ECONOMIC STUDIES

DEPARTMENT OF ECONOMICS
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UNIVERSITY OF GOTHENBURG
241

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Essays on the Design of Public Policies and Regulations

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Acknowledgements

On the first year of PhD studies, I was looking forward to writing the acknowledgments. This means that such a long path successfully comes to the end. It indeed was a long path with numerous moments of joy as well as many difficulties. Being in these shoes now, it is surprisingly hard to summarize thoughts since I was very lucky to be supported by many people who made the moments of joy more pleasant and the difficulties less challenging.

First and foremost, this PhD thesis, as well as tons of other things in my life, would not happen without endless and unconditional support of my family. I cannot fully express gratitude to my wife Anna, who fully shared all the fun and challenges and hence, deserves equal credits for this work (obviously without mistakes, which are entirely mine). All achievements in my life including this PhD thesis would not be possible without my parents Igor and Nadiia. I am truly privileged to have their constant love and support, and I sincerely appreciate all their sacrifices. I love you so much.

I would like to thank my advisors Aico van Vuuren and Mikael Lindahl. Aico was very supportive at each stage of the PhD program. I have learned a lot from our discussions and appreciate his support of my research ideas. I was extremely lucky to have Mikael as my advisor and mentor. His constructive suggestions and advice about research and career, and unconditional support are hard to overestimate. Furthermore, many of my projects would not be possible without his practical support.

I am really grateful to Liran Einav. His research inspired many of my ideas and I owe a lot of gratitude for his invaluable input and support during my visit to Stanford. Randi Hjalmarsson was an excellent mentor, who guided me throughout the PhD program and the job market. I sincerely appreciate that. I am grateful to Måns Söderbom who was very supportive from the first day of the PhD program and was constantly willing to help with all the research and practical obstacles. I would like to thank Mark Duggan whose mentorship and guidance throughout my visit to Stanford made the time there particularly productive.

Research and studying during the PhD program would be much less fun without those who combined the roles of colleagues, co-authors and, most importantly, friends. I am grateful to Simon Schürz for making work not only productive but also fun as well as being truly a friend. I am grateful to Tamas Kiss, who is not only an extremely smart person but also a great friend. I am honored to work with Natalie Bachas from whom I learned a lot and who was very supportive during the job market process.

I have benefited from a very friendly and supportive environment of the Department of Economics at the University of Gothenburg and especially, Labor group. I appreciate all the support

Content

Introduction

Government policies intervene in many areas of the economic and social environment. Examples of such interventions are taxation, provision of public goods, social insurance, education, and market regulations. Most often, the aim is to address undesirable socioeconomic outcomes or market failures that hinder efficiency. The term "market failure" means not only the unsatisfactory market outcome but also the absence of markets that are important for society (Hendren, 2013). Moreover, Reich (2016) argues that adequate government policies are crucial to ensure fair rules of the game and are fundamentally required for markets to work.

Despite their indisputably crucial role, government interventions are often associated with undesirable distortions that lead to efficiency losses. The examples of these adverse effects might be distortion of consumption and labor supply choices in case of taxation or the lack of efforts to mitigate risks in case of insurance programs (e.g. unemployment, health).

The ambiguity of government policies motivates a need for extensive research that not only assesses the necessity for interventions but, more importantly, how various policies should be designed to achieve the desired outcomes while minimizing side effects. Since individual behavioral responses to regulations often generate negative spillovers, understanding the mechanism behind individual decisions is crucial.

The public economics literature has seen many approaches to studying the optimal design of public policies. Theoretical studies often focus on defining credible theoretical models that explains individual decisions (e.g. Mirrlees, 1971; Baily, 1978; Rothschild & Stiglitz, 1978; Acemoglu & Shimer, 1999; Chetty, 2006; Kleven, Kreiner, & Saez, 2009; Farhi & Werning, 2010; Piketty & Saez, 2013) and allow understanding potential consequences of interventions. This approach allows identifying key responses and informs how to balance the trade-off resulting from interventions according to the social preferences. However, the credibility of this approach might be questioned since it relies heavily on having the correctly specified model, which often is a hardly testable assumption. Furthermore, the derived policy recommendations not only depend on the welfare function and the model but also on individual preference parameters that are unknown to the policy makers but fundamentally determine the nature and the magnitude of the responses.

Therefore, another approach adopted in the literature abstracts from a theoretical foundation and attempts to use data to study the responses to policies without imposing a theoretical structure.[1] A large number of studies document the effect of the variety of government pro-

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[1]I also include a so-called sufficient statistics literature in this group of studies. Although the theory is used to derived welfare-relevant metrics, they are usually obtained without specifying a full structural model.

grams and policy measures including unemployment insurance (e.g. Chetty, 2008; Landais, Nekoei, Nilsson, Seim, & Spinnewijn, 2017; Nekoei & Weber, 2017; Kolsrud, Landais, Nilsson, & Spinnewijn, 2018), health insurance (e.g. Finkelstein & Poterba, 2004; Finkelstein, 2004, 2007; Brown, Duggan, Kuziemko, & Woolston, 2014), disability insurance (e.g. David & Duggan, 2007), income taxation (e.g. Gruber & Saez, 2002; Kleven, Knudsen, Kreiner, Pedersen, & Saez, 2011), bequest taxation (e.g. Glogowsky, 2016), wealth taxation (e.g. Seim, 2017), regulations in markets for education (e.g. Hsieh & Urquiola, 2006) and housing markets (e.g. Diamond, McQuade, & Qian, 2017). An advantage of such studies is that they do not rely heavily on the model structure. The limitation of these studies is that although they use credible identification strategy, they only allow studying policies that have been observed (Keane, 2010). At the same time, the essence of policy design is to consider a range of alternative policies and propose ones that satisfy chosen criteria, including those that have not been adopted yet.

Given the pros and cons of the above-mentioned approaches, another option is to use a structural model with a plausibly credible identification strategy. In other words, this approach often combines a theoretical micro-model of individual decisions with data on observed individual choices to identify the key parameters. Since the model and the parameters of individual behavior should be invariant to policies, this allows not only studying mechanisms underlying individual responses to government interventions but also analyzing policies that have not been previously observed (Low & Meghir, 2017). This approach has been widely used in many settings to analyze how individuals respond to existing policy changes and construct alternative designs accordingly (Adams, Einav, & Levin, 2009; Einav, Finkelstein, & Schrimpf, 2010, 2015; Blundell, Costa Dias, Meghir, & Shaw, 2016).

In my thesis, I attempt to combine rich theoretical models of individual behavior with detailed administrative data and appealing institutional details that provide sources of variation required to identify the key parameters. I use this strategy to study counterfactual policy measures that have not been previously observed to understand whether the performance of already adopted policies can be improved. In addition, understanding the mechanism of individual responses allows designing policies that minimize these side effects.

In particular, each of the chapters is dedicated to a separate government program or intervention. In the first chapter of my thesis, "Private Information and Design of Unemployment Insurance", I study the design of unemployment insurance contracts with an emphasize on private information problem. In my second paper, "Behavioral Responses and Design of Bequest Taxation" (with Simon Schürz), I study the optimal design of bequest taxation and a trade-off between estate and inheritance taxes, which are two commonly adopted types of bequest taxation. These two papers use the data and institutional setup of Sweden. In my third chap-

ter, "Determinants of Competition and Student Demand in Higher Education: Evidence from Australia" (with Natalie Bachas), I study the effect of government regulations and responses of students and colleges in a semi-centralized college market in Australia. I describe each of the papers in more detail below.

Chapter One: *Private Information and Design of Unemployment Insurance.* Private information is widely discussed to be the main obstacle to well-functioning insurance markets. Seminal papers by Akerlof (1970) and Rothschild and Stiglitz (1978) show that because individuals know more about their own risk-type, the optimal allocation in selection markets cannot be achieved. These theoretical results led to a large body of literature documenting the presence of asymmetric information (e.g. Chiappori & Salanie, 2000; Finkelstein & Poterba, 2004; Finkelstein & McGarry, 2006; Fang, Keane, & Silverman, 2008; Aron-Dine, Einav, Finkelstein, & Cullen, 2015) and studying policy measures aimed at addressing the problem (e.g. Einav, Finkelstein, & Schrimpf, 2010; Einav, Finkelstein, & Cullen, 2010; Einav, Finkelstein, & Ryan, 2013; Einav et al., 2015; Einav, Finkelstein, & Schrimpf, 2017).

The literature has been mainly focused on health insurance and the evidence of private information in unemployment insurance (UI) is very limited. One of the main reasons is that most of the developed countries have adopted mandatory insurance systems in which all eligible individuals are insured without the option to unenroll. Another reason for such a widespread adoption of mandatory UI is that because unemployment risks can often be predicted by individuals, UI markets are particularly vulnerable (Hendren, 2013, 2017). This leads to difficulties in studying individual responses without observing them. At the same time, such a dominant adoption of mandatory UI raises a question of if this widely-used policy is optimal, especially taking into account the evidence of welfare losses associated with mandates (Einav, Finkelstein, & Schrimpf, 2010).

Therefore, I use unique and appealing institutional features of the Swedish voluntary unemployment insurance system to study the optimal design and regulation of UI. Despite being a theoretically appealing policy, mandates might be undesirable in practice. The reason is that mandates might generate welfare losses due to a fully restricted individual choice that does not allow selection on preferences, which is a positive selection margin. Another paper studying the problem of selection into unemployment insurance is Landais et al. (2017). Despite documenting the presence of private information, it also argues that the use of mandates is not an optimal policy.

However, documenting the presence of selection is often not enough to credibly study policy design primarily because of multiple dimensions of individual heterogeneity. Therefore, I use detailed administrative data to estimate a structural model of insurance choice that captures

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heterogeneity in preferences and private information about future unemployment risks. The rich structure of the model and favorable institutional details allow us not only to study the trade-off of mandatory vs. voluntary insurance participation but also analyzing contract design regulation as an alternative policy instrument. More precisely, I investigate the effect of an alternative voluntary insurance contract that restricts time selection, which means that individuals strategically time enrollment decisions to minimize the amount of insurance premiums. Similar issues have been documented in other insurance markets (Einav et al., 2015, 2017; Cabral, 2016).

The results suggest that imposing the mandate in UI would lead to considerable welfare losses associated with large heterogeneity of preferences for insurance. In contrast, voluntary contracts that adequately restrict relevant dimensions of selection would generate welfare gains. I find that contracts with a fixed length and a predetermined timing of enrollment dominate all other considered options and generate consumer surplus gains from 58% to 95%, on average, depending on the contract duration.

Chapter Two: *Behavioral Responses and Design of Bequest Taxation.* The taxation of intergenerational wealth transfers, which is often represented by estate and inheritance taxes, is in the center of active policy debates. On the one hand, it is argued to be a tax that causes relatively small distortions (Economist, 2017). It is also viewed to be an important policy tool against the intergeneration inequality (Piketty, 2011). Despite these arguments in favor of bequest taxation, a number of countries including Sweden, Norway, Austria, Hungary, Portugal as well as several US states have abolished this tax. However, there are active debates about its re-introduction. One of the main arguments against the tax is the impact on firms and inefficiencies due to a need to split the wealth of a deceased individual.

While these discussions are mostly focused on the issue related to the presence of the tax, the question of the optimal design of bequest taxation plays an important role because individuals have a number of available responses to reduce the taxable amount. Depending on the tax design, old-age individuals can adjust wealth accumulation and inter-vivos gifts and change the distribution of inheritances among heirs. Although it highlights the importance of the design of the bequest tax, the identification of several dimensions of individual preferences that determine bequest decisions is problematic (Lockwood, 2012, 2018).

Therefore, we leverage the unique and appropriate setup of Swedish inheritance taxation and rich administrative data on bequests and the behavior of old-age individuals that allow us to overcome these issues. To understand individual behavior under various tax schemes, we estimate a comprehensive empirical structural model that captures several dimensions of individual responses, namely wealth accumulation and bequest allocation. More precisely, we exploit institutional features that allow individuals with specific family structures to fully avoid

the inheritance tax by redistributing bequests over multiple generations. The presence of this subgroup, whose decisions should not be affected by the inheritance tax, allow recovering pure bequest preferences separately from other parameters that guide the choice of the wealth accumulation process. Furthermore, the availability of a generous social security system for the elderly allows overcoming another identification problem associated with the presence of precautionary savings (Ameriks, Briggs, Caplin, Shapiro, & Tonetti, 2015).

The estimates of the model allow decomposing the determinants of wealth accumulation and a bequest distribution and, shed light on the design of the bequest tax. We find that comparable inheritance and estate taxes result in similar distortions to wealth accumulation and bequest distribution. By limiting strategic avoidance through adjustments in bequest distributions, estate taxation outperforms inheritance taxes in terms of tax revenues. Our model enables policymakers to design a bequest tax that balances distortions, progressiveness, tax revenue and tax incidence according to the chosen social welfare function.

Chapter Three: *Determinants of Competition and Student Demand in Higher Education: Evidence from Australia.* Considerable attention in policy debates is dedicated to college markets and student financing. However, in comparison with the large literature on school choice mechanisms, the literature related to design and regulations in college markets is emerging. A number of theoretical papers emphasized a two-sided feature of the college markets where both students and college programs are active market participants who make strategic choices (Avery & Levin, 2010; Chade, Lewis, & Smith, 2014; Che & Koh, 2016). However, despite the complexity of the market and the long-lasting effects of college education outcomes, the empirical literature on regulations in college markets is small (e.g. Fu, 2014).

In this paper, we use an appealing setup and detailed administrative data from the Australian college admission system to shed light on the determinants of college market outcomes and study the effect of financial regulations. We leverage the variation in tuition charges and government subsidies due to changes in government priority majors that result in changes in the financial conditions for students and college programs. It allows us to separately identify their responses.

We find that students do not show high responsiveness to prices, which is explained by an important role of university and major affiliations in application decisions. Furthermore, we document that university programs display signs of strategic responses to monetary incentives by adjusting the admission requirements. More precisely, an increase in revenues received per student leads to more admitted students, which raises overall revenues but at the same time reduces the average quality of the pool of admitted students.

Upon documenting the responses of students and colleges to the observed variation in financial terms, we proceed to studying alternative financial regulations in college markets. For this

purpose, we start by estimating a structural model of student application decision and the competition of college programs. Since student application decisions take the form of a list of programs submitted in the descending order of desirability, we build and estimate a novel model of the rank application that allows estimating student preferences in the presence of a large number of alternatives to choose from. We use the estimated preferences for colleges to estimate a model of college competition. A college program is modeled as an agent that maximizes the utility of total revenues and the average quality of admitted students.

We find that both student tuition charges and college revenues have important effects on college market outcomes. Despite the fact that changes in college revenues do not directly affect students, colleges re-optimize the admission requirements, which leads to considerable changes in the allocation and composition of students across programs. Although changes in tuition charges only affect students, they also generate reactions from college programs, which internalize changes in student demand. In turn, it leads to a redistribution of students across programs.

Our findings suggest an important role for financial incentives on both sides of the college market and hence, deserve to be further studied to inform the optimal design of price and revenue regulations.

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Chapter 1

Private Information and Design of Unemployment Insurance[*]

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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 the 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 the 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 consumer surplus. A "two-part tariff" contract that fails to sufficiently restrict risk-based selection results in average consumer surplus loss of 3%.

Keywords: unemployment insurance, private information, contract design, mandate

JEL classification: J65, D82, D81, G22, H55

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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. Therefore, 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, this 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, &

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

[2] 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. However, moral hazard is not a focus of this paper but its implications are discussed in robustness selection.

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

Cullen, 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 enrollment timing 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 the previously uninsured (Cabral, 2016). In contrast to the open enrollment contract, this design affects time-selection by discouraging unenrollment when unemployment risks are low to 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 UI designs, 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 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. The estimation of private information types 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 a con-

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[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, it did not affect the labor market itself such that individuals did not become more or less informed about their

siderable variation in risk preferences and the 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. 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 the 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 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 it does not sufficiently restrict selection on risks but imposes the additional fixed costs on individuals. However, an open enrollment contract with 18 months duration is predicted to generate the average welfare improvement of 545 SEK/month per individual ($61 or 95%). In comparison with the entry costs design, it virtually removes time-selection without imposing large additional costs on consumers. In contrast to mandates, it restricts undesirable selection

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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 the welfare analysis to this assumption. I find that the 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.

without severe choice restrictions. A similar design of the open-enrollment contract but with a 24 months duration leads to smaller average welfare gains of 337 SEK/month ($36 or 58%) per individual. These smaller welfare gains stem from higher risk-exposure due to longer contract duration.

This paper contributes to a large literature on private information in insurance programs and markets. Most attention to the importance of private information has been dedicated to 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 primarily been focused on the optimal UI theory[13] and 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 such as Hendren (2017), who 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 be a welfare-improving policy. In this paper, I attempt to look deeper into insurance decision-

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

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

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

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

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

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

[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 the insurance premiums and the generosity of benefits.

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 et al., 2015; Einav, Finkelstein, & Schrimpf, 2017) 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 the structure of benefits 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.

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[16]Azevedo and Gottlieb (2017) study 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. Similarly to mandatory systems, the basic compulsory insurance grants a fixed daily amount of 320 SEK ($35) conditional on meeting basic and work requirements.[17] Individuals are required to be registered at the Public Employment Service (PES), carry out a job-seeking plan and worked 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, the fees for employed and unemployed individuals coincided. As a result of the labor market reform, the fees for employed individuals more than tripled on average. Figure 1 demonstrates the 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] Involuntary unemployment results in an uncompensated period of up to 45 days.[21] The reform in 2007 also reduced the generosity of benefits displayed in Figure 2.

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[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 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/ .

[21]Each benefit period starts with six uncompensated days.

Figure 1: Voluntary Insurance Fees. SEK/month
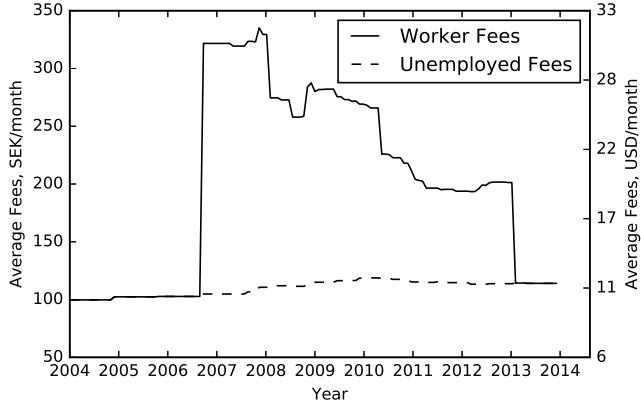
Notes: The figure demonstrates changes in average monthly insurance fees during the period 2004 - 2014. Two lines correspond to fees paid by employed and unemployed individuals, respectively. Those lines coincide during 2004 - 2007 and after 2013. The fees for employed individuals were considerably higher during 2007 - 2013.

Figure 2: Structure of UI Benefits
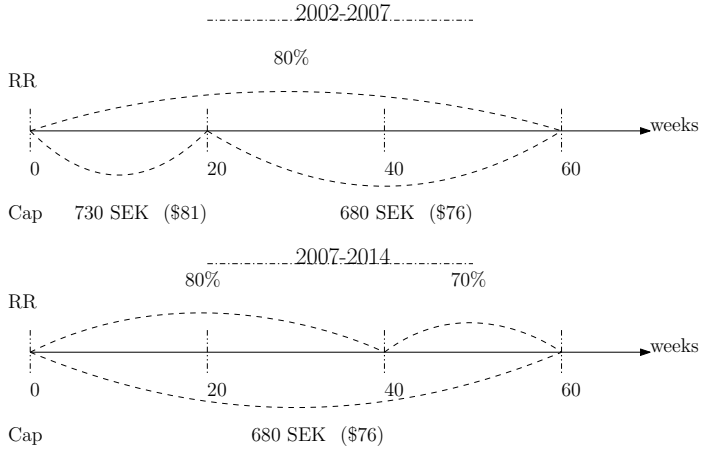
Notes: The figure presents the structure of UI benefits before and after the reform in 2007. The lines with arrows represent schedules of benefits for a maximum of 60 weeks of accumulated unemployment covered by UI. The replacement rate (RR) is presented above the corresponding line. The cap is displayed below the corresponding line.

7

Before the reform in 2007, voluntary UI provided the 80% replacement rate subject to the cap, which depended 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 corresponded to approximately 16 060 SEK ($1 784) and 14 960 SEK ($1 662) of the monthly income, respectively. Basic mandatory insurance benefits amount to 7 040 SEK ($782) of the monthly income. The 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 the 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.[22] The cap became constant for the entire 60 week period and amounted to 680 SEK ($76).[23]

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 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],[25]

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.[26] A rich set of annually observed individual characteristics comes from the Longitudinal Integration Database for Health Insurance and Labour Market Studies (LISA) including a

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[22]Parents with children younger than 18 are eligible for additional 150 days with 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.

[23]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 this into account. Although the presence of additional fund-based insurance affects the parameter estimates, it should not affect the comparative analysis of various UI designs.

[24]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, who are a negligible share of the dataset, are excluded.

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

[26]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 part of a month, I code that 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.[27]

Although the data span a period 1999 - 2014, I limit the 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 sample used in the estimation differs from the full initial 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 the period containing the reform at the beginning of 2007, which provides important identifying variation for model parameters. I exclude individuals who at least once during 2005 - 2009 were registered at PES with categories 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 model tractability, I omit those individuals. It further reduces the sample by 185 321 individuals. I exclude individuals who were constantly either older than 64 or younger than 24 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.[28] Table 1 presents key descriptive statistics of the full sample and the selected baseline estimation sample in comparison with the economically active population of 16 - 64 years old.

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

[28]I randomly split the estimation sample into two equally sized samples. I use a 5% random sample of the first sample in the estimation and the welfare analysis for computational reasons. I use the second sample to investigate the quality of the model fit.

Table 1: Descriptive Statistics, 2008

	Full Sample	Estimation Sample	Swedish population 16 - 64 years old
Employment Income			
Mean, *SEK/month*	24 754	24 834	28 623
Median, *SEK/month*	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%
N	2 167 287	865 363	-

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 comparison purposes. The upper part of the table shows descriptive statistics for 2008, which is one of the years used in the 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 estimation samples are very similar in terms of observables. Slight differences are observed in the share of female, which is 51% in the estimation sample compared to 53% in a full sample. Moreover, the estimation 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 includes lower relatively young individuals who have most likely not finished higher education. Finally, the full sample is represented by a 4% lower share of female individuals.

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

the right in the selected samples.

3   Descriptive Evidence

Unemployment insurance is at risk of a 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. This 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).[29] It would generate a qualitatively similar selection pattern but have different policy implications. The reason is that the absence of a choice imposes the excess burden on individuals who do not value insurance. In addition, the presence of moral hazard might generate a similar positive correlation pattern but require different policy measures. Moral hazard or ex-post selection is a behavioral response to being insured that increases unemployment probabilities. The intuition is that the 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 hinge on risk perceptions and preferences for risks exposure. This ambiguity might result in a need for the opposite policy measures while generating the same "reduced form" 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 design 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 descriptive 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 the cross-sectional variation in the incentives to be insured. This variation stems from differences in insurance premiums across occupation-specific UI funds

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

and in the replacement rate due to a cap, which varies with unemployment duration. Another dimension of the variation is a result of the 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 the reform is associated with changes in a number of aggregate indicators, which might be driven by individual responses to the reform. More precisely, the number of benefits recipients and insured dropped in 2007 (Panels A and B, respectively).[30] However, this aggregate evidence cannot solely be 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, which would lead to 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 be shown with a distribution of a number of enrollment months with which individuals start unemployment spells in the data displayed in Figure 4.

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[30]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.

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

Panel A: Number of Benefits Recipeints

Panel B: Number of Insured Individuals
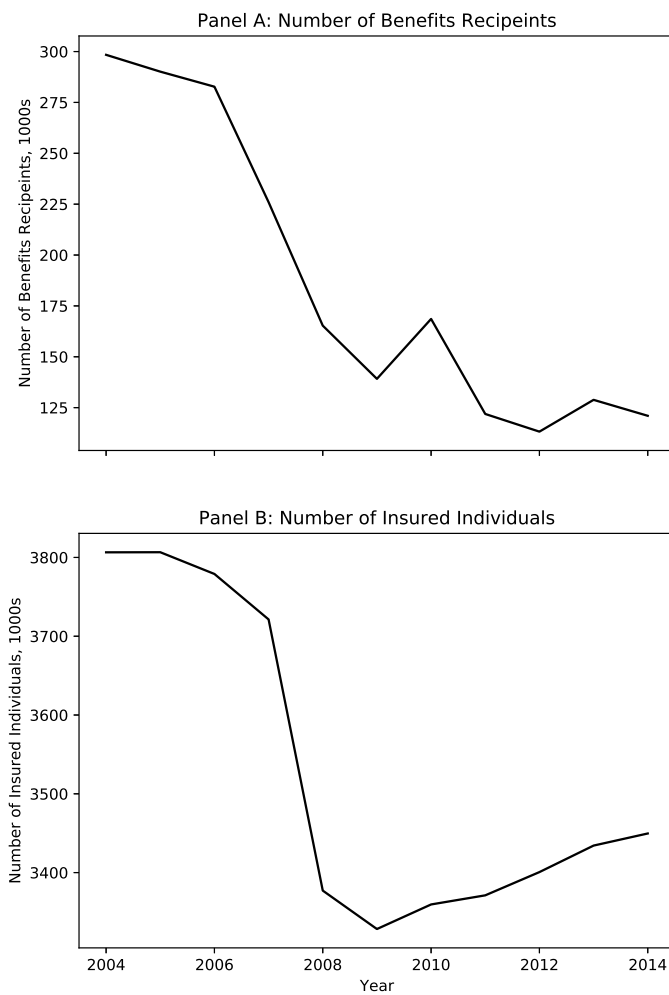
Notes: The figure presents aggregate indicators over time. The source is *Inspektionen för arbetslöshetsförsäkringen.*

Figure 4: Distribution of Accumulated Enrollment Months at the Beginning of Unemployment
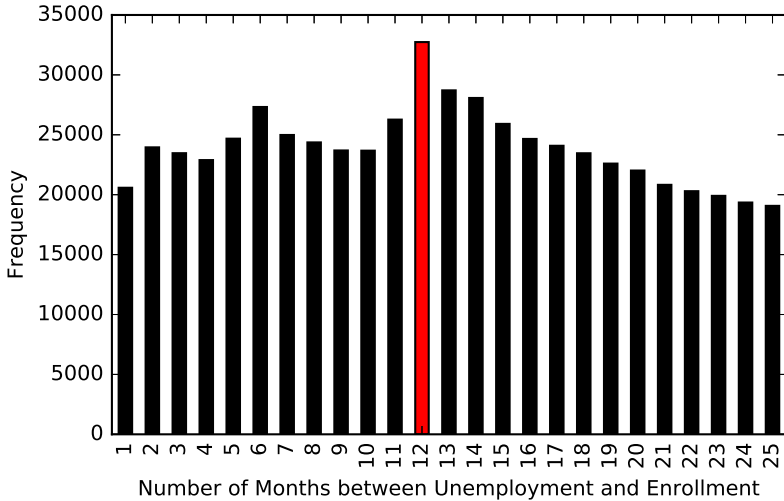
Notes: The figure presents a distribution of a number of accumulated enrollment months before the commencements of unemployment spells. The red bar denotes twelve consecutive months of enrollment required for eligibility. The histogram contains a spike exactly at the red bar, which implies that individuals are more likely to start unemployment spells with twelve months of enrollment.

The distribution 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 required to get eligibility. The area of the distribution to the left of the red spike is non-uniform and non-monotonic, due to differences in private information about future employment outcomes. These differences are a result of various layoff notifications specified in employment contracts, 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 these patterns and attributes them to the differences in information about future employment outcomes. It is important to note that the model is agnostic about the sources of private information since only its existence is welfare-relevant. Time-selection evidence for various subgroups is presented in Appendix C (Figures 17, 18 and 19) and shows identical patterns.

The key identification assumption that will allow us to use changes in the generosity of benefits and premiums to separately identify distributions of risk preferences and private information

14

is that changes in insurance conditions do not affect private information about unemployment. An example of the violation of this assumption would be, for example, if the reform in 2007 not only changed the attractiveness of insurance but also the information about future unemployment. It would imply that changes in insurance decisions are not only driven by changes in the attractiveness of insurance but also by changes in the private information structure. I investigate a potential violation of the identification assumption in the identification section. In this section, I present the time-selection evidence but separately for the periods before and after the reform in 2007 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 in those figures could alert about both changes in information and time-selection accompanied by a moral hazard response. The latter means that individuals not only select the timing of the 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 to be covered even for one month as compared to not paying any 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 jobs 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 also be 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 entire observed period. The maximum number of insurance sequences in the course of the observed period 1999 - 2014 amounts to eleven. The median duration of insurance sequences 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
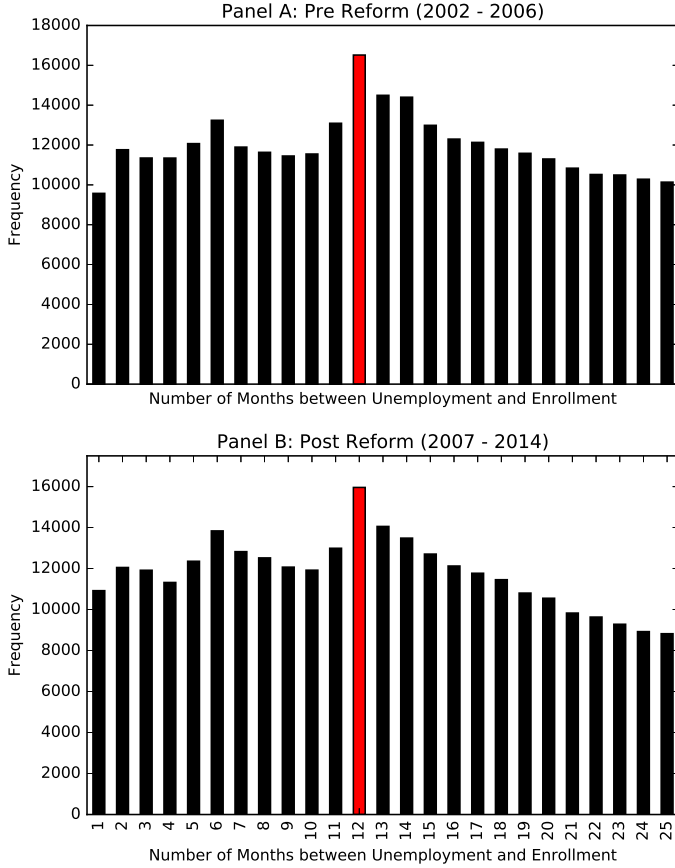
Panel A: Pre Reform (2002 - 2006)

Panel B: Post Reform (2007 - 2014)

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

This section described the main descriptive patterns observed in the data. First, it has been
shown that individuals react to changes in premiums and benefits generosity. Second, 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 Model

I model a forward-looking decision of an individual who faces the risk of unemployment and maximizes expected utility of income. The insurance decisions are monthly, which corresponds to the timing of premium payments. The model resembles an overlapping individual structure depicted in Figure 6.

Figure 6: Structure and Timing of Insurance Decisions
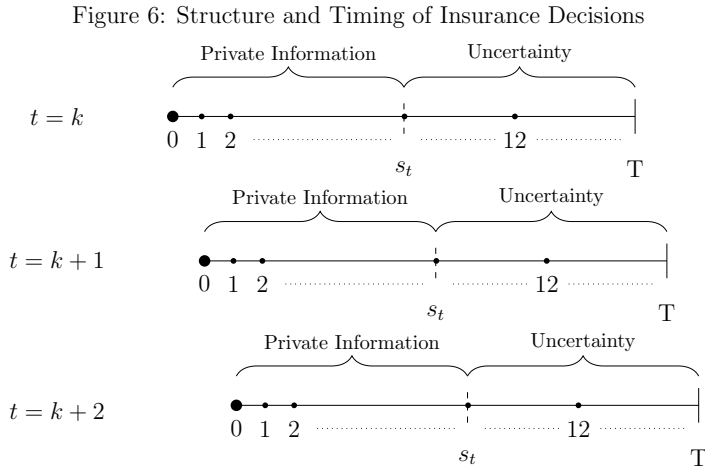
Notes: The figure illustrates the overlapping-individual structure of the dynamic decision in the model. It shows that in each period t an individual solves a new dynamic optimization problem of length T to decide whether to pay monthly insurance premiums at t.

The figure suggests that an individual solves a new dynamic optimization problem each period t to decide whether to pay insurance premiums $l_t \in \{0, 1\}$. The information structure at the time of each decision consists of two parts. The first one denoted "Private Information" means that an individual can perfectly foresee employment outcomes in the next s periods. This knowledge might come from multiples sources, e.g. lay-off notifications or informal information sharing with an employer. I refer to the length of a perfect foresight period s as *private information*

17

type.[31] According to the institutional details, lay-off notifications are restricted to the maximum 12 months. Therefore, I assume that individuals can be any of the types from 1 to 12.[32] The model presented in this paper is agnostic about the sources of this private information since only its existence is important for the welfare analysis presented later in the paper. Another part of individuals' information is denoted by "Uncertainty" and implies that after the window of perfect foresight, a worker is uncertain about employment outcomes for the remaining part of the planning horizon from s to T. In the model, this uncertainty is treated as a collection of all potential employment sequences that might happen from s to T illustrated in Figure 7.

Figure 7: Structure and Timing of Insurance Decisions
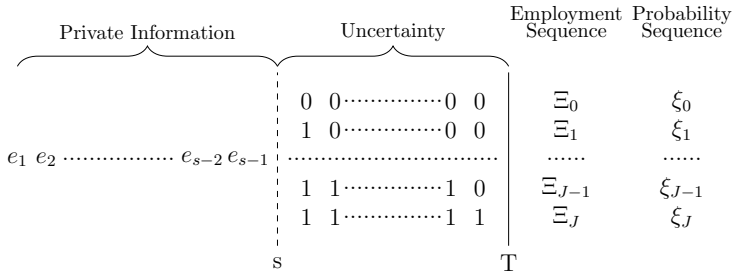
Notes: The figure illustrates the essence of uncertainty and private information in the model. Private information is modeled as the perfect foresight for s periods in the future meaning that an individual can perfectly observe whether she is employed or unemployed in each of these periods. $e \in \{0, 1\}$ denotes the realization of employment/unemployment outcomes. Since an individual does not know if she is employed in periods from s to T, there might be multiple potential employment sequences $j \in J$ spanning all possible combinations of zeros and ones depicted in the figure. Each sequence is denoted by Ξ_j and can occur with the probability ξ_j. The number of sequences is $J = 2^{T-s}$.

The figure shows that individual's information consists of a perfect foresight about employment outcomes from the time of a decision to s months in the future $e = \{e_k\}_{k=1}^s$, and uncertainty that leads to $J = 2^{T-s}$ possible $\{0, 1\}$ sequences of length $T - s$. Each sequence is denoted Ξ_j

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[31]More formally, $\hat{s} = \min\{s, s_u\}$ where $\hat{s}$ denotes the number of periods that can actually be foreseen in the future, s_u is the number of periods until next unemployment and s is the number of periods that can be observed in the future in the absence of earlier unemployment, to which I refer as the private information type. This formulation means that an individual can perfectly know future employment outcomes for s periods unless there is a forthcoming unemployment period. It reflects the fact that individuals cannot observe the end of the unemployment spell. In this case, the information is limited to only one period ahead in the unemployment spell.

[32]Temporary workers can foresee the layoff even further ahead. I discuss the implication of this in robustness section of the paper.

and can occur with probability ξ_j. A current period is indexed by 0 and is already observed.

This overlapping structure is adopted because of the features of UI in Sweden. Each individual decision has a critical impact only on the next 12 months since it determines whether or not she will be eligible for UI benefits during this period. It stems from the discontinuity in the membership eligibility condition that requires paying monthly insurance premiums for 12 uninterrupted months. A current decision will still have an impact on future outcomes after 12 months but only through future decisions. In other words, even if an individual decides not to pay an insurance premium, she can still become eligible for benefits in any period after 12 months if she acts correspondingly in the future. In addition, such a representation of a decision-making process has considerable computational advantages discussed later in this paper. This structure, however, is not a typical dynamic agent model. In particular, this overlapping structure does not force individuals to be committed to the optimal choices computed before and instead solves for an optimal choice each new period upon the arrival of new information. This structure results in more realistic assumptions about state variables in the model, which I discuss in the remainder of this section.

I assume that an individual i decides to pay insurance premiums at time t if this maximizes the expected utility of a sum of incomes over the next T periods.[33]

$$l_t^* = \arg \max_{l_t \in \{0,1\}} U(l_t; \rho_t, s_t) = \arg \max_{l_t \in \{0,1\}} \sum_{j=1}^{J=2^{T-s_t}} \xi_{tj} \cdot \frac{\left(\overbrace{\Pi_j \left(l_t; \{\hat{l}\}_{k=t+1}^{t+T}, \Xi_{tj} \right)}^{\text{Payoff}} \right)^{1-\rho_t}}{1 - \rho_t} \tag{1}$$

where $\hat{l}$ is an insurance decision that an individual plans to make in the future.

The formulation in (1) means that an individual faces the uncertainty of employment outcomes over the next T periods. Although she can perfectly foresee the outcomes of the next s periods because of the private information, she is uncertain about the outcomes after periods s and up to T. It leads to $J = 2^{T-s}$ potential employment sequences in the future. Each of these sequences leads to a different payoff, which is a sum of income streams over the planning horizon of T months conditional on optimally planning future insurance decisions:

$$\Pi_j \left(l_t; \{\hat{l}\}_{k=t+1}^{t+T}, \Xi_{tj} \right) = \sum_{n=t}^{T} \pi(l_n, \kappa_n(l_{n-1}), e_{nj}, \Gamma_n) \tag{2}$$

where e_{nj} is an employment status from one of the employment sequences; κ_n - a number of

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[33]I drop index i from the equation for convenience.

accumulated enrollment periods; Γ_n - a collection of state variables in each period n not affected by individual decisions. It includes wage w_n, replacement rate b_n, cap B_n, insurance premiums τ_n and basic insurance amount in the case of not being eligible $\underline{b}_b$.

The number of enrollment periods (κ) is the only state variable affected by an individual choice and evolves as follows:

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

In turn, κ determines whether an individual is eligible for income-based insurance:

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

A one-period payoff of an individual can be expressed:

$$\pi_t = (1 - e_t) \cdot \underbrace{\left(\overbrace{(1 - \Lambda_t) \cdot \underline{b}_t}^{\text{ineligible}} + \overbrace{(\Lambda_t \cdot \min\{b_t \cdot \bar{w}_t, B_t\}}^{\text{eligible}} \right)}_{\text{unemployed}} + \underbrace{e_t \cdot w_t}_{\text{employed}} - \underbrace{l_t \cdot \tau_t}_{\substack{\text{pay} \\ \text{premiums}}}$$

An individual chooses to pay premiums if this maximizes the expected utility in (1). The model described so far represents an individual decision to pay insurance fees each period as a sequence of static choices under uncertainty, which arises from the absence of perfect information about employment outcomes between s and T.

Although the decision is static, it nests a sequence of dynamic decisions captured in Equation (2). In other words, to determine the optimal insurance path under sequence Ξ_j, she has to solve the dynamic programming exercise. It means that each individual in each period has to solve J number of dynamic programming exercises to decide whether to pay insurance premiums according to (1).

Assumption 4.1. *In each decision period t, individuals have perfect foresight about state variables in $\{\Gamma_n\}_{n=t}^{t+T}$.*

Assumption 4.1 implies that individuals can perfectly foresee all state variables that are not affected by an insurance decision. The sequential structure of the problem makes the assumption being not far from the reality since it only has to hold for T periods in the future. Therefore, the assumption seems reasonable for not very large T. I postpone the discussion of the choice of the planning horizon T until later. In contrast, in more standard models in which individuals would

commit to an optimal strategy and plan until some common terminal period (e.g retirement), this assumption would be questionable since it has to hold for the entire planning horizon.[34]

Assumption 4.2. *Individuals have rational state-dependent beliefs about probabilities of employment in the uncertainty periods conditional on individual and labor market conditions.*

Assumption 4.2 implies two restrictions on indivuduals' beliefs about unemployment probabilities outside of private information. First, the beliefs should be rational in the sense that if identical individual in terms of relevant individuals and labor market characteristics face a probability p of unemployment in some period t, they should believe that with probability p they will also be unemployed in this period t. Second, the assumption allows these beliefs to be state-dependent. It means that unemployment probability p_t is conditional on the employment status in the preceding period e_{t-1}. Given that an individual has conditional beliefs about each of the periods $p_t(e_{t-1}, X_t)$, where X_t is a set of relevant individual characteristics, individuals form unconditional employment beliefs for any period in the future after s as a Markov sequence:

$$E\left[p_{t+n}\right] = E\left[p_{t+n-1}\right] \cdot p_{t+n}^1 + (1 - E\left[p_{t+n-1}\right]) \cdot p_{t+n}^0 \qquad \forall n > t + s + 1 \tag{3}$$

Individuals' beliefs about the probability of each sequence j can be expressed:

$$\xi_{jt} = \prod_{q=t+s+1}^{T} m_{qt} \tag{4}$$

where m_{qt} is the probability that the outcome e_{jq} from sequence Ξ_j is true. If $e_{jq} = 1$, $m_q = E\left[p_q\right]$ and $m_q = 1 - E\left[p_q\right]$ otherwise.[35]

The model presented in this section contains two objects that are observed to individuals but not to us and hence, have to be recovered using the model and the data. These parameters are the distribution of individual risk preferences ρ_{it} and the distribution of individual types s_{it}. The next section discusses the identification of these parameters.

4.2 Identification

Identification of the empirical model outlined in this section concerns separately recovering distributions of risk preferences and types denoted as $F(\rho)$ and $\Phi(s)$. Note that an individual

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[34]Another modeling alternative would be to assume rational expectations about these state variables, in which case multidimensional integration is required. It complicates the process of solving the model and raises concerns regarding the credibility of the assumption.

[35]Note that for the periods from the private information region $q \leq t + s$, $m_q = 1$ if e_q is true and $m_q = 0$ otherwise.

buys insurance ($l_{it} = 1$) if $U(l_{it} = 1; \rho_{it}, s_{it}) > U(l_{it} = 0; \rho_{it}, s_{it})$ according to (1). As shown by Apesteguia and Ballester (2018), for a class of utility functions that include CRRA, there is a unique risk preference parameter denoted by λ_{its} where $U(l_{it} = 1; \rho_{it}|s_{it}) = U(l_{it} = 0; \rho_{it}|s_{it})$ conditional on type s.[36],[37] If the individual's risk preference value is above λ_{its}, she should pay premiums conditional on being a type s. The conditional probability of paying insurance premium is:

$$Pr\left(l_{it} = 1|s_{it}\right) = Pr\left(\rho_{it} > \lambda_{its}\right) = \int_{\lambda_{its}}^{\infty} dF(\rho) \tag{5}$$

The unconditional probability of paying insurance premiums can be written:

$$Pr\left(l_{it} = 1\right) = \int_s Pr\left(\rho_{it} > \lambda_{its}|s\right) d\Phi(s) = \int_s \int_{\lambda_{its}}^{\infty} dF(\rho) d\Phi(s) = \sum_{s=1}^{12} \phi_{its} \int_{\lambda_{its}}^{\infty} dF(\rho) \tag{6}$$

Note that λ_{its} is obtained from the data by solving the model without any information about the distributions of risk preferences and information types. Although it is irrelevant for the identification discussion, it might be useful to mention that the model does not have a closed form solution but λ_{its} can be obtained numerically by solving (1) for each i, t and $s \in \{1, ..., 12\}$. Therefore, λ_{its} can be viewed as the sufficient statistic from the outlined model that fully describes its outcomes. It is useful to view the identification problem as illustrated in Figure 8.

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[36] 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.

[37] Although the indifference point is unique in theory, it is not true numerically since a limit of a utility difference that approaches zero actually becomes zero at some point due to computer precision. I discuss how I deal with the computation of thresholds in Appendix B.

Figure 8: Graphical Interpretation of the Identification Problem
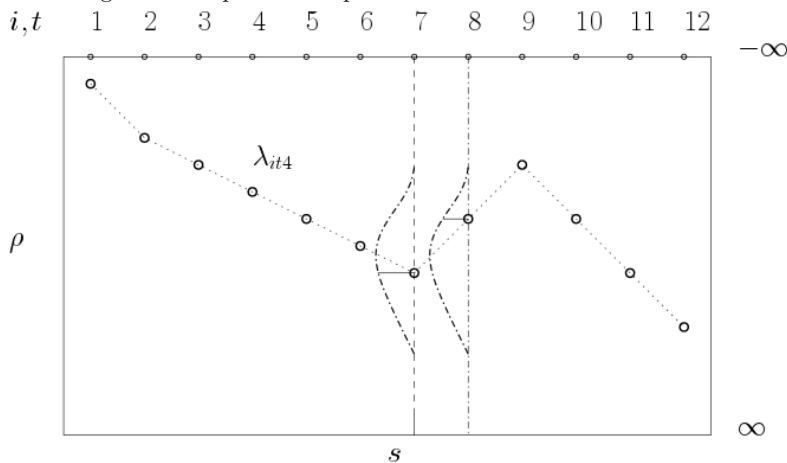
Notes: The figure illustrates the graphical interpretation of the identification of model parameters. The vertical axis denotes the support of the risk preference parameters of the CRRA utility function. The horizontal axis denotes the discrete support of types that can take any value between 1 and 12 assumed in the model. The empty dots denote λ_{its} and depict risk preference thresholds where an individual is indifferent between being insured and uninsured. The bell-shaped curves denote a distribution of risk preferences $F(\rho)$. Conditional on type s_{it}, the probability to buy insurance is the probability that ρ_{it} is higher than λ_{its}, which corresponds to the area above the solid line that connects a bell-shaped curve and a dashed-dotted "type-line". Each of these areas is a graphical representation of Equation (5). The unconditional probability from (6) is a sum of these individual type-conditional probabilities (5) weighted by type probabilities ϕ_{its}.

In summary, I observe the distribution of insurance outcomes and the distribution of state variables that affect insurance decisions. Using the structure of the model, it can be summarized in the distribution of risk preference thresholds. Both distributions of unknown parameters cannot be identified non-parametrically. Below I make an argument for the case in which the model could be identified non-parametrically. Then, I gradually proceed to our case and discuss which additional assumptions are necessary for identification.

The challenge to identify the model non-parametrically stems from the absence of continuous contract choice since individuals face only a binary contract offer, and a fixed duration of the pre-enrollment period (12 months of membership). With a continuous contract choice that maps the generosity of benefits (g) and the duration of a pre-eligibility period (d) to $\tau(g, d)$, observing individual choices would allow pinpointing each individual risk preference value and the duration

of a lay-off notification under some regularity conditions on the function $\tau(g, d)$.[38]

Our case differs in two ways. First, contracts do not vary by in pre-enrollment period duration. Therefore, it is required to impose a parametric assumption on the distribution of individual types $\Phi(s)$. The institutional details of Swedish UI described in Appendix A suggest that displacement rules often vary based on a number of observed characteristics such as tenure at the firm and age. It can also vary by firm or industry. Since types in the model not only represent formal lay-off notification requirements but also informal information sharing, it is reasonable to expect that the type distribution is conditional on relevant individual characteristics. Therefore, in the absence of the variation in pre-enrollment conditions, one has to impose a deterministic functional form of a distribution of types conditional on relevant labor market characteristics. I believe that this assumption is reasonable based on the institutional background.

Although the model lacks the variation in pre-enrollment conditions, there is a variation in the generosity of UI and insurance premiums. The variation mainly results from the reform in 2007, which reduced the generosity of UI benefits for some individuals and raised the insurance premiums for all.[39] One additional assumption is needed at this point.

Assumption 4.3. *Changes in UI generosity and premiums as a result of the UI reform in 2007 do not affect the type distribution $\Phi(s)$.*

Assumption 4.3 requires that a parametric distribution of types $\Phi(s)$ is fixed and does not change together with the UI conditions. Otherwise, one cannot disentangle the response to changes in the UI conditions from the response to changes in private information. Figure 8 suggests that given that the distribution of types $\Phi(s)$ is fixed, one can use responses to changes in the UI conditions to identify risk preferences. More precisely, these differences in the labor market and the insurance conditions are translated into differences in the risk preference thresholds λ_{its}. Since the individual type is now fixed, I return to the case in Equation (5) or an individual point in Figure 8 conditional on being one of 12 types. As a result of the variation due to the reform in 2007, the same individual faces two different insurance choices, which should lead to different λ_{its} conditional on fixed s that can be obtained from the model. The individual responses to these changes allow recovering bounds of individual risk preferences. For example, let a risk preference threshold for buying insurance be 10 before the reform and that I observe her being

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[38]I do not formally show these conditions since this scenario does not correspond to the environment of UI in Sweden and this example serves as an exposition of the identification logic and a need for additional assumptions. However, one can show that identification would require that $\tau(g, d)$ is continuous and strictly increasing in both arguments. It ensures that based on the individual risk preference value and the private information type, there exists the unique contract that is preferred.

[39]Another less salient variation is cross-sectional and it stems from the variation in premiums over insurance funds and the generosity of benefits due to differences in duration of unemployment and employment risks.

insured. After changes in the insurance structure, she should have risk preferences at least as large as 20 to buy insurance and I observe that she stops paying insurance premiums. I am therefore able to conclude that her risk preference value should be between 10 and 20.

To investigate how reasonable Assumption 4.3 is, I plot distributions of time selection before and after the reform in Figure 4.2.

Figure 9: Time-Selection Before and After the Reform in 2007
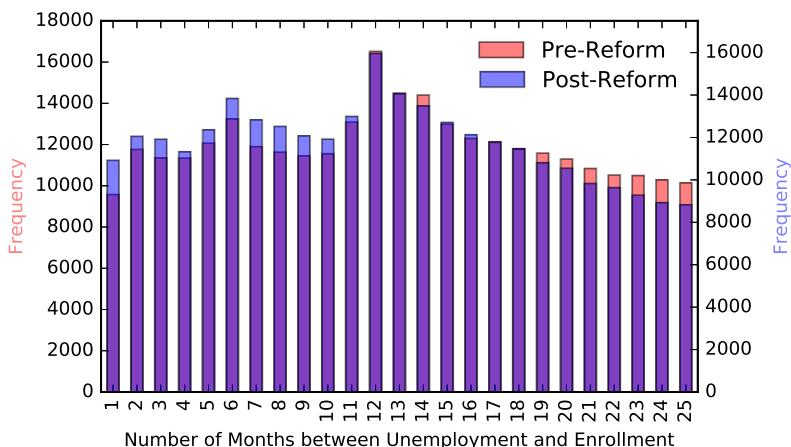
Notes: The figure plots time-selection patterns similar to the evidence presented earlier in the paper separately for the period before and after the reform in 2007.

The figure illustrates time-selection patterns before and after the reform in 2007. Assumption 4.3 requires that the reform does not have an effect on the type distribution. The evidence that would falsify the assumption is differences in time-selection patterns before and after the reform. However, Figure 4.3 suggests that time selection patterns are overall very similar. Although it does not allow concluding that the assumption holds with certainty, at least descriptive patterns in the data do not convincingly reject it.

Note that the model and the assumptions I made only allow pinpointing bounds of risk preference parameters. It is a result of a binary choice that individuals face. Therefore, an additional parametric assumption on the distribution of risk preferences is required for a point identification discussed in the next section.

4.3 Parametrization and Estimation

Before I discuss parametrization of the model, I make one additional assumption regarding the duration of the planning horizon T. I limit the length of a planning problem to $T = 18$. The chosen T must be larger than 12 in order to capture time-selection behavior as a result of the eligibility requirement. Since it is required to solve the 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. In addition, Assumptions 4.1 and 4.2 start being more questionable as T grows. I discuss the importance of a choice of T in the robustness section at the end of the paper.

Assumption 4.4. *Parametric assumptions:*

1. *Individual risk preferences are normally distributed with the mean being a function of in-dividual characteristics $\mu_{it} = \alpha X'_{it}$ and a common standard deviation σ:*

$$\rho_{it} \sim N(\alpha X'_{it}, \sigma) \tag{7}$$

2. *Individuals can be one of 12 types $s \in \{1, ..., 12\}$ with probability ϕ_{its}. Types are drawn from the multinational logit discrete distribution:*

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

Assumption 4.4 contains key parametric restrictions of the model that stem from the identi-fication discussion. A set of model parameters contains a vector of parameters α, a parameter σ and vectors of type distribution parameters $\{\beta_k\}_{k=2}^{12}$.[40]

I estimate the parameters of the model in three steps. First, one of the model assumptions states that individuals have rational state-dependent beliefs about employment probabilities outside of private information. Using the data on employment outcomes and a large set of demographic and labor market characteristics, I estimate the following model.

$$Pr(e_{it} = 1 | e_{i,t-1}) = Logit(Q_{it} | e_{i,t-1}) \tag{9}$$

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

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[40]One vector of parameters in the multinomial logit distribution has to be normalized. I set elements of a vector of type 1 to 0.3.

Equation (9) is estimated separately for those who have been employed and unemployed in the previous period. Upon obtaining parameters of this model, one can predict probabilities of employment for each individual and period in the data conditional on previous employment status. To construct probabilities of sequences in J for each individual and period, I use Equation (4).

In the second stage, I compute risk preference thresholds λ_{its} for each individual i, time t and type s using Equation (1). Recall that an individual chooses to buy insurance if $U(l_{it} = 1; \rho_{it}, s_{it}) \geq U(l_{it} = 0; \rho_{it}, s_{it})$ or, alternatively, if $U(l_{it} = 1; \rho_{it}, s_{it}) - U(l_{it} = 0; \rho_{it}, s_{it}) \geq 0$. As noted by Apesteguia and Ballester (2018), such a utility difference has a unique value of the risk preference parameter ρ_{it} where $U(l_{it} = 1; \rho_{it}, s_{it}) - U(l_{it} = 0; \rho_{it}, s_{it}) = \Delta_{it} = 0$.[41] It means that an individual with a risk preference value that yields $\Delta_{it} = 0$ is indifferent between buying insurance or not. I denote this risk preference value where $\Delta_{it} = 0$ 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 $U(l_{it} = 1; \rho_{it}, s_{it})$ and $U(l_{it} = 0; \rho_{it}, s_{it})$, 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. As discussed in the identification section, an insurance decision can be summarized by a risk preference threshold, which is formally defined as follows:

$$\lambda_{its} = \rho_{its} : \Delta_{its}(\rho_{its}) = 0 \qquad (10)$$

In the third stage, I estimate parameters of the model $\Omega = \{\alpha, \sigma, \{\beta_k\}_{k=2}^{12}\}$. 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.[42] Given a parametric distribution in (7), this probability can be expressed:

$$Pr(l_{its} = 1) = Pr(\rho_{it} \geq \lambda_{its}) = 1 - F\left(\frac{\lambda_{its} - \alpha X'}{\sigma}\right) \qquad (11)$$

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[41]Note that although Δ_{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 approach used in this paper does not suffer from this issue.

[42]The normality assumption of risk preference distribution is common in the insurance markets literature (e.g. Einav, Finkelstein, & Schrimpf, 2010; Handel, 2013). Cabral (2016) uses a log-normal distribution of risk preferences, which rules out the possibility of negative risk preference values. A computed distribution of thresholds presented in Appendix C suggests that the model should allow for risk loving individuals at the expense of imposing the symmetry. I do not allow σ to vary to restrict the model, which already has many parameters. However, heterogeneity in σ might allow restricting a number of predicted risk-loving individuals but is uncommon in the literature.

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

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 a large set of parameters, which makes the estimation burdensome since there are eleven vectors in β (the first one is normalized) for each matrix of characteristics 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 use the Principal Component Analysis to reduce the dimensionality of variables in Z to five dummy variables denoted as cluster allocations.[43] I also add binned age variables which together with a constant comprise a vector of eight parameters in β for each type.

The probability that an individual pays premiums is:

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

Since individuals face complicated and frequent choices, I expect an important role of inertia, which has to be included in the model. The identification of inertia parameters requires an inertia-free group of individuals (Handel, 2013). To account for inertia, I make the following assumption:

Assumption 4.5. *Individuals who observe forthcoming unemployment or were unemployed in the previous period are not affected by inertia ($\eta = 0$) and face the choice affected by inertia otherwise ($\eta = 1$).*

I augment the choice probability equation with the inertia component:

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

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

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

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[43]These five components explain approximately 60% of the variation.

The intuition for such parametrization is that when insured, individuals are more likely to keep being insured. Hence, Υ will be a large positive number, which moves probability $F\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)$ towards zero. Similarly, if previously uninsured individuals are more likely to keep being uninsured, Υ will be close to zero, which forces $F\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)$ 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 likelihood function:

$$
L = \prod_i \prod_t \left(\overbrace{1 - \sum_{s=1}^{12} \phi_{its} F\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)^{\Upsilon_{its}}}^{\text{if insured}} \right)^{y_{it}} \cdot \left(\overbrace{\sum_{s=1}^{12} \phi_{its} F\left(\frac{\lambda_{its} - \alpha X'_{it}}{\sigma}\right)^{\Upsilon_{its}}}^{\text{if uninsured}} \right)^{1-y_{it}} \tag{13}
$$

The modeling and estimation approach described in this section has a number of advantages. First, it is computationally attractive since by searching 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. Second, 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 simulations bias (Train, 2009).[44]

4.4   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 the model using maximum likelihood. I obtain standard errors using bootstrap with 100 draws with replacement. Appendix B provides more details of the estimation of parameters and standard errors.

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

Table 2: 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. An 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 the distribution.

Table 2 presents risk preference and inertia parameters. The table shows that older and higher-income individuals tend to be less risk-averse. Being female, married, higher educated and having children is associated with higher risk aversion. It implies that those characteristics increase the probability of buying insurance conditional on unemployment risks and private information. The model displays considerable unobserved risk preference heterogeneity implied by a fairly large standard deviation in the 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 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 of 0.9, in the absence of inertia, has a probability 0.999 conditional 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 3 with parameters and standard errors is included in Appendix D. Table 4 summarizes the information from type parameters and presents type probabilities. The model results suggest that 73% of individuals have information about only one period ahead while 7% can perfectly foresee employment outcomes for two periods in the future. In line with the time-selection evidence, a considerable share of individuals (15%) have private information about twelve periods in the future, which allows them to perfectly time enrollment. The remaining types are uncommon (around 5% in total). Such a sharp model prediction of a type distribution is to a large extent driven by a 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.

Figure 10: Model Fit - Demand
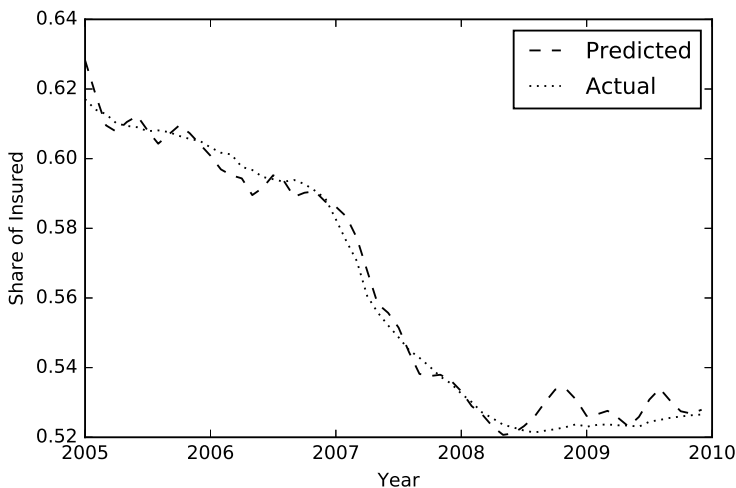
Notes: The figure demonstrates actual (dotted) and predicted (dashed) demand demand functions for 2005 - 2009 on the external sample. The y-axis represents a share of insured individuals. The external sample means that the estimation sample was initially split into two equally sized samples. The estimation is conducted on the first sample and the fit of the model is illustrated on the second to investigate the performance of the model on the part of the sample not used in the estimation.

Finally, Figure 10 shows the model fit on the external sample which was not used in the

estimation.[45] The model predicts patterns that closely match actual evidence. The in-sample fit using the estimation sample is presented in Figure 21 in Appendix C.

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 the 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. First, I consider a contract with fixed costs of six times monthly premiums to be paid when entering the insurance pool.[46] This should discourage time-selection by creating a value of long-term fund enrollment.

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

5.1 Measuring Welfare

The 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. The consumer surplus (CS) can then be measured as a difference between WTP and actual price. It determines the demand for insurance since it 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

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[45]Before the estimation, I split the sample randomly into two equal parts. The estimation procedure is conducted using the first half of the sample. I simulate the outcomes for the second sample, which are presented in the figure. Since the whole sample is sufficiently large, there is no need to perform cross-validation.

[46]I study similar 3 and 9 month contracts, which produce similar results.

even if insurance is valued less than it costs because of choice persistence.[47] Although I attempt to recover inertia in the estimation, 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. In addition, it is theoretically unclear how welfare analysis should be conducted when comparing contracts that are 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 the welfare costs of sub-optimal choices is a controversial question.

The effect on a government budget comes from 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 exactly how welfare conclusions are obtained, I formally define how I construct these components using the model and the 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 premiums for 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 keep the price for unemployed at the actual price. Note that the 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.[48] It implies that all computed objects required for welfare analysis correspond to the systems with no basic insurance.

Since the key sufficient statistic 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 also does this for each unknown type $s \in \{1, ..., 12\}$. It means that the only object obtained from model parameters needed to recovere 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 4. Using the

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

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

same procedure as before, I compute an array of risk preference thresholds $\lambda_{itk}(g)$ for $g \in [\underline{g}; \bar{g}]$.

To calculate the 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 level 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 the expected WTP by integrating over risk preferences:[49]

$$E[WTP_{itk}] = \int_{\hat{\lambda}} \hat{g}_{itk}(\rho) dF(\rho; \alpha X'_{it}, \sigma) \tag{14}$$

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

The intuition of this formula is that the expected individual willingness to pay is a weighted average of WTPs resulting 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:

$$CS_{itk}(g) = \begin{cases} \int_{\rho} \left[\overbrace{(\hat{g}_{itk}(\rho) - g) \cdot \mathbb{1}[\hat{g}_{itk}(\rho) - g > 0]}^{\text{if buys insurance}} \right] dF(\rho; \alpha \cdot X'_{it}, \sigma), & \text{if voluntary system} \\ \int_{\rho} \left[\overbrace{(\hat{g}_{itk}(\rho) - g)}^{\text{always buys insurance}} \right] dF(\rho; \alpha \cdot X'_{it}, \sigma), & \text{if mandatory system} \end{cases} \tag{15}$$

To recover the 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. The expected costs of covering individual $\{i, t\}$ are:

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[49]I use 100 knots to obtain the integral numerically. Instead of integrating from $-\infty$ to ∞, for each case I find risk preferences that correspond to 0.1% an 99.9% percentiles. Then, I construct equally spaced bins and integrate within this interval with 100 knots after reweighing bin probabilities to ensure that they sum up to 1. Since a computational procedure allows obtaining $\lambda_{itk}(g)$ on a grid of values g, I use linear interpolation to fill the values between grid points in the integration.

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

$$\tag{16}$$

I evaluate the welfare by comparing systems 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 (15) and (16), respectively. It implies that those functions can be combined into the correspondence:

$$CS_k(g) \widehat{=} TC_k(g) \tag{17}$$

Equation (17) is a correspondence since it is not guaranteed that each price gives a unique pair of total costs and consumer surplus.[50] 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 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. First, it takes into account that there might be a number of prices that require the same level of

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[50]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.

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.[51]

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. First, individuals react to those changes by enrolling or leaving an insurance pool. Figure 11 demonstrates counterfactual demand functions under various considered policies.

Figure 11: Counterfactual Policies Demand
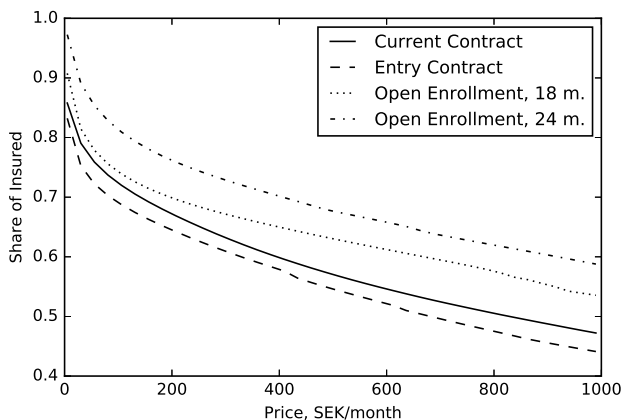
Notes: The figure demonstrates the demand function of the current system, the system with an entry costs contract and open enrollment contracts with 18 and 24 month durations.

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

Figure 12: Average Cost Functions
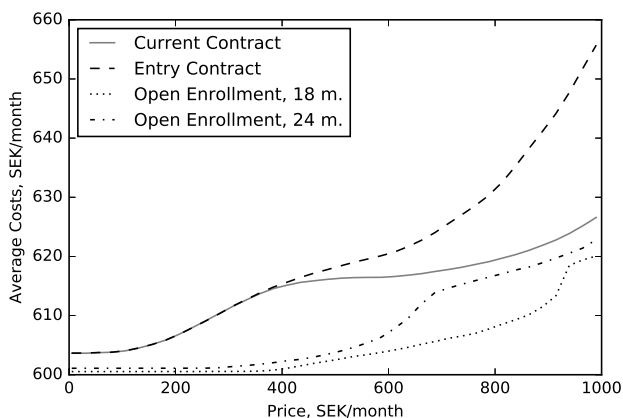
Figure 8 suggests that an entry cost demand function is downward-shifted in comparison to the current contract. Demand functions for open enrollment contracts are less steep on average and are shifted upwards compared to other designs. The demand for the 24 month contract is slightly upward-shifted compared to the 18 month contract since it involves more uncertainty and hence is less attractive.

The second policy-relevant dimension is budget costs. Figure 12 plots average cost functions. The 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 downwards compared to other curves. It signals that these contracts allow restricting selection compared to the current system or the 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 benefit from insurance, whereas it does not provide benefits of holding low-risk individuals in the pool and discourage new enrollments.

Before looking at more formal welfare analysis, the evidence presented in Figures 11 and 12 suggests a number of important insights regarding the welfare consequences of the contracts under consideration. 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 the current system.
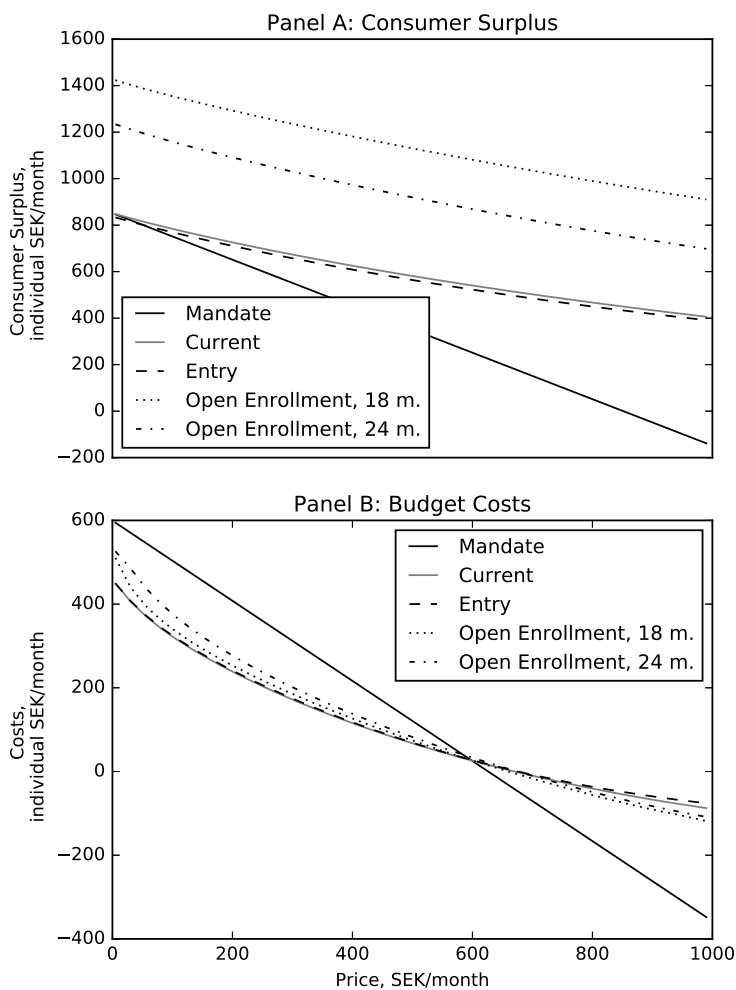
Figure 13 presents consumer surplus and budget costs under various prices. Panel A shows that the open enrollment contract with 18 month duration generates higher consumer surplus under all considered price levels due to its features described above. Other voluntary contracts are similar in terms of consumer surplus. Under mandatory system, price increases have a more 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 the 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 resulting consumer surpluses at various budget costs from Figure 13. It also takes into account that some systems might not allow sustaining any levels of government expenditures at least within a considered interval of prices. It implies that the correspondences from (17) might have different support for various systems in terms of costs.
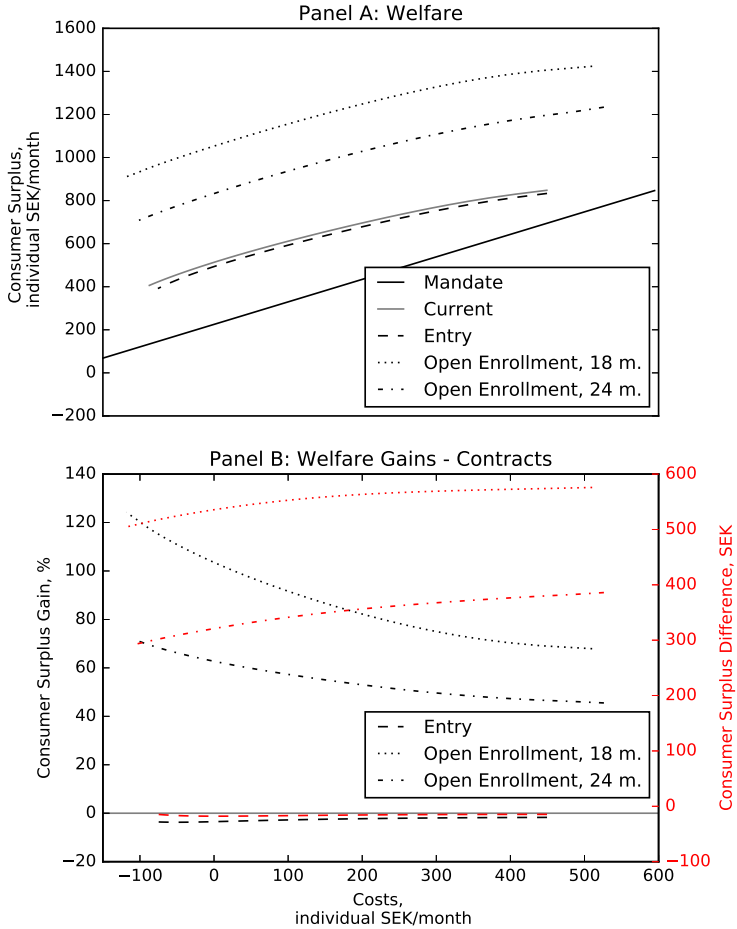
Figure 14 summarizes the welfare analysis. Panel A demonstrates relationships between government costs and generated consumer surplus under considered policies. In other words, Panel A represents the y-axis of Panel A plotted against the y-axis of Panel B from Figure 13. The main point of the figure 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 to be the case in practice.

Figure 13: 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 the resulting 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 14: Welfare

Notes: The figure demonstrates the main results of the welfare analysis. Panel A plots government costs per individual-month for 2005-2008 against the resulting 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 in 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 a system dominates another one under some government cost level if it lies above competing contracts on both Panels. It implies that it results in higher consumer surplus at the same cost level.

Panel A suggests that an entry cost contract is very close to the current system but causes small welfare losses. The 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 this 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 in Panel B of Figure 13, 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 the considered options.

Panel B similarly compares various voluntary designs. It suggests that within the considered range of government costs, the entry cost contract results in 2.9% lower consumer surplus on average along the line. The intuition is that the entry cost 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 month and 58% (338 SEK) for 24 month contracts compared to the current system. There are two features of open enrollment contracts that make them attractive options. First, this contract structure virtually removes a time-selection part of the risk-based selection. Second, the estimates of WTP show that individuals often value this contract more than a current one primarily because of the absence of the 12 month 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 policy among the considered options. Instead, appropriately chosen alternative contract designs tailored to remove harmful selection without considerable distortion to 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 these assumptions.

The first point, which is, however, unrelated to the model and the analysis, is the sample selection. The insurance data lack information about those individuals who have not received any

insurance benefits. It is not a random sample despite similarities to 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 use the model parameters to simulate the choices of individuals whose actual choices are not observed. Figure 15 replicates the results of the welfare analysis from Panel A in Figure 14. In contrast to the results in Figure 14, Figure 15 pretends that individual preferences and type parameters are not affected by sample selection and show welfare conclusions after including missing individuals in the sample.

Figure 15: Robustness of Welfare Analysis - Sample Selection
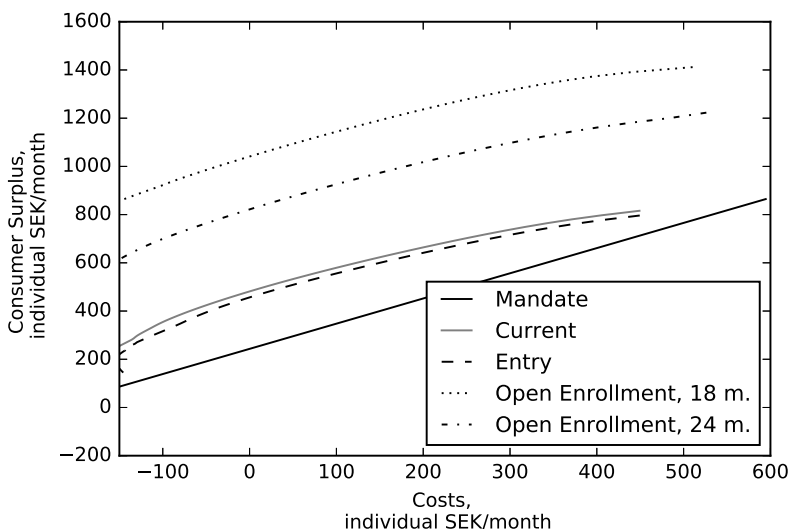
The figure shows that although the levels of curves on the y-axis change, they are located relative to each other similarly to the main results of the welfare analysis. It implies that if estimated model parameters are not considerably affected by the sample selection, the welfare conclusions are robust to omitting a part of the sample. This approach does not take into account the fact that a missing population might have different preferences and the information structure. However, at least within the scopes of the estimated parameters, the welfare conclusions are robust.

Another important feature of the model is the way temporary contracts are treated. A type distribution assumed in this paper can be viewed as being truncated at 12, meaning that individuals should not have information more than 12 months ahead. Although institutional details suggest that this assumption is realistic, there are concerns associated with the presence of temporary contracts in which case individuals might have more than 12 month knowledge. The data contain the variable that denotes the category of unemployment including if an individual is currently on limited-term employment. However, it is difficult to determine the duration of the contract from this information. Therefore, to assess a potential effect on the welfare conclusions, I exclude all individuals who report being on the temporary contract. Figure 16 illustrates the effect of excluding these individuals on welfare results.

Figure 16: Robustness of Welfare Analysis - Temporary Contracts
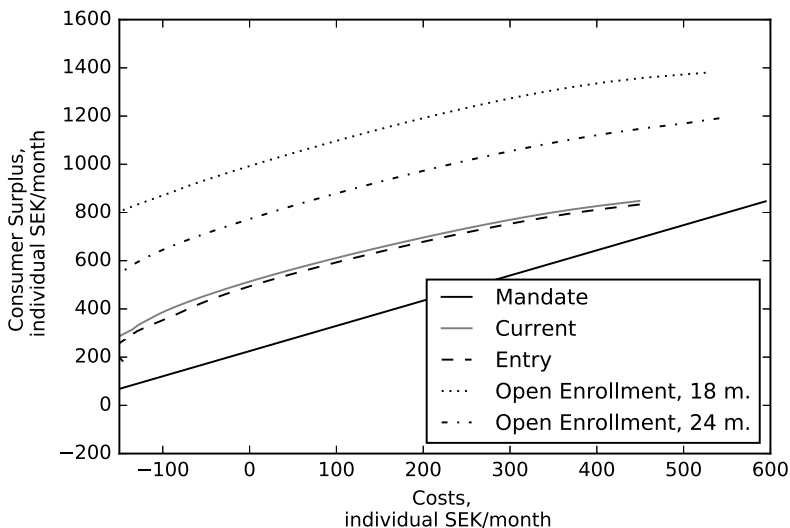
The figure shows similar results to Figure 14. Although the curves shift, their ordinal positions with respect to each other remain the same.

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 considerably affect the results. 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.[52] Therefore, a choice of T remains crucial for computational

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[52]Theoretically, all sequences have non-zero probability but practically there might be zero-probability se-

costs. Appendix B discusses these computational details. To illustrate the effect of this choice on the results, I present a distribution of risk preference indifference points in Figures 22 and 23 in Appendix C using $T = 19$ and $T = 21$ in comparison to $T = 18$, which is used to obtain the main results in this paper. The results suggest that a choice of T proportionally affects how disperse the distribution of thresholds is and hence should not be critical for the welfare analysis.

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 which to a large extent disregards more sophisticated behavioral mechanisms such as the role of the 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   Conclusion

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 should also 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 only correlation evidence that might 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

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quences because of the computer precision limit.

dimensions of heterogeneity. Even taking the model and the parametric assumptions with a grain of salt, this approach allows a 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 available 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 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. First, despite a considerable heterogeneity in the 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. Second, at the very least, the results imply an ambiguous impact of mandates that are widely adopted around the world. Even in the absence of moral hazard responses, it is predicted to be an undesirable policy because of the burden imposed on individuals who have low value of insurance. 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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Appendices

A   Displacement Rules

Time-selection is studied in this paper as an important dimension of private information. Therefore, this section discusses the main rules regarding worker displacement initiated by an employer. I do not discuss job separation initiated by an individual since voluntary employment is not covered within UI at least for the first 45 days.

If a firm decides to displace an employee, it has to provide layoff justification. The absence of work is the most common reason for worker displacement. The employer has to prove the lack of work. If more than five but less than 25 workers are to be displaced based on the absence of work, the firm should inform the Employment Agency at least 2 months in advance. If 25 - 100 or more than 100 workers are to be displaced, the agency should be informed 4 or 6 months in advance, respectively. In this case, the order of displacement is determined by the tenure in the firm.[53] For more details, see Landais et al. (2017). Another reason for worker displacement is unsuitability of a worker for the occupied position. The examples are unsatisfactory performance, threats of violence, theft, refusal to work, unlawful absence, etc. When such reasons constitute a ground for displacement, the displacement procedure is conducted according to the conditions and layoff notification rules specified in the law or in the contract. In the case of particularly serious violation of rules, the individual can be immediately displaced despite the layoff conditions.

In the absence of a collective agreement, tenure in the firm determines the layoff notification duration:[54]

- *less than 2 years*: 1 month

- *2 - 4 years*: 2 month

- *4 - 6 years*: 3 month

- *6 - 8 years*: 4 month

- *8 - 10 years*: 5 month

- *more than 10 years*: 6 month

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[53]Source: https://www.unionen.se/rad-och-stod/varsel-om-uppsagningar
[54]Source: https://www.unionen.se/rad-och-stod/uppsagningstider-om-din-arbetsgivare-sager-upp-din-anstallning

Collective agreements or employment contracts often overrule these regulations. Therefore, the information on tenure does not allow to determine actual time-related private information.[55] Special rules apply to individuals who have reached the age of 55 or older and have more than 10 years of continuous employment in the firm.

Another special employment form, which is fairly common, is a trial employment contract. Such employment implies that before being granted a permanent contract, an individual has several months of employment with a particularly short layoff notice. The duration of trial employment periods varies but cannot be more than 6 months. The most often used notification period is one month.[56]

Temporary contracts with predetermined layoff date are also widely used. Although the exact contract termination date is specified in the employment agreement, the contract can be terminated earlier but a specified layoff notice requirement applies. The maximum length of temporary employment shall not exceed 24 months in last five years.[57]

B   Estimation Details

The estimation procedure in this paper consists of two steps: the computation of risk preference indifference points and the estimation of parameters. I first compute risk preference thresholds where individuals are indifferent between buying insurance or not. For this purpose, I 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.

First, I limit the duration of a planning horizon to 18 periods. It does not fully resolve the issue but linearly reduces the 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 the top 750 sequences or up to a point when sequence probabilities sum up to 0.99.

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[55] Collective agreements that specify layoff notification agreements can be found https://www.unionen.se/rad-och-stod/om-kollektivavtal/sok-kollektivavtal

[56] Source: https://www.unionen.se/rad-och-stod/provanstallning

[57] Source: Paragraph 5 of the Law of Employment Protection.

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 actually become zero at the limit as $\rho \to \infty$ because of numerical constraints.

The part that computes thresholds is written in Python due to the 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. However, it is much more computationally efficient compared to the estimation of parameters jointly with solving the model, which would require reestimating it at each optimization iteration. The second stage is parameter estimation based on the computed thresholds using a maximum likelihood procedure described in the main text. I use the L-BFGS-B algorithm with bounds on parameters and an analytical gradient function.

Bootstrap is used to calculate standard errors. I use 100 draws with replacement and estimate the model in parallel on 20 cores. Such a fairly low number of draws is chosen for computational feasibility reasons since it requires around 8 hours for the optimizer to converge.
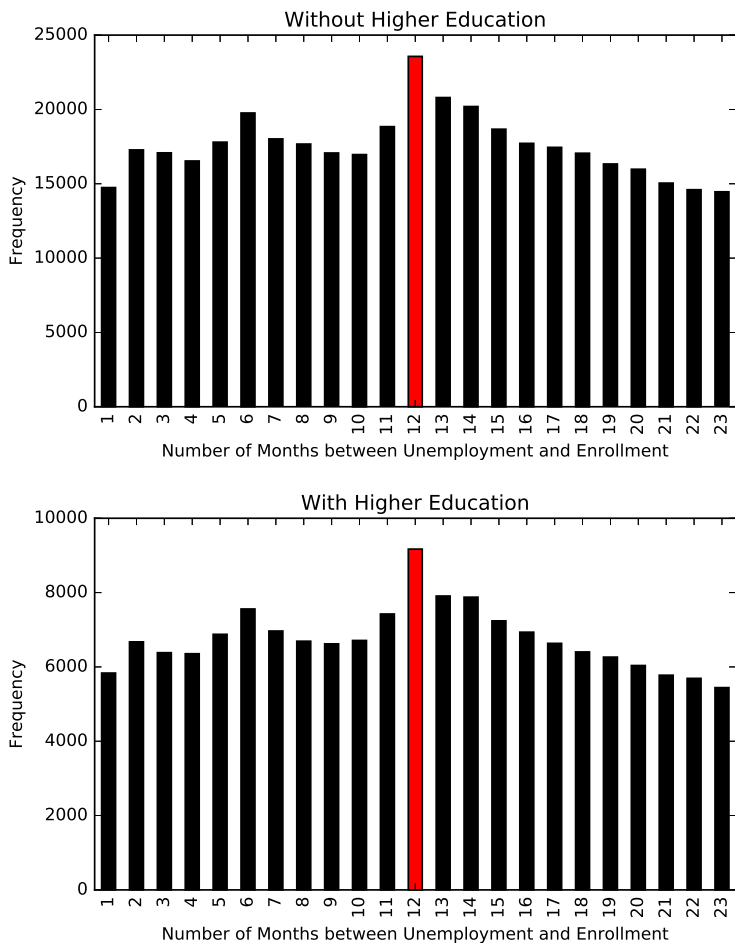
C Supplementary Figures

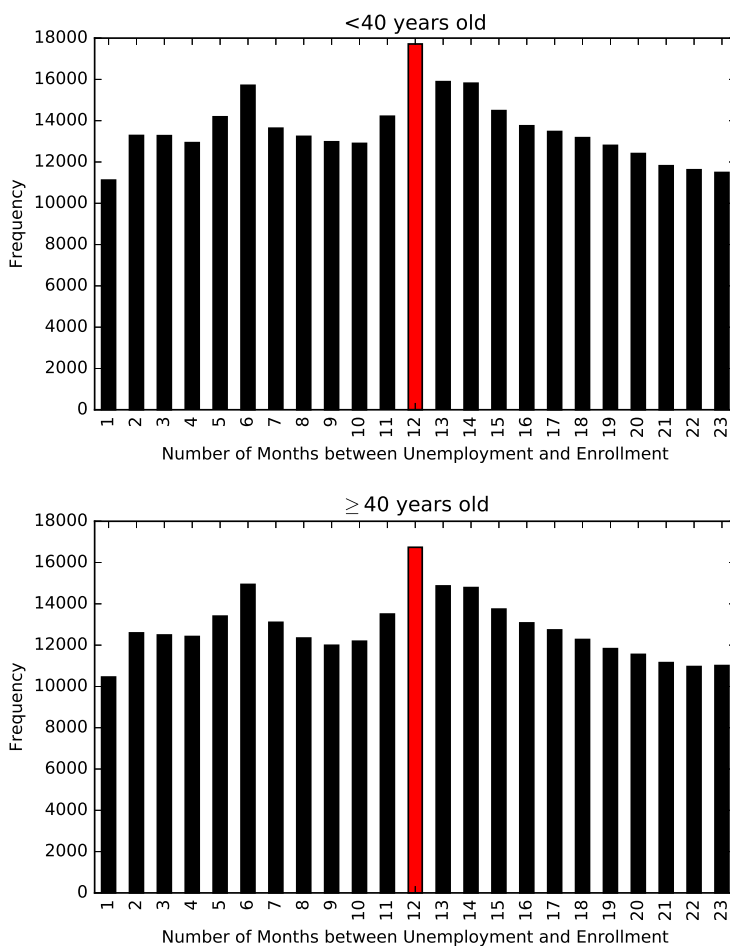Figure 17: Bunching Around the Eligibility Requirement By Income
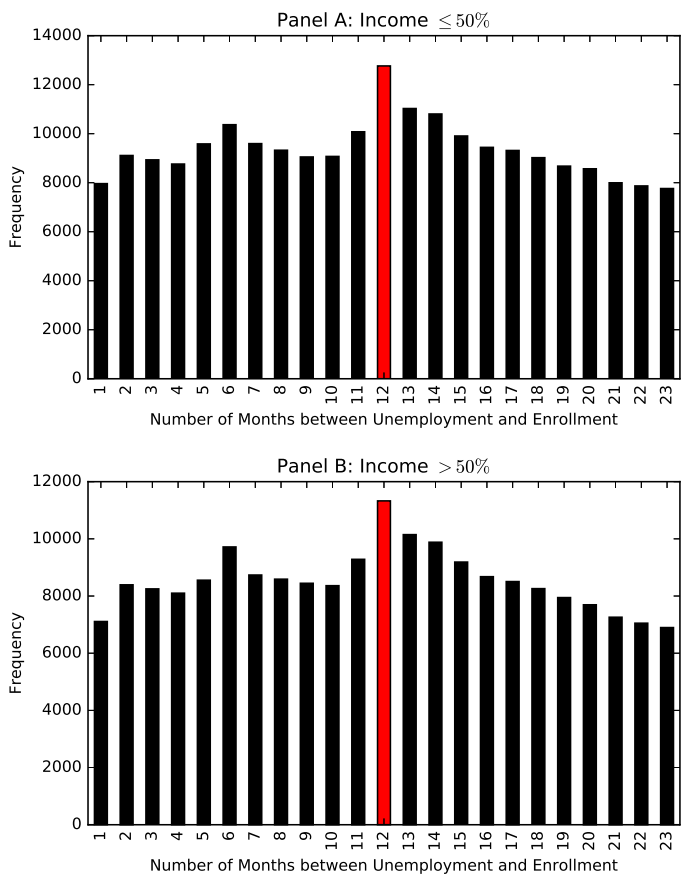
Notes: The figure presents a discrete histogram of a distribution of a number of enrollment months before the start of unemployment spells similarly to the evidence in the main text but separately for individuals with below the median income (Panel A) and above the median income (Panel B).

Figure 18: Bunching Around the Eligibility Requirement by Education

Without Higher Education

With Higher 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 19: 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.

Figure 20: Comparison of WTP under Alternative Systems
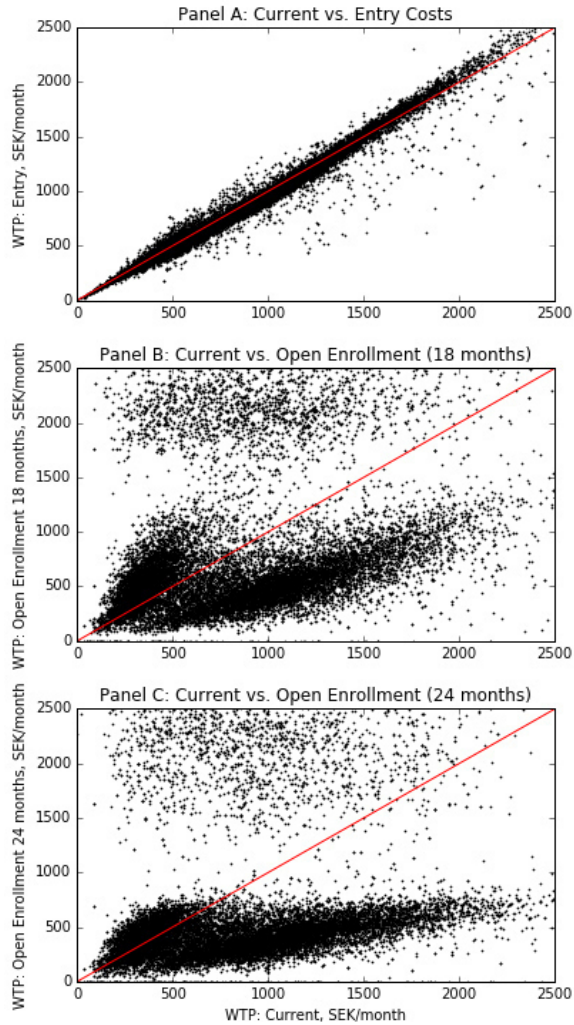
Notes: The figure demonstrates WTP for counterfactual insurance systems (y-axis) against WTP for a current insurance system (x-axis). Red lines have 45^0 angle and allow seeing whether the corresponding system is more valued by individuals. Each point represents average willingness to pay for each individual 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 21: Model Fit - Demand
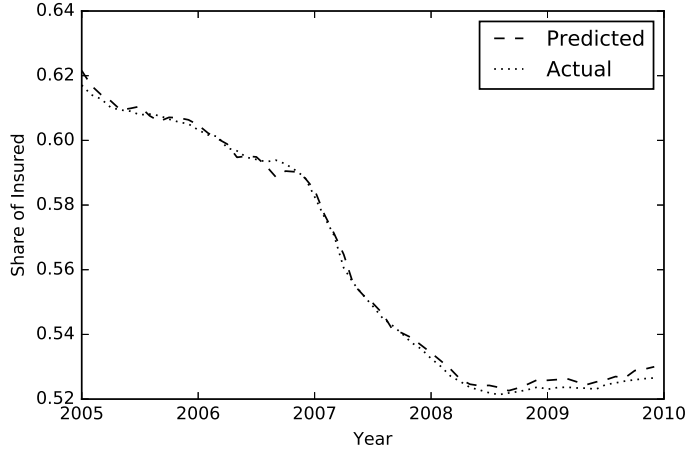
Notes: The figure demonstrates actual (dashed) and predicted demand (solid) demand functions for 2005 - 2009. The y-axis represents a share of insured individuals.

Figure 22: Distribution of Risk Preference Indifference Points - 18 months vs. 19 months
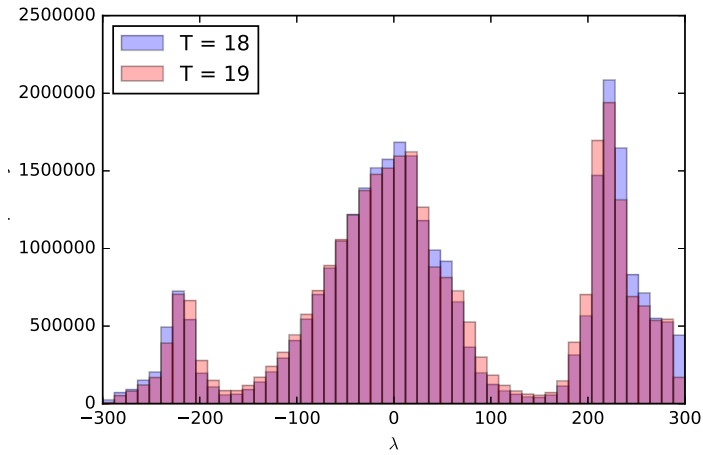
Notes: The figure demonstrates a distribution of thresholds under $T = 18$ and $T = 19$. The y-axis denotes a frequency of the distribution.

Figure 23: Distribution of Risk Preference Indifference Points - 18 months vs. 21 months
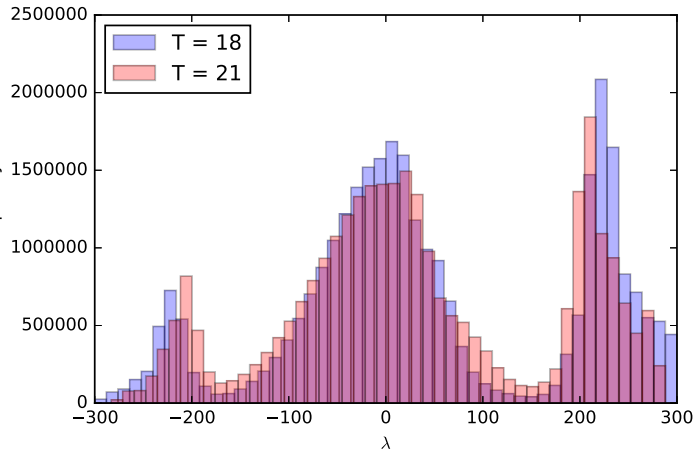
Notes: The figure demonstrates a distribution of thresholds under $T = 18$ and $T = 21$. The y-axis denotes a frequency of the distribution.

D Supplementary Tables

Table 3: Types Parameters

		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
							Types						
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)

59

Table 4: Type Probabilities

Type	Predicted Share
I	73%
II	7%
III	
IV	
V	
VI	
VII	5%
VIII	
IX	
X	
XI	
XII	15%

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

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.

Chapter 2

Behavioral Responses and Design of Bequest Taxation[*]

Maksym Khomenko[†]   Simon Schürz[‡]

Abstract

This paper studies the optimal design of an intergenerational wealth tax, commonly represented by either inheritance or estate taxation. Depending on the tax design, old-age individuals can react with a number of responses, ranging from adjustments of wealth accumulation and inter-vivos gifts to changes in the distribution of inheritances among heirs. We leverage a unique and appropriate setup of Swedish inheritance taxation and rich administrative data. To understand individual responses to alternative tax schemes, we estimate a comprehensive structural model of wealth accumulation and bequest decisions in old age. We find that comparable inheritance and estate taxes result in sizable, but similar distortions to wealth accumulation and bequest distributions. By limiting strategic avoidance to wealth adjustments, estate taxation outperforms inheritance taxes in terms of tax revenues. Our model enables policymakers to design an intergenerational wealth tax that balances distortions, progressiveness, tax revenue and tax incidence according to the chosen social welfare functions.

Keywords: bequest taxation, bequest motives, lifecycle model, tax avoidance

JEL classification: H24, H26, D14, D15, D64

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1   Introduction

Inherited wealth plays a key role in the intergenerational persistence of wealth inequality. This is why, there are active policy debates among economists and policy-makers regarding whether and how to promote social mobility by taxing estates or bequests.[1] While a large body of literature documents the intergenerational and across-family consequences of inherited wealth (Boserup *et al.*, 2016; Elinder *et al.*, 2016; Adermon *et al.*, 2018), the behavior of old-age individuals (bequest donors) with respect to bequests and their responses to taxation is poorly understood. This paper studies the outcomes of different intergenerational wealth tax designs, taking into account the variety of taxpayer reactions.

There are two types of intergenerational wealth transfer taxes commonly adopted around the world: estate and inheritance taxation. In the case of the estate tax, the base of the taxation is the terminal wealth of a deceased individual, whereas inheritance tax is levied on the individual bequest that each heir receives. In the latter case, family structure is an important determinant of the optimal decisions of donors. Therefore, fundamental differences in tax design may lead to different behavioral responses and welfare implications. When donors choose how to optimally transfer wealth to a heterogeneous set of heirs, they can have multi-dimensional responses to intergenerational wealth taxation. For instance, old-age individuals may react by altering the wealth accumulation or use inter-vivos gifts to fully use exemption levels or fall into lower marginal tax brackets (Joulfaian, 2006; Kopczuk & Lupton, 2007; Glogowsky, 2016). If the tax is levied on heirs, donors may decide to change the distribution of individual bequests to their offsprings. Adjusting the share of the terminal estate that heirs receives can position individual bequests at lower marginal tax rates.[2]

The trade-off that old-age individuals face under bequest taxation can be characterized as a *donor trilemma*. Essentially, old-age individuals gain utility from current consumption, the amount of total bequests and how the estate is split. An intergenerational wealth tax triggers a trade-off between these three factors since it reduces the total value of after-tax bequests to heirs. Depending on how donors address the trade-off, their responses affect tax revenues, the values, and distribution of transferred wealth and donor utility. Additionally, responses to specific tax

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[1]Currently fifteen US states collect an estate tax in place and six states tax inheritances. Maryland and New Jersey have both systems. In Europe, bequest taxation is in place in Denmark, France, Spain, Germany and Finland (inheritance tax) and the UK (estate taxation). A large number of European countries, such as Sweden, Norway, Austria, Hungary, and Portugal as well as several US states have repealed bequest taxation in the last 20 years with ongoing debates about re-introduction.

[2]Additionally, in Sweden (1992-2004), bequests could be classified into lower tax brackets if heirs decided to cede part or all of the inheritance directly to their offsprings. We discuss this particular tax avoidance strategy in detail in Section 2C.

schemes interact with individual donor heterogeneity, such as family structure, age and initial wealth. The choice of tax design and taxpayer reactions to intergenerational wealth taxation are therefore inevitably related.

In this paper, we estimate a structural model of donor decisions to document how the complex nature of behavioral responses to bequest taxation plays out under a number of alternative policy designs. More precisely, using detailed data on bequests, wealth, family structure and characteristics of decedents and heirs in Sweden from 2001 to 2004, we estimate a dynamic model of donor decisions, which involves wealth accumulation, inter-vivos gifts, and end-of-life bequests. There is a number of reasons why this structural approach is appropriate and even necessary in this case. First, to define the optimal policy design, it is required to understand the outcomes of policies that have not been observed. By estimating policy-invariant individual preferences, insufficient variation in observed tax designs can be addressed. Second, the model uncovers the interplay between multiple responses to taxation, rather than pinpointing overall or partial elasticities to the tax using, for example, bunching estimators (Saez, 2010; Glogowsky, 2016; Escobar *et al.*, 2019). Third, we can inform policy-makers by studying counterfactual policy designs along several dimensions including wealth accumulation, bequests, and tax revenues.

The model allows us to obtain the fundamental parameters that govern the donors' dynamic trade-off between consumption, the total amount of bequests and the split among heirs. Each period, an old-age individual decides on a fraction of wealth to be consumed or transferred to descendants as gifts. The remaining wealth is conserved for the next period when, depending on whether the old-age individual survives, it is either bequeathed or subject to the same choices. The donor also anticipates that in the case of death, she/he will decide on a split of the terminal wealth among heirs. Finally, the utility from bequeathing is derived from the total after-tax bequest value and the way bequests are split among the potential heirs.

To understand how donors allocate bequests to heirs, it is required to identify policy-invariant bequest preferences. In other words, the model needs to capture the donor's motivation to split the terminal wealth in a specific way in the absence of any taxation. For this purpose, we exploit variation in family structure, wealth and the presence of a ceding rule in the Swedish inheritance tax. This rule allows heirs to transfer all or part of the bequest to direct offsprings upon receipt. Thus, the heir can minimize the tax bill because each recipient of a cede can again make full use of individual exemption levels.[3] We show that a subgroup of donors, whose heirs can all cede and potentially avoid the entire tax bill, do not distort their bequest distribution away from their true preferences as a reaction to taxation.

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[3]Ohlsson (2007) and Escobar *et al.* (2019) document this incentive for Swedish heirs and shows that it is a widely used practice.

Following the conventional approach in the literature, we estimate the structural model in a two-step procedure (French, 2005; Lockwood, 2012; Blundell *et al.*, 2016). First, policy-invariant donor preferences for splitting terminal wealth among heirs are recovered by exploiting the variation in family structures and characteristics of donors and heirs in a subsample of decedents. The obtained parameters then enter a second stage, in which we estimate a dynamic life-cycle model à la Blundell *et al.* (2016) and Lockwood (2018).

Using the resulting parameter estimates, counterfactual wealth paths and bequests are simulated under various tax schemes. We find, compared to the no tax case, that donors accumulate significantly lower levels of wealth in old age when intergenerational wealth transfers are taxed. When taxes are progressive, this effect is mainly driven by individuals at the upper tail of the wealth distribution. Consequently, estates are lower and large masses in the bequest distribution are allocated below the kinks of the marginal tax rates. Estate and inheritance tax schedules perform similarly in terms of distortions when marginal tax rates are comparably progressive. Importantly, estate taxes lead to higher tax revenues because they limit donor responses to the adjustment of terminal wealth. Under inheritance taxation, donors can react to the policy by adjusting each individual bequest. Generally, we find that the more flexible the policy is in terms of allowing the donor to react based on the family structure, the higher are the behavioral responses that distort wealth and bequest distributions as well as tax revenues.

This paper contributes to the literature on bequest taxation in several ways. Broadly speaking, this paper is related to a number of papers studying the life-cycle behavior of old-age individuals that, among other things, involve wealth accumulation and bequest decisions (French, 2005; Laitner *et al.*, 2018; Lockwood, 2012, 2018). Our contribution is to propose a novel model to analyze inheritance tax designs under multiple behavioral responses and several dimensions of policymaker objectives. The comprehensive structural model covers taxpayer reactions from adjusting the wealth accumulation (Slemrod & Kopczuk, 2000; Joulfaian, 2006; Kopczuk & Lupton, 2007), inter-vivos gifts (Joulfaian, 2005; Ohlsson, 2011) and strategic changes in individual bequests. It allows studying consequences of such responses on wealth holdings, bequest distributions, and government tax revenues. An important feature of the institutional setting of Sweden is its generous social security system, which includes elderly and health care. It allows us to recover behavioral patterns which are distorted by precautionary saving behavior to a very minor extent. Therefore, this institutional set-up is particularly suitable to study this question in comparison to, for instance, the US where precautionary saving motives must be an important determinant of the end-of-life wealth decisions (Lockwood, 2018).

To our knowledge, this paper is the first to estimate such a comprehensive model of bequeathing with detailed micro-level data. In particular, the structural empirical approach is

crucial to overcome the complexity of the problem, to deal with limitations of data availability and to ensure the possibility of studying these policy counterfactuals of interest. In particular, it addresses the common problem of non-identification of policy-invariant bequest preferences due to the lack of micro-level data on bequests when no taxation is in place. By providing a micro-level analysis of old-age individual behavior, we complement macro evidence on life-cycle models (De Nardi, 2004; Piketty & Saez, 2013; De Nardi & Yang, 2014) and reduced form evidence on bequest distribution (Light & McGarry, 2004; Erixson & Ohlsson, 2014; Escobar *et al.*, 2019).

More generally, we contribute to the literature on intergenerational wealth taxation by empirically studying the equity-efficiency trade-off under taxpayer responses (Piketty & Saez, 2013). We also touch upon research on bequest motives (Barro, 1974; Becker & Tomes, 1979; Behrman *et al.*, 1982; Cox, 2003; Arrondel & Masson, 2006; Lockwood, 2012, 2018) by incorporating the decedent's altruistic and equality preferences.

The remainder of the paper is structured as follows: Section 2 describes the data, the Swedish institutional background and provides a descriptive analysis of bequest distributions. Section 3 discusses the structural model and Section 4 presents the estimation strategy. Section 5 introduces the counterfactual analysis and reports the results. Section 6 concludes.

2 Data, Institutional Environment and Sample Selection

A Data Sources

The study draws on a population-wide dataset on all bequests in Sweden between 2001 and 2004 provided by the Statistics Sweden (SCB). This so-called *Belinda* Population Database is a complete dataset of inheritances from 2001-2004 including an identifier for the deceased, the value of the terminal estate, the individual bequest, tax payments, and identifiers and characteristics of the heirs.[4] The bequest database is merged with detailed registry data to obtain background information on donors and heirs, such as labor market status, wealth, demographic characteristics, education, and income. The Swedish Multi-generational Registry is used to identify relationships between decedent and heirs and between heirs. To proxy expected conditional survival probabilities, we use life tables provided by SCB.

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[4]See Elinder *et al.* (2014) for a detailed description of the database.

B   Institutional Details

Bequest taxation has had a long-standing tradition in Swedish tax policy. From 1885 to 2004, intergenerational wealth transfers were taxed at the heir level (Henrekson *et al.*, 2014). After peaking in 1970, the tax rates decreased steadily until the abolition, which was motivated by high administrative costs compared to small revenues and a long-lasting opposition by entrepreneurial interest groups. While fiscally not important, the main purpose of the tax was the reduction of intergenerational transfers at the upper end of the wealth distribution. To adhere to the ability-to-pay principle of taxation, the scheme was designed in a progressive fashion (Kendrick, 1939).

The inheritance and gift ordinance (*Lagen om arvs- och gåvoskatt*) stipulates the legislation for intergenerational wealth transfers. If an individual passes away, the decedent's estate is documented in the inventory estate report, which contains real and financial assets, private insurance, consumer durables, and debt. If the decedent is a surviving spouse herself, it may also include part of the spouses' wealth (*giftorätt*).

Inheritance rules define the default succession order and the distribution of bequests. If the decedent is survived by his/her spouse, she/he inherits the entire estate, except if the decedent has children with a different partner. The spouse has free disposal of the inheritance but cannot alter the bequest distribution set by the decedent. Such inheritances from previous decedents are separately marked in our data and we will consequently exclude spousal bequests from the analysis. Otherwise, the first non-empty parentelic group inherits equal splits of the final estate. Adoptive children are equal to biological offsprings before the law. Further groups are considered only if there are no heirs in the previous group. Any inheritance intended for a minor under 18 is directed towards the legal guardian of the child. Therefore, we will focus on heirs aged above 18 years.

A stipulated will can redefine the order and distribution of bequests with the limitation that a fraction, 50% of the inheritance without a will, is reserved for direct descendants (*Laglotter*). This puts institutional non-binding boundaries on how terminal wealth can be split among heirs. Clearly, wills are also set up for other purposes than unequal splits, for instance, the inclusion of further heirs or specific property transfer. Therefore, a will is a necessary but not sufficient condition for unequal bequests. Gifts and insurance claims are included in the legislation. In our study period, they were generally taxed independently of their intergenerational character, but gifts 10 years prior to the death were taxed jointly with inheritances under the *summation rule*. This measure was introduced to counteract tax avoidance. Furthermore, gifts represent a way of transferring wealth to a set of heirs unequally in the absence of a testament. If an heir

receives an inheritance, she/he can decide to cede part of or the total amount of the value to direct heirs, e.g. grandchildren of the decedent. When ceding, both the sender and the recipient can make full use of the individual inheritance tax exemption. This practice was widely used as a legal form of tax avoidance (Ohlsson, 2007; Escobar *et al.*, 2019).

The tax scheme in our study period is made up of three brackets. The details of the tax brackets are displayed in Table 1. Inheritances to the first parentelic group (except spouses) over 70.000 SEK were taxed with 10%, followed by 20% and 30% rates for bequests exceeding 300.000 and 600.000 SEK, respectively. We focus on the tax scheme for most direct descendants, further schemes for relatives, friends and institutional recipients differ in exemption values, but not in marginal tax rates. Figure 1 depicts how the changes in marginal tax rates result in kinks in the overall tax scheme.

Figure 1: Kinks in the Swedish Inheritance Taxation for Parentelic Group 1
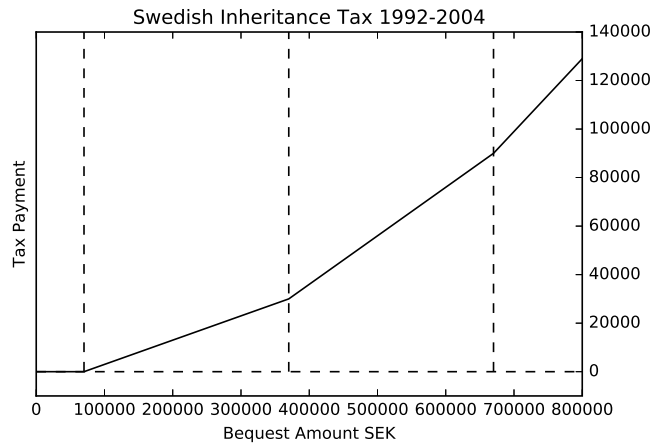
Notes: Tax scheme for the first parentelic group (spouses, children, grandchildren) with an exemption level of 70 000 per heir. Kinks of the marginal tax rate at SEK 370 000 and 670 000.

Table 1: Tax Schedule for Children, Spouses and Grandchildren, 1992-2004

Tax bracket, SEK	Tax (lump sum + tax rate)
0 - 300 000	0 + 10%
300 000 - 600 000	30 000 + 20%
> 600 000	90 000 + 30%
Basic Exemptions, SEK:	Amount
Children:	70 000
Gifts:	10 000

Notes: This tax scheme represents the marginal tax rates and exemption levels for the first parentelic group, including an annual inter-vivos gift exemption of SEK 10 000.

C   Potential Responses under Swedish Inheritance Taxation

The Swedish inheritance tax between 1992-2004 allows the donor to respond to the tax in multiple ways. Old-age individuals can adjust their terminal wealth, such that the total tax burden for heirs is reduced or the intended after-tax value of bequests is conserved. Changes in terminal wealth are achieved either with higher or lower levels of consumption or with gifts, which have a yearly tax exemption of 10 000 SEK. The sign of the wealth adjustment is theoretically ambiguous and depends on the utility weights that are placed on consumption and bequests. The optimal response to a tax with a change in the level of wealth, however, requires high planning efforts and is costly due to uncertainty regarding the timing of death.

To give an example of a possible wealth response to taxation, consider a donor with wealth SEK 160 000, who wants to equally bequeath to her two children. She can gradually decrease her wealth via gifts or consumption, such that the terminal wealth of 140 000 positions both individual bequests (SEK 70 000 each) below the first tax bracket.

Alternatively to changes in the terminal wealth, an inheritance tax, which is based on the heir level, allows the donor to respond by adjusting individual bequests. By stipulating a will, the donor can change the relative shares to heirs in order to place one or several individual bequests at or below the thresholds of tax brackets. While this strategy may limit distortions in the wealth accumulation, it requires the donor to depart from the preferred split of bequests.

For example, a donor who wants to leave SEK 50 000 and 100 000 to her/his two children, respectively, may want to switch to a SEK 70 000/80 000 split in order to save SEK 2 000 in taxes.

Last but not least, ceding is a modification of the bequest distribution conducted by the heirs. Under the Swedish inheritance law, a bequest can be dissipated downstream within the family

7

line. Ceding is therefore limited to heirs who have descendants of their own. In particular, if ceding can eliminate the entire tax bill, donors may not exhibit any response to taxation.

For example, an heir that receives a bequest of SEK 200 000 may want to cede SEK 70 000 to each of her two children (the donor's grandchildren), such that, due to the individual exemption levels, all three individual bequests then fall below the first tax bracket. Table 2 summarizes all potential donor responses and alternatives for legal tax avoidance.

If the bequest taxation takes the form of the estate tax, adjusting the terminal estate through wealth decumulation and inter-vivos gifts are the only available responses to old-age individuals. In this paper, we focus on wealth adjustment through consumption, gifts, and changes to individual bequests. As we document, these responses are widely used in Sweden 2001-2004 and are available to donors in most countries with bequest taxation. The ceding rule is very specific to the Swedish context and plays a key rule in identifying the interaction of the remaining responses to inheritance taxation. For simplicity and due to extremely low incidence and special tax exemptions, we exclude the strategic component of bequeathing to non-children heirs and assume a constant share per donor that is left to these types of heirs.

Table 2: Strategic Responses and (legal) Incentives for Bequest Tax Avoidance

	Estate Taxation	Inheritance Taxation
Wealth accumulation	✓	✓
Within family distribution	—	✓
Gifts	✓	✓
Cedes	—	(✓)

Notes: The availability of strategic responses of donors to inheritance and estate taxes depends on the definition of the tax-base. Taxation at the heir level allows for additional reactions by adjusting the distribution of bequests among heirs or, if the legislation provides this possibility, by ceding.
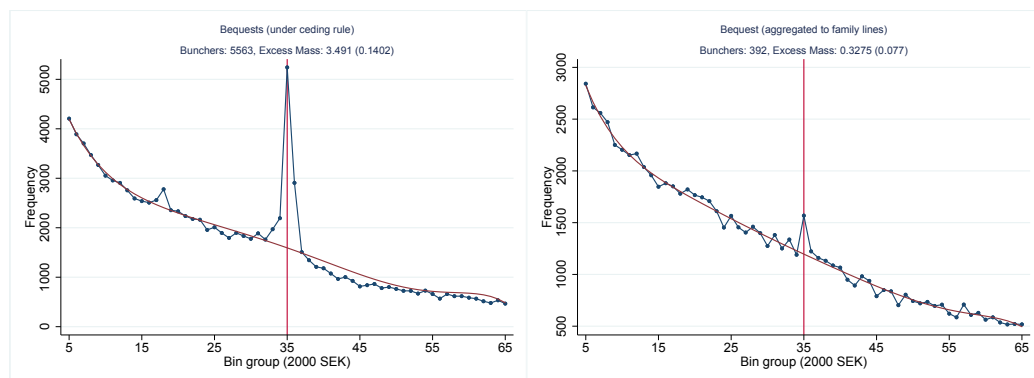
D Undistorted Bequest Distribution

A crucial step to study responses to bequest taxation is the identification of preferences that govern the donor's decision to allocate individual bequests to heirs, i.e. how to split the terminal wealth among potential heirs. Due to the ceding rule in the Swedish institutional set-up, heirs could transfer part or all of their bequests to direct descendants upon receipt and thereby minimize the tax bill. This final bequest distribution in the data is significantly distorted by taxation and does therefore not allow us to assess policy-invariant bequest preferences of donors.

By aggregating bequests over family lines that originate at the children of the donor, we can eliminate any such distortions from the ceding rule. The resulting distribution reflects true bequest preferences for children's family lines, if i) all children of the donor had the possibility to cede, ii) these children were, on their own, able to eliminate the entire tax bill of the donor through ceding and iii) after aggregating over family lines, the sample distribution of bequests is smooth, in particular at the kinks of the tax schedule. While conditions i) and ii) ensure that there are no strategic responses of the donor with respect to a subset of heirs, the smooth distribution suggests that donors' choices are not distorted by any other form of bequest adjustment.

Figure 2 shows that before the aggregation, there is a massive bunching of individual bequests at the first tax kinks (70 000 SEK) of 3.5 times the average height of neighboring distribution bins. After aggregating, it becomes clear that ceding constitutes 90.6% of this excess mass. According to the set of potential legal avoidance mechanisms, the remaining bunching at the kink could originate from wealth adjustment or distortions in the optimal bequest distribution of donors.

Figure 2: Raw Data vs. Aggregated over Family Lines

Notes: The graph on the left-hand side plots the raw bequest distribution. Bunching at the first kink of the marginal tax rates is mostly attributable to the ceding rule. When aggregated over family lines (to reverse the ceding rule) a much smaller, yet significant excess mass at the kinks remains.

Figure 3: Aggregated over Family Lines and Full Ceding Possible
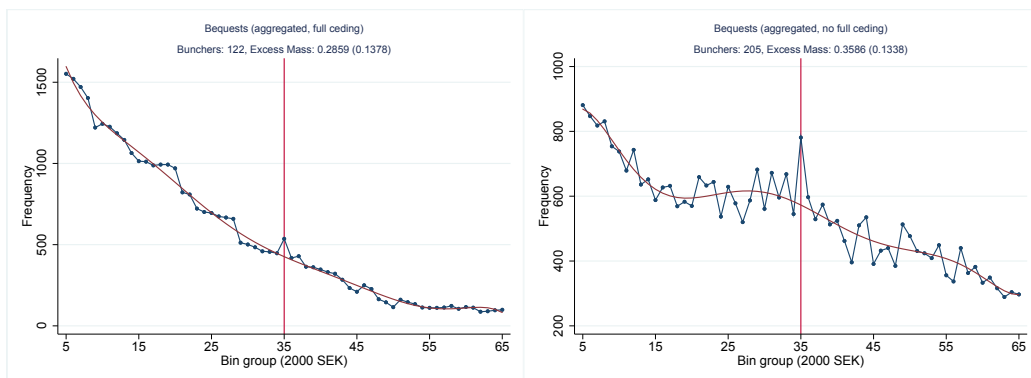
Notes: The graph on the left-hand side plots bequests aggregated over family lines for donors, whose children can fully eliminate the tax bill through the ceding rule. The complementary subgroup of donors, whose children cannot fully eliminate the tax bill through ceding, is shown on the right-hand side.

Figure 4: Aggregated over Family Lines, Full Ceding Possible and Estate Adjustment
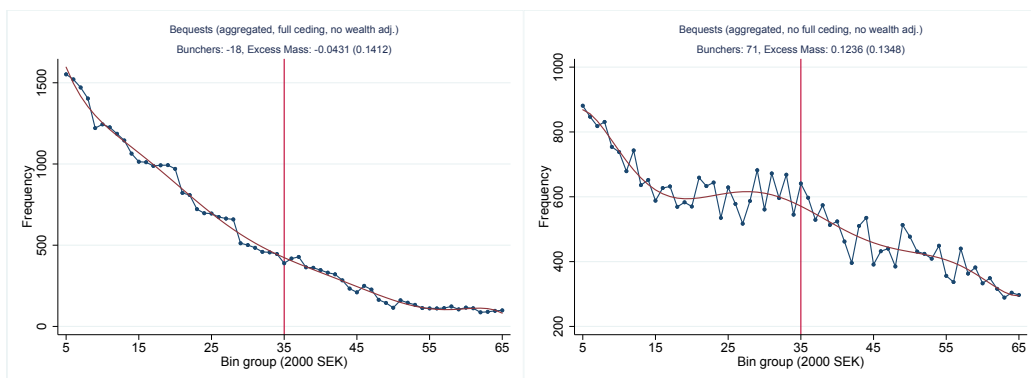
Notes: The graph on the left-hand side plots bequests aggregated over family lines for donors, whose children can fully eliminate the tax bill through the ceding rule. It further excludes donors whose terminal wealth divided by the number of children results in bequests precisely on the tax kink ($\geqslant$ SEK 500) in case of equal splitting. The complementary subgroup of donors, whose children cannot fully eliminate the tax bill through ceding and do not adjust wealth, is shown on the right-hand side.

Figure 3 shows that donors, whose heirs do not fulfill conditions i) and ii) (right=hand graph), are concentrated over-proportionally at the tax kink compared to the bequest distribution of heirs, who can eliminate the entire donor tax bill through ceding (left=hand graph). The bunching excess mass of 0.358 (0.134) for heirs, who cannot fully cede, exceeds the value of their ceding counterparts of 0.286 (0.138). Furthermore, the right bequest distribution exhibits non-smoothness at several intervals.

Finally, the left-hand graph of Figure 4 provides evidence that any remaining bunching of donors, who can fully cede, is entirely explained by wealth adjustments. These are decedents whose estates divided by the number of children falls within a close range of the tax kink. Since wealth adjustment will be captured in the donor's wealth accumulation part of our model, the bequest distribution aggregated over family lines is undistorted. The right-hand graph of figure 4 shows that the distribution for heirs who cannot fully cede is not smooth, even after accounting for strategic wealth adjustments by donors.

In the remainder, we proceed by estimating *true* undistorted bequest preferences on a sub-sample which excludes those donors, for which at least one child is unable to cede to a direct offspring. Notice that while we estimate undistorted, optimal preferences with this selected sample, the estimation of the dynamic problem including wealth accumulation and bequest shares as well as all counterfactual simulations are conducted on the full sample of aggregate family line bequests.

E   Samples

After restricting the universe of decedents to surviving spouses aged above 65 (to capture intentional bequests) with up to four children, the sample includes 61 044 donors. Summary statistics of decedents and heirs are presented in Table 3. Estates are on average 226 519 SEK while bequests received by a child's family line amount to 115 068 SEK. Around 3% of decedents distribute the inheritance unequally across the children's family lines (the within-family standard deviation greater than 1000 SEK). A fifth of the decedents have stipulated a will and about 9% have transferred wealth to their heirs via inter-vivos gifts within ten years prior to their death.

The subsample used to recover bequest preferences from the undistorted distribution of inheritance is restricted to old-age individuals, of whom all heirs had the possibility to fully cede and eliminate the entire tax bill. We identify these heirs by matching them to their direct off-springs via the Swedish Multi-generational Register. This subsample is selected and shows on average shows even smaller estate and bequest values. This is for two main reasons. First, rich donors would require the heirs to have a large number of descendants to enter this subsample

11

and second, heirs with numerous direct offsprings may receive higher values of inter-vivos gifts. The full and ceding subsample are, however, well-balanced with respect to all other covariates.

Table 3: Summary Statistics

	Full Sample		Full Ceding Sample	
			(preference estimation)	
Heir Characteristics	Mean	Sd	Mean	Sd
Bequest	121087.8	(298984.7)	59822.0	(73320.8)
Share	0.506	(0.260)	0.561	(0.284)
Heir female (0/1)	1.495	(0.500)	1.517	(0.500)
Education of heirs	11.52	(2.162)	11.35	(2.096)
Married heir (0/1)	0.586	(0.493)	0.692	(0.462)
Age of heir	54.11	(9.577)	56.46	(7.936)
Income of heir	2024.9	(2746.6)	1922.0	(2585.1)
Observations	123659		58460	
Donor Characteristics				
Estate size	241106.6	(497310.1)	107260.2	(93262.0)
Will (0/1)	0.195	(0.396)	0.167	(0.373)
Inter-vivos transfers (0/1)	0.0942	(0.292)	0.0846	(0.278)
Donor female (0/1)	1.664	(0.472)	1.716	(0.451)
Education of donor	11.57	(3.826)	11.72	(4.051)
Age at death	84.10	(9.065)	85.91	(7.430)
Wealth at death	597325.9	(2076097.2)	296266.6	(362468.1)
Number of children	2.677	(0.747)	2.610	(0.725)
Unequal split of bequest	0.0315	(0.175)	0.0185	(0.135)
Observations	64707		33970	

Notes: Education denotes years of schooling, coded consistently with Holmlund *et al.* (2011): 9 years for primary school, 9,5 for post-primary school, 11 for short high school, 12 for long high school, 14 for short university, 15.5 for long university and 19 for PhD university education.
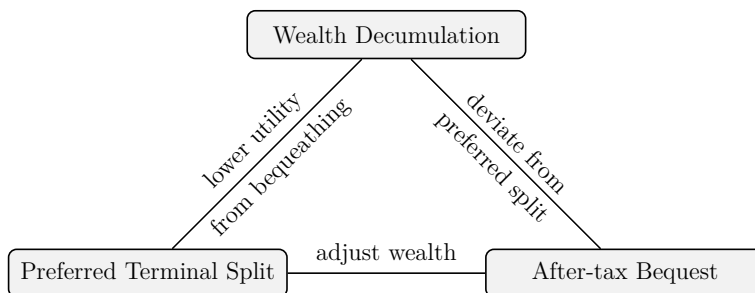
3   Wealth Accumulation and Bequest Model

We now introduce a dynamic life-cycle model of a retired individual who plans the wealth path and end-of-life bequests in the spirit of De Nardi *et al.* (2010) and Lockwood (2018). In an environment with a strong welfare state, old-age individuals jointly optimize utility from consumption and bequeathing, i.e. warm glow. The latter is a function of both the total value of the bequest and the split among heirs. Introduction of a tax on intergenerational wealth transfers creates a trade-off between the two sources of utility. In the absence of any response,

the tax reduces after-tax bequests. Depending on the tax design, the donor can change the wealth accumulation process or the way the terminal wealth is split among heirs to re-optimize her utility.

Figure 5 shows this 'trilemma' of an old-age individual when the the bequests are subject to taxation. If the individual decides to keep the wealth path and bequest distribution unchanged, the tax will reduce utility from the value of the post-tax bequest. If the preferences for a specific wealth path and the after-tax value of bequests dominate the desire to split the terminal wealth in the specific way, then a deviation from the initially preferred split delivers a tax-relief. Finally, if the preferred split and after-tax bequests ought to be undistorted, wealth adjustments or inter-vivos gifts are the tools to maximize utility.

Figure 5: The "Bequest Trilemma" Under Bequest taxation

Notes: The nodes define three objectives of the donor, when making decisions in old-age on wealth accumulation and bequeathing. The edges show the individual's reaction in order to keep the objectives in the two connected nodes constant when a bequest tax is levied on inter-generational transfers. As the preferred terminal split does not play a role under estate taxation, the trilemma is transformed into a dilemma under such a tax scheme.

Consequently, individual behavior is summarized by three groups of parameters. The first group of parameters describes the trade-off outlined above and represents the main object of interest in this paper. More precisely, these parameters represent the weight an old-age individual places on after-tax bequests and a bequest split among heirs relative to consumption. The second group of parameters is solely related to the donor preferences over how bequests are distributed to children, conditional on donor and heir characteristics. The third group includes parameters of a standard life-cycle model without labor choice, namely a discounting rate and risk aversion.

Essentially there are three building blocks of the model: a dynamic problem of wealth accu-

mulation in old age, utility from bequeathing and policy-invariant preference for giving individual bequests to the potential set of heirs.

A   Life-Cycle Problem of Old-Age Individuals

Consider an old-age individual who acts in the model from the time of retirement at 65 ($t = 0$) and up to the age 100.

Figure 6: Dynamic Model Time-Line
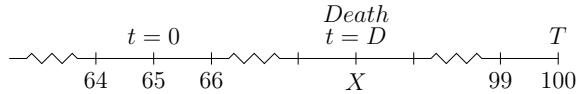
In each period, individuals maximize expected discounted utility of consumption and bequests by choosing the consumption path $\{c\}_{t=1}^{T}$ and the vector of individual bequest split $s = \{s_1...s_j\}$ to children $1...J$ if the donor dies in the following period. This implies that the model assumes that individuals can adjust the allocation costlessly in every new period. By consumption in this model, we mean either actual consumption or inter-vivos gifts to children using the yearly tax exemption of SEK 10 000 or higher.[5] The value of holding individual wealth W at $t + 1$ depends on the probability of surviving $1 - D$ and the utility of bequeathing B in case of death D. The value function of this dynamic programming problem at time t consists of the utility from consumption and gifts and the expected value function at time $t + 1$, discounted by a factor δ.

$$V_{it}(W_{it}) = u(c_{it}) + \delta \left[D_{it} \overbrace{B(s, W_{it+1})}^{\text{Bequest Utility}} + (1 - D_{it}) \overbrace{E_{it}[V_{it+1}(W_{it+1})]}^{\text{Utility of Survival}} \right] \tag{1}$$

We assume a CRRA utility function of consumption with risk parameter η:

$$u(c) = \frac{(c)^{1-\eta} - 1}{1 - \eta} \tag{2}$$

Old-age individuals have rational beliefs about survival probabilities in line with mean death

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[5]Any inter-vivos gifts above the exemption within 10 years prior to death are taxed as inheritance and should, therefore, be inelastic to changes in the tax rate. Uncertainty over future wealth shocks makes transfers above the basic annual exemption for gifts costly for the bequest donor.

probabilities conditional on age and gender (D).[6] The only state variable directly affected by the individual's choice at time t is the next period wealth W_{t+1}, which is either kept as wealth or transformed to estate if the individual dies. Wealth evolves as an auto-regressive process with normally distributed random shocks v. The donor's consumption possibility is restricted to her wealth, which implies that borrowing is not allowed in the model. Income is fairly stable in the data and mainly consists of pension income and social benefits. Therefore, donors are assumed to expect to receive their mean observed income in future periods. The formulation of wealth evolution leaves the possibility of a negative realization of wealth. We allow for a minimalistic uncertainty structure since we do not observe large wealth fluctuations in the data.

$$W_{i,t+1} = W_{it} + (y_{it} - c_{it}) + v_{it} \tag{3}$$

$$v_{it} = \mathbb{N}\left(0, \sigma_W^2\right) \tag{4}$$

B Bequest Utility

Next, consider the bequest function B, which determines the interplay between wealth accumulation and bequeathing. We adopt the general functional form for bequest utility from Lockwood (2018), which generalizes the approaches used in the literature. It allows capturing a range of components of bequest preferences. For instance, it implies that bequest motives kick in after a consumption threshold c_b. Under this value, individuals do not leave bequests. If $c_b > 0$, bequests are a luxury good, over which individuals are less risk-averse than over consumption. λ_1 denotes the marginal propensity to bequest from left-over wealth after consuming at least c_b.

This functional form is combined with a term with weight λ_2, which represents the donor's preference on how to split bequests among the potential heirs. Essentially, the model punishes the donor for deviating from preferred individual bequest shares $s^* = \{s_1^*, ..., s_j^*\}$. This vector s^* represents the policy-invariant preferences for bequeathing to specific heirs with a specific share of the terminal estate. As discussed above, the donor might deviate and choose a different vector $s = \{s_1, ..., s_J\}$ if it reduces the tax bill by placing individual bequests at lower marginal tax rates.

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[6]We ignore the marginal endogeneity of survival with respect to taxes, as documented in Kopczuk & Slemrod (2003) and Eliason & Ohlsson (2013).

$$B\left(s, s^*, W\right) = \left(\frac{\lambda_1}{1-\lambda_1}\right)^\eta \cdot \overbrace{\frac{\left(\frac{\lambda_1}{1-\lambda_1} \cdot c_b + \sum_{j=1}^{J}(1-\tau_j) \cdot s_j \cdot W\right)^{1-\eta}}{1-\eta}}^{\text{utility from after-tax bequests}}$$

$$+ \lambda_2 \cdot \overbrace{\left(g(s_1^*, ..., s_J^*) - g(s_1, ..., s_J)\right)}^{\text{Disutility from deviating}} \tag{5}$$

Parameters λ_1 and λ_2 represent the weights of this pair of bequest utilities with respect to the utility from consumption and inter-vivos gifts (weight normalized to 1). As λ_2 is sensitive to the number of children, we allow it to vary with this characteristic.

C   Bequest Preferences

The preferred split of the terminal estate s^* is specified as the bequest shares that a donor would choose in the absence of the intergenerational wealth. We assume that each donor has a utility function over the bequest shares that her children $j \in 1, ..., J$ receive.

$$g = \sum_{j=1}^{J} \exp(\phi_j) \cdot \log(s_j) \tag{6}$$

The preference parameter ϕ_j determines how large the bequest to child j is relative to the siblings. However, ϕ_j does not include equality preferences, which are captured by switching costs of deviating from the default option of equal shares defined below. Preference parameter ϕ_j is parametrized to be a linear function of observable heir characteristics $\phi_j = \alpha X_j$, where X_j contains age, gender and income. We denote the vector of preferred shares as:

$$\hat{s} = \{\hat{s}_1, ..., \hat{s}_J\} \quad \text{with} \quad \hat{s}_j = \frac{\exp(\phi_j)}{\sum_{k=1}^{J} \exp(\phi_k)} \tag{7}$$

Motivated by the prevalence of exactly equal allocations in the data (the default split in the institutional set-up in the absence of the will), we assume that donors face fixed costs ψ of deviating from a vector of equal shares $1/J$. These fixed switching costs reflect both a preference for equality across children and monetary costs of deviation, such as writing a will. We assume that switching costs are normally distributed with variance σ_ψ^2 and with linear in observables mean:

$$\psi_i \sim N(\beta Z_i, \sigma_\psi^2) \tag{8}$$

where the set of donor characteristics Z_i includes a constant, years of schooling, age at death, estate value and dummies that control for the number of children of the decedent.

If the difference between utilities derived from the vector that maximizes g and equal shares $\frac{1}{J}$ is smaller than these switching costs (ψ), the individual remains with the default of the equal share allocation and chooses to be optimal split otherwise:

$$s^* = \begin{cases} \{\hat{s}_1, ..., \hat{s}_J\} & \text{if} \quad g\left(\hat{s}_1, ..., \hat{s}_J\right) - g\left(\frac{1}{J}, ..., \frac{1}{J}\right) > \psi \\ \{\frac{1}{J}, ..., \frac{1}{J}\} & \text{otherwise} \end{cases} \tag{9}$$

D   Solution Method

The model is solved using backward induction from a terminal age 100. The model has two choice variables: consumption and bequest shares. We discretize bequest shares depending on the number of children using steps of 5% in addition to equal split shares. For example, for a family with three children, equal split shares are 33%, which would not be covered by a 5% grid.[7] The discretization yields a number of bequest allocations depending on the number of children. For instance, a donor with two children has the following choices: $(25\%, 75\%)$, $(30\%, 70\%)$, ... , $(50\%, 50\%)$, ... , $(70\%, 30\%)$, $(75\%, 25\%)$. Note that the allocations, in this case, are limited to an individual minimum of 25% per child because of the legal restriction that each heir is eligible to a minimum of 50% of the default allocation.

Introducing both a discrete (shares) and a continuous (consumption) choice variable does not suffer from the problem associated with secondary kinks in the value function (Fella, 2014; Blundell *et al.*, 2016; Iskhakov *et al.*, 2017). The reason is that the time-invariant bequest utility is only a function of terminal wealth and bequest shares and can be pre-computed on a wealth grid. These pre-computed values are then used to solve the dynamic model with linear interpolation if the realized value of wealth is not on the grid point. Hence, the dynamic problem only involves one continuous choice variable conditional on precomputed utilities of bequests for various wealth levels.

In the estimation, the state variable wealth is discretized and inter- or extrapolation is used when the state variable value is not on the grid. To integrate over wealth shocks, we employ Hermite quadratures. The solution method is roughly the same as in, e.g., French (2005) and

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[7]This discretization could be avoided with continuous shares. However, besides avoiding computational issues, it is likely that individuals think in terms of such discrete shares which is supported by the data.

Lockwood (2018). The main difference is related to the structure of the bequest function. It includes additional parameters and introduces a richer structure of the donor bequest decision required to study the responses to bequest taxes.

4   Estimation

To estimate the model, we use the Simulated Method of Moments (SMM). It extends the minimum distance estimator to cases when a closed form solution of the problem cannot be obtained. The estimation of life-cycle style models is usually separated into two steps. In the first stage, all parameters that can be identified without solving the model are estimated. In the second stage, these parameters are fed into the estimation process of the remaining parameters, which requires solving a dynamic model. Such a two-step procedure allows reducing the computational costs of repeatedly solving the dynamic model to search for a large set of parameters.

In our model estimation, we use this two-step approach to first estimate bequest preference parameters that define the preferred vector of bequest shares. To identify these parameters, we leverage the *ceding rule*, which is a special institutional feature of Swedish inheritance tax. It provides a unique opportunity to identify these policy-invariant preferences without a need to observe bequests in the absence of taxation. The rule enables heirs to transfers part or all of the received bequest directly to their own descendants, i.e. grandchildren of the deceased. Ceding is therefore only available to those heirs who have children of their own. As discussed in Sections 2D and 2E, we use a subset of decedents for whom all children have the possibility to fully cede and avoid all taxes. As a result, bequest shares observed for old-age individuals in this sample represent their true preferences and allows us to recover the underlying parameters α, β and σ_ψ.

The estimates of step one are used in the second stage, i.e. the dynamic model. Here we recover the remaining parameters for the wealth accumulation and the bequest utility function $\lambda_1, \lambda_2, \eta, c_b, \sigma_W$. We use a discount factor δ from the literature since it is not well-identified separately from other parameters of interest. The remainder of this section describes the estimation of the first- and second-stage parameters.

A   Bequest Preferences - Stage One

We start by estimating preferences for bequest shares. From equation (9), the probability of donor i to deviate from the equal allocation is defined as:

$$P_i = F\left(\frac{g_i\left(\hat{s}_1, ..., \hat{s}_J\right) - g_i\left(\frac{1}{J}, ..., \frac{1}{J}\right) - \psi_i}{\sigma_\psi}\right) \tag{10}$$

where $F(\cdot)$ denotes the normal cumulative density function. It describes the probability that individuals' switching costs are lower than the utility gains from deviating from the equal share default. Consequently, the expected allocation of bequest shares to children is given by the weighted sum of unequal and equal share vectors.

$$\{s_1^*, ..., s_J^*\} = P_i \cdot \{\hat{s}_1, ..., \hat{s}_J\} + (1 - P_i) \cdot \left\{\frac{1}{J}, ..., \frac{1}{J}\right\} \tag{11}$$

There are two important clarifications regarding donor and heir characteristics used in this part of the model. First, the matrix X does not contain a constant. The reason is that bequest preferences are modeled as shares, which implies that only characteristics of heirs in relation to each other matter. Second, Z contains dummies for the number of children to adjust each donor's switching cost to the family structure. We set a constant term in Z to 1 since it is also not identified separately.[8]

This first-stage model implies that the vector of heir-level coefficients and the parameters of the distribution of switching costs are estimated jointly: $\varphi = \{\alpha, \beta, \sigma_\psi\}$. We use the Generalized Method of Moments to find parameters that match the moments of the observed bequest distribution for the *ceding* subsample.

$$\varphi^* = \arg\max(m(\varphi) - \hat{m}(\varphi))'W(m(\varphi) - \hat{m}(\varphi)) \tag{12}$$

where $m(\varphi)$ are the observed moments of the data that we match, $\hat{m}(\varphi)$ denotes the corresponding moments generated by the model and W - optimal GMM weighting matrix. We match three groups of moments. First, we match a percentage of non-equal splits by a number of kids and age bins $\{< 75, [75; 85), \geq 85\}$. Second, since the preferences over heirs are primarily informed by those who actually give unequal bequests, we match the distribution of shares for those heirs who deviated from the default.[9]

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[8]More precisely, a constant parameter of switching costs is not identified separately from the level of parameters in Z.

[9]Equal splits also inform parameters since preferences over heirs also affect how large the fixed costs should be to keep a default choice.

B   Dynamic Model - Stage Two

Upon estimating the first-stage parameters, we proceed to recover the parameters of the life-cycle model in the presence of the Swedish inheritance tax scheme of 1992-2004. More precisely, these are the parameters that give utility weights to bequests, the parameter of standard deviation of the wealth process and a risk preference parameter: $\xi = \{\lambda_1, \lambda_2^{2kids}, \lambda_2^{3kids}, \lambda_2^{4kids}, c_b, \sigma_W, \eta\}$.

To identify the parameters of interest, we use a discount factor $\delta = 0.96$ in line with De Nardi (2004) and De Nardi & Yang (2014).[10] Probabilities of survival conditional on age and gender are recovered from the life tables provided by the Statistics Sweden (SCB). Due to the evaluation of the estate by the tax authority at below-market prices, each individual knows with certainty that the terminal wealth is reduced by a constant percentage before bequests are distributed.[11] The Simulated Method of Moments (SMM) estimator minimizes the distance between data and model-generated moments:

$$\xi^* = \arg\max(m(\xi) - \hat{m}(\xi))'W(m(\xi) - \hat{m}(\xi)) \tag{13}$$

where W is GMM optimal weighting matrix. To minimize the criterion function, we first run a global stochastic Covariance Matrix Adaptation Evolution Strategy (CMA-ES) optimizer from various starting values (Hansen, 2006). After convergence, we start the local derivative-free simplex optimizer from the best parameters generated by the global optimizer to refine the solution.[12]

5   Results

A   Parameter Estimates

Table 4 reports the parameter estimates for the undistorted bequest preferences of decedents (estimation stage one). Donors exhibit preferences that reinforce existing differences in income. This behavior is consistent with a wide range of theories, such as evolutionary bequeathing,

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[10] Authors use this calibration for both Swedish and US data.

[11] Actual asset evaluation (as a percentage of market value) depends on the asset type and therefore on the composition of wealth: 75% for real estate and stocks traded on the main Swedish exchange lists and foreign exchanges, 100% for cash, inventories and debt, 30% for stocks on minor Swedish exchange lists and NASDAQ and 30% of the book value for firms. The evaluation percentage of apartments depends on the net wealth of the housing society. For simplicity, we fix the evaluation percentage at the observed value in the data. Additionally, surviving spouses may hold some estate from the deceased spouse. While they are allowed to consume this wealth, it cannot be bequeathed and does therefore not affect any strategic behavior to avoid taxes.

[12] In fact, the concept of convergence of global optimizers does not exist. Therefore, by convergence, we mean the best value obtained from a stochastic pattern-based search algorithm after a fixed number of iterations.

exchange motives or altruistic theories. The positive coefficient towards female partly reflects the size of the heirs' family line.

Table 4: First-Stage Model Parameter Estimates

	Coefficient	Std. Errors
Heir Characteristics (ϕ)		
Female (0/1)	1.044	(0.213)
Age	0.001	(0.004)
Income	0.014	(0.022)
Distribution of Donors' Deviation Costs		
Constant	*1*	—
Gender (0/1)	-0.523	(0.008)
# Children = 3 (0/1)	0.0003	(0.329)
# Children = 4 (0/1)	-0.362	(0.109)
σ	1.383	(1.232)

Notes: Second column in brackets presents GMM asymptotic standard errors.

Table 4 shows plausible coefficients that relate to either the monetary and cognitive costs of deviating from the default split. Male and older donors are more likely to stipulate a will to deviate from the default. Finally, Table 13 confirms that due to the flexible form of the utility function for bequest shares, the model fits targeted moments well.

Table 5: Main Model (Second-Stage) Parameter Estimates

		Coef.	Std. Err
Propensity to bequeath	λ_1	0.99	(0.001)
	λ_2^{2kids}	< 0.001	(< 0.001)
Weight of the disutility term from deviation	λ_2^{3kids}	< 0.001	(< 0.001)
	λ_2^{4kids}	< 0.001	(< 0.001)
Std. Dev. of wealth shocks	σ	947.96	(14.43)
Consumption threshold for bequest motives	c_b	10765.49	(60.83)
CRRA risk aversion parameter	η	3.78	(0.27)

Notes: Second column in brackets presents GMM asymptotic standard errors explained in more detail in Appendix C.

Figure 7: Model Fit

Panel A: Wealth Profiles Moments

Panel B: Bequest Distribution Moments
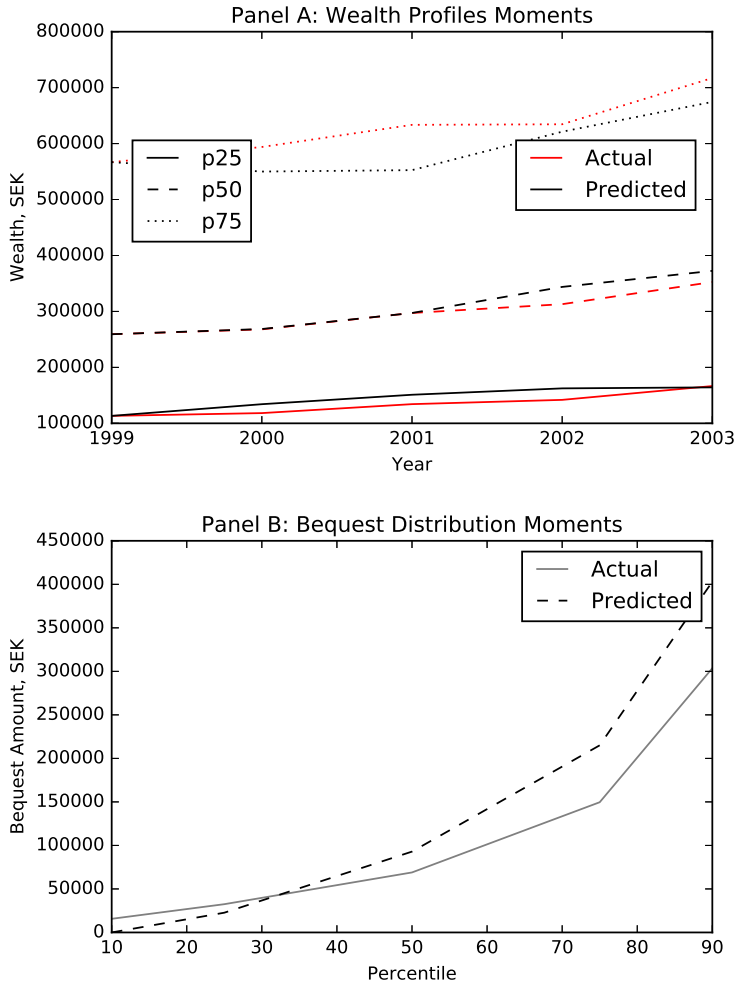
Notes: Actual and predicted moments of the wealth and bequest distributions. Predicted values result from simulating the wealth accumulation model with bequest utilities using the estimated parameters.

For the second stage parameter estimates, Table 5 reports the weights on bequest utility.

In line with Lockwood (2018), we find a large propensity to bequeath and a high risk aversion parameter (3.78). The threshold of minimum consumption at which bequest motives kick in is SEK 10 765 and partly reflects the inter-vivos gift tax exemption which, is part of the consumption. The variance of wealth shocks is 884. The model fit is shown in Figure 7. Overall, the model fits the moments reasonably well.

B   Counterfactuals

To analyze behavioral responses to bequest taxation, counterfactual wealth paths and bequest distributions are simulated for alternative tax designs. It means that we fully simulate donors' decisions and responses to any given tax using our estimates of preference parameters and individual characteristics. The resulting wealth paths and bequest distributions for each alternative tax scheme represent the bases of our further analysis.

0. No taxation of intergenerational wealth transfers (baseline)

1. The 1992-2004 Swedish inheritance tax scheme, excluding the ceding rule

2. Estate tax with marginal tax rates, exemption levels and tax rate kinks comparable to (1)

3. Estate tax with fixed exemption levels and kinks. Marginal tax rates comparable to (1)

The no-tax case (0.) is the baseline counterfactual. It describes the wealth path and bequest distribution in the absence of taxation. Alternatively, one can think of this as the potential tax base of any policy if there were no behavioral responses of any kind. In this case, donors would make their decisions as if there was no tax in place. Conveniently, we can anchor various alternative tax designs at this zero-tax counterfactual to make them comparable. In fact, any policy that collects equivalent tax revenues when applied to the no-tax (no response) counterfactual wealth and bequest distributions is comparable from the government's budget point of view. Table 6 shows the tax schedules of comparable counterfactual policies. The marginal tax-rates result from anchoring at the no-tax counterfactual.

Table 6: Tax Schedules of the Policy Counterfactuals

1. Inheritance Tax	
Tax bracket, SEK	Tax (lump sum + tax rate)
0 - 300 000	0 + 10%
300 000 - 600 000	30 000 + 20%
> 600 000	90 000 + 30%
Basic Exemptions: SEK 70 000 per child	
2. Estate Tax with Flexible Kinks	
0 - 300 000 × # children	0 + 10%
300 000 × # children - 600 000 × # children	30 000 × # children + 20%
> 600 000 × # children	90 000 × # children + 30%
Basic Exemptions: SEK 70 000 per child	
3. Estate Tax with Fixed Kinks	
0 - 600 000	0 + 9.76%
600 000 - 1 200 000	58 560 + 19.52%
> 1 200 000	175 680 + 29.28%
Basic Exemptions: SEK 140 000	

Notes: The table presents tax schedules used in counterfactual policy simulations. The first counterfactual is no tax and is not listed in the table. The upper tax schedule presents the existing inheritance tax. The remaining two counterfactual tax schemes mimic similar tax scheme to the inheritance tax with fixed and flexible kinks.

C   Taxes and Bequest Distribution

Responses to bequest taxation lead to overall changes in the distribution of terminal bequests. Figure 8 shows the bequest distribution of the Swedish inheritance tax (1) and a comparable estate tax (2) in contrast to the no-tax counterfactual (0). Panels A and B show that any type of bequest taxation reduces the total mass in the bequest distribution. The taxes provide an incentive to bequeath less in general, and at lower marginal tax rates in particular. The latter incentive is particularly strong in the upper tail of the bequest distribution. The tax kinks in both tax schedules at SEK 70 000, 370 000 and 670 000 create visible excess masses of bequests that are absent in the no tax case. These bequest adjustments highlight the elasticity of bequest to taxation caused by the behavioral responses of donors. Panel C shows that the two alternative bequest taxes (1 and 2) fare similarly compared to each other. Slight differences are due to the additional potential strategy of donors to avoid taxes by changing individual bequest rather than the total estate.

Figure 8: Effect of Taxation on Bequest Distributions, Counterfactual Policies 1 and 2
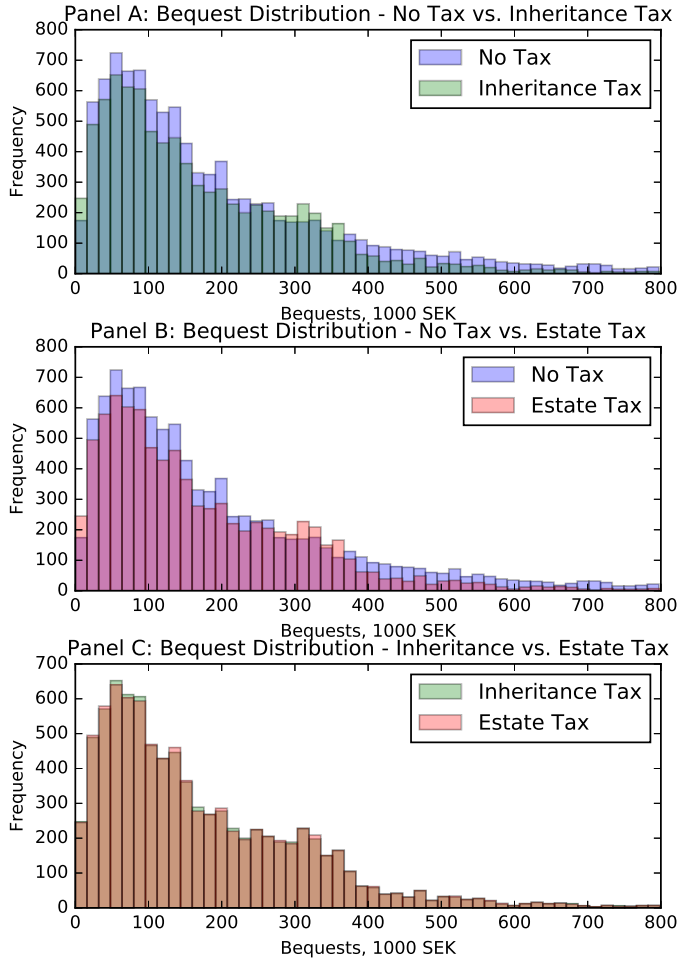
Notes: Bins of the bequest distribution for the inheritance and estate tax counterfactuals (1. and 2.) in comparison to the no-tax counterfactual.

Figure 9: Effect of Taxation on Bequest Distributions, Counterfactual Policies 1 and 3
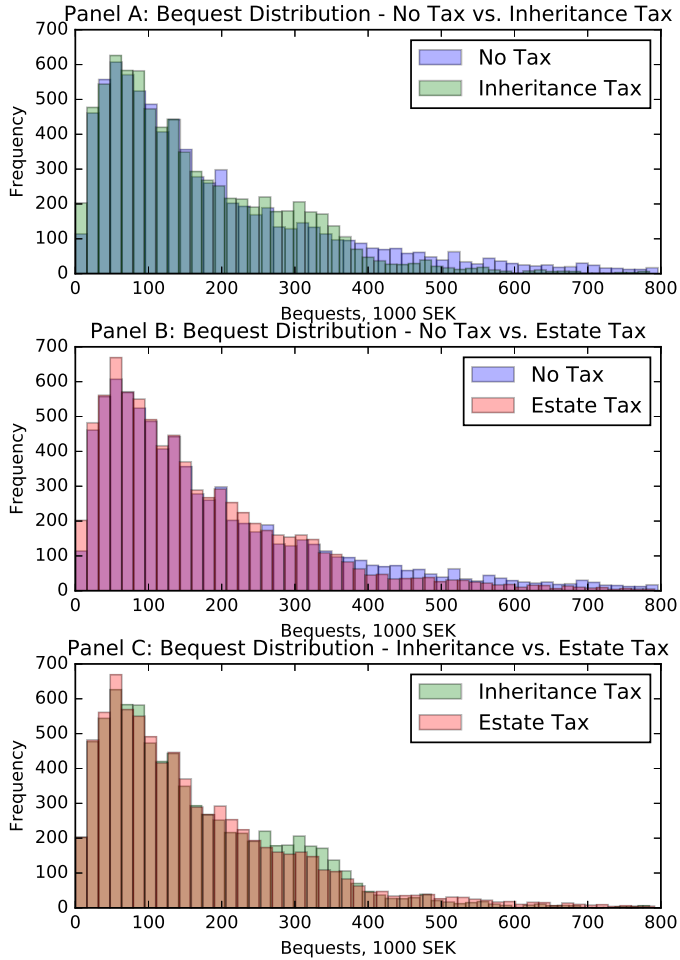
Notes: Histogram of the bequest distribution for the inheritance and estate tax counterfactuals (1 and 3) in comparison to the no-tax counterfactual (Panels A and B). Panel C compares the distributions under the two taxes to each other.

While inheritance and estate taxes with comparable schedules affect the bequest distribution in a very similar way, an estate tax with fixed exemption levels and tax rate kinks (3) may

generate a very different distribution. One example of this widely used tax design, which is not affected by family structure, is shown in Figure 9. It suggests that policymakers need to be aware of the incentives that family-specific exemptions provide for donors to avoid paying taxes. In particular, such an estate tax design imposes larger burden on large and wealthy families.

Notice that a tax on intergenerational wealth transfers can create incentives for donors to transfer more wealth via inter-vivos gifts since a SEK 10 000 annual exemption is applied to them. While the model allows for this strategic response, it is ignorant about the exact levels and recipients of such transfers. The bequest distributions in this paper only reflect transfers out of the terminal wealth.

D   Effect on the Wealth Accumulation Process in Old Age

A fundamental concern with respect to bequest taxation is whether behavioral responses to the tax lead to distortions in wealth accumulation. Such behavior can lead to a wide range of second-order effects, e.g. the change in the overall saving rate and inequality across families and generations. We find relatively large responses to both inheritance and estate taxation in the wealth accumulation of old-age individuals compared to the no-tax counterfactuals. Figure 10 plots the wealth levels per age for the 25th, 50th and 75th percentile of the wealth distribution for the comparable counterfactual policies 1 and 2.[13] Due to the progressiveness of both taxes, wealthier donors are adjusting their wealth paths to a larger degree. Due to the similarity of policies 1 and 2 in terms of the tax schedule, the inheritance and the estate taxes affect the wealth accumulation process almost equally. These changes in the wealth path in old age translate directly into the distribution of terminal estates in Figure 12.

Once more, if a more common estate tax design with fixed progressiveness is chosen, the behavioral responses may differ significantly, as shown in Figure 11. Non-individual exemption levels and tax rate kinks reduce the incentive for many families to engage in tax avoidance via wealth accumulation and therefore reduces the wealth distortion. This is due to the fact that for many families, lower tax-brackets are out of reach. The caveat of such policy is the tax incidence is shifted particularly towards large families.

The effects of taxation on terminal wealth are in line with the literature. The elasticity of the terminal estate to a tax of 0.22 generated by our model compares well to the 0.1-0.2 elasticities estimated by Slemrod & Kopczuk (2000), Joulfaian (2006) and Glogowsky (2016) as well as to the 0.09-0.27 elasticity of wealth to the Swedish wealth taxation documented by Seim (2017).

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[13]Wealth levels per age group are subject to the cohort composition effect, as they are pooled over different calendar years.

Figure 10: Effect of Taxation on Wealth Accumulation: Counterfactual Policies 1 and 2
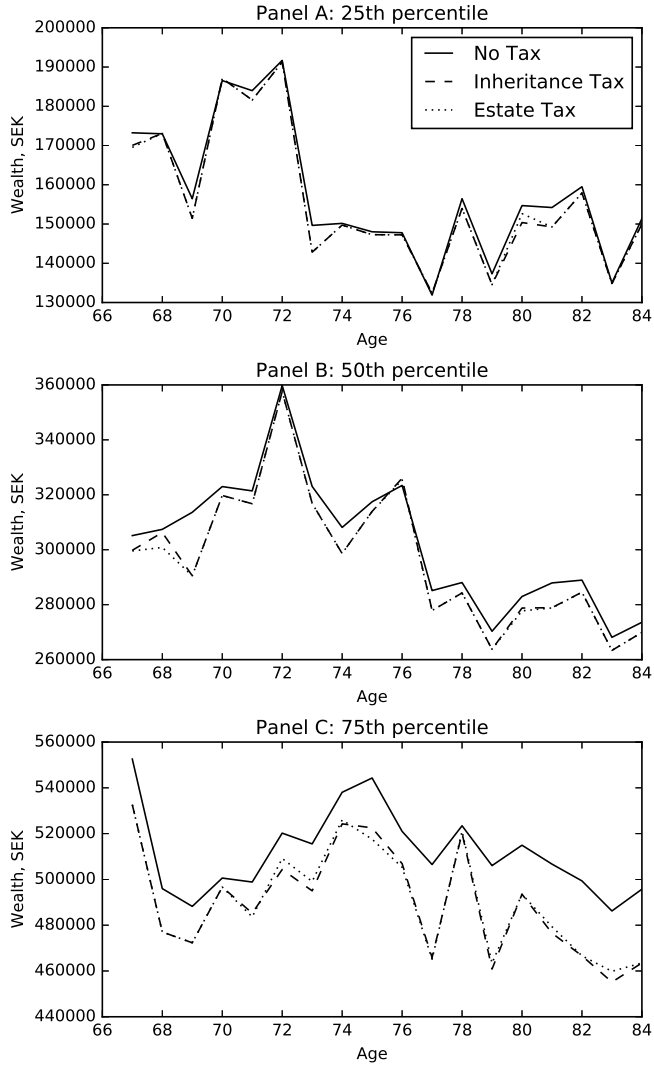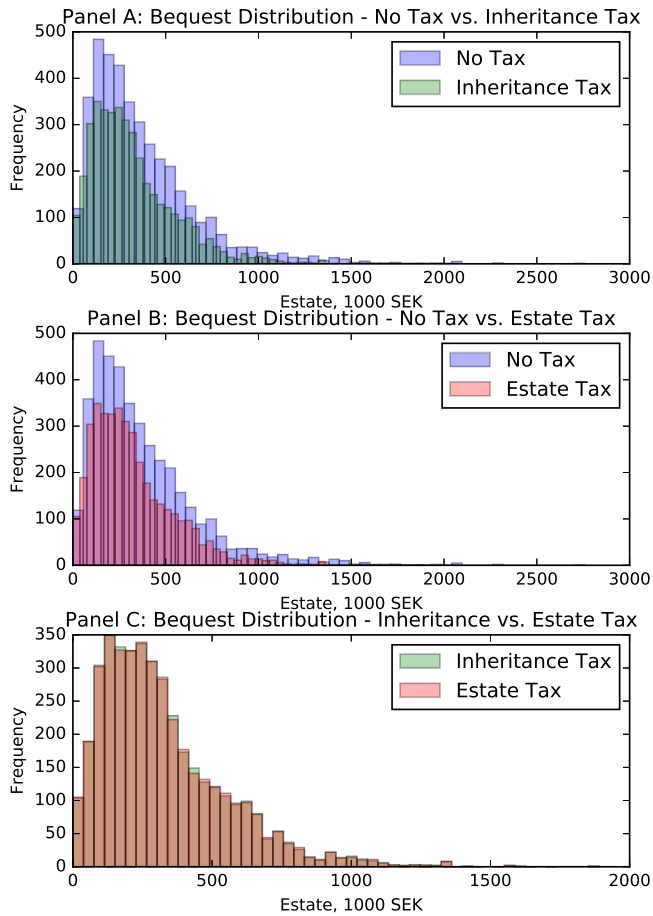

Notes: Wealth distribution for the 25th, 50th and 75th percentiles by age group for the inheritance and estate tax counterfactuals (1 and 2) in comparison to the no-tax counterfactual (Panels A and B). Panel C compares the distributions under the two taxes to each other.

Figure 11: Effect of Taxation on Wealth Accumulation: Counterfactual Policies 1 and 3
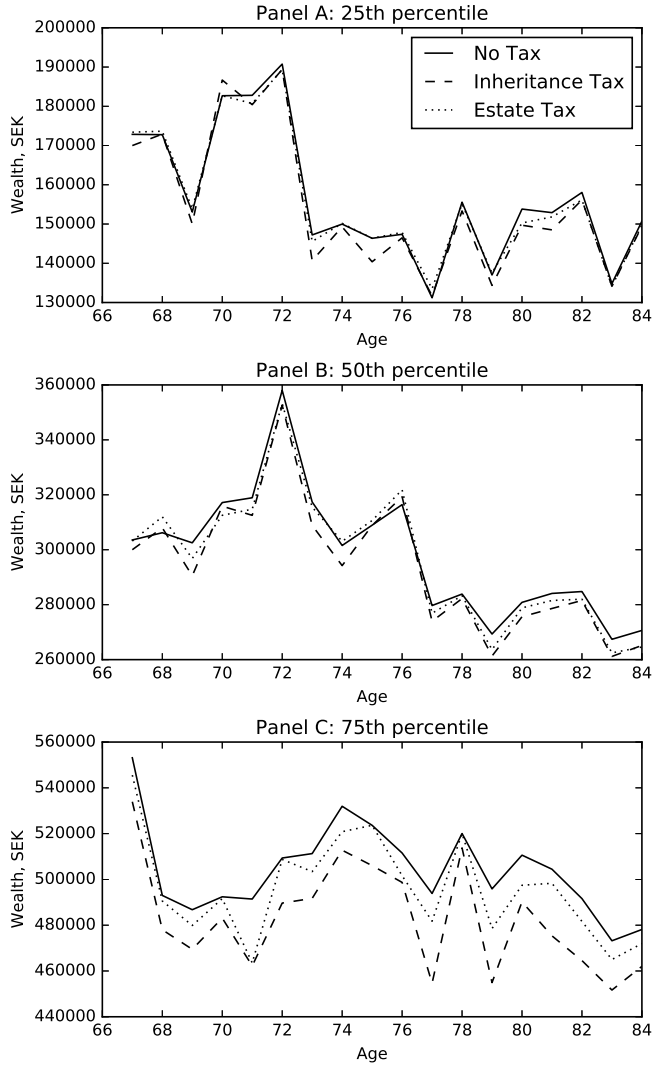
Panel A: 25th percentile

Panel B: 50th percentile

Panel C: 75th percentile

Notes: Wealth distribution for the 25th, 50th and 75th percentiles by age group for the inheritance and estate tax counterfactuals (1 and 3) in comparison to the no-tax counterfactual.

Figure 12: Effect of Taxation on Terminal Wealth: Counterfactual Policies 1 and 2

Notes: Distribution of terminal estates for the inheritance and estate tax counterfactuals (1 and 2) in comparison to the no-tax counterfactual (Panels A and B). Panel C compares the distributions under the two taxes to each other.

E   Response Decomposition and Tax Revenue

The counterfactuals allow decomposing the responses to bequest taxation. As documented above, the wealth reactions to the tax are almost equal if the inheritance and the estate tax have comparable schedules. In addition, we find that for the case of inheritance taxation, 1.4% of the individuals change their bequest distribution among children to minimize the tax bill. Given the low incidence of unequal bequests in the Swedish context (2-5%), this represents a non-trivial fraction of the donors.

Finally, in light of the high administrative costs of bequest taxation, policymakers care about the impact of responses to taxation on the generated tax revenue. As the estate and inheritance tax in our counterfactuals are designed to have an equal tax revenue in the absence of any behavioral responses, it is possible to measure the loss for the government revenues from taxpayers' reactions. We find a significant loss in revenue of 34.4% for inheritance and 29.3 % for estate taxations. While the bulk of this loss is explained by the adjustment in wealth accumulation, in particular of wealthy donors, the difference between the tax designs has two origins. First, under the inheritance taxation, donors can use an additional strategy to avoid taxation, i.e. changing the bequest distribution. Second, strong preferences for unequal bequests under the inheritance tax may lead some donors to not fully use the individual exemption levels, which gives an additional incentive to adjust the wealth path.

6   Conclusion

The bequest taxation is often at the center of policy debates because of being a tool for correcting distributional inefficiencies propagated over generations with bequests. In addition, this tax is often viewed as a tax that does not cause any undesirable distortion. For example, the Economist writes: *"In fact, people who are against tax in general ought to be less hostile to inheritance taxes than other sorts. However disliked they are, they are some of the least distorting"*, Economist (2017).

Although this statement is theoretically appealing, this paper shows that bequest taxation implies a range of behavioral responses that should be taken into account by policymakers who aim at minimizing tax distortions, while simultaneously collecting tax revenues. More precisely, progressiveness and exemption levels are the predominant tools to control the incidence of the tax on particular groups in the population. Using a comprehensive structural model that captures the main behavioral responses of old-age individuals, we can compare the impact of various tax designs on wealth accumulation, bequest distributions, and tax revenue, which are main policy

outcomes of interest. Our results show that comparable inheritance and estate tax schedules have similar but important effects on individual behavior. At the same time, due to additional margins of strategic behavior under the inheritance taxation, the estate taxes lead to higher overall tax revenues. Therefore, this paper emphasizes that at the cost of relaxing the control over tax incidence, estate taxation can be designed to further minimize distortions.

Our model is comprehensive and flexible enough to allow for the simulation of counterfactuals for the universe of alternative bequest tax designs. Various tax structures enable policymakers to balance distortions, progressiveness, tax revenues, and tax incidence according to their social welfare functions. The context in which we apply the structural model is ideal, since it, to a large degree, abstracts from precautionary savings, due to a generous social welfare system in Sweden. The results are therefore likely to be applicable to other contexts. Due to strong preferences for equal bequests in our sample, the differences between estate and inheritance taxation are relatively modest. They may be amplified in contexts like the US, where up to 20% (Light & McGarry, 2004), which is ten times the percentage in Sweden, leave unequal bequests to their children and therefore have potentially higher responses through changes in the bequest distribution.

The findings in this paper also open up several paths for future research. One important question is to consider inter-generational wealth taxation in a general equilibrium framework that takes into account wealth taxation and returns to capital. The large wealth effects in our model emphasize that the design of the inheritance tax might have important spillovers on the wealth taxation and capital markets more broadly. Another important area is spousal tax-planning in old ages since distortions due to the tax and responses to it are often realized at the household rather than the individual level. In addition, the relevance of behavioral responses to bequest taxation for inequality should be investigated. Taxes on inter-generational transfers are almost always designed to redistribute wealth from the upper to the lower tail of the distribution. However, if strategic responses benefit specific subgroups, the effectiveness of the tax might be harmed. Finally, although we touched upon the question of within-family inequality, further works might be needed to study the aggregate implications of changes in the within-family wealth allocation.

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Appendices

A Supplementary Figures

Figure 13: Model Fit
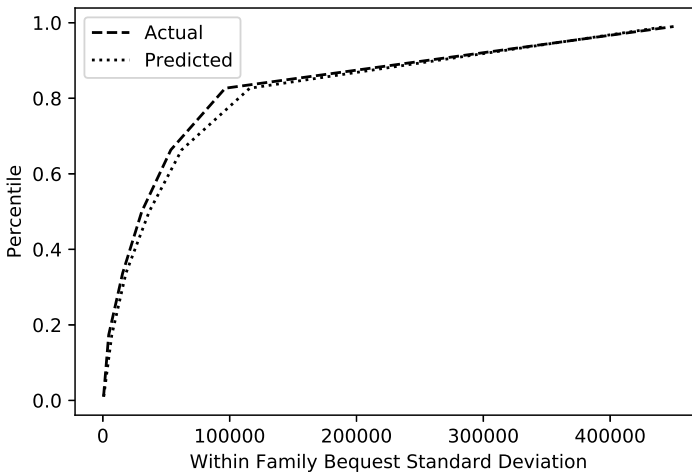
Notes: Figure illustrates a fit of the first stage model. In particular, we plot a distribution of standard deviation moments of within family bequests.

B Dynamic Model - Euler Equations

The Euler equations for the two choice variables in the dynamic problem show the fundamental trade-off that the donor faces when deciding on c and s. First, a change in the expected marginal utility of consumption and gift transfers must correspond to a change in the expected marginal utility from bequeathing at death.

$$u_{ct} - (1 - D_{t+1})\delta E_t\left[u_{ct+1}\right] = \delta E_t D_{t+1}\left[B_{Wt+1}\right] \tag{14}$$

37

Second, the Euler equation for each element j of the bequest share vector s requires optimality for the current wealth level of each period.

$$B_{s_{jt}} = 0 \qquad (15)$$

Incorporating the functional form of the bequest function yields the following Euler equation for c_t and the first-order condition for the optimal bequest share s to child l:

$$\overbrace{c_t^{-\eta} - (1 - D_{t+1})\delta E_t \left[c_{t+1}^{-\eta} \right]}^{\Delta\text{marginal utility of consumption}} \qquad (16)$$
$$= \delta D_{t+1} E_t \left[\overbrace{\left(\frac{\lambda_1}{1 - \lambda_1} \right)^{\eta} \left(\frac{\lambda_1}{1 - \lambda_1} \cdot c_b + \sum_{j=1}^{J}(1 - \tau_j)s_j W \right)^{-\eta}}^{\text{marginal utility from bequeathing}} \sum_{j=1}^{J} s_j \left(1 - \tau_J - W\tau_W \right) \right]$$

$$\left(\frac{\lambda_1}{1 - \lambda_1} \right)^{\eta} \overbrace{\left[\frac{\lambda_1}{1 - \lambda_1} \cdot c_b + \sum_{j=1}^{J}(1 - \tau_j)s_j E_t(W_{t+1}) \right]^{-\eta}}^{\text{marginal utility from sum of after-tax bequests}} E_t(W_{t+1}) \left[1 - \tau_l - s_l \tau_{s_l} \right] \qquad (17)$$
$$= 2\lambda_2 \left[U^s(s_1 ... s_J) - U^s(s_1{}^* ... s_J^*) \right] \underbrace{\frac{\exp(\phi_l)}{s_l}}_{\text{marginal disutility through share deviation}}$$

with $\sum_{j=1}^{J} s_j = 1$. These two equations guide the optimal behavior of donors and illustrate the identification of λ_1 and λ_2.

C   Estimation Details

As described in the main text, the estimation of the model consists of two steps. First, we estimate true allocation preferences. These parameters obtained on the first-stage are used to estimate the main parameters from the dynamic model. Overall, the model contains seven second-stage parameters and eight first-stage parameters. More parameters required to be estimated leads to more iteration of the optimization algorithm. Therefore, reducing the number of parameters estimated on the second stage while solving computationally intensive dynamic model provides large computational gains.

The estimation of the first-stage parameters is fairly computationally light and is conducted on the full sample of "eligible" individuals from the bequest dataset. To estimate the second-stage model, we draw a 20% random sample. We use 10 cores to solve the model at each iteration of the optimization algorithm. Both estimation procedures match chosen moments that describe features of individuals' behavior. Both models have more moments than parameters. We use a two-stage optimal GMM matrix for both models.

Theoretically, our second-stage estimator is consistent and asymptotically normally distributed (Pakes & Pollard, 1989; Duffie & Singleton, 1997).

$$\xi \sim N\left(0, (G_\xi' W G_\xi)^{-1} G_\xi' W \left[(1 + \frac{N_d}{N_s})\Omega_\xi + G_\varphi \Omega_\varphi G_\varphi'\right] W G_\xi (G_\xi' W G_\xi)^{-1}\right) \tag{18}$$

where G_φ, G_ξ are the gradient matrices of moments with respect to first-stage and second-stage parameters, correspondingly. $\Omega_\varphi, \Omega_\xi$ denote moment variance-covariance matrices of the first and second stage, correspondingly, and N_d, N_s are sample and simulation sample size.

To estimate the parameters of the model, we use a stochastic global optimizer to explore the parameter space. More precisely, we use the CMA-ES algorithm from different starting values. Then, we use the simplex algorithm starting from the best parameters obtained from the global optimizer to refine the solution.

Chapter 3

Determinants of Competition and Student Demand in Higher Education: Evidence from Australia

Natalie Bachas[*]   Maksym Khomenko [†]

Abstract

How consumers make their choices and how firms compete are the central questions for many markets. Despite the importance of college education choices, there is limited evidence of how college markets function and what the role of government interventions is. In this paper, we use an appealing setup and detailed administrative data from an Australian college admission system to shed light on these questions. Using variation in tuition charges and government subsidies due to changes in government priority majors, we find that students show low price sensitivity. Furthermore, we document that university programs display signs of strategic responses to monetary incentives by adjusting the admission requirements. To study alternative price regulations in college markets, we estimate a structural model of student application decisions and competition of college programs. Our findings suggest that student tuition charges and college revenues have an important effect on the number of admitted students and their distribution across programs.

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1   Introduction

Markets for education have attracted considerable attention in the economic literature because of the long-lasting effect on economic and social well-being associated with educational opportunities and choices. Furthermore, education is closely linked to a variety of outcomes in society such as political participation, health, unemployment, and crime (Chetty, Friedman, & Rockoff, 2014).

Most of the attention of the literature has been focused on school education. The main feature of the college admission is that applicants, in comparison with the school admission, can be ranked in terms of their "quality" signaled by test scores.[1] In addition, in contrast to a school setup where most applicants tend to agree on preferred schools, college programs differ not only in the prestige but also in majors and specializations. This implies that preferences for college programs might be more disperse (Abdulkadiroglu & Sönmez, 2003). Because of considerable heterogeneity of candidates, colleges might compete with each other to attract a specific subset (Roth & Shorrer, 2015).

Although pricing mechanisms are not used in school choice, it is an indispensable part of college markets. The literature studying college markets and related policies has not reached the consensus regarding the determinants of demand in college markets. Furthermore, it lacks the conclusive evidence of how colleges compete. Despite active policy debates about regulations in college markets and student finance, we also have limited evidence of the effect of government interventions and optimal design of policies (Bachas, 2017).

This paper analyzes how students make college decisions and how university programs compete for students. To study these questions, we use a set-up of an Australian college admission system. It resembles a structure of semi-centralized college admission systems in several countries such as Sweden, Ireland, and the UK, which are currently a subject to active policy debates.[2] It also has a number of particularly appealing institutional features for our study.

First, the admission mechanism encourages truthful revelation of students' preferences by submitting a rank-ordered list (ROL) of programs. However, since the size of ROL is limited to be maximum of 9 programs, it might provide incentives to take into account admission probabilities and "misreport" true program ranking for those who are interested in more programs (Fack, Grenet, & He, 2017; Agarwal & Somaini, 2018). However, more than half of the students do not submit the maximum allowed nine programs, which suggests that the length of lists is

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[1]School choice mechanisms grant priorities based on distance to a school or socioeconomic background. However, schools do not usually actively select students based on the test scores from previous levels of education and other ability signals.

[2]For examples, see http://www.matching-in-practice.eu/higher-education-in-uk/

enough to apply for all programs of interest for many students.[3] Despite the fact that misrepresentation of preferences should not play a crucial role, we adopt a conservative strategy and use a subpopulation of those who submit less than nine programs in the estimation where the truthfulness of ROLs is crucial.[4]

Second, students in our setting have a clear signal of their abilities used by programs to make admission decisions. All school graduates in Australia take a sequence of exams. The results of these tests are aggregated to the ATAR score.[5] This score represents the percentile in the overall distribution of test results and is used by colleges as the main screening device.

Third, the Australian government has control over tuition fees by setting them at the major-based level. Tuition charges are often only adjusted for inflation. However, because of national major priorities, which have been changing repeatedly over time, there are a number of considerable changes unrelated to the inflation adjustment. The government also pays per-student subsidies directly to colleges. These government contributions are also major-based and vary depending on national priorities. Such changes in priorities provide two distinct plausibly exogenous sources of variation in tuition charges and college revenues, which allow overcoming a price endogeneity problem and enables us to separately identify college behavioral parameters.[6]

We use detailed administrative data from the college admission clearinghouse for the New South Wales and Australian Capital Territory. The admission center collects students' ranked order application lists and relevant information for admission decisions. Colleges decide whether to give an offer to a student who has applied and send decisions to the admission center. We observe detailed data on students' submitted rankings and ATAR scores which to a large extent determine the admission decisions of colleges. We also observe detailed data on college programs such as campus location, college affiliation, program name, major and various levels of major and specialization.

The data also contain a key college program decision outcome - an admission cutoff or a minimum ATAR score that resulted in an offer in a given year. It allows students who apply the next application year to assess the chances to be admitted to a program with their test score. However, the ATAR cutoff provides a noisy signal of an admission outcome. It does not ultimately determine whether a student will actually be admitted since programs might admit students who have lower ATAR because of other merits or change cutoffs the next academic

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[3]Furthermore, given the complexity of choosing the ranking with nine programs, the admission center allows submitting only five programs from the 2018 admission year.

[4]Note that the fact that a student has submitted nine programs does not imply that she is interested in more than nine programs. In this case, she also should truthfully submit her program preferences.

[5]ATAR is the abbreviation for Aggregated Tertiary Admission Rank.

[6]By price endogeneity we mean that if colleges select prices it does not allow directly recovering student responsiveness to prices. Therefore, prices have to be instrumented for this purpose.

year.

We start off by providing evidence of how students respond to changes in tuition charges. Using exogenous price changes, we find that an increase in the student price by 1000 AUD results in 0.0003 lower probability of listing the program first and 0.000025 lower probability of including at all. This is a fairly low price response. We also find that raising the ATAR cutoff results in 0.000014 lower likelihood that the program is listed first and 0.000016 lower of being listed at all. It suggests that a cutoff has a very small effect, which is expected since if students submit preferences truthfully, admission probabilities should not impact the decisions.

Next, we proceed to studying the responses of colleges. We find that most programs respond to higher revenues by lowering down the cutoffs by on average 0.0005 point as a result of a revenue increase by 1000 AUD. The effect is very heterogeneous, which might suggest differences in preferences of colleges potential and the presence of strategic behavior.

We build a model that combines a student's application decision and the college programs' choice of admission cutoffs. A student problem in a raw form is a ranked choice of 9 programs out of approximately thousand programs offered each year. We model a decision as a two-stage process. At the first stage, students choose a subset of programs of interest from the entire set of offered programs. This step is to a large extent motivated by the presence of non-full ROLs, which suggests that for many students the choice sets do not contain the whole set of offered programs. At the second stage, students rank programs from the choice set and submit the resulting list.

College programs choose admission cutoffs to maximize their utility taking into account student preferences. We assume that their utility is a function of two components: total revenues and the average quality of admitted students represented by the average ATAR of enrolled students. In this case, the cutoff choice is aimed at balancing these two components. For example, a decrease in a cutoff leads to a higher expected number of admitted students and hence, higher revenues but lower average ATAR since it requires admitting low ATAR students. The average ATAR component can be viewed as a proxy for reputation related to admitting higher-performing students.

An outcome of a program not only depends on own choices but also on the choices of competitors. However, because of a large number of programs available each year, estimating a full game is not feasible.[7] In addition, different competitors might provide a different level of threat given the differences in the degree of substitutability between programs.[8] Therefore, we use an

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[7]A number of programs vary slightly over time.

[8]For example, Arts and Medicine programs might not be substitutes for each other compared to other Arts and Medicine programs, correspondingly

approach to estimating the model by constructing expectations about competitors' responses as a function of government-set prices as relevant state variables. This approach mimics the formation of beliefs about competitors' strategic responses when the set of competitors is large.[9]

We use the model to study a number of counterfactual regulations to understand responses of the college market to alternative financial conditions. More precisely, we simulate market outcomes under both changes in revenues per student while keeping student prices constant, and prices faced by students while keeping college revenues unchanged. We find that both policies would result in considerable responses by colleges in the form of adjusted admission requirements. As a result, this changes the enrollment patterns and the composition of admitted students. In contrast, changes in student prices lead to students' responses because of a threat that students choose another program. As a result, colleges attempt to compensate for the loss of students by lowering the admission cutoffs. Since it would also result in lower overall quality of a student pool, some colleges do not respond to such changes either because of strong preferences for the quality of the admission pool or because of relative price insensitivity of students who tend to be interested in the program.

Related Literature. This paper contributes to a number of strands in the literature. Firstly, we augment the literature by providing additional evidence of the determinants of applicant decisions in college markets. A number of papers including Hastings, Neilson, and Zimmerman (2013), Kirkeboen, Leuven, and Mogstad (2016) and Wiswall and Zafar (2014) conclude an important role of the major in the program choices. Furthermore, Bordon and Fu (2015) suggest potential gains from postponing major decisions given a potential major-ability mismatch due to uncertainty. In addition, Avery, Glickman, Hoxby, and Matrick (2012) show that apart from majors, the reputation of college has an important effect on the decisions. Our findings suggest the important role of both major and university affiliation. We propose a novel two-stage model that not only allows estimating preferences when students face a large number of programs but also imposes a more realistic structure that supports the evidence that many students are interested in a very limited set of programs.[10]

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[9]This approach can be viewed as similar to the idea behind estimating dynamic games proposed in Bajari, Benkard, and Levin (2007)

[10]A number of papers study whether students can make complicated ranking decisions. Calsamiglia, Haeringer, and Klijn (2010) find that restrictions of the portfolio size have an important effect on how individuals make the decisions. At the same time, Arcidiacono, Hotz, and Kang (2012) show that although the perception of abilities and the expectation of future earnings are important determinants of the college-major choice, student choices are considerably affected by a sizable forecast error. Kapor, Neilson, and Zimmerman (2018) conclude an important role of admission probability prediction error in the school choice. As a result, the authors argue that such behavioral limitations should be taken into account while designing a matching mechanism. Artemov, Che, and He (2017) also find that students might not behave optimally using the data from another Australian

We also contribute to the literature studying competition among educational entities, which predominantly focuses on the competition at the school level. The literature has documented the effect of school choice programs on market entry (Hsieh & Urquiola, 2006; Epple & Romano, 2008; Bordon, Fu, Gazmuri, & Houde, 2016) and an important role of cream-skimming of students that might have an ambiguous effect on market welfare because of a business-stealing effect. Education market policies are also found to be closely related to student performance and outcomes (Neilson, 2013; Böhlmark & Lindahl, 2015).

While the literature on school competition is active, less evidence is available from college markets. A number of theoretical papers have studied decentralized college markets. Chade, Lewis, and Smith (2014) develop a model of decentralized college admission with students' heterogeneity. The results of the model suggest that in the setup with student portfolio applications, colleges can utilize a number of competition strategies including toughness or discrimination in admission requirements. Avery and Levin (2010) show that early college admission is a mechanism used by colleges to screen student preferences for a specific program. Che and Koh (2016) present a model that incorporates strategic screening by colleges. More precisely, colleges target high-quality students who are likely to be overlooked by competitors. As a result, given the multidimensional quality of students, colleges have incentives to put more weight on college-specific performance measures such as essays to avoid the direct competition.

The empirical literature studying college competition is, however, very limited. Arcidiacono (2005) finds an important effect of admission rules and financial terms on educational outcomes. Fu (2014) argues that the heterogeneity of students' preferences for colleges is an important determinant of market outcomes. It also implies that expanding the supply of colleges would not necessarily lead to higher enrollment. As a result, tuition fees and restricted supply are not found to be an important obstacle to an expansion of college attendance. The findings also suggest that competition on both tuition fees and admission requirements might lead to adverse consequences for overall welfare. We contribute to this strand of the literature by providing evidence on how students respond to changes in tuition charges and how it affects the competition among colleges. Furthermore, in our counterfactual analysis, we document how are predicted to respond to changes in revenues and prices that students pay. As a result, it allows isolating the effect of the sensitivity of student demand from the supply responses by university programs. In addition, it also enables us to understand how colleges use admission requirements as a strategic variable in the absence of the control over prices.

This paper is organized as follows. Section 2 describes data and institutional details. Section

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admission center in Victoria. Similar evidence that students cannot optimally structure application lists are found by Shorrer and Sóvágó (2018).

3 presents evidence of the students' and colleges' behavioral responses to government regulations. Section 4 describes a structural model of student decision and college competition. Section 5 simulates counterfactual policies and discusses their impact. Section 6 concludes.

2 Data and Institutional Environment

2.1 College Admission System

The Australian college admission system is divided into regional admission centers. Each territory has a clearinghouse that accepts applications and matches students to programs. In this paper, we focus on the University Admission Center for New South Wales and the Australian Capital Territory (UAC).[11]

To apply for colleges, applicants submit a ranked ordered list of programs from the colleges in the region. During the period from 2004 to 2017 covered by our data, students could submit ROLs with a maximum of nine university programs.[12] The admission procedure resembles the Deferred Acceptance mechanism in the sense that it provides incentives to truthfully submit ROLs. More precisely, each candidate has to submit a ROL before the deadline and pay application fees.[13] After the application deadline, student preferences are transmitted to colleges in the order of ranking meaning that programs ranked higher will be contacted on behalf of a student earlier. If the student does not receive an offer from the preferred program, the next program on the list is contacted. Despite this sequential structure, the UAC clearly states that:

> "If you're not selected for your first preference, you'll be considered equally with all other eligible applicants for your second preference and so on. Your chance of being selected for a course is not decreased because you placed it as a lower order preference. Similarly, you won't be selected for a course just because you entered that course as a higher order preference." (source: UAC website)[14]

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[11]It is possible that students apply to several admission centers. In this case, we do not observe the whole market. However, the ATAR scores are calculated by the admission centers based on the test results of 10 subjects. Therefore, the ATAR in one admission center might differ from others. For the purpose of our study, this does not pose any threats since the presence of other admission centers only affects students' outside option. Furthermore, the presence of other admission centers should not affect the competition among universities since they are only competing directly with the universities in the same region based on the admission requirements.

[12]Currently students can submit up to five programs.

[13]Candidates submit the list of programs earlier than September and can costlessly change them until the admission decisions in January. Students are monetarily incentivized to submit early applications to encourage thorough decisions. To encourage early applications, application fees are reduced to 70 AUD for submissions before the end of September in contrast to 200 AUD for later applications.

[14]For more details see https://www.uac.edu.au/future-applicants/how-to-apply-for-uni/selecting-your-course-

It means that despite the sequential admission process which is similar to the Boston mechanism, the student performance measures determine whether the student is admitted to the program but not the position in the ranking. As UAC suggests, an optimally-behaving student should rank programs in the order of preferences without taking into account admission probabilities. However, the restrictions on the number of programs on a list might provide incentives to deviate from the truthful strategy for those students who are interested in more than nine programs. In the presence of restrictions on the size of ROLs, students who are interested in more than nine programs might find it worthwhile to include programs with lower requirements that are ranked below top nine programs. Such incentives might result in ROLs that do not necessarily represent the ordering in terms of preferences. We discuss the implications later in the paper when analyzing student application decisions.

As mentioned in the previous paragraph, the main determinant of admission decisions is the ATAR score. High school graduates take a number of exams in core subjects. The results of these exams are aggregated and normalized to represent percentiles of the student performance distribution. It means that the ATAR score is in the range between 0 and 100. Although the ATAR score is the key factor in admission decisions, programs might also take into account additional admission criteria such as personal statement, questionnaire responses, portfolio, audition, interview or tests.[15] To form beliefs about admission probabilities, students use test score cutoffs from the previous admission years. These cutoffs denote the lowest test score that resulted in an offer in the previous application period.[16] However, students are warned that although these cutoffs provide a strong signal, they might change the next application period and, moreover, should be irrelevant for the optimal choice.

The vast majority of programs, which are also the focus of the analysis in this paper, are Commonwealth-Supported Place (CSP) courses. The CSP courses have tuition fees, which are partly covered by the government. It means that the total tuition charges received by college programs are partly paid by students and the remaining share is paid by the government. Both price components are regulated by the government, which sets college revenues per student and student fees.[17] These tuitions and contributions are set at the major level ("band"). The

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preferences

[15] As mentioned above, despite the fact that the ATAR is argued to be a dominant student selection indicator, Che and Koh (2016) show that these additional selection criteria are used to screen students and avoid direct competition.

[16] Very few institutions indicate a guaranteed ATAR, which is the score that will lead to admission without any uncertainty.

[17] More precisely, government regulations are formulated in the form of maximum tuition fees that can be charged by a college. However, colleges predominantly set tuition charges at the cap (Cardak, Bowden, & Bahtsevanoglou, 2016). Therefore, in this paper, we consider government price regulations as being binding. This can be viewed as a sort of tacit collusion outcome in a pricing game.

government has repeatedly changed priority majors, which resulted in considerable and plausibly exogenous changes in overall charges or/and government contributions. The term exogenous here refers to the fact that changes in priorities stem from government preferences for majors, which are potentially driven by expected labor supply needs in various fields. As a result, these changes are exogenous to current demand and supply forces, which would be a typical concern with market interactions data where firms make strategic price decisions. The next subsection describes the data and illustrates this price variation over time across majors.

2.2 Data

We use data from the University Admission Center for New South Wales and the Australian Capital Territory (UAC). The data cover 2004 - 2017 admission years and contain submitted ROLs and student ATAR scores, which, as discussed before, to a large extent determine college admission decisions. We also observe a set of program characteristics including university, campus location and various levels of major allocation and specialization. In addition, the data provide the information about the lowest ATAR which led to an offer in a given year and called *cutoff*.

Table 1 presents main descriptive characteristics of a student population. We separately provide summary statistics for students who have not reached the maximum allowed number of programs in the ROL and those who exhausted all list positions. The distinction between these groups of students plays a central role in the identification of student preferences discussed later. Therefore, it is important to consider differences in these two groups at least in terms of observables. In our sample, 59% of the students across all years have not submitted full ROLs. Those students who submitted full application lists have 1.4 points higher ATAR. The courses they apply for have slightly higher cutoffs on average. At the same time, programs chosen by students who exhaust all list positions are slightly cheaper in terms of tuition charges paid by students and attract on average 160 AUD less of government contributions. It might mean that those who submitted nine programs included safe options and did not rank programs in the descending order of desirability. Finally, students who submit full rankings have a median number of majors and universities on the list being 5 and 4 while a median number of considered universities and majors among those who have not submitted a full list is 3. These differences can be considered mechanical since individuals with longer lists are more likely to have more diverse rankings.

Table 1: Summary Statistics of Student Population

	ROL size < 9	ROL size = 9	Full Sample
	(1)	(2)	(3)
ATAR, *mean*	72.6	74.09	73.21
Cutoff, *list mean*	78.95	79.75	79.38
Student Price, *list mean AUD*	7029.76	6970.02	6997.81
Government Contribution, *list mean AUD*	9312.39	9177.58	9240.29
N. of Majors, *median*	3	5	4
N. of Universities, *median*	3	4	3
N	316 307	220 752	537 059

Notes: Table presents descriptive statistics of a population of students pooled over admissions years 2004 - 2017. Column (1) presents statistics of students who submitted a list containing less than a maximum allowed program to which we refer as truthful lists. Column (2) describes students who have submitted full application lists containing 9 programs. Column (3) presents statistics for the whole population of students.

Figure 1 describes distributions of the size of submitted and a number of majors and universities included in the portfolio. Panel A demonstrates that submitting a full ranking is the most popular choice but this is observed in only 41% of the cases. Approximately 2% of students submit only one program and around 3% submit two programs. The shares of those who submit from five to eight programs each amount to 10%. The figure also suggests that most students have fairly diverse preferences in terms of majors and universities. More precisely, the vast majority of students' ROLs contain between two and six majors included in a list. A similar pattern is observed for a number universities with most students having three different universities listed in their portfolio.

Figure 1: Distribution of a Number of Listed Programs and List Diversity

Panel A: Number of Programs

Panel B: Number of Majors

Panel C: Number of Universities
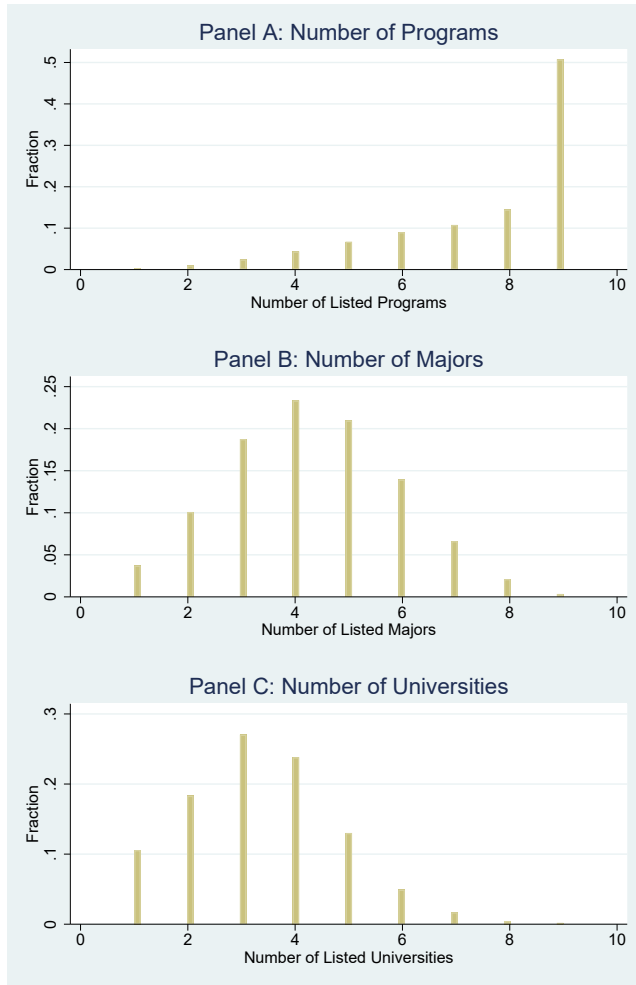
Notes: Figure illustrates a distribution of a number of programs (Panel A), majors (Panel B) and universities (Panel C) included in the ROLs pooled over admission years from 2004 to 2017. A maximum number of programs and, hence, universities and majors one can submit is nine.

Figure 2: Tuition Fees and Government Contributions
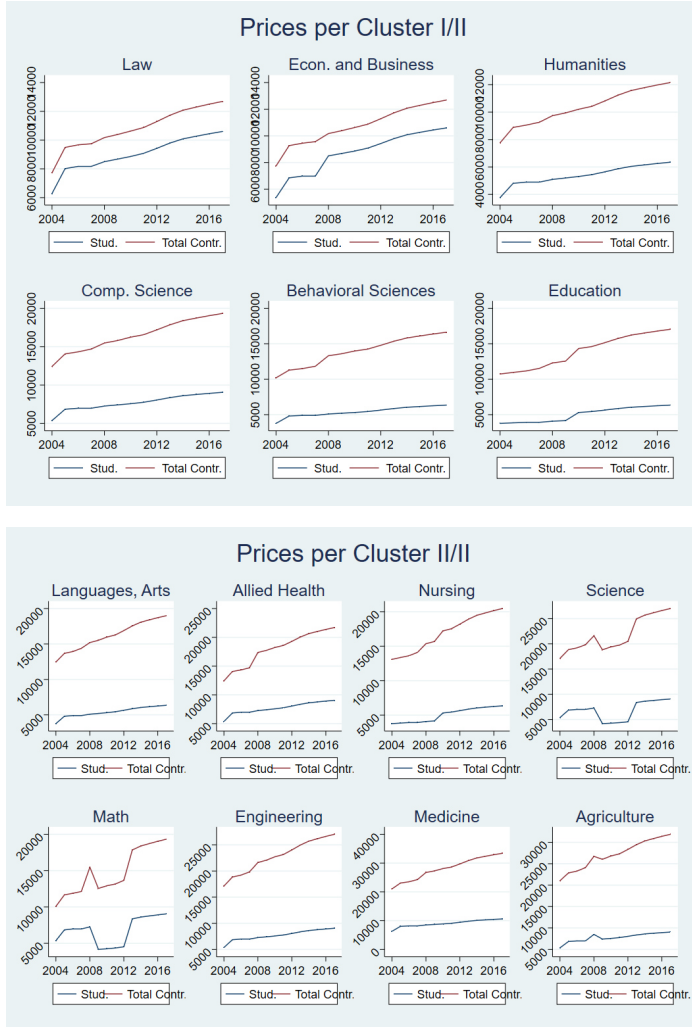
Notes: Figure illustrates variation in student tuition charges and government contributions paid to universities for each student.

There are two important price variations leveraged in this paper that are displayed in Figure 2.

First, apart from changes in prices due to the inflation adjustment, student tuition charges jump because of major-based priority changes depicted by the blue line. We group majors according to the tuition bands. It leads to 14 major categories, namely Law, Economics and Business, Humanities, Computer Science, Behavioral Sciences, Education, Languages and Arts, Allied Health, Nursing, Science, Math, Engineering, Medicine and Agriculture. These broad major groups are the level at which financial terms differ over time. The examples of such major-based price variation due to priority changes are 2005 for Law or 2005 and 2006 for Economics and Business. One can observe similar jumps for nearly all other majors at some point in time within the period under consideration. These changes are important for identification of student price sensitivity.

Another valuable source of variation comes from changes in government contributions. The presence of student price changes is useful for identifying student preference parameters but has limited use for a separate identification of programs preferences since colleges internalize potential student responses to prices. In this case, the identification would heavily rely on functional form assumptions. Therefore, additional variation due to changes in contributions is required. As Figure 2 shows, the overall per-student revenues are closely linked to student prices but in some cases varied solely due to changes in government contributions. The examples of such cases are Allied Health in 2006, Nursing in 2010 and Engineering in 2006.

In the next section, we examine how the college market responded to government regulations and changes in financial incentives.

3   Behavioral Responses in College Markets

In this section, we present the evidence of how a college market responds to changes in government priorities for majors, which leads to the variation in tuition charges and revenues per student. We start by exploring changes in the average ATAR of applicants by major, which is a level at which financial terms vary. The evidence is presented in Figure 3.

Figure 3: Average ATAR by Major
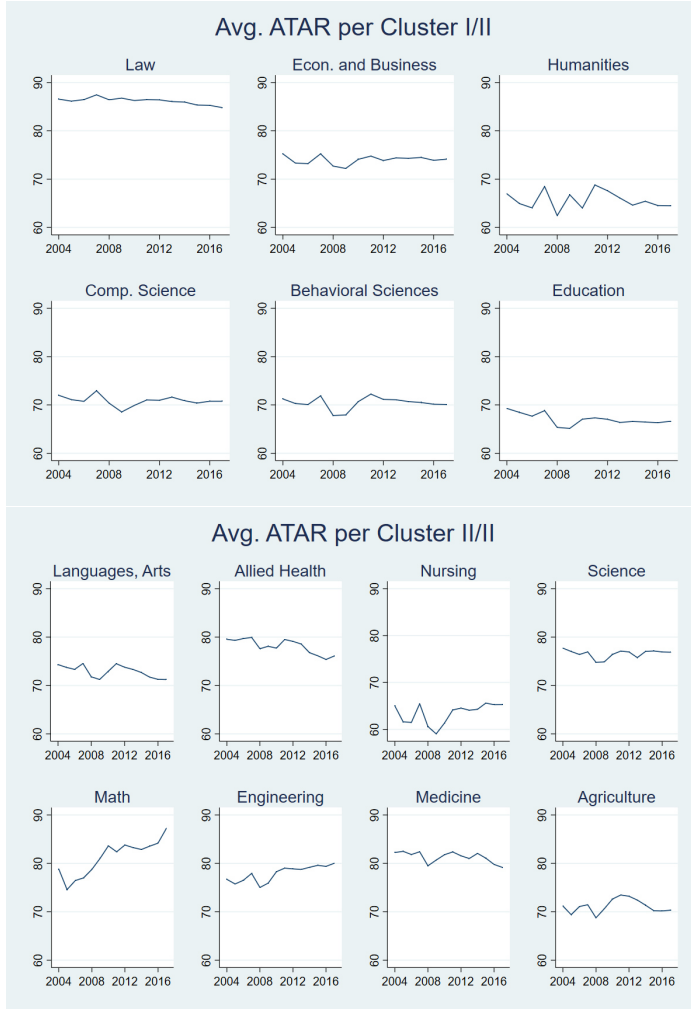
The figure suggests that the average ATAR among applicants who included programs from a given major varied considerably over time. Note that ATAR represents quantiles, which means

that it should display the relative attractiveness for students with various performance levels. Law programs tend to constantly attract high-performing students without experiencing any significant price fluctuations. The ATAR composition in other programs varied considerably over time and cannot be solely explained by changes in prices since most of the time, price changes are a result of the inflation adjustment. On average, programs in Nursing and Humanities attract students with the lowest average ATAR. All other majors attract students with the average ATAR score between 70 and 80. Math tends to attract more high-performing students over time and it reaches Law in terms of the popularity among top-performing students. A sudden rise in popularity of Math coincides with Math being a priority program, which led to lower reduced tuition charges from 2009 to 2013. Two forces might be contributing to such patterns. First, lower tuition charges attract more high-quality students, who might also be more price-sensitive. At the same time, Math programs also receive lower total revenues per student, which implies that they have incentives to reduce the number of students by introducing more stringent admission rules.

Figure 4: Average Cut-off by Major
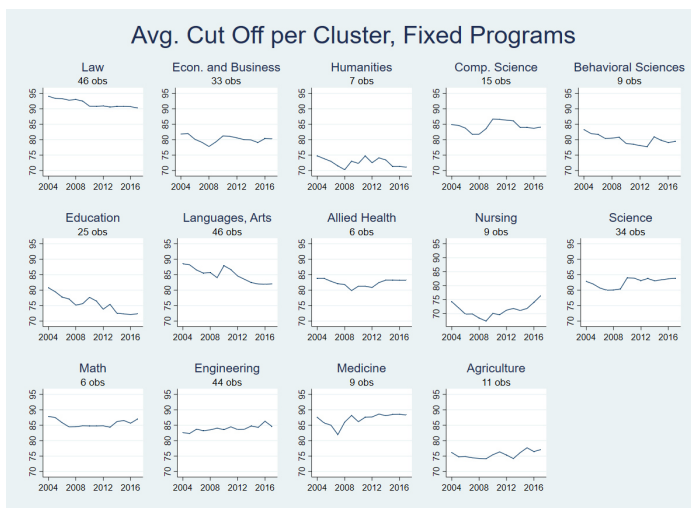
Notes: Figure illustrates a variation in the average cutoff in each major group from 2004 to 2017. This evidence only includes those programs which were available during the entire period under consideration to isolate variation from entry and exit.

To explore additional forces that might affect the composition of students, Figure 4 describes changes in admission cutoffs by major over time. Cutoffs have an effect on the composition of

applicants through a signal of the score that an individual has to have to be admitted. The first important observation is that Math programs did not considerably raise the admission cutoffs, which implies that an upward trend in the average applicant ATAR must be attributed to price sensitivity rather than the programs' actions. At the same time, such majors as Medicine and Allied Health display co-movement patterns in cutoffs and an average applicants' ATAR.

To further exploit the patterns of student decisions, Figure 5 shows how the share of students who included a given major either on the list or ranked first varied over time. The evidence suggests that Business and Economics is the most popular major meaning that around 40% of students included courses from this major in the list and around 15% ranked a course first. Majors that usually attract high ATAR students such as Math and Law are among the least popular. This implies that a high average ATAR is achieved by attracting top-performing students. In addition to Economics and Business, popular programs are Computer Sciences, Language and Arts, Education and Science.

Figure 5: Market Shares by Majors
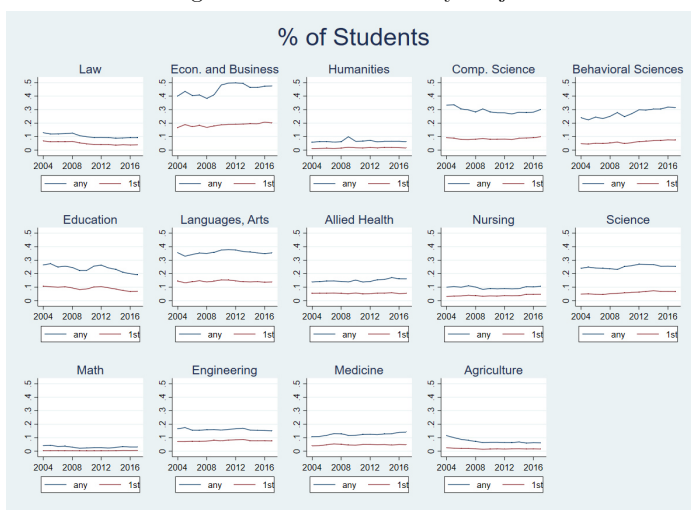
Notes: Figure demonstrates market shares by majors. The red line denotes the percentage of students who ranked the program first. A blue line corresponds to a share of students who included at least one program from a given major on the list. Note that in the latter case, market shares should not sum up to one.

In the remainder of this section, we explore more systematically how the college market responds to exogenous changes in financial incentives created by the reversal of government

major priorities. More precisely, we look at how tuition charges affect decisions to apply to a given program. We estimate the following regression:

$$Y_{it} = \beta_0 + \beta_1 \cdot p_{it} + \beta_2 \cdot c_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

where p_{it} - price paid by students; c_{it} - program cutoff; γ_i - course fixed effects; δ_t - year fixed effects; Y_{it} - market share outcomes, which include a share of students who rank a specific programs among the first k programs.

Figure 6: Effect of Tuition Charges and Admission Probabilities on Application Decisions
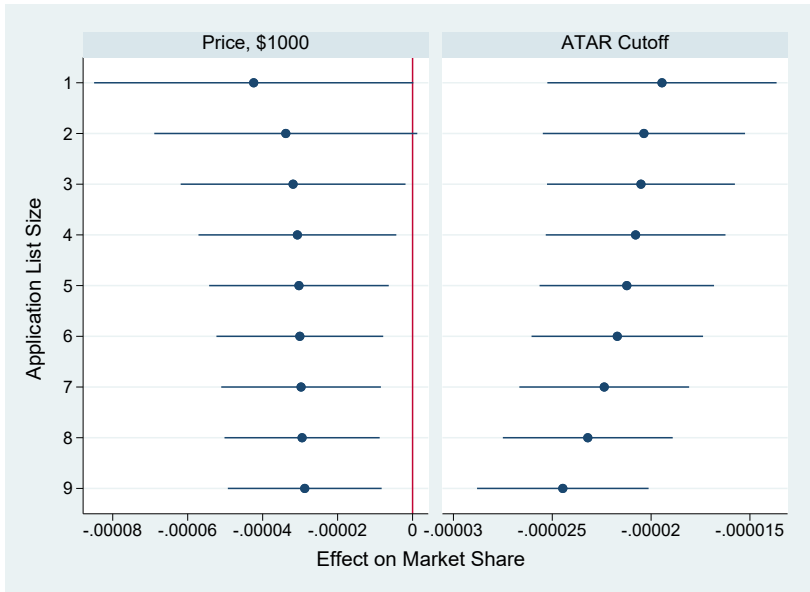
Notes: Figure demonstrates coefficients from equation (1). Standard errors are clustered on a program level. The left panel presents the price coefficient and the right panel corresponds to the cutoff coefficient. The vertical axis shows estimates for different size of the list varying from one, which corresponds to listing the program first, to nine which corresponds to including the program at all in the list.

Figure 6 demonstrates the coefficients from equation (1). The left panel presents the coefficient β_1 for different k, whereas the right panel plots the coefficient β_2. Standard errors are presented at the 95% confidence level and clustered at a program level. The y-axis denotes the number of ranks included in the outcome market share variable (k). For example, the upper

coefficient on the left panel shows how the student price affects the share of students who ranked the program first, whereas the bottom coefficient on the left panel illustrates the effect on the share of students who included a program at all.

Overall, the results suggest that student decisions are moderately sensitive to prices and admission cutoffs. The left panel suggests that the price has the most significant effect on the share of students who rank a program first. The coefficients for other market shares are constant around 0.00003, meaning that an increase in tuition charges by 1000 AUD decreases the share of students who include the program in the list by 0.00003. The effect on listing the program first is around 0.00004. Such a stronger effect is expected since students mostly care about the program listed first. The reason is that most students are admitted to the first program on their list (Cardak et al., 2016).

The effect of program cutoffs on a market share is opposite to what is observed for the effect of price. The largest negative effect of the admission requirements is observed for being listed at all on the list. Such a pattern is also in line with the logic of student ranking formation. Given that the list may include up to nine programs and many students do not submit full lists, the programs ranked at the top should not be affected by admission probabilities. The reason is that students who are not bounded by the list size should rank programs in the order of preferences disregarding the admission probabilities. The effect on being ranked from 1st to 6th place is around -0.00002. The coefficient gradually goes down and reaches -0.000025 for being included in the list at all. A stronger effect of admission requirements at the bottom of the list suggests that strategic incentives start playing a role in the form of the inclusion of a safe option. However, given a small difference in the effect at the bottom and at the top of the list, it is reasonable to believe that the size of the list is long enough to reveal preferences in the order of preferences. It might mean that an overall significant but small effect of cutoffs on the market share comes from a signal about the quality of the match and the peer effect rather than a strategic portfolio choice.

To investigate the effect of financial incentives on the behavior of colleges, we study how they respond to changes in per-student revenues, which consists of the price paid by a student and the government contribution. We estimate the following regression:

$$Y_{it} = \alpha_0 + \alpha_1 \cdot r_{it} + \gamma_i + \delta_t + \varepsilon_{it} \qquad (2)$$

where r_{it} - per-student revenues; γ_i - program fixed effects; δ_t - year fixed effects.

Figure 7: Effect of Per-Student Revenues on Admission Requirement
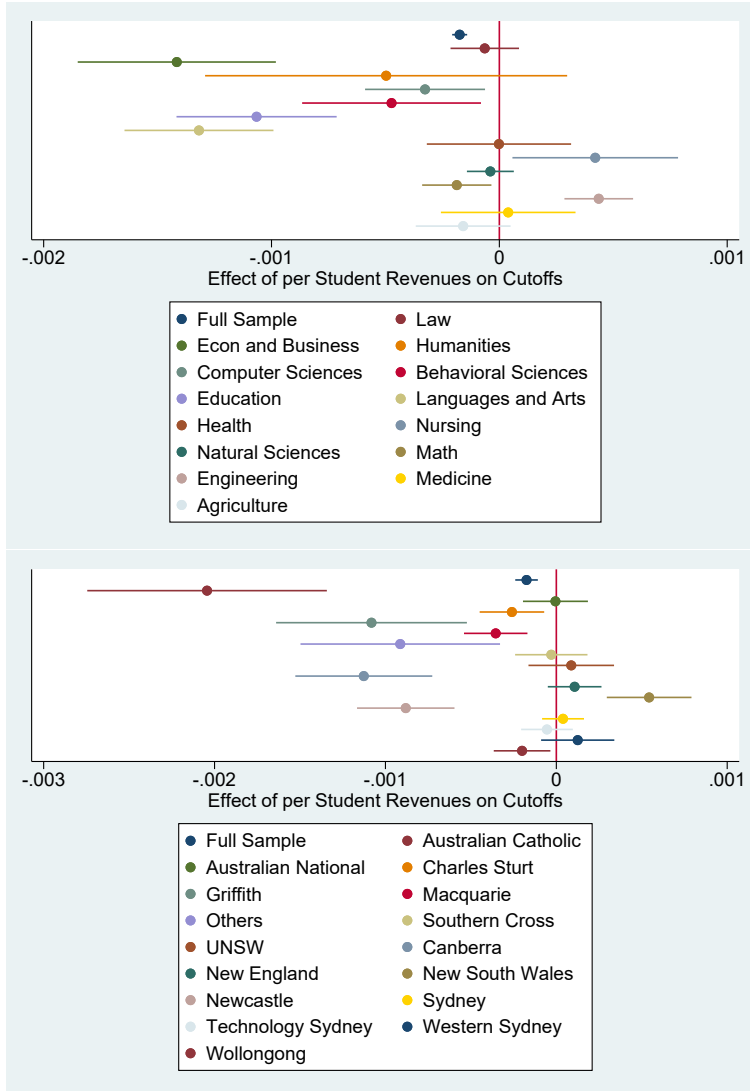
Notes: Figure presents estimates of α_1 from (2) estimated separately by major (upper figure) and university (lower figure). Standard errors are clustered at the program level.

We estimate this regression separately by major and then by university to understand the heterogeneity of the responses. The results are presented in Figure 7. The upper part of Figure 7 shows that for most majors, an increase in revenues per student results in less strict admission requirements, which is in line with the existence of a trade-off between financial incentives and the benefits of admitting better students. A significant and positive effect, which contradicts the previous logic, is observed for Nursing and Math, which usually attract low and high ATAR students, respectively. The effect for Law, which is another major that constantly attracts the highest performing students and imposes the strictest admission requirements, is statistically insignificant. The estimate of the effect using the whole sample is negative.

The lower part of Figure 7 presents results by universities. The effect is also negative and significant for most universities. The universities that deviate from this pattern are Wollongong and New England Universities.

The evidence presented in this section was intended to shed some light on how the college market responds to financial regulation. We find that tuition charges affect application decisions. This effect is especially pronounced for the probability of listing the program first. The choice of the first program is the most important since it tends to have the highest probability of enrollment. At the same time, we find that students internalize the ATAR cutoff that might signal the quality of the match between a program and a student. We observe mixed evidence of programs responses to changes in revenues per student. One potential explanation is that colleges should also internalize responses from competitors. The model described in the next section attempts to describe forces that supposedly determine college market equilibria and will be used to study the effect of alternative college market regulations.

4   Structural Model of College Market

4.1   Student Choice Model

4.1.1   Model

In this section, we present the model of student choice. There are a number of institutional features that motivate modeling choices. First, there are many programs from which students choose and rank up to nine programs. A naive approach requires solving a problem of finding an optimal application composition out of up to 1000 programs available each year. It is a burdensome computational problem and it is unrealistic to assume that students actually solve it. Another important feature of the institutional environment is the presence of choice restrictions meaning that a student cannot submit more than nine programs. It poses a threat to identifi-

cation of preferences from the observed ROLs (Agarwal & Somaini, 2018). The intuition is that such restrictions might result in the inclusion of programs that are ranked below nine programs to ensure admission to at least a low-risk program if it is preferred to an outside option.[18] Despite the fact that we are taking a defensive approach to student preferences estimation, a number of theoretical papers concluded that a question of misreporting in large markets might not be important.[19]

Our model has two features that are aimed at addressing these concerns. First, since the main threat to recovering student preferences arises from the restrictions on the size of the ROLs, we estimate student preferences using a subset of those who did not include all nine programs in the list. These students should submit all programs of interest in the descending order of desirability.

We also make an assumption that a restricted choice list is the only reason why students would submit non-truthful application lists and it is exogenous to other preference parameters. Previous literature has documented a number of alternative sources of misrepresentation of preferences such as "skipping the impossible" (Fack et al., 2017). We disregard these concerns since a student model will be used as the first stage for a program competition model. We believe that this level of abstraction is sufficient for this purpose.

We assume that students who have not submitted full list are only interested in the submitted programs. It means that the excluded programs are not better than not being admitted at all. To decide on the optimal order, a student has to rank only programs from the choice set. We assume that the probability of being in the choice set is a function of a student ATAR, university, and major allocation:

$$P\left[j \in S_i\right] = \frac{\exp(\alpha' Z_{ij})}{1 + \exp(\alpha' Z_{ij})} \tag{3}$$

where Z_{ij} contains a constant, university FE, major FE and interaction terms of university and major FE with student ATAR.

After a student has drawn a set of programs of interest, she ranks them in the order of desirability. We assume that a student has the following utility of being admitted to a program j from a choice set S represented by the following function:

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[18]An outside option is not being admitted, which might differ among students and is not necessarily an undesirable outcome.

[19]Kojima and Pathak (2009) show that a share of students who misrepresent their preferences approaches zero in a market with many participants under the student-optimal stable mechanism. Azevedo and Budish (2018) propose a concept of strategy-proofness in the large instead of just strategy-proofness. It is shown that when the mechanism "prices" are treated by an applicant as exogenous to her choice, truthful reporting is a dominant strategy.

$$U_{ij} = \beta' X_i + \varepsilon_{ij} \tag{4}$$

where X_i is a vector of program characteristics that includes price, major and university fixed effects; ε_{ij} is an error term distributed as the Type 1 extreme value.

The probability that a student ranks a program j higher than other programs in the choice set S is:

$$P(U_j > U_k, \quad \forall k \in S_i) = \frac{\exp(\beta' X_j)}{\sum_{k \in S_i} \exp(\beta' X_k)} \tag{5}$$

A practical advantage of this two-stage structure is that we can treat the observed submitted ROLs as realizations of random draws of programs and then as a ranking problem of considerably reduced choice sets. It implies that the set of programs observed to be included in the ranking is the entire choice set for those students who left some places in the ranking empty.

The key object from the student model used in the estimation of college preferences is a probability that a student i chooses a program j if she satisfies the admission requirements. This probability is a composition of the probability that a program j is in the choice set of a student i, a probability that a program j is ranked above all other programs in the choice list S_i and that a student satisfies the admission requirements of program j as well as all other programs in a choice set.

$$P_{ij} = \frac{P[j \in S_i] \cdot \mathbb{1}[ATAR_i > \xi_j] \cdot \exp(\beta X_j)}{\sum_{k \in S_i} P[k \in S_i] \cdot \mathbb{1}[ATAR_i > \xi_k] \cdot \exp(\beta X_k)} \tag{6}$$

Equation (6) is essentially a composition of equations (4) and (5). More precisely, the formula expresses the probability of being ranked first by a student i, taking into account the probabilities that each program is in her choice list of and that the student satisfies the test score admission requirements.

4.1.2   Estimation

Given this two-stage structure of the model, we estimate the vectors of parameters α and β separately. As discussed above, since restricted choice lists raise concerns about the truthfulness of submitted ROLs, we use a sub-population of students who have listed less than nine programs in their applications to estimate student preferences. An important assumption is that preferences obtained from the chosen sub-sample are generalizable to the remaining part of the student population. One important note is that not all students who submitted all nine programs necessarily deviate from a truthful ranking of programs. The reason is that those who

have exactly nine programs in their choice sets also do not have incentives to "misrepresent" preferences. However, since it is impossible to disentangle those who "manipulate" application from those who truthfully rank programs, we use a subset of those who have ranked strictly less than nine programs.

We first estimate a logit model whether a student i includes a program j in the application portfolio using maximum likelihood based on equation (4):

$$\log L = \sum_i \sum_i y_{ij} \cdot \log\left(P\left[j \in S_i\right]\right) + (1 - y_{ij}) \cdot \log\left(1 - P\left[j \in S_i\right]\right) \tag{7}$$

Using only the actual observed ranking data, we estimate a ranked-order logit model based on equation (5). The probability of observing a given ranking of the programs from the choice set is:

$$P_i\left[\{r = j\}_{r=1}^R\right] = \prod_{r=1}^R \frac{\exp(\beta' X_j)}{\sum k \in S^r \exp(\beta' X_k)} \tag{8}$$

where r is a given place in ranking; S^r is a choice set after excluding programs that were included in the rank at the position above r. More precisely, for $r = 1$, S^r is an initial set S. For $r = 2$, S^r is the same as S but excluding the program that was ranked first.

Equation (5) leads to a simple ranked ordered logit model.

4.2   College Market

4.2.1   Model

In this section, we describe a model of the choice of admission requirements in the form of ATAR cutoffs. The model attempts to capture key features of competition for students among colleges. We assume that colleges' decisions are affected by the total revenues and the quality of the admitted pool of students in the form of the average ATAR score. Therefore, a college program j chooses a cutoff ξ_j that maximizes the following utility function:

$$V_j = \left[\alpha \cdot (D(\xi_j, \psi_j) \cdot R_j)^r + (1 - \alpha) \cdot \bar{ATAR}(\xi_j, \psi_j)^r\right]^{\frac{1}{r}} \tag{9}$$

where $D(\xi_j, \psi_j)$ is an expected number of admitted students for program j as a function of own cutoff ξ_j and the expected cutoffs of all other programs presented on the market except j, ψ_j; R_j - per-student government-regulated revenues that vary across majors over time; $\bar{ATAR}(\xi_j)$

is the average expected ATAR of admitted students.

Although the share parameters α denote the weight on revenues compared to the average ATAR, the scale of the parameter also depends on the scales of the components in the function. In other words, one component in the utility function is total revenues in thousands of Australian dollars that has a support of any positive number, whereas the average quality of the student pool has a support from 0 to 100. It implies that the coefficient α partly reflects scale differences and partly actual weights in the utility function. A parameter r is bounded above by 1, where the revenues and the quality of a student pool are perfect complements. If r goes to $-\infty$, these components become perfect substitutes. $r = 0$ is a special case which leads to a Cobb-Douglas function. Although the Cobb-Douglas function itself might seem an appealing functional form choice, it exhibits an undesirable property. Because of the multiplicative form of total revenues consisting of demand and per-student revenues, the latter has no effect on the cutoff choice. It can be shown using the first-order condition of the Cobb-Douglas production function. The component R^{α} would simply play the role of the technology component and hence, does not affect the cutoff decision. This property is undesirable and unrealistic with respect to the goal of the model and the main variation that allows us to identify the parameters of the model. Therefore, a more general CES utility function is chosen.

The expected number of enrolled students follows from equation (6) and can be expressed:

$$D(\xi_j, \psi_j) = \int_{\xi_j}^{100} P_{ij}(\eta, \psi_j) \cdot dF(\eta) \qquad (10)$$

Equation (10) suggests that the expected demand is just a sum over probabilities that program j is in the list and is ranked first across students who meet the ATAR requirements ξ_j. One important limitation of our data is that although we observe all cutoffs, we do not observe the actual admission and enrollment decisions. It means that observing a minimum cutoff of 70 implies that no students with an ATAR 70 were admitted but does not imply that all students with ATAR higher than 70 were admitted. Therefore, we have to make an assumption that if a program gives an offer to a student with ATAR ζ, it must also offer a place to all students with the ATAR score above ζ. A need for this assumption is as a consequence of the measurement error. Deviations from the published cutoffs might come from colleges taking into account other minor factors not captured by the ATAR score such as essays or extracurricular activities. Since the UAC website and anecdotal evidence suggest that ATAR is the main determinant of the admission decisions, we believe that this measurement error should not play a crucial role.

The expected ATAR of admitted students is defined as follows:

$$AT\bar{A}T(\xi_j) = \frac{\int_{\xi_j}^{100} P_{ij}(\eta, \psi_j) \cdot \eta \cdot dF(\eta)}{\int_{\xi_j}^{100} P_{ij}(\eta, \psi_j) \cdot dF(\eta)} \tag{11}$$

One of the components of enrollment probability from equation (6) is a probability that a student i meets the admission requirements of all other college programs in the admission year. This is where ψ_j, which is the cutoff decisions of all other colleges on the market, plays an important role. This element introduces a competition channel. It means that when deciding on the cutoff, college programs have to internalize the probability that each student will be offered a place by all competitors if she applies. The fact that each application year contains slightly less than 1000 programs and around 40 000 students makes the problem of finding the Nash equilibrium of the game highly multidimensional and problematic to solve. Furthermore, solving it once will not be enough since the game has to be solved repeatedly to find a set of college program behavioral parameters. Therefore, we impose the following equilibrium concept, which we refer to as the Large College Market Equilibrium (LCME):

Definition 1. *Large College Market Equilibrium (LCME):*

1. *College programs have beliefs about the cutoff responses of other colleges to market state variables. These beliefs are based on previously observed changes in per-student revenues $\psi(\mathbb{R})$, where $\mathbb{R}$ is a collection of all per-student revenues on the market.*

2. *Each program chooses the cutoff that maximizes the utility function (9) given beliefs about the behavior of competitors defined by a function $\psi(\mathbb{R})$.*

Such a definition of a market equilibrium has a number of convenient and, in our view, realistic features. First, college programs compete on the same market over many years and, most likely, have extensive information about the strategic behavior of competitors. It motivates the idea that when making its own strategic decision and knowing changes in market prices, they can use a basic inference model to predict the responses of the competitors. Apart from being realistic, this assumption also allows us to overcome the computational burden of solving this model, which otherwise would require looping over all possible strategies of all competitors to find a Nash equilibrium in a market with many players.

We parametrize the beliefs about a competitor k cutoff decisions as follows:

$$\psi_{t,k}(\mathbb{R}) = \left(\gamma_0 + \sum_{m=1}^{M} \gamma_m R_m + \gamma_\psi \psi_{t-1,k}\right) \cdot \sum_{n=1}^{M} \mathbb{1}[m_k = n] \cdot \delta_n \tag{12}$$

The formulation in equation (12) means that colleges have linear beliefs about competitors'
cutoffs, which depend on a previous observed cutoff $\psi_{t-1,k}$ and revenues in each major $m \in M$.
The component $\sum_{n=1}^{M} \mathbb{1}[m_k = n] \cdot \delta_n$ means that all coefficients in the linear prediction function
vary over majors themselves.[20]

4.2.2 Estimation

We estimate the model using Generalized Method of Moments. We match equally spaced 50
percentiles of the cutoffs distribution. We find parameters by minimizing the following criterion
function:

$$\theta^* = \arg\min(m - \hat{m}(\alpha, r))'W(m - \hat{m}(\alpha, r)) \tag{13}$$

where m is a vector of data moments; $\hat{m}(\alpha, r)$ - vector of parameters generated by the model;
W - weighting matrix.[21]

4.3 Results

This section presents the main results of the structural model outlined in this section. We start
with the results of the student decision model. Tables 4 and 3 in Appendix present parameter
estimates. In this section, instead, we present substitution patterns that stem from the model
estimates. Figure 8 describes substitution patterns across majors while Figure 9 illustrates sub-
stitution patterns across universities. More precisely, each of the figures denotes price elasticity
averaged over majors or universities.

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[20]Note that a linear form might result in predicted cutoffs being outside of the support $[0, 100]$. In this case,
we substitute the value outside of the support with a closest bound of the support.

[21]We use an identity matrix. To obtain standard errors, we use bootstrap with 100 draws with replacement.

Figure 8: Demand Substitution across Majors
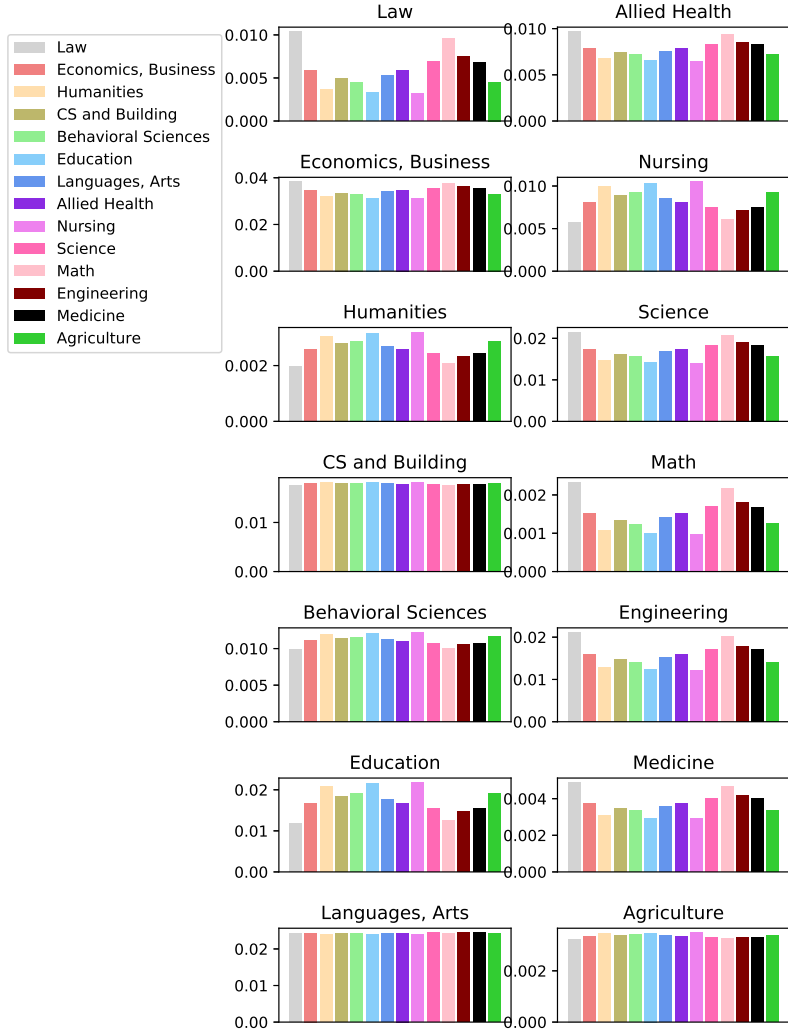
Notes: Figure presents estimates of elasticities by majors. Each box contains a number of bars for each major. Each bar denotes the percentage of students who would switch to a given major if a price for a program increases by 1%

Figure 8 presents subplots for each major. Each bar denotes a percentage of students who switch to a program in the corresponding major if a price for a given program increases by one percent. For example, the upper left bar for Law programs shows that if the price for a Law program increases by one percent, most of the switchers (0.1% of demand) would choose another Law program. The next popular choice would be Math (0.08% of demand). Other majors with a dominant "self-substitution" pattern are Nursing and Education. Languages and Arts, Agriculture and Computer Science, and Building have evenly distributed substitution patterns across all majors. Law is the most popular major to switch to. For example, in addition to being a dominant substitution option for itself, it is also the most popular for Allied Health, Economics and Business, Science, Math, Engineering and Medicine programs. Nursing is also a popular substitution option, especially for Humanities, Nursing, Behavioral Sciences, and Education. Overall, the figure suggests that students have very heterogeneous preferences for majors since an increase in prices is predicted to result in an application to programs from different majors. These results are intuitive and follow directly from the fact that many students tend to be interested in many majors simultaneously and include them in the application lists.

Apart from the substitution patterns, the overall elasticity to price changes differs across majors. The highest elasticity is observed for Economics and Business, Languages and Arts and Computer Science and Building. Agriculture, Math, and Medicine are among the price inelastic majors.

Figure 9 demonstrates similar evidence across universities. In contrast to the previous case, preferences over universities are more salient, meaning that none of the universities have uniformly distributed cross-elasticities among other colleges. In most of the cases, the University of New South Wales or Southern Cross Universities are the main switching options. Students prefer to switch to programs from the same university for Australian National University, Southern Cross University and University of New South Wales. The universities with the most elastic demand are Australian Catholic University, Macquarie University, University of Sydney, University of Newcastle, University of Technology Sydney and University of Wollongong.

Figure 9: Demand Substitution across Universities
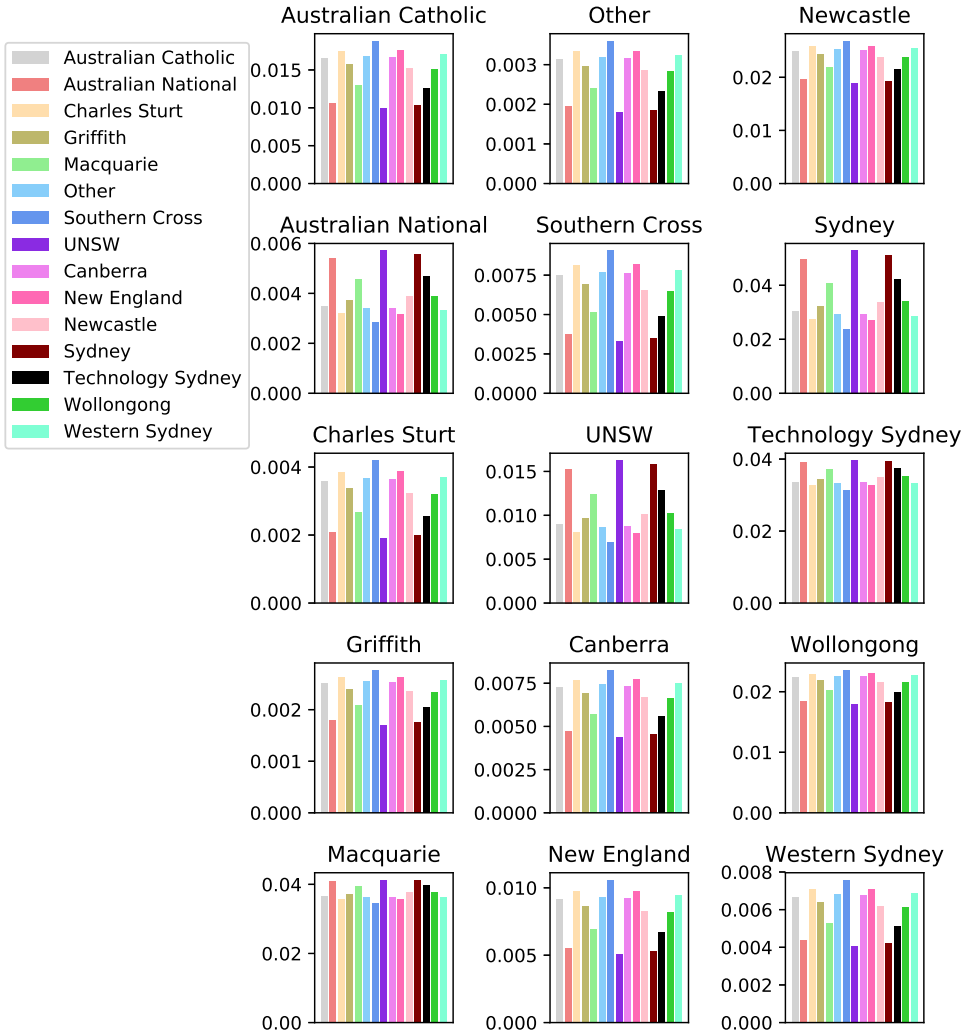
Notes: Figure presents estimates of elasticities by universities. Each box contains a number of bars for each university. Each bar denotes the percentage of students that would switch to a given university if the price for a program increases by 1%

The second step of the model is the estimation of program preferences that together with the preferences of students determine the outcomes of the market. Recall that the parameters that explain college cutoffs in the model are the share parameter of the CES production function (α), which is a weight that colleges put on a specific component of the utility function and the parameter r that expresses the degree of substitution between revenues and the expected quality of admitted students. In the main specification presented in the paper, we allow all these parameters to be university-specific for sufficient heterogeneity in the model.[22] Table 2 presents parameters of the model.

Although the absolute values of α parameters in the model are hard to interpret, a relative comparison is possible. The parameters suggest that programs from Australian Catholic University and Charles Sturt University (all campuses) place the highest weight on financial gains compared to all other programs. In contrast, programs from University of Sydney, University of New South Wales and Macquarie University have a strong focus on the overall quality of students when making admission decisions. These parameters suggest that most prestigious universities in the region focus on the quality of the admitted pool, which might signal an important role of reputation, whereas less prestigious colleges react more to price changes. The model estimated in this paper is static in the sense that the decisions of colleges are entirely determined by current market conditions meaning that programs do not internalize the impact of the decisions on future outcomes through, for example, reputation. Therefore, we do not explore this question in more details in this paper. Overall, we find significant heterogeneity in α parameters across universities. It not only reflects different preferences for monetary gains but possibly differences in cost structures as a result of being affiliated to different universities.

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[22]The reason is that the key variation in the model that allows identifying parameters of interest is the variation in subsidies and prices across majors.

Table 2: College Model Parameters

	α	r
Australian Catholic University	0.214397	-0.135049
	(0.00200952)	(0.00210807)
Australian National University	0.173522	-0.037721
	(0.00117618)	(0.00780676)
Charles Sturt University	0.0206467	-0.621324
	(0.00731124)	(0.266071)
Charles Sturt University - Bathurst	0.125085	-0.118208
	(0.00574016)	(0.124865)
Charles Sturt University - Wagga Wagga	0.093215	-0.702761
	(0.0162217)	(0.301881)
Griffith University	0.118947	0.368549
	(0.00215637)	(0.00986394)
Macquarie University	0.0304149	-4.98925
	(0.00736678)	(0.0130811)
Other	0.128765	0.0134385
	(0.00160913)	(0.0224744)
Southern Cross University	0.111901	-0.186905
	(0.000930401)	(0.0366673)
UNSW Australia	0.060354	-0.493937
	(0.00132744)	(0.0814062)
University of Canberra	0.133444	0.217833
	(0.00083535)	(0.0190935)
University of New England	0.0999119	-0.198914
	(0.00079801)	(0.0094933)
University of New South Wales	0.0725893	-0.399736
	(0.00202217)	(0.0378579)
University of Newcastle	0.0932283	0.189342
	(0.000777019)	(0.00274217)
University of Sydney	0.075227	-4.41869
	(0.00720078)	(0.45144)
University of Technology Sydney	0.0853021	-0.0776609
	(0.00132436)	(0.0102248)
University of Western Sydney	0.117248	0.091255
	(0.000384809)	(0.00251997)
University of Wollongong	0.0973293	0.0894362
	(0.00188962)	(0.0392899)
Western Sydney University	0.115891	0.173925
	(0.000479805)	(0.00629672)

Notes: Standard errors presented in parentheses are estimated using bootstrap with 100 draws.

We also find considerable heterogeneity in the complementarity of monetary gains and the quality of admitted students. Complementarity in this model means that in the event of considerable changes in revenues, colleges cannot fully react by changing the admission requirements, which would move the average quality of admitted students to the opposite direction. We find that programs in such universities as Australian National University, Griffith University, University of Canberra, University of New England and Western Sydney University show signs of high substitutability between average ATAR of admitted students and revenues, which allows them to react more to price changes. Macquarie University and University of Sydney display high complementary between financial gains and the quality of the admitted students.

The model fits the data well, which is presented in Figure 10. We present the model fit results in terms of the moments used in the estimation, which correspond to the CDF of a cutoff distribution.

Figure 10: Model Fit
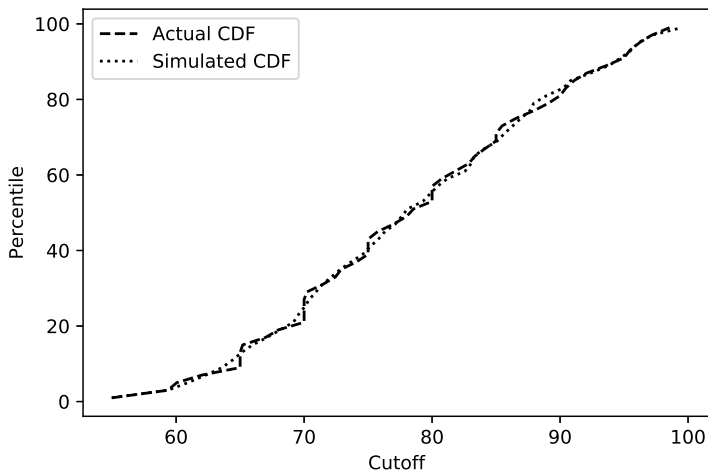
Notes: Figure demonstrates a model fit in terms of percentiles of a cutoff distribution pooled over all years.

In the next section, we use the model and the estimated parameters to study counterfactual policies that affect program revenues and tuition charges.

5 The Effect of Financial Regulations in College Markets

In this section, we use the model to study a number of counterfactual regulations in college markets. We study the effect of two types of interventions. First, we simulate counterfactual market outcomes in terms of college admission requirements (cutoffs), enrollment patterns and student composition under different revenue levels. Another counterfactual policy concerns changes in student prices while keeping college revenues constant.

The choice of counterfactual policies is driven by both the interest in the effect of financial terms on college market outcomes and the credibility of the analysis given the structure of the model. The latter means that an important assumption in the model that significantly restricts the choice of counterfactual policies is a structure of beliefs about competitors' responses. Proposed counterfactual policies fit well into this model since it is intended to capture these patterns. However, another potentially interesting set of counterfactual policies such as the effect of the removal of price regulations, which would allow colleges to freely set both prices and cutoffs, is inappropriate for this model. The reason is that the proposed equilibrium concept would not hold not only because the changes are too dramatic but also because programs will not have the price information to make predictions about competitors' responses. In this case, the model requires a different equilibrium concept which handles a price setting scenario. However, in the absence of the variation in the data that would inform the parameters responsible for price competition, such counterfactual policies might be an unconvincing extrapolation exercise.

To analyze the effect of counterfactual policies, we focus on the 2017 admission year. We start with the effect of alternative regulations of college revenues. More precisely, we study how admission requirements and enrollment change if the revenues of all programs are reduced to the minimum and raised to the maximum observed values in 2017. It means that we consider identical revenues per student for all colleges. Figure 11 demonstrates the effect of such changes.

In these counterfactuals, we change revenues from being unequally distributed across majors and hence universities to being identical. It means that depending on the major affiliation, different programs will face different price changes. We depict actual price changes averaged on university (Panel A) and major levels (Panel B). The only channel for how these policy changes affect the market is through changes in admission requirements. Colleges change the admission requirements because they have to re-optimize according to the utility function. In addition, colleges need to adjust the cutoffs even if the revenues have not been changed because of competitors' responses.

Figure 11: Effect of Changes in College Revenues on Market Outcomes
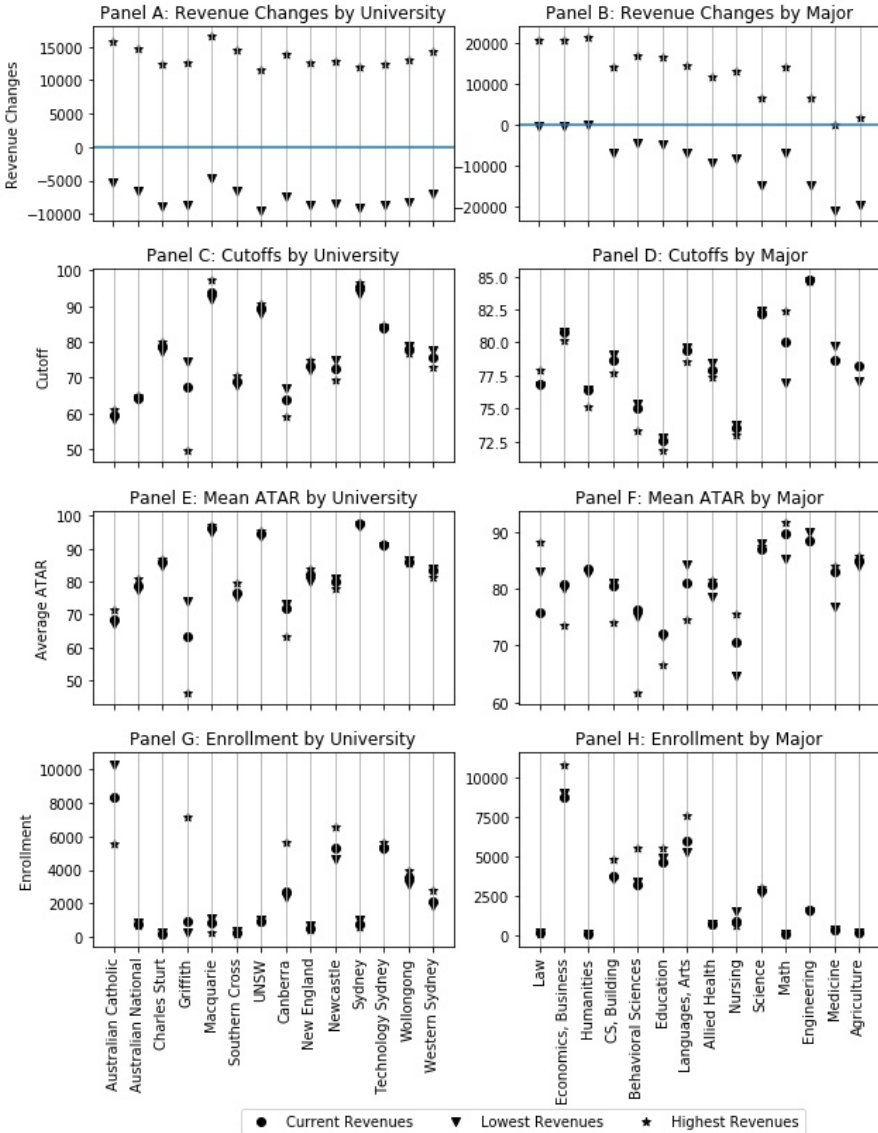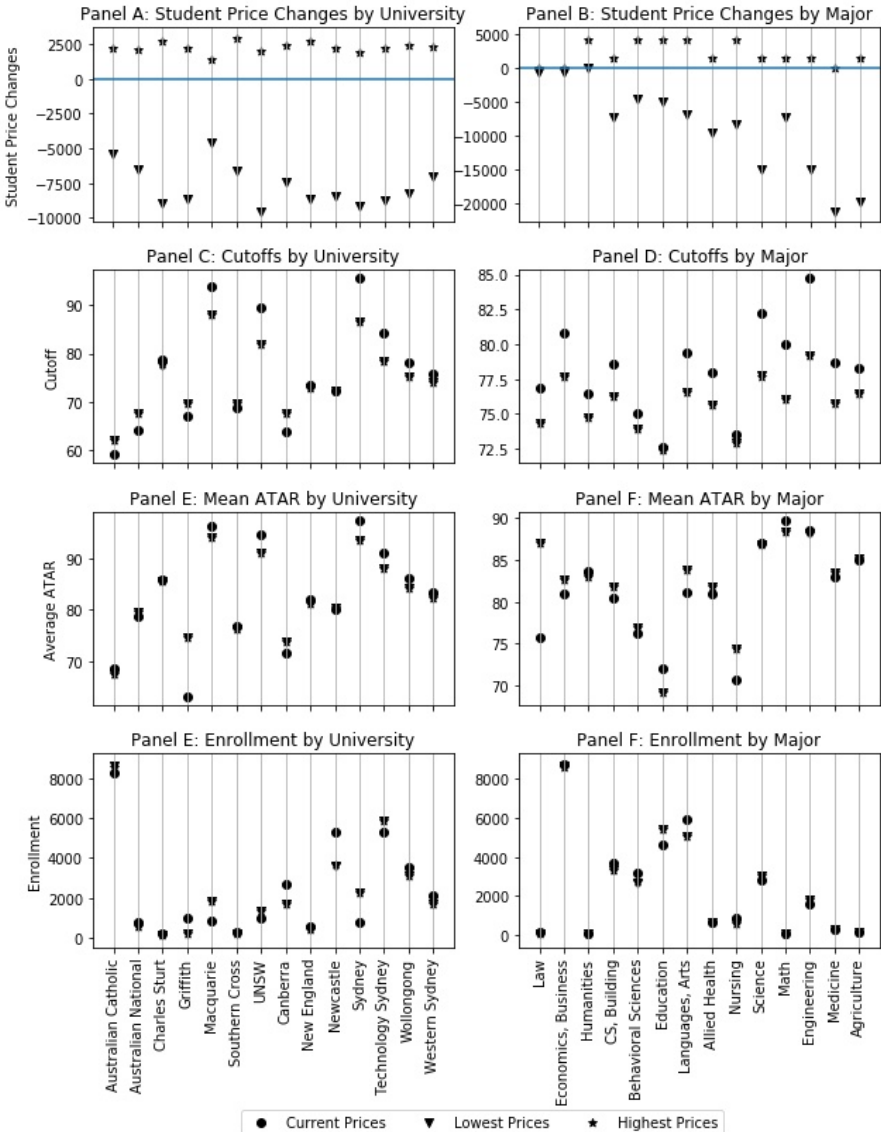

Notes: Panel A and B demonstrate counterfactual changes in financial terms. Panels C and D show how colleges would respond by changing admission requirements. Panels E and F present the market outcomes in terms of resulted average ATARs while G and H in terms of a number of enrolled students.

The results suggest that changes in college revenues would result in heterogeneous responses from university programs. Looking at the aggregation by universities, most of the changes in terms of the admission cutoffs would come from Griffith University, Macquarie University, University of Canberra and University of Newcastle. The results suggest that none of the prestigious universities would significantly react by changing the admission requirements despite fairly considerable changes in the financial incentives. Despite fairly modest responses in terms of the admission requirements, some universities will experience sizable changes in enrollment. For example, although programs from Australian Catholic University almost do not adjust cutoffs on average, considerably higher enrollment is expected as a result of reduced revenues, whereas 2000 less students are expected to enroll. The reduction in enrollment comes from the responses of competitors. Considerable changes in the composition of students by the ATAR score would only be observed by schools that experienced changes in enrollment.

The results aggregated by majors presented in the right column suggest the absence of such dramatic jumps as in the case of the aggregation by university. Law majors would respond slightly in terms of cutoffs and would not experience considerable demand changes despite the fact that a composition of students will increase under both scenarios. This would happen even for the case of reducing student prices, which would imply no changes for Law programs. The effect is fully attributed to the responses from other majors and substitution of students to and from Law programs. Economics and Business programs would only experience higher revenues and would lower the cutoffs as a result. It would bring about nearly 2000 more enrolled students but overall reduce average ATAR by 18 points. The most considerable changes are observed for Behavioral Sciences in which case a price increase leads to a 3 point lower average cutoff but more than 15 point lower average cutoff translated into around 1500 more enrolled students. Similar ordinal responses are predicted for CS, Languages and Art, and Education programs. Nearly no changes are expected for Math, Engineering, and Agriculture on average.

Next, we proceed to analyzing the market responses to changes in prices paid by students illustrated in Figure 12.

Figure 12: Effect of Changes in Student Tuition Charges on Market Outcomes

Notes: Panel A and B demonstrate counterfactual changes in financial terms. Panels C and D show how colleges would respond in terms of changing admission requirements. Panels E and F present the market outcomes in terms of resulting average ATARs while G and H in terms of a number of enrolled students.

The reason why programs have incentives to respond by changing the admission requirements is to compensate students for higher prices and prevent them from switching to competitors. The overall results are very similar while looking at both aggregation levels. The overall composition of ATAR and the enrollment patterns would remain nearly the same for most programs. Changes would only be observed at the aggregate level for Griffith University, Macquarie University, University of Newcastle and University of Sydney. The enrollment patterns across majors would be very similar to the status quo case. Changes in the student composition are observed for Law, Education, Languages and Art, and Nursing.

6   Conclusion

This paper is one of the first attempts to systematically study the determinants of equilibria in college markets. We leverage an appropriate set-up of the Australian higher education system that provides both detailed administrative data and an appealing institutional environment that includes the variation in student prices and university revenues.

We provide novel empirical evidence of the effect of government price regulations on market outcomes of student demand for college programs and college admission requirements. First, we find that students are relatively price-insensitive. One of the explanations is that pricing is major based. The presence of strong preferences for majors or universities might suppress responses to major-based price changes. Second, we observe very heterogeneous responses of colleges to changes in financial incentives.

Upon documenting this evidence, we construct and estimate a student choice and college competition model. Conditional on student preferences and financial terms, colleges compete with each other by setting the admission requirements. The estimation of the model allows obtaining student preference parameters including price sensitivity as well as major and university preferences. Estimated student preferences, which are overall in line with the reduced form evidence, show small price sensitivity and strong preferences for the major and college affiliation. The results of the model of college competition suggest considerable heterogeneity in preferences, which should be an important channel through which government price interventions affect the market outcomes.

Using the model, we study the effect of changes in financial conditions for students and colleges on admission requirement and enrollment patterns. We conclude that changes in college revenues would result in changes in admission requirements lead to redistribution of enrollment since programs would adjust the admission cutoffs. These results suggest an important role of financial incentives in college markets.

The main limitation of the study is the measurement error in the college admission decisions. Therefore, future work studying student decisions in college markets might be required. The competition model estimated in this paper allows overcoming computational burden associated with the market size. However, given considerable heterogeneity, a promising approach to estimating the game with many players might be to use a machine learning algorithm to cluster programs in the sub-markets where competition is more severe. It would allow reducing the burden of estimating the game on a larger market by substituting it with many smaller markets instead of imposing the assumption about the structure of beliefs about competitors' responses.

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Appendices

A   Supplementary Tables

Table 3: Program Ranking Model

	rank		
price	-0.0035054	4.cuni	0.1551681
	(0.0026431)		(0.0145366)**
2bn.cgroup	0.8296572	5.cuni	0.1396567
	(0.0090693)**		(0.0158576)**
3.cgroup	0.7678708	6.cuni	0.1223081
	(0.0169507)**		(0.0163961)**
4.cgroup	0.9334394	7.cuni	-0.1601216
	(0.0106660)**		(0.0074258)**
5.cgroup	1.0280744	8.cuni	0.3895526
	(0.0138866)**		(0.0162219)**
6.cgroup	0.9296877	9.cuni	0.2666595
	(0.0147267)**		(0.0130224)**
7.cgroup	0.8562755	10.cuni	-0.5532454
	(0.0136761)**		(0.0094154)**
8.cgroup	0.5711292	11.cuni	0.3274917
	(0.0117139)**		(0.0118495)**
9.cgroup	0.7998642	12.cuni	0.1370143
	(0.0164372)**		(0.0119731)**
10.cgroup	1.1423147	13.cuni	-0.4605595
	(0.0120233)**		(0.0079889)**
11.cgroup	1.0189921	14.cuni	-0.1014521
	(0.0193433)**		(0.0092748)**
12.cgroup	0.7269325	15.cuni	-0.5339515
	(0.0118453)**		(0.0072696)**
13.cgroup	0.7619506	16.cuni	-0.3983852
	(0.0120960)**		(0.0072867)**
14.cgroup	1.0301927	17.cuni	0.0540999
	(0.0137471)**		(0.0072434)**
15.cgroup	1.1211195	18.cuni	-0.2179875
	(0.0136587)**		(0.0086653)**
2bn.cuni	-0.2571268	19.cuni	-0.0446628
	(0.0136588)**		(0.0121284)**
3.cuni	0.0546605	N	1,508,091
	(0.0167268)**		

* $p < 0.05$; ** $p < 0.01$

Notes: Table presents results of the rank ordered logit model based on pre-selected into choice set programs.

Table 4: Selection in the Choice Set Model

	Parameters	Std. Errors
2.cgroup	7.1896578	(0.1511461)**
3.cgroup	6.9349832	(0.1655056)**
4.cgroup	7.6474777	(0.1524289)**
5.cgroup	7.5656049	(0.1528365)**
6.cgroup	8.5298571	(0.1514722)**
7.cgroup	7.3846193	(0.1517630)**
8.cgroup	5.1977329	(0.1624109)**
9.cgroup	7.8934658	(0.1554531)**
10.cgroup	6.0314418	(0.1554143)**
11.cgroup	1.9132708	(0.2760250)**
12.cgroup	5.7293555	(0.1588721)**
13.cgroup	3.6886528	(0.1746649)**
14.cgroup	6.2491104	(0.1640343)**
15.cgroup	6.5188498	(0.1554640)**
2.cuni	-5.3317243	(0.1557347)**
3.cuni	-1.0660354	(0.1017142)**
4.cuni	-0.9409696	(0.0997257)**
5.cuni	-1.5690692	(0.1092466)**
6.cuni	-1.8020550	(0.1157411)**
7.cuni	-1.2752882	(0.0640810)**
8.cuni	-1.2647041	(0.1134505)**
9.cuni	-0.0409580	(0.0788016)
10.cuni	-5.2752688	(0.1099343)**
11.cuni	-0.7355024	(0.0831773)**
12.cuni	-0.3518560	(0.0766283)**
13.cuni	-3.8243905	(0.0808241)**
14.cuni	-0.0243183	(0.0614077)
15.cuni	-3.9202510	(0.0678565)**
16.cuni	-1.4208890	(0.0629519)**
17.cuni	1.4167146	(0.0561684)**
18.cuni	-0.4225894	(0.0641340)**
19.cuni	-0.7616461	(0.0873632)**
2.cgroup#c.atar	-0.0144630	(0.0011465)**
3.cgroup#c.atar	-0.0390164	(0.0015092)**
4.cgroup#c.atar	-0.0301862	(0.0011817)**
5.cgroup#c.atar	-0.0304977	(0.0011917)**
6.cgroup#c.atar	-0.0413959	(0.0011629)**
7.cgroup#c.atar	-0.0217964	(0.0011623)**
8.cgroup#c.atar	-0.0059246	(0.0013625)**
9.cgroup#c.atar	-0.0421144	(0.0012722)**
10.cgroup#c.atar	-0.0100588	(0.0012338)**
11.cgroup#c.atar	0.0102948	(0.0029390)**
12.cgroup#c.atar	-0.0089671	(0.0012961)**
13.cgroup#c.atar	0.0072755	(0.0015505)**
14.cgroup#c.atar	-0.0302163	(0.0014411)**
15.cgroup#c.atar	-0.0159356	(0.0012583)**
1b.cuni#c.atar	0.0017284	(0.0012910)
2.cuni#c.atar	0.0598063	(0.0020552)**
3.cuni#c.atar	-0.0030499	(0.0017407)
4.cuni#c.atar	-0.0031632	(0.0017211)
5.cuni#c.atar	0.0043798	(0.0017917)*
6.cuni#c.atar	0.0048170	(0.0018591)**
7.cuni#c.atar	0.0314050	(0.0012144)**
8.cuni#c.atar	-0.0042452	(0.0018973)*
9.cuni#c.atar	-0.0102833	(0.0014603)**
10.cuni#c.atar	0.0707664	(0.0015793)**
11.cuni#c.atar	0.0015486	(0.0014743)
12.cuni#c.atar	-0.0014208	(0.0014035)
13.cuni#c.atar	0.0601466	(0.0013325)**
14.cuni#c.atar	0.0121389	(0.0012065)**
15.cuni#c.atar	0.0704902	(0.0012241)**
16.cuni#c.atar	0.0355667	(0.0012030)**
17.cuni#c.atar	-0.0053981	(0.0011704)**
18.cuni#c.atar	0.0145435	(0.0012313)**
Constant	-9.7856088	(0.1554758)**
N	7,606,812	

* $p < 0.05$; ** $p < 0.01$

Notes: Table presents results of the logit model of including a program in a choice set from the equation (3).

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