to capture time-selection behavior as a result of eligibility requirement. Since, it is required to solve a dynamic model many times for each individual, time, type and sequence to compute payoffs of each action, it becomes computationally burdensome for a large T. I experiment with different values of T and taking more periods into consideration after $T = 18$ does not considerably affect results but adds computational costs as discussed in the robustness section. In addition, a number of employment sequences grows exponentially with T. To make the computation feasible and not to solve the dynamic programming for each sequence, I limit the attention only to those sequences, which have non-zero probabilities.[31] Therefore, a choice of T remains crucial for computational costs. Appendix A discusses these computational details.

I assume that individuals have CRRA utility over payoffs of the sequences:

$$u(\Pi_j) = \frac{(\Pi_j)^{1-\rho}}{1-\rho}$$

Recall from the previous section that an individual chooses to buy insurance if $EV(l_{it} = 1) \geq EV(l_{it} = 0)$ or, alternatively, if $EV(l_{it} = 1) - EV(l_{it} = 0) \geq 0$. As noted in Apesteguia and Ballester (2018), such a utility difference has a unique value of a risk preference parameter ρ where $EV(l_{it} = 1) - EV(l_{it} = 0) = \Delta_{it} = 0$.[32] It means that an individual with risk preference

[31] Theoretically, all sequences have non-zero probability but practically they do because of the computer precision limit.

[32] Note that although ΔV_{it} has a unique intersection with a zero line for a finite value of ρ, the function is not monotonic in ρ, which creates complications in the estimation of discrete choice models under uncertainty. The

value that yields $\Delta_{it} = 0$ is indifferent between buying insurance or not. Denote a risk preference value ρ where $\Delta EV_{it}(\rho) = 0$ as λ. Any $\rho < \lambda$ would imply that an individual should not buy insurance since she is sufficiently "risk-loving". Similarly, if an individual has $\rho > \lambda$, she should buy insurance. Since the data provide all information required to estimate both $EV(l_{it} = 1)$ and $EV(l_{it} = 0)$ for all individuals i, observed periods t and potential types s, it is possible to numerically compute a value of risk preferences λ at which $\{i, t, s\}$ is indifferent between paying premiums or not. This cutoff not only differs across individuals and time but also by a type s, which is unknown but observed by an individual. The following example demonstrates the logic.

Example 3. *Assume for expositional purposes that an individual has the following true employment sequence in the future (always employed):*

$$e = \{1 \quad 1 \quad 1 \quad 1 \quad 1 \quad ... \quad 1 \quad 1 \quad 1\}$$

In the absence of any information about the future, an individual would have the following beliefs about employment probabilities for each of those periods:

$$p = \{0.92 \quad 0.92 \quad 0.87 \quad 0.84 \quad 0.89 \quad 0.97 \quad ... \quad 0.95 \quad 0.94 \quad 0.95\}$$

Depending on an individual type $s \in \{1, ..., 12\}$, there might be different threshold risk preference levels at which an individual is indifferent between buying insurance or not demonstrated in Table 3:

approach used in this paper does not suffer from this issue. I discuss this in more details in the identification section.

Table 3: Example of a Role of Types

(i,t)		Time (from t to $t+T$)									
		1	2	3	4	5	6	...	16	17	18	$\boldsymbol{\lambda_{its}}$
Types (s)	1	1	0.92	0.87	0.84	0.89	0.97	...	0.94	0.95	0.94	12.1
	2	1	1	0.87	0.84	0.89	0.97	...	0.94	0.95	0.94	8.7
	3	1	1	1	0.84	0.89	0.97	...	0.94	0.95	0.94	6.1
	4	1	1	1	1	0.89	0.97	...	0.94	0.95	0.94	4.2
	5	1	1	1	1	1	0.97	...	0.94	0.95	0.94	2.1
	6	1	1	1	1	1	1	...	0.94	0.95	0.94	1.2
	7	1	1	1	1	1	1	...	0.94	0.95	0.94	-0.1
	8	1	1	1	1	1	1	...	0.94	0.95	0.94	-1.2
	9	1	1	1	1	1	1	...	0.94	0.95	0.94	-3.4
	10	1	1	1	1	1	1	...	0.94	0.95	0.94	-5.2
	11	1	1	1	1	1	1	...	1	0.95	0.94	-6.7
	12	1	1	1	1	1	1	...	1	1	0.94	-12

Notes: The Table demonstrates an example of the role of types in insurance decisions. It shows that despite having the same beliefs about future employment probabilities, being a different type affects a risk preference indifference point presented in the column λ_{its}.

An example shows various information structures that an individual might have depending on type $s \in \{1, ..., 12\}$. In addition, as the column λ_{its} suggests, even for an individual i and time t, there might be twelve different risk preference thresholds depending on a type.

As the example shows, an insurance decision can be summarized by a risk preference threshold, which formally is defined as follows:

$$\lambda_{its} = \rho_{its} : \Delta_{its}(\rho_{its}) = 0 \tag{5}$$

Note that everything in equations (5) is known or can be inferred from the data except λ_{its}. It implies that λ_{its} can be computed numerically by solving the model for each i,t,s repeatedly to find the value ρ_{its} that satisfies (5). The only object not observed from the data directly is beliefs about unemployment probabilities ($\{p_k\}_{k=t+s}^{t+T}$) beyond type-dependent private information. As mentioned above, I assume that individuals have rational expectations about unemployment outcomes. Therefore, I recover beliefs about probabilities of employment in any relevant period in the future separately by preceding employment status using a model:

$$Pr(e_{it} = 1|e_{i,t-1}) = Logit(Q_{it}|e_{i,t-1})$$

where Q_{it} includes observed labor market and individual characteristics and year fixed effects; $e_{i,t-1}$ - previous employment status.

Using recovered probabilities for each (i,t), I construct the probabilities ξ_j from (4) using equation (3). As a result, for each individual and period, I numerically obtain twelve different threshold risk preference values at which an individual is indifferent between buying insurance or not.

Although estimated risk preference thresholds do not provide a distribution of risk presences and types, which are fundamental model primitives required for further welfare analysis, it is a key step to recover them. Note that the probability that an individual pays premiums is the probability that her risk preference value is at least as large as the estimated threshold. I assume that risk preferences are normally distributed in the population with a mean $\alpha X'$ and a standard deviation σ, where α is a vector of unknown parameters to be estimated and X is an array of individual characteristics to account for heterogeneity:

$$\rho_{it} \sim N(\alpha X'_{it}, \sigma) \tag{6}$$

where X_{it} contains a constant, binned age, gender, family, higher education dummy, an indicator if there are children in a family, and binned income.

A probability that (i,t,s) with the risk preference threshold λ_{its} buys insurance is a probability that the actual risk preference value is larger than λ_{its}. Given a parametric distribution in (6), this probability can be expressed:

$$Pr(l_{its} = 1) = Pr(\rho_{it} \geq \lambda_{its}) = 1 - \Phi\left(\frac{\lambda_{its} - \alpha X'}{\sigma}\right) \tag{7}$$

where $\Phi\left(\frac{\lambda_{its}-\alpha X'}{\sigma}\right)$ is a cumulative normal distribution denoting a probability that an actual risk preference value is below λ_{its}.

A need for this parametric assumption arises from a discrete insurance choice. If the choice was from a continuous set of contracts, it would be possible to recover risk preferences without this parametric assumption.

I assume that a probability that (i,t) is type s has a multinomial logit form:

$$\phi_{its} = \frac{\exp(\beta_s Z'_{it})}{\sum_{k=1}^{12} \exp(\beta_k Z'_{it})} \tag{8}$$

There are twelve vectors β_s corresponding to each type. I normalize the first vector by setting all elements to 0.3. Z_{it} is an array containing observables that are expected to determine type probabilities. As discussed earlier, the institutional details suggest that the probability depends on the labor market affiliations and demographic variables such as age. Therefore, I include a large set of labor market variables (e.g industry, occupation type, education level, education specialization). It generates in a large set of variables, which makes estimation burdensome since there are eleven parameters in β (the first one is normalized) for each variable in Z. However, many variables in Z are highly correlated since, for instance, education and labor market affiliations are closely related to each other. Therefore, I cluster individuals based on these variables to reduce the dimensionality of variables in Z to five dummy variables denoted as cluster allocations. I also add binned age variables which together with a constant comprise a vector of eight parameters β for each type.

The probability that an individual pays a premium is:

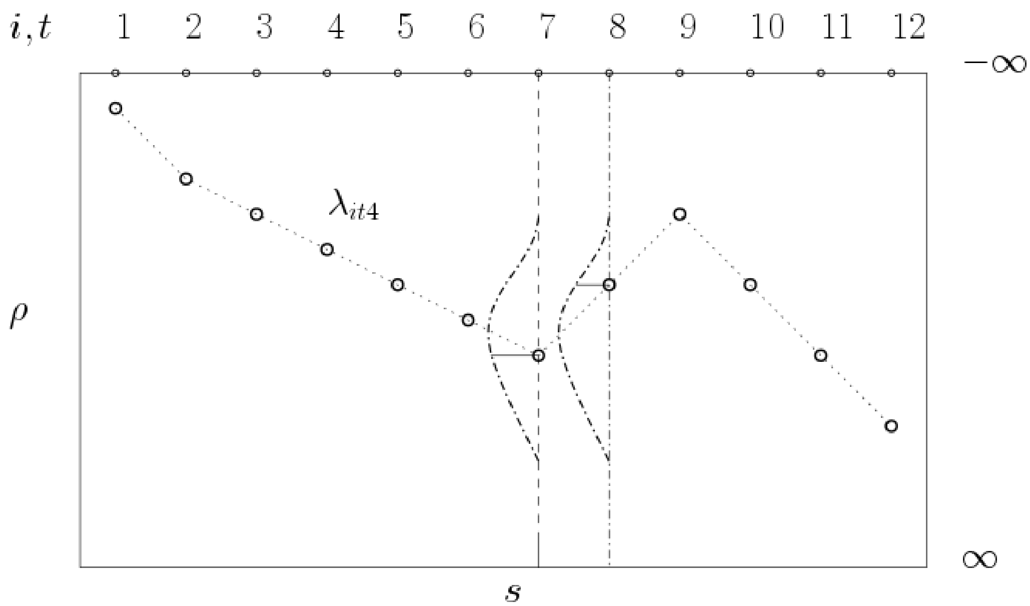
$$Pr_{it}(l=1) = 1 - \sum_{s=1}^{12} \phi_{its} \Phi\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right) \tag{9}$$

It yields a likelihood function:

$$L = \prod_i \prod_t \left(\overbrace{1 - \sum_{s=1}^{12} \phi_{its} \Phi\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)}^{\text{Insurance Probability}} \right)^{y_{it}} \left(\overbrace{\sum_{s=1}^{12} \phi_{its} \Phi\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)}^{\text{1 - Insurance Probability}} \right)^{1-y_{it}} \tag{10}$$

To illustrate the logic behind the likelihood function and an estimation approach consider Figure 6. The Figure illustrates that for a particular individual, time and type s, a probability of buying insurance is the area to the bottom (towards infinity) of a density function. The probability that an individual buys insurance is a weighted sum of those areas where type probabilities from (9) serve as weights.

Figure 6: Probability of Buying Insurance



Notes: The Figure graphically summarizes the estimation logic. The y-axis denotes a range of risks preference values of ρ from $-\infty$ to ∞ (from the top to the bottom). The x-axis denotes discrete types from one to twelve marked above the plot. Empty dots are λ_{its} points. The bell-shaped curves represent probability density functions of risk preferences (normal distribution). The areas to the bottom of each perpendicular line from normal densities to the dashed type-line denote probabilities that an individual of the corresponding type has a risk preference value above the threshold denoted by empty dots. The probability that (i,t) buys insurance is a weighted by type-probabilities sum of these areas.

The final part of the model is inertia. The identification requires an inertia-free group of individuals (Handel, 2013). I assume those who because of private information have observed forthcoming unemployment or were unemployed at the period before are not affected by inertia ($\eta = 0$). Those who are affected by inertia ($\eta = 1$), have the following choice probabilities:

$$Pr_{it}(l = 0|s) = \Phi\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)^{\Upsilon_{it}}$$

$$\Upsilon_{it} = \underbrace{\eta_{it} \cdot \left[\overbrace{(1 - l_{i,t-1}) \cdot \gamma_0}^{\text{previously uninsured}} + \overbrace{l_{i,t-1} \cdot \gamma_1}^{\text{previously insured}}\right]}_{\text{with inertia}} + \underbrace{(1 - \eta_{it}) \cdot 1}_{\text{without inertia}}$$

where l_{t-1} - previous insurance status; $\{\gamma_0, \gamma_1\}$ - inertia parameters.

The intuition for such parametrization is that when insured individuals are more likely to keep being insured, Υ will be a large positive number, which moves probability $\Phi\left(\frac{\lambda_{its}-\alpha X'_{it}}{\sigma}\right)$ towards zero. Similarly, if previously uninsured individuals are more likely to keep being uninsured, Υ will be close to zero, which forces $\Phi\left(\frac{\lambda_{its}-\alpha X'_{it}}{\sigma}\right)$ to go to one and, thus the insurance probability to zero. When an individual is affected by inertia, Υ is one, which leaves the insurance probability unchanged. It yields a modified likelihood function:

$$L = \prod_i \prod_t \left(\overbrace{1 - \sum_{s=1}^{12} \phi_{its} \Phi\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)^{\Upsilon_{its}}}^{\text{if insured}} \right)^{y_{it}} \cdot \left(\overbrace{\sum_{s=1}^{12} \phi_{its} \Phi\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)^{\Upsilon_{its}}}^{\text{if uninsured}} \right)^{1-y_{it}} \tag{11}$$

A modeling and estimation approach described in this section has a number of advantages. Firstly, it is computationally attractive since to search for parameters which maximize the likelihood function, it is not required to recompute the model with a computationally intensive dynamic programming. Instead, pre-estimated thresholds λ_{its} are sufficient to estimate parameters of a likelihood function and allow for rich model heterogeneity. Secondly, the likelihood function is smooth and has an analytical gradient, which makes it computationally attractive to optimize using fast gradient-based non-linear optimizers. Furthermore, it does not require simulation methods, which are prone to the simulations bias (Train, 2009).[33]

4.4 Identification

Identification of the empirical model outlined in this section concerns separately recovering parametrized distributions of risk preferences and types as well as inertia parameters that together with pre-estimated thresholds determine insurance probabilities $\mathbb{P}_{its}(\alpha, \beta, \gamma_0, \gamma_1 | \lambda_{its})$.

Firstly, identification requires uniqueness of λ_{its}. Otherwise, there will be multiple insurance probabilities for one observed decision. The uniqueness results follow from Apesteguia and Ballester (2018). Before discussing the uniqueness of these indifference points, note that for lotteries that are not first-order stochastic dominance related, the utility difference $\Delta = EU_{insured}(\rho) - EU_{uninsured}(\rho)$ is increasing in some interval but since any CRRA utility function approaches to zero as $\rho \to \infty$, the difference also converges to zero. It implies that multiple risk preference parameters yield the same utility difference, which might create an identification problem. It also means that a probability of being insured does not monotonically rise with a

[33] Note that although the likelihood function treats the insurance decisions i, t as independent, the interdependence is introduced indirectly through the estimation of thresholds.

degree of risk aversion and often used additive error terms start dominating the utility difference at large risk preference values. Although the utility difference is non-monotonic in a risk preference parameter, which complicates the estimation of discrete choice models under uncertainty, the approach in this paper is immune to this issue. For the case of choices with a dominant option, there is no indifference point which implies that a dominant option should be chosen. For the most cases where being insured and uninsured might be preferred depending on the risk preference value, the indifference point is unique, which follows from Apesteguia and Ballester (2018).[34,35]

To disentangle the components of $\Omega = \{\alpha, \beta, \gamma_0, \gamma_1\}$, I make two key identification assumptions apart from the structure of the model. Firstly, I assume that changes in the generosity of insurance, which in this case primarily come from the reform in 2007, do not change a structure of private information meaning that parameters $\{\beta\}_{s=1}^{12}$ are fixed. It allows comparing the insurance take-up responses to changes in premiums and benefits generosity to recover a distribution of risk preferences. The empirical identification of type parameters leverages patterns of enrollment timing with respect to forthcoming unemployment and changes in unemployment risks.

Another assumption is required to identify inertia. I assume that individuals who observe forthcoming unemployment because of the type-specific private information, or who were unemployed at the preceding periods make a choice without inertia. It allows obtaining a group of individuals who make decisions driven by only preferences and information about the risks. Disentangling inertia without this kind of assumptions is challenging. For example, same high probability of insurance can be a result of both a very high level of risk aversion and inertia. Since initial choices are unobserved or difficult to recognize in this setting, this assumption is necessary.

4.5 Parameter Estimates and Model Fit

The model outlined in the previous section has 13 parameters of a risk preferences distribution, two inertia parameters, and 88 type distribution parameters. I estimate a model using maximum likelihood. I obtain standard errors of the parameters using bootstrap with 100 draws with replacement. Appendix A provides more details of estimation of parameters and standard errors.

[34] Apesteguia and Ballester (2018) do not prove the uniqueness of an indifference point directly but they prove that the upper bound of an interval, where the difference is monotonic, converges to this unique indifference point as $t \to \infty$ where $t > 0$ multiplies the outcomes of the lottery.

[35] Although the indifference point is theoretically unique, it is not computationally true since because of computer precision constraints, a limit of a utility difference that approaches zero actually becomes zero at some point. I discuss how I deal with the computation of thresholds in Appendix A

Table 4: Parameters of a Risk Preference Distribution and Inertia

		Coefficients	Std. Errors
α:	Constant	50.535	(0.11)
α:	Age $(30; 40]$	-2.581	(0.033)
α:	Age $(40; 50]$	-2.661	(0.346)
α:	Age > 50	-1.5	(0.555)
α:	Gender	0.234	(0.337)
α:	Family	0.642	(0.529)
α:	Higher Education	3.99	(0.831)
α:	Has Children	1.308	(0.218)
α:	Income $(25\%; 50\%]$	-56.148	(0.241)
α:	Income $(50\%; 75\%]$	-68.218	(0.372)
α:	Income $> 75\%$	-35.370	(0.652)
σ:	Std. Deviation	113.757	(0.169)
γ_1	Inertia	178.251	(0.2)
γ_0		0.006	(< 0.001)

Notes: The Table presents parameter estimates of a risk preference distribution and inertia together with bootstrapped standard errors in the brackets in the corresponding column. Income variable is binned into groups according to the percentiles of the distribution. For example, a variable Income $(50\%; 75\%]$ denotes if an individual has an income within 50% - 75% percentiles of a distribution.

Table 4 presents risk preference and inertia parameters. The Table shows that older and higher income individuals tend to be less risk-averse. Being a female, married, with higher education and having children is associated with higher risk aversion. It implies that those characteristics increase the probability of buying insurance conditionally on unemployment risks and private information The model suggests considerable unobserved risk preference heterogeneity implied by a fairly large standard deviation in a risk preference distribution. I do not provide an extensive discussion of the model parameters since their main use is to recover demand, willingness-to-pay and cost functions for the welfare analysis.

The model also shows an important role of inertia implied by the corresponding parameters that take a value of 178.251 for previously insured and 0.006 for previously uninsured. To put this into perspective, an individual who has a probability of buying insurance 0.9 in the absence of inertia has a probability 0.999 conditionally on being insured before and 0.001 if uninsured before upon adjusting for inertia.

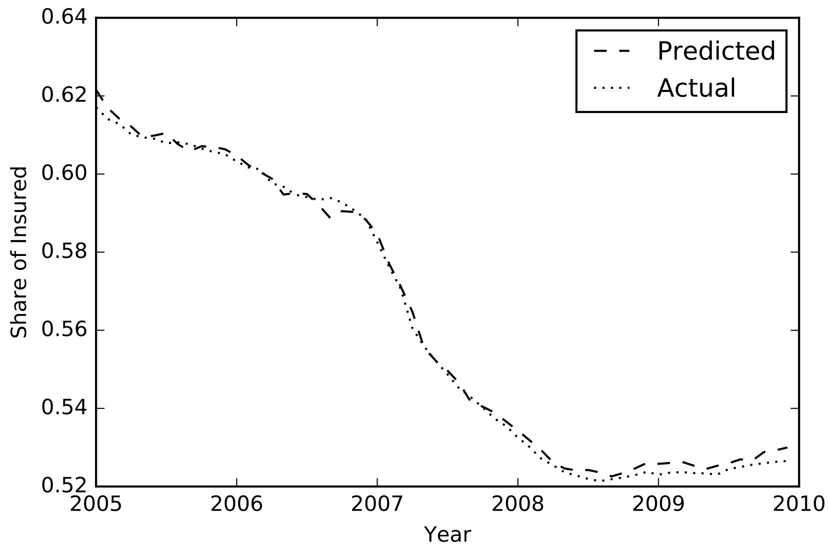
In addition to a risk preference distribution, the model generates 88 parameters of a type distribution. Table 7 with parameters and standard errors is included in Appendix C. Table 8 summarizes the information from type parameters by presenting a resulted type probabilities in the estimation sample. The model results suggest that 77.21% individuals have information only about one period ahead while 7.74% can perfectly foresee employment outcomes for two periods in the future. In line with the time-selection evidence, a considerable share of individuals (13.54%) have private information about twelve periods in the future, which allows them to perfectly time enrollment. The remaining types are uncommon (each has less than 1%). Such a sharp model prediction of a type distribution is to a large extent driven by a very limited number of variables included in vector Z for computational reasons. It implies that allowing for richer heterogeneity by including more relevant characteristics will most likely produce higher probabilities for uncommon types. However, the distribution of probabilities is still in line with the priors based on the anecdotal evidence.

Table 5: Model Fit - Share of Insured Individuals by Subgroups

	Shares of Insured Individuals	
	Actual	Predicted
Age ≤ 30	0.569	0.569
Age $(30; 40]$	0.561	0.563
Age $(40; 50]$	0.562	0.563
Age > 50	0.555	0.556
Gender	0.572	0.571
Family	0.562	0.563
Higher Education	0.558	0.558
Has Children	0.563	0.565
Income $\leq 25\%$	0.571	0.574
Income $(25\%; 50\%]$	0.563	0.563
Income $(50\%; 75\%]$	0.558	0.556
Income $> 75\%$	0.556	0.558

Notes: The Table demonstrates the actual and predicted shares of insured individuals by subgroups of individuals based on income, family, gender and education characteristics.

Figure 7: Model Fit - Demand



Notes: The Figure demonstrates actual (dashed) and predicted demand (solid) demand functions for 2005 - 2009. The y-axis represents a share of insured individuals.

Finally, Figure 7 and Table 5 suggest that the model predicts insurance patterns that closely match actual evidence both over time and by subgroups. The quality of this in-sample fit, however, should be taken with a caution as a measure of the validity of the model since it is not surprising that such a rich model fits the data well.

5 Welfare

This section describes how the estimates of the model are used to compare various regulations in UI. Although a mandate is one of the most widely discussed regulations in insurance markets and can be viewed as a policy that eliminates adverse selection, it also imposes a burden on those who prefer being uninsured. Therefore, alternative contracts, which also restrict the scopes of private information but impose milder choice restrictions, might be preferred to traditional pricing mechanisms and mandates. While there are many potential counterfactual contracts, I focus on two alternatives that target specific features of private information. Firstly, I consider a contract with fixed costs amounting to six times monthly fees to be paid when entering the insurance pool.[36] It should discourage time-selection by creating a value of long-term fund enrollment.

[36] I study similar 3 and 9 months contracts that produce similar results.

Secondly, I consider an often called "open enrollment period" contract that allows entering a fund only at the specific month and has the prespecified duration. I look at 18 and 24 months contracts. I do not consider a 12 months contract, for example, because estimates suggest that some individuals might have private information about up to 12 months in the future. As a result, this contract does not leave much uncertainty and should be avoided. An open enrollment contract is aimed at directly eliminating time-selection. Welfare analysis is based on the pooled sample of individuals over years 2005-2009 (60 months).

5.1 Measuring Welfare

Welfare analysis requires obtaining a number of components using estimated parameters to construct relevant welfare-metrics. There are two dimensions in which various regulations have an impact: consumer welfare and government budget costs.

To understand the effect on consumers, one needs to recover willingness to pay for a particular insurance contract, which is the maximum price that would be paid by every individual each month. Consumer surplus (CS) can then be measured as a difference between WTP and actual price. It determines demand for insurance since the policy should be purchased only if WTP is larger than price. Such a relationship might not be true in the presence of inertia. In this case, insurance premiums might still be paid even if insurance is valued less than it costs because of choice persistence.[37] Although I recover inertia in the estimation since it seems to play an important role in frequent monthly decisions, I do not take it into account in the welfare analysis. The reason is that the focus of the paper is on how contract design can generate welfare gains by restricting risk-based selection and preserving insurance choices. Inertia would act as a third force and deviate the discussion from this focus. In addition, it is theoretically unclear how welfare analysis should be conducted when comparing contracts that clearly prone to inertia (current and entry costs contracts) with alternatives that presumably should not exhibit such properties because of considerably less frequent choices (open enrollment contracts). Finally, to which extent the government should internalize welfare costs of suboptimal choices is a controversial question. Therefore, to avoid these conceptual ambiguities, I focus on pure predicted responses to consider competing policies.

The effect on a government is a result of two main components: demand and total cost functions. In summary, the essence of the welfare analysis in this set-up involves understanding how various changes affect insurance take-up, consumer surplus, and government costs. Before defining how exactly welfare conclusions are obtained, I formally define how I construct these

[37]Similarly, insurance might not be bought even if it is valued more than it costs.

components using the model and parameter estimates.

Recall that the voluntary part of UI in Sweden has two different prices: for employed and unemployed individuals. Since most price variation is observed for "worker" premiums and most of the time individuals are employed, the former price is a more important strategic variable, to which I refer as g. Therefore, I choose it to be varied in the counterfactual analysis and fix the actual price for unemployed. Note that all components necessary for welfare analysis are contract/regulation-specific and should be separately obtained for each considered policy k. Also, to even up the comparison of voluntary contracts and mandates, I consider voluntary contracts in the absence of basic insurance since it would be unavailable under the mandatory system.[38] It implies that all the computed objects required for welfare analysis correspond to the systems with no basic insurance.

Since a key sufficient statistics in the model is risk preference thresholds described in the previous section, all counterfactual price or policy changes require reestimating those thresholds, which is the most computationally intensive part of the model. To be more precise, for each counterfactual policy I solve the model to obtain an array of thresholds for each individual i at each time t and policy k on a grid of prices $g \in [\underline{g}; \bar{g}]$. The computational procedure described in the previous section does this also for each unknown type $s \in \{1, ..., 12\}$. It means that the only object obtained from model parameters needed for recovering counterfactual thresholds are types. To overcome a need to carry out this exercise twelve times for each type, I take a random draw of types using probabilities recovered from the model and summarized in Table 7. Using the same procedure as before, I compute an array of risk preference thresholds $\lambda_{itk}(g)$ for $g \in [\underline{g}; \bar{g}]$.

To calculate an expected WTP for each $\{i, t\}$, I use the following approach. A threshold recovery procedure allows obtaining maximum risk preference values (λ) at which insurance would be bought under each policy k and price g for each individual and time period. Since the indifference levels function $\lambda_{itk}(g)$ must be smooth and monotonically increasing in price g, it can be inverted to obtain $\hat{g}_{itk}(\hat{\lambda})$, which would represent a maximum price that an individual with risk preferences $\hat{\lambda}$ would be willing to pay. Therefore, I can calculate expected WTP by integrating over risk preferences:[39]

[38] The basic insurance system is a mandatory system and the introduction of an alternative universal mandate will automatically remove this basic coverage.

[39] I use 100 quadratures to obtain the integral numerically. Instead of integrating from $-\infty$ to ∞, for each case I find the risk preferences that correspond to 0.1% an 99.9% percentiles. Then I construct equally spaces bins and integrate within this interval with 100 quadratures after reweighing bin probabilities to ensure that they sum up to 1. Since computational procedure allows obtaining $\lambda_{itk}(g)$ on a grid of values g because the function cannot be derived analytically, I use linear interpolation to fill the values between grid points in the integration.

$$E[WTP_{itk}] = \int_{\hat{\lambda}} \hat{g}_{itk}(\rho) dF(\rho; \alpha X'_{it}, \sigma) \tag{12}$$

where $F(\rho; \alpha X'_{it}, \sigma)$ is an individual-specific risk preference normal CDF that depends on recovered parameters α and σ, and individuals-specific vector of characteristics X_{it}.

The intuition of this formula is that an expected individual willingness to pay is a weighted average of WTPs resulted from all potential risk preference values weighted by probabilities of having each of those values. Using identical logic, one could obtain consumer surplus for each $\{i, t\}$ as follows:

$$CS_{itk}(g) = \begin{cases} \int_\rho \left[\overbrace{(\hat{g}_{itk}(\rho) - g) \cdot \mathbb{1}[\hat{g}_{itk}(\rho) - g > 0]}^{\text{if buys insurance}} \right] dF(\rho; \alpha \cdot X'_{it}, \sigma), & \text{if voluntary system} \\ \int_\rho \left[\overbrace{(\hat{g}_{itk}(\rho) - g)}^{\text{always buys insurance}} \right] dF(\rho; \alpha \cdot X'_{it}, \sigma), & \text{if mandatory system} \end{cases} \tag{13}$$

To recover expected costs, I start by using detailed unemployment data to predict probabilities of being unemployed for all individuals i at all periods t in the sample as a function of labor market characteristics denoted as ζ_{it}. The costs of covering (H_{it}) in the case of unemployment are determined by observed income, cap and a replacement rate. Expected costs of covering individual $\{i, t\}$ are:

$$TC_{itk}(g) = \begin{cases} \int_\rho \left[\overbrace{\left(\zeta_{it} \cdot \left(H_{it} - \underline{g}\right) - (1 - \zeta_{it}) \cdot g\right) \cdot \mathbb{1}[\hat{g}_{itk}(\rho) - g > 0]}^{\text{if buys insurance}} \right] dF(\rho; \alpha \cdot X'_{it}, \sigma), & \text{if voluntary system} \\ \overbrace{\left(\zeta_{it} \cdot \left(H_{it} - \underline{g}\right) - (1 - \zeta_{it}) \cdot g\right)}^{\text{always buys insurance}} & \text{if mandatory system} \end{cases} \tag{14}$$

I evaluate the welfare by comparing systems are contracts under various government expenditure levels in terms of total generated consumer surplus. Recall that the model allows obtaining total consumer surplus $CS_k(g)$ and total government costs $TC_k(g)$ under all systems k and price g defined in (13) and (14), correspondingly. It implies that those functions can be combined into the correspondence:

$$CS_k(g) \widehat{=} TC_k(g) \tag{15}$$

The equation (15) is a correspondence since it is not guaranteed that each price gives a unique pair of total costs and consumer surplus.[40] As a result, it is possible that there is a set of prices that yield the same value of budget costs χ and consumer surplus levels. At the same time, it is possible that there are no prices that allow sustaining a given budget level χ. For example, the government might not be able to achieve a high profit from a voluntary system if it requires a considerable rise in prices since it would force all individuals out of the insurance pool. It would imply that for this budget balance χ the set of prices is empty.

I define a set of prices that yields total costs χ under system k as $\varepsilon_k(\chi)$. The system k is said to be welfare-dominant with respect to a system m under a budget balance χ if under all prices $g \in \varepsilon_k(\chi)$ and $q \in \varepsilon_m(\chi)$ a system k always leads to higher consumer surplus than under m. More formally:

Definition 1. *A system k welfare-dominates a system m under a budget balance χ if $\forall g \in \varepsilon_k(\chi)$ and $\forall q \in \varepsilon_m(\chi)$:*

$$CS_k(g) > CS_m(q)$$

This definition embraces a number of desired properties of a welfare criterion for this case. Firstly, it takes into account that there might be a number of prices that require the same level of budget costs for the government even within the same system. At the same time, it also takes into account that some subsidy levels are unattainable for some systems. It implies that systems can be directly compared only under reachable budget balances. It is especially important when analyzing mandates since these policies should theoretically be able to support a wider range of costs because of restrictions on individual responses.[41]

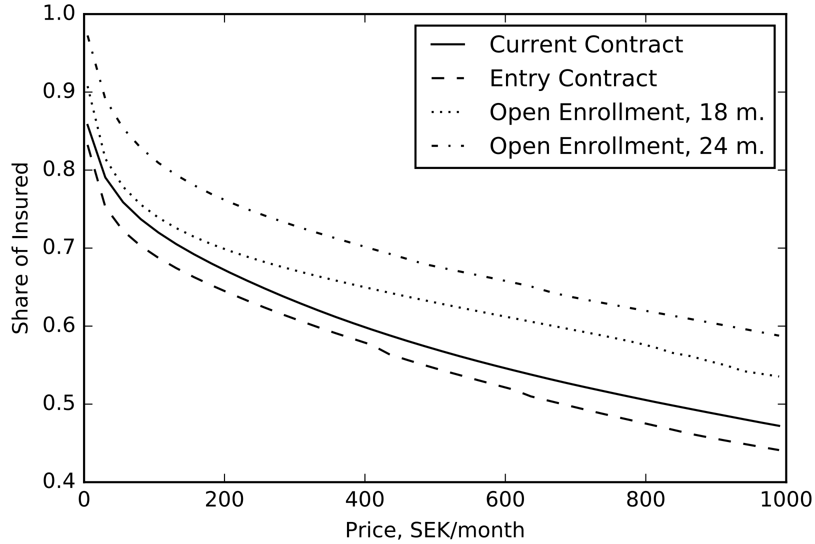
5.2 The Welfare Consequences of Alternative UI Designs

As discussed in the previous section, changes in the structure of the contract and prices affect welfare through a number of channels. Firstly, individuals react to those changes by enrolling or leaving an insurance pool. Figure 8 demonstrates counterfactual demand functions under various considered policies.

[40] The reason is that a change in prices affects both probabilities of insurance, which also translates into changes in a risk composition among insured individuals, and government revenues through the sum of collected premiums.

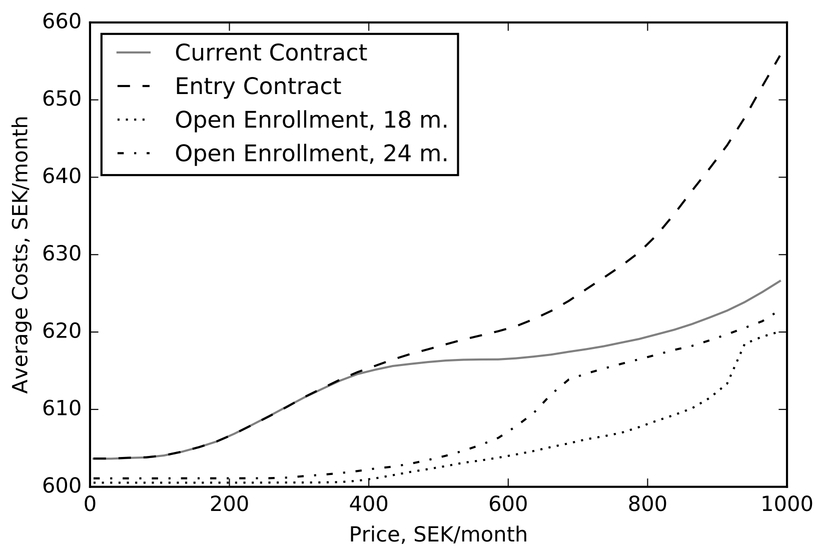
[41] This statement might not be true if there is a large moral hazard response to mandates.

Figure 8: Counterfactual Policies Demand



Notes: The Figure demonstrates the demand function of a current system, a system with an entry costs contract and open enrollment contracts with 18 and 24 months durations.

Figure 9: Average Cost Functions



Notes: The Figure demonstrates average costs of insuring individuals under voluntary systems. The curves are obtained by dividing each value in a cost function by an expected number of insured individuals.

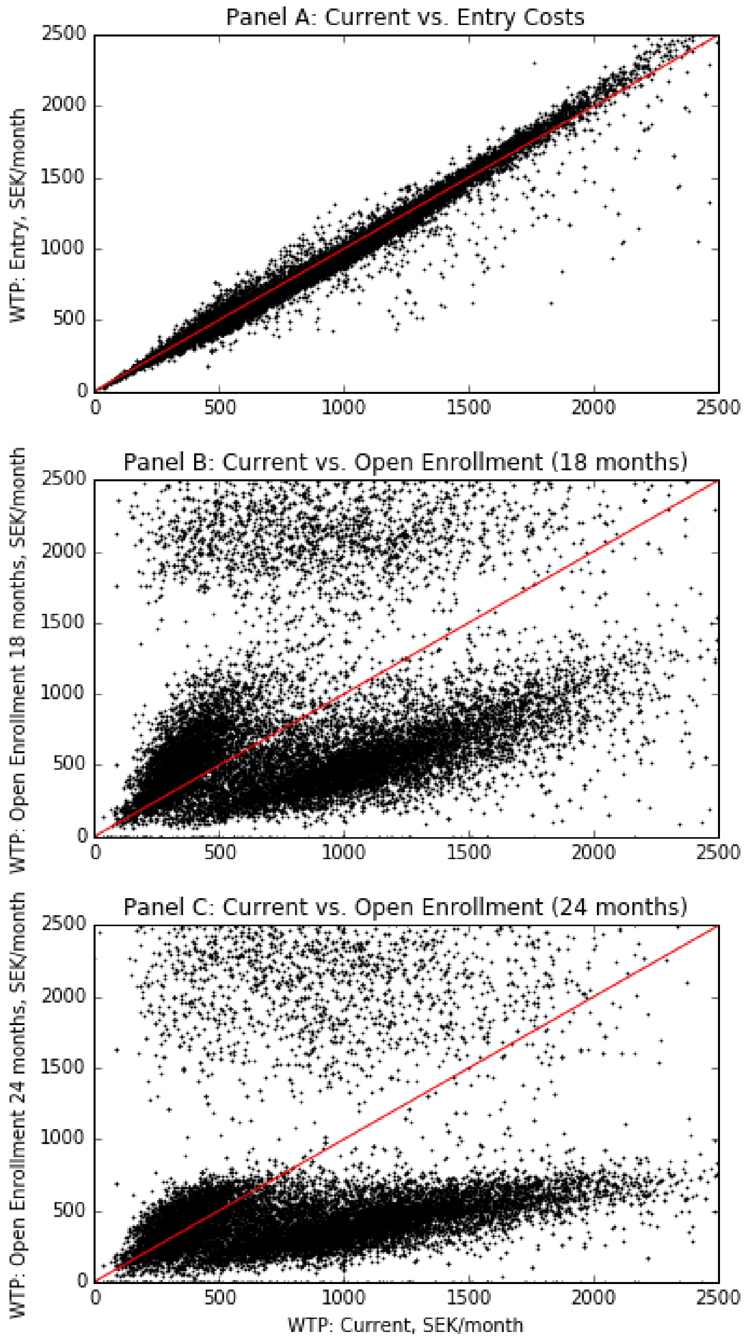
Figure 8 suggests that an entry costs demand function is downward-shifted in comparison to the current contract. Demand functions for open enrollment contracts are less steep on average and are shifted upwards compared to other designs. The demand for the 24 months contract is slightly upward-shifted compared to the 18 months contract since it involves more uncertainty and hence is less attractive.

The second policy-relevant dimension is budget costs. Figure 9 plots average cost functions. Presented cost functions show upward slopes in prices. It corresponds to downward-sloping cost curves in a number of insured individuals, which signals the presence of adverse selection (Einav, Finkelstein, & Cullen, 2010). The average cost curves for open enrollment contracts are less steep and shifted down compared to other curves. It signals that these contracts allow restricting selection compared to a current system or an entry cost contract. An interesting feature of the entry cost contract is that it actually results in more selection. The intuition is that entry fees keep high-risk individuals who expect to benefits from insurance, whereas it does not provide benefits from holding low-risk individuals in the pool and discourages new enrollments. Before looking at more formal welfare analysis, the evidence presented in Figures 8 and 9 suggests a number of important insights regarding the welfare consequences of the contracts under consideration. More precisely, open enrollment contracts attract more individuals and, at the same time, cost less per individual. In contrast, entry costs contracts attract fewer individuals but cost weakly more per individual. It suggests potentially large welfare gains of open enrollment contracts and welfare losses associated with entry costs contracts in comparison to a current system.

The last required object is willingness-to-pay. Figure 10 demonstrates a distribution of expected WPTs of alternative systems in comparison with a current system. In other words, Figure summarizes the attractiveness of alternative contracts in comparison with a current system. The red lines allow comparing distributions of WTP. Points that lie above the red line correspond to individuals who value the alternative contract more than a current system.

Panel A demonstrates that current and entry costs contracts are very similar, which is in line with the evidence from demand functions. Most of the points lie on or below a red 45^0 line, which means that the contracts are identically valued or a current contract is preferred. The reason is that the entry costs contract imposes costs on future re-enrollment thus is less attractive unless a person foresees unemployment in the future. Panels B and C show that open enrollment differs considerably from other designs. Such differences are driven by the fact that open enrollment contracts change the timing of decisions. which imply that choices are made under different information about risks. In addition, open enrollment contracts generate value for individuals by removing pre-eligibility periods but reduce the value by restricting the possibility of re-enrollment before the next enrollment window.

Figure 10: Comparison of WTP under various systems



Notes: The Figure demonstrates WTP for counterfactual insurance systems (y-axis) against WTP for a current insurance system (x-axis). Red lines have 45^0 angle and allow seeing whether the corresponding system is more valued by individuals. Each point represents average willingness to pay for each individual within the considered time periods. If a given point lies above the red line, the corresponding alternative contract is on average valued more by this individual.

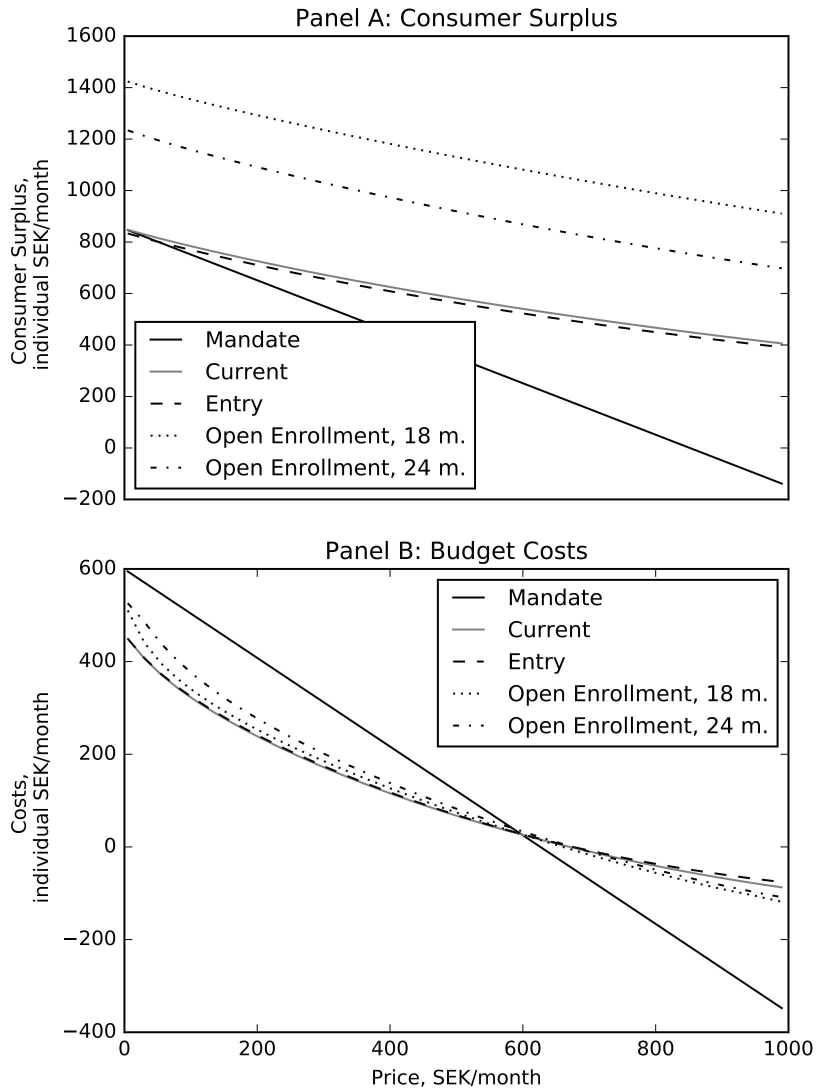
Figure 11 presents consumer surplus and budget costs under various prices. Panel A shows that the open enrollment contract with 18 months duration generates higher consumer surplus under all considered price levels due to its features described above. Other voluntary contracts are similar in terms of consumer surplus. Under a mandatory system, price increases have more a pronounced negative impact on consumer surplus since individuals are not allowed to respond to a price increase by leaving the insurance pool. Therefore, a mandatory system is most detrimental for consumer surplus.

However, a mandatory system is capable of considerably reducing budget costs since individuals are locked in and cannot unenroll as demonstrated in Panel B. All voluntary contracts have similar performance in terms of cost reduction. For high prices, current and entry costs systems allow reaching lower expenditure levels compared to the open enrollment contracts.

To conclude whether a contract structure welfare dominates a competing design at some government costs, one should compare the resulted consumer surpluses at various budget costs from Figure 11. It also takes into account the fact that some systems might not allow sustaining some levels of government expenditures at least within a considered interval of prices. It implies that the correspondences from (15) might have different support for various systems in terms of costs.

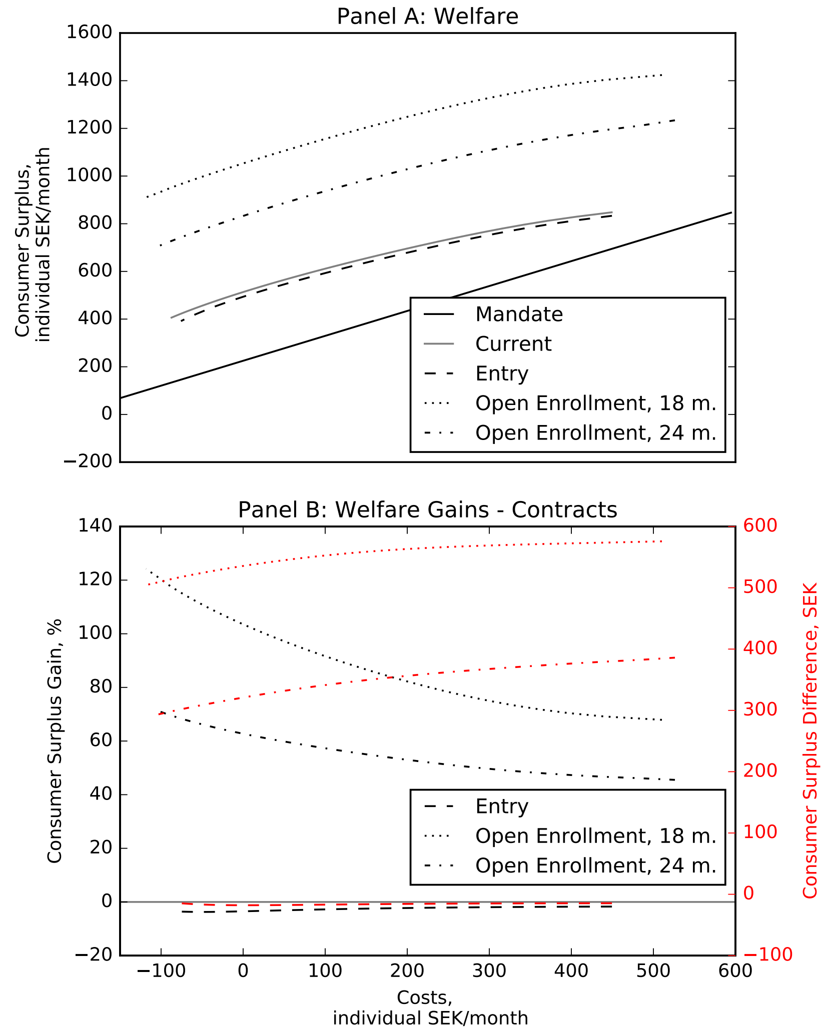
Figure 12 summarizes the welfare analysis. Panel A demonstrates relationships between government costs and generated consumer surplus under considered policies. In other words, Panel A represents the y-axis of Panel A plotted against the y-axis of Panel B from Figure 11. The main point of the Figure is to illustrate which policies lead to higher consumer surplus while requiring the same subsidy levels. This approach allows being agnostic about optimal pricing. If the system is located above on the y-axis, it should be preferred since it yields higher consumer surplus at the same cost level. Although a part of the previous section was devoted to emphasizing and clarifying the fact that it is theoretically possible to have multiple consumer surpluses, it appears not be the case in practice.

Figure 11: Effect of Premiums on Consumer Surplus and Budget Costs



Notes: Panel A plots a monthly price against consumer surplus. Panel B presents the relationship between premiums and resulted budget costs. I divide total consumer surplus and total costs by a number of "active" individual-months observations for expositional purposes instead of presenting the sums over individuals and observed months. Note that in contrast to average cost curves, this normalization is constant and does not vary with a number of insured individuals for all prices.

Figure 12: Welfare



Notes: The Figure demonstrates the main results of welfare analysis. Panel A plots government costs per individual-month for 2005-2008 against the resulted consumer surplus. I divide total costs and consumer surplus by a number of "active" individual-months observations for expositional purposes. Panel B presents the same evidence as on Panel A but in terms of percentage welfare gains compared to a current system at the corresponding budget level and in terms of a difference on the right y-axis colored in red. The interpretation is that the system dominates another one under some government cost level if it lies above on both Panels. It implies that it results in higher consumer surplus at the same cost level.

Panel A suggests that an entry costs contract is very close to a current system but cause small welfare losses. A figure indicates that mandates generate sizable welfare losses. Finally, the results suggest that open enrollment contracts would be the best option for nearly all achievable levels of expenditures.

To put it into perspective, a mandate would lead to 48.8% or 243 SEK/month per individual consumer surplus loss compared to a current system on average over the considered price levels. The reason is that, as demonstrated on Panel B of Figure 11, mandates are effective to reduce costs only at high prices. At lower prices, all voluntary systems are less expensive. At the same time, a mandate is the worst system in terms of the effect on the consumer surplus. Therefore, the results suggest that it is the least favorable design of UI among considered options.

Panel B similarly compares various voluntary designs. It suggests that within the considered range of the government costs, entry contract results in 2.9% lower consumer surplus on average along the line. The intuition is that entry costs contract is worse for consumers since it is more expensive at the same premium levels. At the same time, average cost curves show that it leads to even more selection, especially at high prices.

Finally, the results suggest that open enrollment contracts would welfare dominate all other options. The average gains amount to 95% (545 SEK) for 18 months and 58% (338 SEK) for 24 months contracts compared to the current system, correspondingly. There are two features of open enrollment contracts that make them an attractive option from the welfare point of view. First, this contract structure virtually removes a time-selection part of risk-based selection. Secondly, the estimates of WTP shows that individuals often value this contract more than a current one primarily because of the absence of the 12 months pre-eligibility period.

To sum up, the results of this section show that in line with the concerns regarding the effect of mandates, it is predicted to be the least desirable policies among the considered options. Instead, appropriately chosen alternative contract designs tailored to remove harmful selection without considerable distortion of individual choices are predicted to generate sizable welfare gains.

5.3 Robustness and Discussion

The model presented in this paper requires many assumptions that might raise concerns regarding the validity and sensitivity of the welfare analysis. Therefore, it is important to discuss the role of those assumptions.

The first point, which is, however, unrelated to the model and analysis directly, is a sample selection. The insurance data lack information for those individuals who have not received insurance benefits. It is not a random sample despite similarities with a general population in terms of observables. Most likely, a sample contains a relatively risky part of the population. At the same time, the share of insured individuals is smaller in the sample compared to a full population by roughly 10%. It implies that a missing population is risk-averse, has less information about employment perspectives (types) or displays more inertia. To examine the importance of the sample selection for the welfare analysis, I re-estimate the model while pretending that all the missing individuals are always or never insured. It does not change welfare conclusions qualitatively. I also use obtained model parameters to simulated insurance decisions for a missing sample without re-estimating the model. The welfare analysis also remains robust to these changes. This approach does not take into account the fact that a missing population might have different preferences and information. However, at least within the scopes of estimated parameters, the welfare conclusions are robust.

In the model, I assume that a planning horizon T is limited to 18 periods. Experimenting with different options around the chosen value does not affect results considerably. I also use various specifications for the estimation of beliefs, which are fed into the decision model. Variables entering the prediction model also have a minor effect on the estimates.

In addition to potential concerns regarding the assumption required for identification of inertia, there is a multitude of alternative functional forms that could be used to incorporate it in the model. Changes in this functional form do have an impact on estimates and willingness to pay. However, since the main purpose of the analysis is to compare current and alternative regulations in UI, this assumption does not qualitatively change conclusions. To be more precise, excluding inertia, allowing for heterogeneity in inertia, and introducing separate inertia coefficients for previously insured and uninsured does not change any of the conclusions presented in this section.

The counterfactual analysis does not take moral hazard into account. The main concern associated with that would be that counterfactual policies not only change insurance decisions but also risks. To minimize concerns associated with this model abstraction, I consider modest price changes that should not create large labor market responses.

Finally, a bigger picture concern is the validity of such a neoclassical-type model that to a large extent disregards more sophisticated behavioral mechanisms such as the role of family in income insurance or borrowing. The data show that individuals react to incentives as expected (e.g. higher prices, less generous insurance, and lower risks reduce the demand for insurance). All other potential behavioral components are falling under the risk preferences and an inertia parameter. An implicit assumption in the dynamic model is the absence of a discount factor since it is not identified. The assumption does not seem to be extreme since I model monthly dynamics in which case future-discounting should not play an important role. It also should not have any effect on the observed bunching patterns since even sizable variation in time preferences will not affect the bunching incentives in the presence of information about the future.

6 Conclusions

This paper attempts to provide one of the first comprehensive analyses of the optimal regulations in unemployment insurance. Existing literature documents a positive correlation between insurance and unemployment risks often attributed to risk-based selection. I augment this evidence by showing the importance of understanding an interplay among risks, private information structure and preferences to analyze the effect of alternative counterfactual policies. I conclude that potential regulations are not limited to mandates and pricing policies but also should include contract design regulations. These regulations either encourage long-term enrollment or mechanically restrict time-based selection.

One of the key messages of this paper is a difficulty to provide welfare suggestions using just correlation evidence that often arise from multiple dimensions of individual heterogeneity (Finkelstein & McGarry, 2006; Einav, Finkelstein, & Ryan, 2013). This paper develops a model and a computationally attractive estimation approach that attempts to recover some of those dimensions of heterogeneity. Even taking all the model and parametric assumptions with a grain of salt, such an approach allows more comprehensive exploration of the interplay among various forces affecting individual decisions. As a result, it enables recovering welfare-relevant indicators to illustrate the outcomes of alternative policies. Furthermore, it allows widening the spectrum of potential policies and considering the contract design as an alternative to widely-discussed pricing regulations and mandates. Moreover, the results suggest that appropriate contract designs would provide relatively large welfare gains.

The results of this paper should not be directly extrapolated outside of the context because of a sample selection and considerable differences among labor markets in Sweden and other countries. However, the analysis provides a number of insights applicable to a broader audience. Firstly, despite a considerable heterogeneity in estimated willingness to pay, individuals do value insurance. It might suggest that individuals in countries with weaker social security and less stable labor markets have even more need for unemployment insurance. At the same time, private markets are unlikely to play this role due to a considerable amount of private information. Therefore, apparently, UI will remain a part of government policies. Secondly, the results imply at the very least an ambiguous impact of mandates that are widely adopted around the world. Even in the absence of a moral hazard response, it is predicted to be an undesirable policy because of the burden imposed on individuals who have low insurance value. Instead, alternative contracts such as restricted enrollment timing seem to provide considerable gains by reducing private information without imposing excess costs on individuals. It raises concerns regarding a nearly universal adoption of mandatory UI, which suggests that the optimal regulation in UI is an open policy-relevant issue for future research.

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Appendix

A Estimation Details

The estimation procedure in this paper consists of two steps: computation of risk preference indifference points and estimation of parameters. I firstly compute risk preference thresholds where individuals are indifferent between buying insurance or not. To do that, I need to solve a dynamic programming problem for each individual i, time t, type s and each potential employment sequence j. A major complication arises from a large number of employment sequences since it amounts to 2^{T-s}, where T is a length of an optimization horizon and s is a number of periods observed in the future. As can be seen, a number of sequences grows exponentially. Therefore, I make two restrictions to keep the estimation feasible.

Firstly, I limit the duration of a planning horizon to 18 periods. It does not fully resolve the issue but linearly reduces computational time and still dramatically decreases the number of sequences. Although the number is still extremely large, a vast majority of sequences have a probability close to zero. Therefore, I calculate probabilities for all potential sequences, which would be impossible without the restrictions on T. I rank the sequences in the descending order of likelihood. Then I select top 750 sequences or up to a point when sequence probabilities sum up to 0.99.

I use the bisection method to compute thresholds where the expected utility of buying insurance equals to expected utility of being uninsured. Although the bisection method is slower than, for example, the Brent method, it is safer for this type of non-monotonic problems. It requires imposing bounds, which I set to very high and very low-risk preference values. This also allows solving the issue with the zero limit of utility differences. More precisely, although the utility difference has the unique value of risk preferences where it equals zero, it might become actual zero at the limit as $\rho \to \infty$ because of numerical constraints.

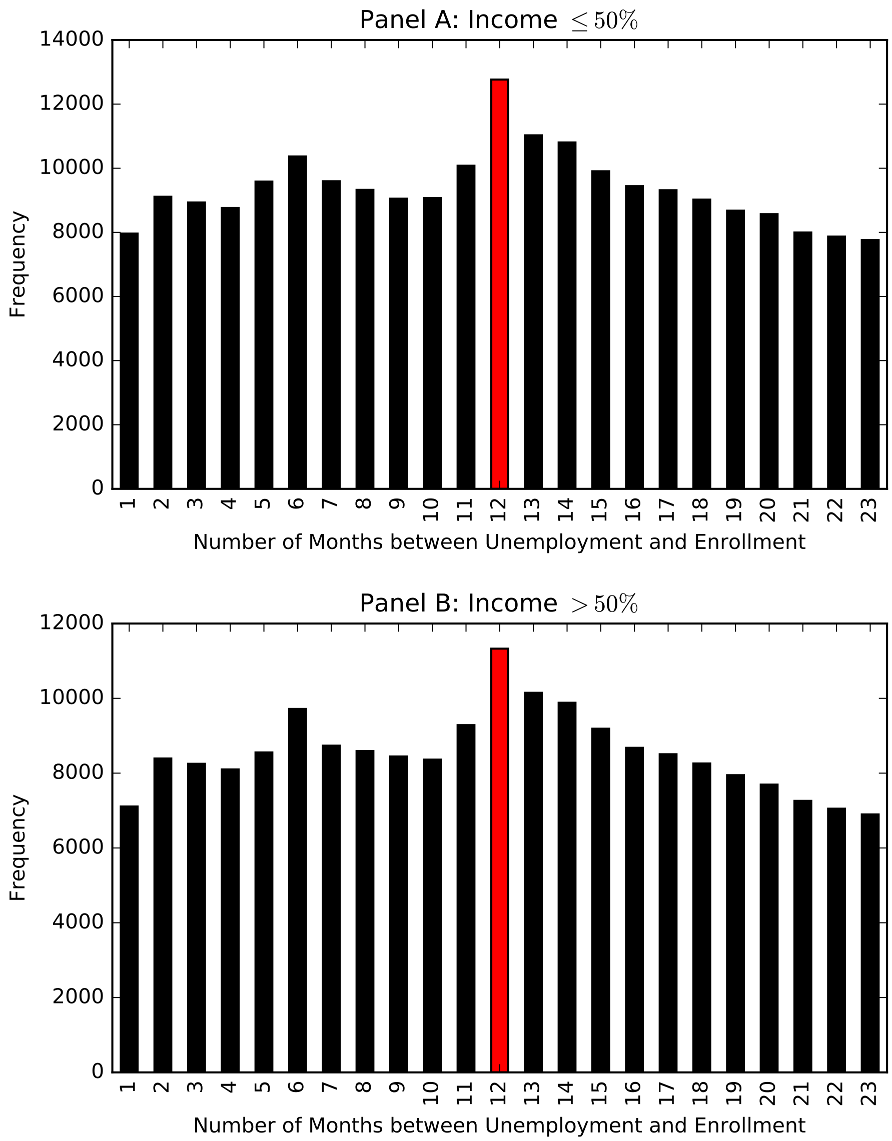
The part that computes thresholds is written in Python due to requirements of Statistics Sweden, which does not allow using ahead-in-time compiled languages (e.g. C/C++) on their servers with the data. I pre-compile all computationally intensive parts of the code using a just-in-time compiler, which provides significant speed-up. I use 50 cores in the estimation. As a result, computing thresholds for a 5% random sample takes approximately 5 hours. It is, however, much more computationally efficient compared to the estimation of parameters jointly with solving the model, which would require reestimating it at each call of an optimization algorithm.

The second stage is parameter estimation based on the computed thresholds using a maximum likelihood procedure described in the main text. I use a L-BFGS-B algorithm with bounds on parameters and a user-defined analytical gradient function. I do not use asymptotic standard errors since some of the type parameters are supposed to be as large or as small as possible. As a result, a parameters search algorithm climbs up along the likelihood curve until the derivative becomes close to zero where it stops. The issue is that the second derivative of the likelihood function does not exist in this case since the function is just a zero-slope line with respect to this parameter around the optimum. Therefore, an attempt to obtain a numerical or analytical Hessian matrix fails since it contains non-finite values and thus is not invertible, which is required for asymptotic standard errors.

Therefore, I opt for the bootstrap. I use 100 draws with replacement and estimate the model in parallel on 20 cores. I use the obtained distribution of parameter estimates to calculate standard errors presented in this main text. I use only 100 draws since it takes around 8 hours for an optimizer to converge.

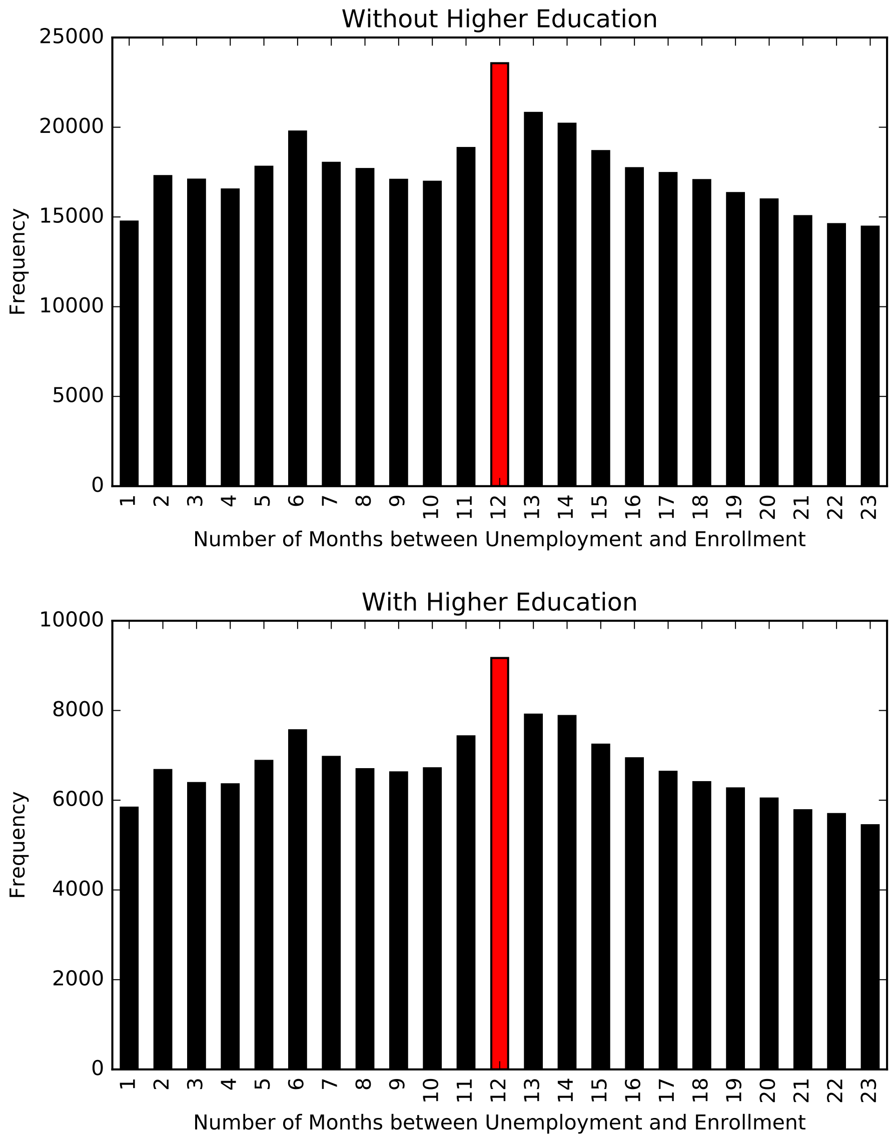
B Supplementary Figures

Figure 13: Bunching Around the Eligibility Requirement By Income



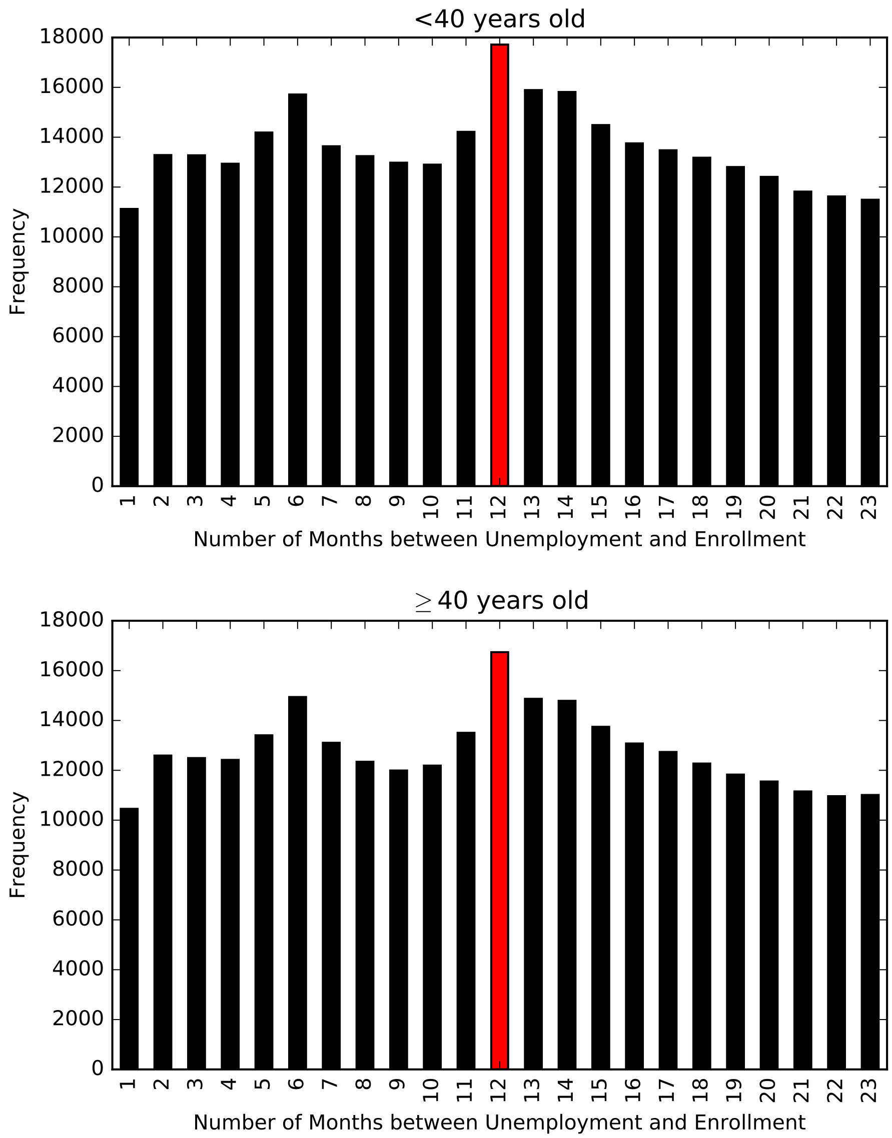
Notes: The Figure presents a discrete histogram of a distribution of a number of enrollment months before the start of unemployment spells similarly to the evidence in the main text but separately for individuals with below the median income (Panel A) and above the median income (Panel B).

Figure 14: Bunching Around the Eligibility Requirement by Education



Notes: The Figure presents a discrete histogram of a distribution of a number of enrollment months before the start of unemployment spells similarly to the evidence in the main text but separately for individuals without higher education (Panel A) and with higher education (Panel B).

Figure 15: Bunching Around the Eligibility Requirement by Age



Notes: The Figure presents a discrete histogram of a distribution of a number of enrollment months before the start of unemployment spells similarly to the evidence in the main text but separately for individuals younger (Panel A) and older (Panel B) than 40 years old.

C Supplementary Tables

Table 6: Types Parameters

	Types											
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Constant	0.3	-16.150	-17.053	-8.729	-10.437	-4.759	-18.600	-9.208	-10.003	-10.486	-18.143	-1.253
	(—)	(1.137)	(0.693)	(1.016)	(0.036)	(1.950)	(0.470)	(0.103)	(0.154)	(1.070)	(0.305)	(0.062)
Cluster 1	0.3	0.233	6.090	4.909	0.632	-7.971	-3.830	-2.831	-0.863	-6.258	16.239	0.053
	(—)	(1.336)	(0.783)	(1.039)	(0.026)	(0.095)	(0.168)	(0.002)	(0.031)	(0.629)	(0.305)	(0.124)
Cluster 2	0.3	0.028	5.479	-11.025	-8.332	-3.430	9.123	-3.607	-7.397	-3.573	-9.267	0.175
	(—)	(1.443)	(0.726)	(0.010)	(0.000)	(0.627)	(0.471)	(0.003)	(0.000)	(0.628)	(0.309)	(0.059)
Cluster 3	0.3	9.292	-11.637	-0.086	-0.161	1.474	-2.122	-0.552	0.027	2.144	-1.170	0.206
	(—)	(2.527)	(0.004)	(1.075)	(0.015)	(1.236)	(0.168)	(0.025)	(0.040)	(1.026)	(0.309)	(0.088)
Cluster 4	0.3	-25.240	-4.194	-0.958	-0.978	-3.249	-11.460	-0.704	0.121	7.120	-10.282	-0.185
	(—)	(0.057)	(0.003)	(0.625)	(0.016)	(0.607)	(0.168)	(0.022)	(0.082)	(0.915)	(0.309)	(0.090)
Age (30; 40]	0.3	15.572	-9.704	-0.294	0.762	-9.110	4.487	-1.846	-0.753	-19.911	-2.773	0.421
	(—)	(1.280)	(0.004)	(1.837)	(0.028)	(0.095)	(0.445)	(0.011)	(0.019)	(0.629)	(1.414)	(0.094)
Age (40; 50]	0.3	4.797	-2.338	0.895	-3.468	-3.215	-0.226	-1.061	0.568	0.924	-2.707	0.153
	(—)	(1.506)	(0.008)	(1.761)	(0.001)	(0.340)	(0.249)	(0.034)	(0.106)	(1.364)	(1.354)	(0.071)
Age > 50	0.3	-1.690	5.842	-3.831	-5.903	2.103	-6.244	-8.028	-1.111	0.495	-2.719	0.278
	(—)	(0.080)	(0.670)	(1.190)	(0.000)	(1.300)	(0.168)	(0.000)	(0.036)	(1.400)	(1.264)	(0.056)

Table 7: Type Probabilities

Type	Predicted Share
I	77.21%
II	7.74%
III	<1%
IV	<1%
V	<1%
VI	<1%
VII	<1%
VIII	<1%
IX	<1%
X	<1%
XI	<1%
XII	13.54%

Notes: The Table shows mean predicted type probabilities in the estimation sample determined by estimated type parameters.