Essays in Applied and Theoretical Microeconomics

Inauguraldissertation

zur Erlangung des Grades eines Doktors
der Wirtschaftswissenschaften

durch

die Rechts- und Staatswissenschaftliche Fakultät der
Rheinischen Friedrich-Wilhelms-Universität Bonn

vorgelegt von

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aus Bonn

2022

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Tag der mündlichen Prüfung:	27. April 2022

Acknowledgements

To my late father,
Joachim Russ
1956 - 2016

In hindsight it is save to say that I started grad school without knowing much about economics (let alone anything else). In large part due to the heavy focus on mathematics during my undergraduate studies it took until 2015 – and a seminar at the University of Cologne – that I seemingly accidentally stumbled upon the world of modern public finance. I was immediately hooked by the prospect of combining theoretical models and empirical evidence to design more effective public and economic policies. This initial spark of curiosity has resulted in an intellectual journey beyond my wildest imagination. My path has been everything except straight, but I keep reminding myself that utter confusion tends to be the dawn of a new understanding.

First and foremost, I thank Armin Falk for his kindness, humility and generosity. He took me in as his PhD student when I was truly lost, provided invaluable guidance and support and made me feel welcome at the research group at briq. Although based at the LSE for most of my research, I always looked forward to returning to Bonn. This thesis would have not been possible without Armin's intellectual breadth and the freedom he provided me with to pursue my own research. For his generous support over all these years I am grateful to Armin.

Second, I thank Johannes Spinnewijn for his continued guidance, for countless meetings and discussions and for lots of constructive criticism throughout various stages of this thesis. Most of all, I am indebted to him for building and heading such a dynamic, open and welcoming public economics research group at the LSE which took me as one of their own. Johannes' enthusiasm and light-footedness set an aspiring example and profoundly shaped the way I envision my own career. I thank Johannes for his trust in my academic abilities, for the high standards he set for me and for his insistence to push me to do better.

I am grateful to the Bonn Graduate School of Economics and the London School of Economics for financial and administrative support. This thesis greatly benefited from an exceptional set of coauthors. I am indebted to Luca Citino, Alan Manning, Vincenzo Scrutinio and Justus Winkelmann. On a personal level, I am fortunate to have been part of two outstanding cohorts of PhD students and thank my friends Thomas Gräber, Leander Heldring, Lukas Püttmann, Chris Roth and Fabian Walders at the University of Bonn, and Nicolas Chanut, Amanda Dahlstrand, Nicola Fontana, Ruth Fortmann, Clara Martinez-Toledano and Martina Zanella at the LSE.

Nothing of the below would have been possible without the love and support of my family. I count myself extremely fortunate to have been born into a wonderful home. I am deeply grateful to my mother for her unconditional love and for providing an environment any child could hope for. Finally, I thank my girlfriend, Lisa, not least for her unwavering support during the final stage of this project. She has already profoundly influenced the way I see the world and my role in it. Our life together is my inexhaustible source of inspiration and happiness.

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Introduction

Science is the discovery of knowledge. The process of this discovery is based on two ingredients: hypothesizing – often guided by theoretical abstraction and deductive reasoning – and testing in the form of empirical investigation and experimentation. The cadence of theoretical and empirical inquiry builds the cornerstone of today's understanding of the natural world and has fueled remarkable scientific achievements. Modern economic research in many aspects strives to emulate these principles originally pioneered by the natural sciences.

Economists today seek not only a better understanding of the origins and consequences of individual and societal economic decision making, but frequently find themselves drawn upon to harness their insight and to provide evidence and recommendation for practical policy design. While our profession devotes considerable care in separating positive analysis from normative judgements it has become evident that sound evidence-based policy advice – much like science itself – stands on two pillars: theory and empirics.

This thesis uses the toolkit of modern microeconomic analysis to contribute to three broad policy-relevant areas of economics: unemployment, immigration and voting. How should we design targeted unemployment insurance that mitigates some of the adverse consequences of job loss? What is the impact of immigration on productivity in the economy? And, are there better ways to organize collective decision making than voting by simple Majority rule? The content of this work is motivated by a deep belief that economic research stands to gain from a close integration of theoretical and empirical analysis. Accordingly, the work below draws on methods from applied microeconomic theory, sufficient statistics, quasi-experimental and observational methods, voting theory and mechanism design.

In this vain, chapter 1 studies the design of optimal targeted social insurance both from a theoretical and empirical perspective. Motivated by an ever increasing amount of available information and strained government budgets, tying public benefits to observable individual characteristics holds the potential to increase cost-effectiveness while helping those most in need. Indeed, the targeting of public policies on the basis of observable individual characteristics is ubiquitous in OECD countries. Governments tax individuals based on their marital status, provide welfare payments which depend on the number of children in the household, and tie disability insurance to particular medical conditions. The theoretical desirability for targeting based on immutable tags has long been recognized (Akerlof (1978)). In practice however, policy makers often rely on endogenous tags, which leave room for strategic manipulation and selection into benefit schemes. Yet we lack a tractable framework to think about optimal policy in this context.

Chapter 1, which is joint work with Luca Citino and Vincenzo Scrutinio, proposes a sufficient statistic framework to guide the design of optimal targeted social insurance in the presence of manipulation opportunities through which individuals select into policies not intended for them. Our theory reveals three effects through which manipulation alters the desirability of differentiated social insurance: (i) the extent to which unintended recipients are selected on moral hazard as measured by the behavioral to mechanical cost ratio, (ii) the extent to which they are selected on consumption smoothing value and (iii) a manipulation externality capturing the extent to which more differentiation induces more manipulation. Importantly, our theoretical formula is expressed in terms of a few high-level elasticities and selection effects that can be credibly estimated empirically.

We implement our framework in the context of Italian Unemployment Insurance (UI) which features a discontinuous jump from eight to twelve months of potential UI coverage around an age-at-layoff threshold. Using novel bunching techniques we document pervasive manipulation in the form of strategically delayed layoffs. Affected workers collect significantly more UI benefits through manipulation. However, most of the estimated increase is the mechanical result of longer UI coverage because manipulators are highly selected on long-term nonemployment risk. The implied responsiveness to UI benefits is modest and, in particular, not higher than for non-manipulators, implying that the presence of manipulation does not alter the design of optimal differentiated policy through the moral hazard selection effect in the Italian context.

Chapter 2 focuses on one of the most divisive and contentiously debated topic in the public sphere: the effects of immigration. Acknowledging that immigration is far from a purely economic phenomenon, the economic literature has thus far predominantly focused on its effect on the labor market (e.g. Card (2009), Borjas (2014) and Dustmann, Schönberg, and Stuhler (2016) among others). Chapter 2 contributes to a better understanding of the consequences of immigration by studying its effect on productivity and thus economic growth. While immigration undeniably increases total gross domestic product (GDP), its impact on productivity, that is, output per worker, is far from obvious. In Chapter 2, Alan Manning and I use newly released, spatially dis-aggregated county by sector GDP data from the US to shed new light on the impact of immigration on productivity. Our empirical analysis is theoretically guided by a production function approach at the commuting zone level in which inputs into production are different types of labor differentiated by native vs. immigrant status and skill level. We find robust evidence that increasing the share of high-skill immigrants while reducing the share of low-skill natives raises output per worker, with estimates generally larger than for the impact of increasing the share of high-skill natives. Further, we find small and mostly insignificant effects of low-skill immigration on productivity. We address concerns about the selection of workers into sectors and areas using a shift-share IV strategy. Comparing the impact of immigration on productivity with its impact on wages, we provide evidence that most of the increase appears to be captured by the workers themselves.

While a theoretical framework and empirical evidence provide invaluable guidance for policy design, the ultimate policy choice also critically depends on the political process and rules that govern collective decision making. Liberal democracies cherish individual freedoms, political participation and fairness. In practice almost all decisions end up being made by means of simple Majority rule. We overwhelmingly base decisions on how *many* individuals favor or oppose a reform rather than how *much* everyone cares. This inherent weakness of direct democracy based on Majority Rule has long been recognized as the *Tyranny of the Majority* (De Tocqueville (1835)), and raises the question whether there are better ways to make collective decisions.

Chapter 3, which is joint work with Justus Winkelmann, gives an affirmative answer to this question if one is willing to bundle decision problems together rather than to decide on them separately. We illustrate that bundling provides the opportunity for a simple and intuitive class of mechanisms, which we label Ranking Mechanisms, to outperform Majority rule substantially. The key idea is to allow agents to rank decision problems themselves to communicate which topic they care relatively more about. These rankings are then used to assign weights to agents' votes in a classical voting mechanism. Our theoretical analysis proves that agents indeed find it in their own self-interest to report their preferences truthfully as long as all other agents do so too. We derive a closed form solution for the ex-ante efficient weight vector. The optimal Ranking Mechanism ex-ante Pareto dominates Separate Majority Voting for an arbitrary number of individuals and decision problems. In the final step, we illustrate how the idea of ranking can be extended to non-identical distributions of preferences between agents and across problems. While our work focuses on establishing the theoretical properties of Ranking Mechanisms, their ultimate potential lies in their intuitive appeal and practical applicability.

In sum, this thesis demonstrates the scope of modern microeconomic research, its methodological and conceptual breadth and its practical value for real world policy making and applications.

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Chapter 1

Manipulation, Selection and the Design of Targeted Social Insurance*

1.1 Introduction

The looming COVID-19 pandemic, the ensuing economic crisis and an ever increasing amount of available information have resulted in an unprecedented demand for *targeted* government interventions. Tying public benefits to observable information holds the potential to increase cost-effectiveness while providing assistance and support to those most in need. Even in less extreme times, the targeting of public policies on the basis of observable individual characteristics is ubiquitous in OECD countries. Governments tax individuals based on their marital status, provide welfare payments which depend on the number of children in the household, and tie disability insurance to particular medical conditions. The theoretical desirability for targeting based on immutable *tags* has long been recognized (Akerlof, 1978). In practice however, policy makers often rely on endogenous tags, which leave room for strategic manipulation and selection into benefit schemes.

* This chapter is a revised version of an earlier paper which circulated under the title "Happy Birthday? Manipulation and Selection in Unemployment Insurance". For valuable comments and discussions we are grateful to Andrea Alati, Andres Barrios Fernandez, Miguel Bandeira, Fabio Bertolotti, Rebecca Diamond, François Gerard, Simon Jäger, Felix König, Camille Landais, Attila Lindner, Stephen Machin, Alan Manning, Clara Martinez-Toledano, Matteo Paradisi, Michele Pellizzari, Frank Pisch, Jörn-Steffen Pischke, Michel Serafinelli, Enrico Sette, Johannes Spinnewijn, Martina Zanella, Josef Zweimüller, and seminar participants at briq, EUI, INPS and the LSE. This project was carried out while Kilian Russ was visiting the London School of Economics as part of the European Doctoral Programme in Quantitative Economics. Financial support from the London School of Economics and the Bonn Graduate School of Economics is gratefully acknowledged. The realization of this project was possible thanks to the VisitInps initiative. We are very grateful to Massimo Antichi, Elio Bellucci, Mariella Cozzolino, Edoardo Di Porto, Paolo Naticchioni and all the staff of Direzione Centrale Studi e Ricerche for their invaluable support with the data.

How should we design targeted public policies in the presence of manipulation opportunities? In particular, how does manipulation alter the desirability of differentiated policy? Finally, once we know which empirical moments are relevant, how do we estimate them in practice?

This chapter breaks new grounds on these questions in the context of optimal social insurance and makes three main contributions. First we propose a simple, yet robust, theoretical framework to study the design of optimal differentiated social insurance in the presence of manipulation. To this end we introduce differentiation and manipulation opportunities into a classical Baily-Chetty framework (Baily, 1978; Chetty, 2006). In its simplest form, our sufficient statistic formula reveals three effects through which manipulation alters the desirability of tagging: (i) the extent to which unintended recipients, henceforth manipulators, are selected on moral hazard as measured by the behavioral to mechanical cost ratio, (ii) the extent to which they are selected on consumption smoothing value and (iii) a manipulation externality capturing the extent to which more differentiation induces more manipulation. The latter makes insurance under manipulation more costly and thus calls for less insurance overall. However, selection effects might work to amplify, mitigate or reverse these conclusions depending on their sign and strength. Intuitively, if manipulators value additional benefits more than their social cost, more differentiation – inclusive of manipulation – might be welfare improving. Conversely, if manipulators are adversely selected on moral hazard, manipulation exacerbates the cost of differentiation.

Our second contribution is to develop novel bunching techniques that allow us to estimate several key parameters. Building on Diamond and Persson (2016), our methodology exploits the local nature of manipulation and combines traditional bunching and regression discontinuity design (RDD) estimates to uncover selection on both observables and unobservables. We illustrate how the latter can reveal selection effects and treatment effect heterogeneity. In particular, our methodology lets us directly estimate the extent to which manipulators are selected on risk and moral hazard, which links to our theoretical results. Estimating selection on moral hazard has proven notoriously difficult in practice, resulting in relatively little empirical work on the topic, with Einav, Finkelstein, Ryan, Schrimpf, and Cullen (2013) and Landais, Nekoei, Nilsson, Seim, and Spinnewijn (2021) representing two notable exceptions in the context of health and unemployment insurance, respectively. Our methodology requires neither knowledge about manipulators' identity nor reform-induced policy variation over time, making it readily applicable in other settings.

As a third contribution, we apply our methodology in the context of Italian unemployment insurance (UI) and connect the empirics to our theory. Exploiting a discontinuous jump from eight to twelve months of UI coverage around an age-at-layoff threshold, we provide clear graphical evidence of manipulation in the form of systematic delays in the exact timing of layoffs. We find that over 15% of all layoffs occurring within six weeks before workers' fiftieth birthday are strategically delayed. Over the subsequent nonemployment spell affected workers collect on average 2,239 additional Euro each, which correspond to a 38,5% increase in total UI benefit receipt. A survival analysis reveals that approximately 80% of this increase in UI benefit receipt is mechanically due to higher coverage, while the remaining 20% is the result of a decrease in job search effort. This implies that the government pays an additional 25 cents for each euro of mechanical UI transfer to manipulators. Interestingly, we find virtually the same result when studying non-manipulators, i.e. individuals who were laid off just before their fiftieth birthday. This implies that manipulators are not adversely selected on moral hazard and that selection on moral hazard does not alter the design of optimal policy in our setting.

From a positive perspective our findings mitigate concerns about anticipated moral hazard being the prime motive for selection into manipulation. Rather, we document that manipulators are highly selected on long-term nonemployment risk. Even absent manipulation, manipulators would have exhausted eight months of UI benefits with 16.8 p.p. higher probability than non-manipulators. The underlying firm-worker collusion decision to delay the date of layoff thus acts as an effective screening mechanism for long-term nonemployment risk, while preventing selection on moral hazard. In the last part of the chapter we investigate this mechanism further by documenting observable worker and firm characteristics that are associated with manipulation. Manipulation is pervasive among permanent contract workers in private sector firms. We find no evidence of manipulation in public sector firms or among temporary contracts. It is relatively more prevalent among female, part-time, white-collar workers and in firms with less than 50 employees. This suggests that lower adjustment costs and proximity between workers and supervisors may facilitate manipulation in our context.

Our work relates to several strands of the literature. The theoretical model introduces the concept of *tagging* (Akerlof, 1978) into the design of optimal social insurance, in the spirit of Baily (1978) and Chetty (2006) on UI benefit levels and Schmieder, von Wachter, and Bender (2012) and Gerard and Gonzaga (2021) for potential UI duration.[1] In particular, we study the case of endogenous tags which are perfectly observable at zero cost but subject to manipulation. Importantly, we assume the absence of any verification technology that would allow the government to learn about individuals' (un-manipulated) types. This is in contrast to a large literature on tagging in optimal transfer programs and disability insurance which focuses on imperfect tags that are noisy signals about individual types, but verifiable (at some cost) by the planner, see e.g. Stern (1982), Diamond and Sheshinski (1995), Parsons (1996), Kleven and Kopczuk (2011) among others.

Our setup is both empirically relevant and theoretically interesting. Many policies do indeed tag on perfectly observable individual characteristics – such as marital

1. See Spinnewijn (2020) for a discussion on the importance of more conceptual work on optimal differentiated social insurance as well as for suggestions on how to get started.

status, number of dependents or, as in our case, age – with often no ability of inferring manipulation at the individual level. Second, our setting gives rise to both selection on risk and moral hazard, which have traditionally been analysed separately.[2] Recent efforts to integrate the two are presented in Landais et al. (2021), Hendren, Landais, and Spinnewijn (2020) and Marone and Sabety (2021). All three contributions study the welfare implications of offering some form of choice in (regulated) insurance markets.[3] Importantly, and conceptually different from our setup, these papers focus on policies that do not discriminate between different individuals but rely on self-selection through market prices.[4]

It is worth pointing out that our focus is on how to design optimal differentiated policy under manipulation based on a *given* (endogenous) tag, in our case, age at layoff. Although interesting in its own right, we do not directly speak to the appropriateness of tagging on age *per se*, nor do we empirically evaluate how much differentiation would be optimal. Notably, tagging on age has been discussed in several contexts, including in UI from a life-cycle perspective Michelacci and Ruffo (2015) and in optimal Mirrlessian taxation, see Weinzierl (2011), Best and Kleven (2013), among others.

The fact that we find positive selection on long-term nonemployment risk also speaks to a recent literature studying the role of private information and adverse selection in unemployment insurance, see e.g. Hendren (2017). This literature studies the role of private information about job loss risk in shaping the market for UI. Our results indicate that individuals hold information about their expected duration of unemployment at the point of layoff. Understanding to what degree this information is held privately is beyond the scope of this paper.

From a methodological perspective, our empirical strategy is most closely related to recent work by Diamond and Persson (2016), who study manipulation in Swedish high-stakes exams. They propose a bunching estimator to estimate the effect of teacher discretion in grading around important exam thresholds on students future labor market outcomes. They also show how these techniques can be used to study selection on observables. We extend their methodology to investigate selection on unobservables and to uncover treatment effect heterogeneity. We borrow several ideas from standard bunching techniques recently surveyed by Kleven (2016). Conceptually, our empirical insights also relate to the literature on "essential heterogeneity" in instrumental variable settings, in which individuals select into treatment

2. While moral hazard is the key concept in most of the work on unemployment insurance design, adverse selection has received a lot of attention in the context of health insurance, in particular, in the US context.

3. In their work Landais et al. (2021) provide the first assessment of the desirability of a UI mandate in the Swedish context. Adverse selection under a universal mandate has also been studied in the context of health insurance, see Hackmann, Kolstad, and Kowalski (2015).

4. Barnichon and Zylberberg (2021) show that it might be theoretically desirable to offer a menu of contracts to the unemployed screening individuals by how they trade lump-sum severance payments with UI benefits.

in part based on their anticipated treatment effect, see e.g. Heckman, Urzua, and Vytlacil (2006).

On the empirical side, a large body of work studies the disincentives effects of UI exploiting similar policy variation, see e.g. Card, Chetty, and Weber (2007), Lalive (2007), Schmieder, von Wachter, and Bender (2012), Landais (2015), Nekoei and Weber (2017), Johnston and Mas (2018) among others. Contrary to our setting, these papers rely on the *absence* of manipulation to identify the treatment effects of interest, whereas we study the effect of manipulation in a setting where it does occur. Two recent contributions by Doornik, Schoenherr, and Skrastins (2020) and Khoury (2019) also study manipulation in UI systems around an eligibility and seniority threshold in Brazil and France, respectively. Doornik, Schoenherr, and Skrastins (2020) provide evidence of strategic collusion between workers and firms who time layoffs to coincide with workers' eligibility for UI in Brazil. Khoury (2019) exploits a discontinuity in benefit levels for workers laid off for economic reasons and estimates an elasticity of employment spell duration with respect to UI benefits of 0.014. While both of these papers suggest that manipulation in social insurance contexts are widespread, neither studies the welfare consequences of manipulation or estimates selection effects as we do.

The remainder of this chapter is organized as follows: Section 1.2 covers the theoretical analysis for which Section 1.2.1 introduces the formal model, Section 1.2.2 discusses the main assumptions, Section 1.2.3 derives our main results and Section 1.2.4 connects our theory to the data; Section 1.3 contains our empirical application with Section 1.3.1 presenting the institutional setting and data, Section 1.3.2 outlining the empirical strategy and Section 1.3.3 reporting our results and robustness checks; Section 1.4 concludes.

1.2 Theory: Optimal Targeted Social Insurance with Manipulation

This section lays out a model for the design of optimal differentiated social insurance in the presence of manipulation opportunities. We stay deliberately close to our empirical setting to facilitate the connection between the theoretical and empirical part of the paper. Although the model is derived in the context of unemployment insurance duration, our results readily extend to other social insurance settings.

1.2.1 The Model

1.2.1.1 Setting

We assume there are two groups of individuals, referred to as the "young" and the "old" and denote their exogenous share in the population by G and $1-G$, respectively. Young and old individuals differ in their utility of consumption, job search costs and their ability to manipulate (more on this below). All individuals are unemployed in $t = 0$, retire at a finite time horizon T and are hand-to-mouth consumers.[5]

The government provides unemployment benefits b, financed through a lump-sum UI tax τ. Young and old individuals enjoy consumption $c_u + b$ when unemployed and covered by UI, c_u when unemployed and not covered, and $c_e = w - \tau$ when employed, where w denotes the exogenous wage rate. The governments sets two separate UI schemes of varying generosity characterized by two different potential benefit durations P_y and P_o, with $P_o \geq P_y$. It targets the longer potential UI benefit duration P_o to the old. When doing so it faces a challenge: young individuals have the ability to manipulate their eligibility status (at some cost) and might endogenously select into the more generous scheme intended for the old.[6] In order to study how a benevolent government should optimally set P_y and P_o in this context, we begin by formally stating individuals' job search problems.

1.2.1.2 The Old

Preferences and Job Search. Old workers are homogeneous, always eligible for longer potential benefit duration P_o, and face the standard job search problem. They enjoy flow utility $u^o(c)$ at consumption level c and choose job search intensity s_t^o at time t, normalized to the arrival rate of job offers, at utility cost $\phi_t^o(s_t^o)$. Formally, old individuals maximize:

$$V^o(P_o) = \max_{s_t^o} \left\{ \int_0^{P_o} S_t^o u^o(c_u + b) + \int_{P_o}^{T} S_t^o u^o(c_u) + \int_0^T \left(1 - S_t^o\right) u^o(c_e) - \int_0^T S_t^o \phi_t^o(s_t^o) \right\},$$

where $S_t^o = exp\left(-\int_0^t s_{t'}^o dt'\right)$ denotes the nonemployment survival probability at time t and all integrals are taken w.r.t. dt. We denote the old's implied benefit and nonemployment duration by

$$B^o(P_o) = \int_0^{P_o} S_t^o(P_o)dt \quad \text{and} \quad D^o(P_o) = \int_0^T S_t^o(P_o)dt.$$

1.2.1.3 The Young

Preferences and Job Search. Young individuals have heterogeneous preferences and are characterized by utility of consumption u^i, job search cost function ϕ^i and fixed

5. The model setup closely follows previous work on optimal potential benefit duration in UI, e.g. Schmieder, von Wachter, and Bender (2012) and Gerard and Gonzaga (2021).

6. Since the two policies differ only in terms of their potential benefit duration, with $P_o \geq P_y$, we w.l.o.g. restrict attention to one-sided manipulation.

cost q^i. Conditional on eligibility for potential benefit duration $\tilde{P}$, young individuals maximize search effort as follows:

$$\tilde{V}^i(\tilde{P}) = \max_{s_t^i} \left\{ \int_0^{\tilde{P}} S_t^i u^i(c_u + b) + \int_{\tilde{P}}^T S_t^i u^i(c_u) + \int_0^T \left(1 - S_t^i\right) u^i(c_e) - \int_0^T S_t^i \phi_t^i(s_t^i) \right\},$$

where $S_t^i = exp\left(-\int_0^t s_{t'}^i dt'\right)$ denotes individuals' nonemployment survival probability at time t and all integrals are w.r.t. dt. Denote an individual's implied benefit and nonemployment duration by:

$$B^i(\tilde{P}) = \int_0^{\tilde{P}} S_t^i(\tilde{P}) dt \quad \text{and} \quad D^i(\tilde{P}) = \int_0^T S_t^i(\tilde{P}) dt.$$

Manipulation. At time zero, young individuals can engage in manipulation by incurring a fixed cost $q^i \geq 0$ to become eligible for potential benefit duration P_o rather than P_y, with $P_o \geq P_y$. Formally, a young individual i with fixed cost q^i maximizes:

$$\begin{aligned} V^i(P_o, P_y) &= \max_{a^i \in \{0,1\}} \left\{ \left(\tilde{V}^i(P_o) - q^i\right) \cdot \mathbb{1}_{a^i=1} + \tilde{V}^i(P_y) \cdot \mathbb{1}_{a^i=0} \right\} \\ &= \tilde{V}^i(P_y) + \max_{a^i \in \{0,1\}} \left\{ \left(\tilde{V}^i(P_o) - \tilde{V}^i(P_y) - q^i\right) \cdot \mathbb{1}_{a^i=1} \right\}, \end{aligned}$$

where a^i encodes the choice of whether ($a^i = 1$) or not ($a^i = 0$) to manipulate. Thus, young individual i manipulates if and only if

$$q^i \leq \bar{q}^i(P_o, P_y) \equiv \tilde{V}^i(P_o) - \tilde{V}^i(P_y). \tag{1.1}$$

Preferences and fixed costs are distributed according to a continuously differentiable pdf $f(u^i, \phi^i, q^i)$. We denote the share of young individuals who manipulate – henceforth manipulators – by $M(P_o, P_y)$) and the benefit and nonemployment durations of manipulators and non-manipulators respectively by:

$$\begin{aligned} B^m(P_o, P_y) &= \mathbb{E}\left[B^i(P_o) | a^i(P_o, P_y)) = 1\right] \quad \text{and} \quad D^m(P_o, P_y)) = \mathbb{E}\left[D^i(P_o) | a^i(P_o, P_y)) = 1\right], \\ B^n(P_o, P_y)) &= \mathbb{E}\left[B^i(P_y) | a^i(P_o, P_y)) = 0\right] \quad \text{and} \quad D^n(P_o, P_y)) = \mathbb{E}\left[D^i(P_y) | a^i(P_o, P_y)) = 0\right]. \end{aligned}$$

The average benefit and nonemployment durations for the young are

$$\begin{aligned} B^y(P_o, P_y)) &= M(P_o, P_y)) \cdot B^m(P_o, P_y)) + \left(1 - M(P_o, P_y))\right) \cdot B^n(P_o, P_y))\big) \\ D^y(P_o, P_y)) &= M(P_o, P_y)) \cdot D^m(P_o, P_y)) + \left(1 - M(P_o, P_y))\right) \cdot D^n(P_o, P_y))\big), \end{aligned}$$

and we denote by $V^y(P_o, P_y) = \mathbb{E}\left[V^i(P_o, P_y)\right]$ the average utility of the young and use superscripts to denote conditional expectation operators.

1.2.1.4 The Planner's Problem

A benevolent social planner sets (P_o, P_y) to maximize ex-ante social welfare taking into account the incentive constraints, including the fact that manipulation might occur. Concretely, the planner's objective is given by:

$$W(P_o,P_y) \ = \ (1-G) \cdot V^o(P_o) + G \cdot V^y(P_o,P_y),$$

subject to the budget constraint:

$$L \cdot \tau \ = \ U \cdot b + R,$$

with total labor supply $L = (1-G)(T - D^o(P_o)) + G(T - D^y(P_y)) + GM(D^m(P_y) - D^m(P_o))$, total unemployment covered by unemployment benefits $U = (1-G)B^o(P_o) + GB^y(P_y) + GM(B^m(P_o) - B^m(P_y))$ and exogenous government spending R.

1.2.2 Simplifying Assumptions

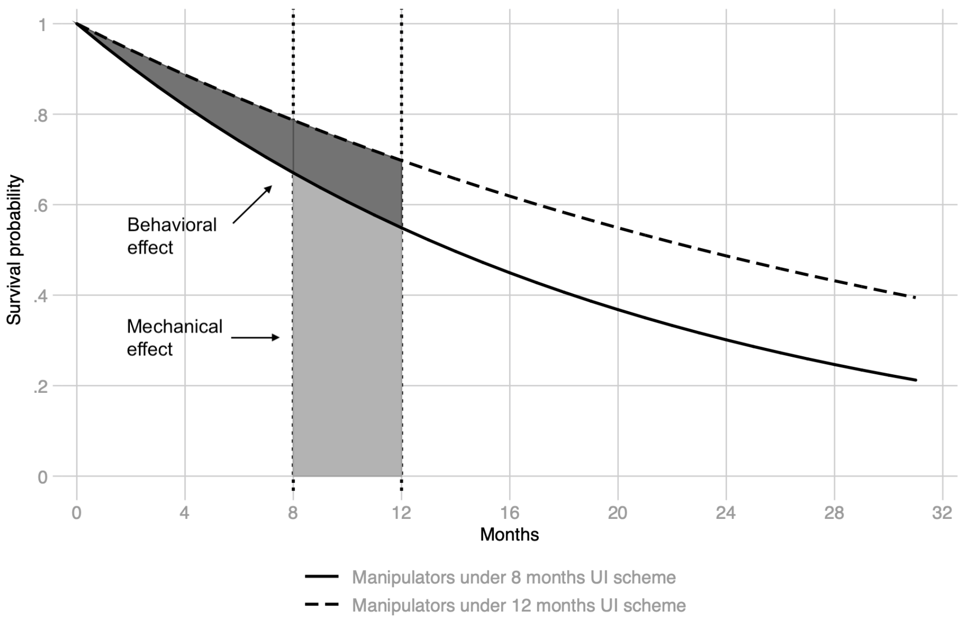
We assume that the planner's optimization problem is well-behaved warranting a first-order approach. In order to ease the exposition and gain tractability, we impose two additional simplifying assumptions: The first corresponds to a constant elasticity assumption while the second restricts dynamic screening opportunities. The formal derivations in Appendix 1.A make explicit how each assumption is used and how our results generalize. To state our assumptions precisely we introduce two key concepts for the analysis.

The first is a measure of the disincentive or moral hazard effect of UI in the context of extended potential benefit duration (PBD). Note that in the case of PBD, extra statutory coverage may mechanically lead to higher benefit receipts if individuals stay unemployed during the additional months with and without extra coverage. This cost increase for the government is not due to distorted job search incentives but simply reflects nonzero exhaustion risks during the relevant months of nonemployment. Because there is no distortion, such mechanical transfer is not, by itself, welfare relevant. What matters is by how much individuals change their behavior, and thereby increase the cost of UI, for each dollar of such mechanical transfers.

Concretely, we follow Schmieder and von Wachter (2017) and define the behavioral to mechanical cost ratio for individual i when marginally increasing PBD P as:

$$\frac{BC_P^i}{MC_P^i} \ = \ \frac{b \cdot \int_0^P \frac{dS_t^i}{dP} dt + \tau \cdot \int_0^T \frac{dS_t^i}{dP} dt}{b \cdot S_P^i}. \tag{1.2}$$

The above BC/MC ratio has a classical leaking bucket interpretation. It captures by how many additional dollars total UI expenditure goes up for each dollar of mechanical transfer from the government to the unemployed.[7] We illustrate BC/MC ratios graphically in Figure 1.1 and refer to it simply as moral hazard throughout.



Note: The figure displays two hypothetical nonemployment survival curves for manipulators, namely, under eight months of PBD (solid line) and twelve months of PBD (dashed line). The dashed line is above the solid line assuming that higher PBD lowers the exit hazard rate from nonemployment. The curves are simulated as negative exponentials with a constant hazard rate of 5% and 3%, respectively. The total increase in UI benefit receipt due to higher coverage (shaded areas) consists of two components: (1) a mechanical part (light grey area) which captures additional UI benefit payments that would occur even absent any behavioral change; (2) a behavioral component (dark grey area) which is due to a shift in the survival curve. The BC/MC ratio defined in equation (1.2) is given by the ratio of (2) and (1).

Figure 1.1. The Moral Hazard Cost of Extended UI Coverage

Second, we define the "marginal" utility of individual i at the point of benefit exhaustion $\tilde{u}'_i$ as

$$\tilde{u}'_i = \frac{1}{b}\int_0^b (u^i)'(c_u + x)dx = \frac{u^i(c_u + b) - u^i(c_u)}{b}. \qquad (1.3)$$

Since we are working with benefit duration extensions, the relevant utility gap is between receiving and not receiving UI benefits during unemployment (which

7. An important property of this measure of moral hazard is its comparability across different (groups of) individuals. This is especially important in the context of unemployment duration because individuals might have heterogeneous exhaustion risk and thus face different incentives to respond to PBD extensions. As in previous work, it turns out that it is precisely this re-scaled moral hazard effect that is relevant for optimal policy in our setting.

are the numeraire in the right-most term in equation (1.3)). We conveniently recast this gap into the appropriately weighted marginal utility. Note that neither consumption nor utilities are time dependent in the current setup which makes (1.3) time-invariant. However, it is straightforward to allow for time dependence in utility and consumption.

Equipped with the above concepts we impose the following assumptions. First, we assume a constant, i.e. time-invariant, moral hazard cost for the young. Concretely, we assume:

Assumption 1. Moral hazard is constant over the UI spell. Formally, for each I subset of the young we have

$$\frac{BC_P^I}{MC_P^I} = \frac{BC_{P'}^I}{MC_{P'}^I} \quad \text{for all } P, P'.$$

Second, we assume that exhaustion risks and marginal utilities are uncorrelated.

Assumption 2. Exhaustion risks and marginal utilities are uncorrelated: Formally, for all I subset of the young we have

$$\mathbb{C}ov^I\left[S_{\tilde{P}}^i, \tilde{u}_i'\right] = 0 \;\text{ for all }\; \tilde{P}.$$

Assumption 1 is akin to a constant elasticity assumption. It requires that the behavioral to mechanical cost ratio remains constant over the UI spell which intuitively assumes a time-invariant responsiveness to UI transfers. Assumption 2 implies that exhaustion risks are uninformative of marginal utilities. On the one hand, high-marginal utility individuals might have stronger incentives to find a job which would violate assumption 2. However, to the extent that unemployed individuals deplete their assets over the UI spell, marginal utilities might in fact increase over the spell which would push the correlation in the opposite direction. Assumption 2 thus requires that such forces exactly offset each other. Both assumptions are assumptions on individual behavior but also implicitly restrict the space of possible selection pattern among the young because they have to hold for each subset of the young.[8] This makes the analysis considerably more tractable but rules out dynamic screening possibilities. For instance, exhaustion risks cannot be used to dynamically screen high marginal utility individuals. We regard our simplified setup as a natural starting point for the analysis and leave its generalization to future work.

8. It suffices if assumptions 1 and 2 hold for all possible sets of manipulators and non-manipulators.

1.2.3 Characterizing Optimal Policies

We parameterize policy $(P_o, P_y) = (P + \Delta P, P)$, such that P represents the level of baseline coverage and $\Delta P \geq 0$ reflects the amount of extra coverage. Before turning to the full optimum, we briefly focus on two related (sub-)problems that help building intuition. First we look at the case without manipulation.

Optimum without Manipulation. In Appendix 1.A we show that the optimal policy in the absence of manipulation opportunities is given by:

Proposition 1 (Optimum without manipulation)**.** The optimal policy (P_o^*, P_y^*) without manipulation, i.e. $M \equiv 0$, satisfies:

$$\frac{\tilde{u}'_o - \bar{u}'}{\bar{u}'} = \frac{BC^o}{MC^o} \quad \text{and} \quad \frac{\tilde{u}'_y - \bar{u}'}{\bar{u}'} = \frac{BC^y}{MC^y},$$

where $\bar{u}' = (1-G) \cdot (T - D^o) \cdot (u^o)'(c_e) + G \cdot (T - D^y) \cdot (u^y)'(c_e)$ is the average marginal utility of the employed and $\tilde{u}'_j$ and $\frac{BC^j}{MC^j}$ defined in (1.3) and (1.2) for $j = y, o$.

Proposition 1 follows previous results in the literature on optimal UI benefit duration, e.g. Schmieder and von Wachter (2017). As in the classical Baily-Chetty formula, the optimal policy without manipulation equates consumption smoothing benefits with moral hazard costs for the old and the young *separately*.[9]

Introducing Manipulation. To build further intuition, we now study the introduction of manipulation by first imagining a world without the old, i.e. $G = 1$. The extra coverage ΔP now simply represents an alternative contract into which some of the young might self-select. As we show in Appendix 1.A, the (re-scaled) welfare effect of marginally increasing extra coverage ΔP starting from the case where there is none $\Delta P = 0$ is given by:

$$\frac{1}{M \cdot MC^m_{P_y} \cdot \bar{u}} \cdot \frac{dW}{d(\Delta P)}\bigg|_{\Delta P = 0} = \frac{\tilde{u}'_m - \bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m} \tag{1.4}$$

What matters for welfare at the margin is the insurance surplus, that is the difference between the consumption smoothing benefits and the moral hazard cost, of manipulators. It is instructive to evaluate this expression at the optimal manipulation-free policy P_y^* from Proposition 1.

Proposition 2 (The marginal welfare effect of manipulation at $\boldsymbol{P_y^*}$)**.** The marginal budget-balanced welfare effect of increasing extra coverage at P_y^* from Proposition

9. Note that the current setup imposes a common tax rate for the old and the young and the problem is thus not entirely separable across groups. It is straightforward to allow for different tax schedules across groups.

1 is given by:

$$\frac{1}{M \cdot MC^m_{P_y} \cdot \bar{u}} \cdot \frac{dW(P^*_y)}{d(\Delta P)}\Big|_{\Delta P=0} = \underbrace{\left(\frac{\tilde{u}'_m - \tilde{u}'_y}{\bar{u}'}\right)}_{\text{selection on consumption smoothing value}} - \underbrace{\left(\frac{BC^m}{MC^m} - \frac{BC^y}{MC^y}\right)}_{\text{selection on moral hazard cost}}$$

Proposition 2 shows that the welfare effect of additional coverage depends on the extent to which manipulators are selected on consumption smoothing value and moral hazard cost at the optimally set manipulation-free policy P^*_y. If manipulators have higher insurance surplus than the average young individual, manipulation increases welfare and vice versa. This result mimics that of Hendren, Landais, and Spinnewijn (2020) who study the welfare effect of allowing for choice in a social insurance context.[10]

It turns out that selection effects, like the one in Proposition 2, remain crucial for determining the full optimal policy with manipulation which we turn to next.

Optimum with Manipulation. We now analyze the design of optimal policy in the presence of both groups young and old, i.e. $G \in (0,1)$ *and* with (potential) nonzero manipulation. At the optimum, small budget-neutral changes $d\Delta P$ in extra coverage ΔP which cannot increase welfare. In Appendix 1.A we show that this implies

$$\begin{aligned}(1-G) \cdot S^o_{P_o} \cdot \left[\frac{\tilde{u}'_o - \bar{u}'}{\bar{u}'} - \frac{BC^o}{MC^o}\right] + G \cdot M \cdot S^m_{P_o} \cdot \left[\frac{\tilde{u}'_m - \bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m}\right] \\ + G \cdot (1-M) \cdot S^n_{P_y} \cdot \epsilon_{1-M,\Delta P} = 0,\end{aligned} \tag{1.5}$$

where all variables are defined as above and $\epsilon_{1-M,\Delta P}$ refers to the cost-weighted elasticity of manipulation w.r.t. extra coverage ΔP which we define formally below. Equation (1.5) generalizes equation (1.4) by introducing two additional terms (the first and third term). The first term takes into account that the old, who are always entitled to receiving higher coverage P_o, have a direct welfare effect from increases in extra coverage. The third terms captures the fact that marginal manipulators might cause non-marginal changes in the government budget, because we are no longer starting at a point without any additional coverage. Concretely, define the fiscal externality from manipulation, that is the budgetary cost arising from higher benefit receipt and lower tax revenue, of all individuals of type $i = (u_i, \phi_i)$ as

$$FE^i = \left(B^i(P+\Delta P) - B^i(P)\right) \cdot b + \left(D^i(P+\Delta P) - D^i(P)\right) \cdot \tau \tag{1.6}$$

10. While Hendren, Landais, and Spinnewijn (2020) are interested in price surcharges required for extra coverage, a feature one could also include in our setup, we model manipulation as an entirely private choice without any *direct* financial implications for the government. The manipulation fixed cost q^i is relevant for individual utilities but not for government revenue.

and the share of these individuals who end up manipulating because their fixed cost falls below the threshold $\bar{q}^i$ in equation (1.1), as

$$M^i = \int_0^{\bar{q}^i} f(q|u_i, \phi_i)dq. \tag{1.7}$$

Equipped with these two quantities we formally define the cost-weighted elasticity of manipulation w.r.t. extra coverage introduced in equation (1.5) as follows

$$\epsilon_{1-M,\Delta P} = \mathbb{E}^n \left[\frac{FE^i}{MC^n_{P_y} \cdot \Delta P} \cdot \epsilon_{1-M^i,\Delta P} \right]. \tag{1.8}$$

Thus the elasticity term captures by how much each share M^i, as measured by $1 - M^i$, responds to increases in extra coverage weighted by the cost that such changes impose on the government budget.

Turning to the optimal level of baseline coverage, we again have that at the optimum, marginal budget-neutral changes dP in baseline coverage P cannot increase welfare. As shown in Appendix 1.A, by the envelope theorem this implies

$$\begin{aligned} &(1-G) \cdot S^o_{P_o} \cdot \left[\frac{\tilde{u}'_o - \bar{u}'}{\bar{u}'} - \frac{BC^o}{MC^o} \right] + G \cdot S^y_{P_y} \cdot \left[\frac{\tilde{u}'_y - \bar{u}'}{\bar{u}'} - \frac{BC^y}{MC^y} \right] \\ &+ G \cdot M \cdot \left(S^m_{P_o} - S^m_{P_y} \right) \cdot \left[\frac{\tilde{u}'_m - \bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m} \right] + G \cdot (1-M) \cdot S^n_{P_y} \cdot \epsilon_{1-M,P} = 0, \end{aligned} \tag{1.9}$$

where $\epsilon_{1-M,P}$ is the cost-weighted elasticity of manipulation w.r.t. baseline coverage P, defined analogously as in equation (1.8) but with respect to baseline coverage P. Intuitively, when deciding how much baseline coverage to provide, the planners weighs the surplus from the old (first term), the young (second term), an adjustment accounting for the fact that a subset of the young are in fact manipulators with now different exhaustion risk (third term) and the effect of baseline coverage on the extent of manipulation (fourth term).

Combining equations (1.5) and (1.9) leads to our main proposition regarding the optimal policy under manipulation.

Proposition 3 (Optimum with manipulation)**.** The optimal policy with manipulation satisfies:

$$\frac{\tilde{u}'_y - \bar{u}'}{\bar{u}'} - \frac{BC^y}{MC^y} = \underbrace{\epsilon_{1-M,\Delta P}}_{\substack{\text{manipulation externality}\\ \text{of extra coverage}}} - \underbrace{\epsilon_{1-M,P}}_{\substack{\text{manipulation externality}\\ \text{of baseline coverage}}}$$
$$+ M \cdot \underbrace{\left(\frac{S^m_{P_y}}{S^y_{P_y}}\right)}_{\substack{\text{selection on risk}\\ \text{scale factor}}} \cdot \left\{ \underbrace{\left(\frac{\tilde{u}'_m - \tilde{u}'_n}{\bar{u}'}\right)}_{\substack{\text{selection on consumption}\\ \text{smoothing value}}} - \underbrace{\left(\frac{BC^m}{MC^m} - \frac{BC^n}{MC^n}\right)}_{\substack{\text{selection on moral}\\ \text{hazard cost}}} \right\} \tag{1.10}$$

and

$$(1-G) \cdot S^o_{P_o} \cdot \left(\frac{\tilde{u}'_o - \bar{u}'}{\bar{u}'} - \frac{BC^o}{MC^o}\right) + G \cdot S^y_{P_o} \cdot \left(\frac{\tilde{u}'_y - \bar{u}'}{\bar{u}'} - \frac{BC^y}{MC^y}\right)$$
$$= G \cdot (1-M) \cdot \left(\left(S^n_{P_o} - S^n_{P_y}\right) \cdot \epsilon_{1-M,\Delta P} - S^n_{P_o} \cdot \epsilon_{1-M,P}\right) \tag{1.11}$$

First note that without manipulation, i.e. $M \equiv 0$, Proposition 3 nests Proposition 1. However, the presence of manipulation induces a wedge in the provision of insurance for both young and old. Equation (1.10) shows that the wedge for the young is determined by two elasticities, namely that of extra and baseline coverage, and by a selection term, capturing the extent to which manipulators are selected on consumption smoothing value and moral hazard cost. Equation (1.11) implies that the wedge for the old is the direct counterpart of that for the young together with an effect on the overall level of insurance (RHS). In order to build intuition, it is instructive to consider two special cases.

Fixed, nonzero M. First, consider a scenario in which a fixed subset of young individuals manipulate irrespectively of policy and always obtain higher UI coverage. In this case the share M is nonzero and unresponsive to the design of UI. As a consequence, all elasticity terms in Proposition 3 are zero. It is straightforward to show that equation (1.10) implies that

$$\frac{\tilde{u}'_n - \bar{u}'}{\bar{u}'} - \frac{BC^n}{MC^n} = 0, \tag{1.12}$$

which means that consumption smoothing benefits and moral hazard cost for non-manipulators or the 'endogenous young' are equated. Similarly equation (1.5) shows the same holds true for the 'endogenous old', i.e. the group of the old and manipulators. Note that equation (1.11) implies that such manipulation induces no distortion in the desired overall level of insurance. Intuitively, this is a case of pure re-labelling, in which the planner regards a subset of the young as old because their manipulation choice is unresponsive to policy.

Homogeneous young. Suppose there is no heterogeneity among the young, except potentially in their manipulation fixed cost. In this case the selection term in equation (1.10) vanishes and the wedge of the young is governed only by the two elasticities. If one assumes that additional coverage weakly increases the share of manipulators and that additional baseline coverage weakly decreases it, then the wedge of the young is unambiguously negative, calling for overinsurance. Intuitively, it is optimal for the planner to grant the young additional surplus, above and beyond their manipulation-free level, because of their manipulation threat. To the extent that additional coverage mitigates manipulation the planner finds it optimal to provide such insurance to the young. Contrary, by equation (1.11), the old will be underinsured by more than the wedge for the young representing the fact that shifting insurance surplus is now costly due to the fiscal externality associated with manipulation.

1.2.4 Connecting Theory and Empirics

This section lays out how to connect our theoretical framework to the data. There are several points worth emphasizing. First and foremost, the purpose of our theory is to guide the design of differentiated policy w.r.t. a *given* endogenous tag, not for choosing among several potential tags or assessing their appropriateness more generally. A full implementation of proposition 3 would nevertheless reveal whether or not differentiation w.r.t. to a tag has any potential benefit or if the optimal policy is in fact undifferentiated. Finding out which heterogeneities allow welfare-improving targeting in different policies is a fruitful avenue for future research, although policy makers might ultimately refrain from exploiting some of them, because of e.g. administrative costs or horizontal equity and fairness concerns.[11]

Second, our theory takes the *degree* of initial differentiation, that is, the grouping of individuals, in our setup two groups of young and old, as given. This has important consequences for any empirical implementation in which the classification itself is a policy choice. Our theory does not directly speak to the optimal classification but rather analyses the effect of manipulation for a given grouping of individuals. This implies that any statement about the welfare-relevance of manipulation is always with respect to a reference degree of differentiation, over which there might be empirical ambiguity.

To illustrate this point, consider a scenario in which group membership is defined by a cutoff rule in some cardinal individual characteristic which can be manipulated by individuals at some cost, as will be the case in our empirical application below. If the manipulation cost increases with distance form the threshold, manipulation will tend to be locally concentrated around the threshold. Whether or not manipulation matters for welfare in this setting depends on the definition of what constitutes the relevant groups. For instance, if a large number of individuals is located far away from the threshold and one considers all of these individuals as part

11. Although not part of the current model, it is straightforward to incorporate other objectives, e.g. welfare weights, in the analysis.

of the two groups, one might trivially conclude that manipulation is not globally welfare-relevant, essentially because $M \approx 0$. However, this is precisely the case in which the policy is a two-part policy in a large population and thus not very ambitiously targeted. The importance of manipulation increases mechanically with the degree of differentiation, *ceteris paribus*. The smaller the group of targeted individuals the more relevant manipulation effects become, because it is easier for the share M of manipulators to rise to meaningful levels.

Third and relatedly, given that there is no "correct" classification, our empirical application focuses on developing a methodology to estimate the empirical moments in Proposition 3, rather than to provide a welfare assessment of any one particular policy. We do point out explicitly how to connect our estimates to the theory as well as which other moments might be of interest. Concretely, we illustrate how bunching techniques can be used to reveal the extent of selection on moral hazard even in the absence of policy reforms. Although of equal theoretical interest, we lack the data, variation and methods to estimate the corresponding selection on value counterpart.[12] We do discuss some tentative findings based on our selection on observables analysis in Section 1.3.2.4.

1.3 Empirics: Manipulation in Italian Unemployment Insurance

1.3.1 The Italian Unemployment Insurance Scheme

1.3.1.1 Institutional Setting

We study manipulation in Italy's *Ordinary Unemployment Benefits* (OUB) scheme.[13] The OUB was in effect from the late 1930s until its abolishment and replacement in January 2013.[14] OUB covered all private non-farm and public sector employees who lost their job either due to the termination of their temporary contract, or due to an involuntary termination (a layoff), or a quit for just cause, such as unpaid wages or harassment. Other types of voluntary quits and the self-employed were not eligible for OUB.[15]

12. Identifying and estimating the consumption smoothing benefit of UI has proven a considerable challenge in the literature by itself. Our setting features two additional complications: the fact that we are interested in estimating the difference in marginal utilities between two groups of individuals and that this gap is measured at the respective time of benefit exhaustion. We are unaware of any work which estimates marginal utilities of UI exhaustees directly.

13. *Indennità di Disoccupazione Ordinaria a Requisiti Normali* in Italian. We are not the first to study the Italian OUB scheme, see e.g. Anastasia, Mancini, and Trivellato (2009), Scrutinio (2018) and Albanese, Picchio, and Ghirelli (2020), of which we discuss the last in more detail in Appendix 1.C.

14. OUB was introduced through *Regio Decreto 14.* in April 1939 and replaced by ASPI on of January 1, 2013.

15. For convenience, in the rest of the paper we will use the term "layoff" to indicate all job terminations that are eligible for UI.

To qualify for OUB, workers were also required to have some labor market attachment. Concretely, workers needed to have started their first job spell at least two years before the date of layoff, and to have worked for at least 52 weeks in the previous two years.[16]

Benefit levels were based on the average monthly wage, calculated over the three months preceding the layoff. The replacement rate was declining over the unemployment spell: 60% of the average wage for the first six months; 50% for the following two months and 40% for any remaining period. OUB did not involve any form of experience rating.

PBD under OUB was a sole function of age at layoff and amounted to eight months if the layoff preceded the worker's fiftieth birthday and twelve months if it followed it. This discontinuous change (a notch) in coverage created a strong incentive for workers to delay their date of layoff so that it falls after their fiftieth birthday.

1.3.1.2 Data

We use confidential administrative data from the Italian Social Security Institute (INPS) on the universe of UI claims in Italy between 2009 and 2012 and combine them with matched employer-employee records covering the universe of working careers in the private sector. Information on UI claims comes from the SIP database,[17] which collects data on all income support measures administered by INPS as a consequence of job separation. For every claim we observe the UI benefit scheme type, its starting date, duration and amount paid. We further observe information related to the job and the firm. This includes details about the type of the contract and a broad occupation category.

The SIP database does not contain the date of re-employment after receiving UI. We therefore retrieve this information from the matched employer-employee database (UNIEMENS) and construct nonemployment durations as the time difference between the layoff date in the SIP and the first re-employment in UNIEMENS.[18] The UNIEMENS database provides additional information on workers' careers in the private sector, including detailed information on wages and the type of contract. We observe individuals in the UNIEMENS database until 2016, which gives us at least four years of observations for all workers. We therefore censor all nonemployment durations at this horizon.

16. Two other UI benefit schemes were in place in Italy at the same time of our analysis: Reduced Unemployment Benefits (RUB) and Mobility Indemnity (MI). However, neither one is likely to interfere with our analysis due to different eligibility conditions and less generous benefit coverage. For completeness, we present the two other UI schemes in Appendix 1.B.

17. *Sistema Informativo Percettori* in Italian.

18. We restrict the latter to be later than the former, which excludes a few short-term jobs that are compatible with the continuation of UI benefit receipt.

For our main sample we restrict our attention to individuals who lost their job between February 2009 and December 2012, were between 46 and 54 years of age at the time of layoff, and claimed OUB. Unfortunately, our data does not cover the years prior to February 2009 and the introduction of a new UI scheme in January 2013 prevents us from including later years. We further restrict attention to individuals who separate from an employer in the private sector after a permanent contract. The motivation for this is twofold. First, we show in Section 1.3.2.4 that manipulation is confined to permanent contracts in the private sector. Second, the UNIEMENS database does not contain job information for public sector jobs, which means we have no information about the previous work arrangement, nor would we observe re-employment. At this point, one might be worried that we are missing some re-employment events, namely, those into public sector jobs. This in unlikely to affect our results because transitions from private into public sector jobs should be rare for workers at such late stage in their careers. After the exclusion of a few observations with missing key information we are left with 249,581 separation episodes that led to UI claims.

Table 1.1 reports summary statistics for our main sample. The average worker receives UI for about 30 weeks (7 months) corresponding to roughly one third of the 90 weeks (21 months) average nonemployment duration. An average of 50% and 39% of workers are still nonemployed after eight and twelve months, respectively, implying substantial exhaustion risk. Our sample of workers is predominately male, on full-time contracts, and employed in blue-collar jobs. Workers have spent about 27.5 years in the labor market since their first job and almost 6 years in their last firm. In terms of geographic distribution, 46% of workers are laid off in the South or the Islands.[19] Workers earned about 70 Euro per day (gross) which is equivalent to $70 \times 26 = 1820$ Euro per month if working full-time.[20] The separating firm is relatively old (14 years) and large (28.16 employees), but this is driven by a few very large firms. Indeed, more than 60% of workers come from firms with less than 15 employees while only 18% come from firms with more than 50 employees. Because our main sample contains workers in their late forties and early fifties, one might be concerned that transitions into retirement could play a non-negligible role. However, this is not the case with only about 1,500 or 0.6% of workers in our sample claiming retirement benefits before the end of our observation window (4 years since layoff).[21] We now turn to a description of our objects of interest and identification strategy.

19. This area encompasses the following regions: Abruzzo, Basilicata, Calabria, Molise, Puglia, Sardegna and Sicilia.

20. This information is consistent with the monthly wage reported in our second data source, the SIP database, which reports an average monthly wage of 1,735 Euro in the three months preceding the layoff.

21. For these workers we define the nonemployment spell as the period between the end of the previous employment and the date at which they claim their pension.

Table 1.1. Summary Statistics

	Mean	SD	Min	Max
Nonemployment outcomes				
UI Benefit receipt duration (in weeks)	29.853	15.923	0.14	52.00
Nonemployment duration (in weeks)	89.995	79.092	0.00	208.00
Nonemployment survival prob. 8 months	0.502	0.500	0.00	1.00
Nonemployment survival prob. 12 months	0.388	0.487	0.00	1.00
Individual characteristics				
Female (share)	0.311	0.463	0.00	1.00
Experience (in years)	27.656	8.552	2.00	40.00
White-collar (share)	0.208	0.406	0.00	1.00
North (share)	0.367	0.482	0.00	1.00
Center (share)	0.174	0.379	0.00	1.00
South and islands (share)	0.459	0.498	0.00	1.00
Previous job characteristics				
Full-time (share)	0.807	0.395	0.00	1.00
Tenure (in years)	5.931	6.113	0.08	30.00
Daily income (in Euro)	69.900	70.300	0.04	13,981.01
Firm age (in years)	14.367	12.115	0.00	109.83
Firm size	28.158	259.010	1.00	14,103.00
Firm size below 15 (share)	0.606	0.489	0.00	1.00
Firm size between 15 and 49 (share)	0.213	0.409	0.00	1.00
Firm size above 49 (share)	0.181	0.385	0.00	1.00

Note: The table reports summary statistics of our main sample consisting of all OUB claims from Feb 2009 to Dec 2012 from individuals who are employed in permanent private sector work arrangements and are between 46-54 years of age at the time of layoff. The sample contains a total of 249,581 nonemployment spells from 210,041 individual workers. Nonemployment duration is censored at four years and defined as the time distance between the date of layoff and the date of the first re-employment event that leads to UI benefit termination. Experience is equal to the number of years since the first social security contribution. Tenure is defined as the total number of years (not necessarily uninterrupted) spent with the last employer. The geographical South and Islands dummy encompasses employment in one of the following regions: Abruzzo, Basilicata, Calabria, Molise, Puglia, Sardegna and Sicilia.

1.3.2 Empirical Strategy

This section sketches our empirical strategy and explains the sources of variation in the data that we use to pin down different parameters of interest. The main idea is to exploit the local nature of manipulation by extrapolating outcomes from regions that are unaffected by it, to learn about what would have happened in a counterfactual world without it. We first assess the range of the manipulation region with standard bunching techniques. We then fit polynomials to the unmanipulated part of the data and interpolate to construct a counterfactual layoff frequency and recover the number (and share) of manipulators. Similarly, we construct counterfactuals of outcomes that are not directly manipulated, such as subsequent benefit receipt or nonemployment survival probabilities, to learn whether these outcomes respond to manipulation. Intuitively, any unusual change in these outcomes near the cutoff together with how many manipulators are causing it, let us recover manipulators' responses. Under plausible assumptions, we also recover the response of non-manipulators, a group of individuals laid off just before their fiftieth birthday. We also illustrate how we can use part of the procedure just described to study selection into manipulation. Our approach is closely related to that of Diamond and Persson (2016).

1.3.2.1 Quantifying manipulation

Consider a hypothetical manipulated layoff density as in Figure 1.2a. Absent any manipulation we would expect the frequency of layoffs to be smooth in the neighborhood of the cutoff. Manipulation instead causes a sharp drop in the number or layoffs right before and a spike right after age fifty. We refer to the first region as the "missing" and the later the "excess" region which together make up the "manipulation" region. As in standard bunching techniques, we recover the counterfactual frequency of layoffs by fitting a polynomial to the unmanipulated parts of the data (on the left and right of the cutoff) and interpolate inwards. The difference between the observed frequency and the fitted counterfactual lets us recover missing and excess shares, as well as the number of manipulators in the missing and excess regions. This estimation strategy assumes that manipulation takes the form of a pure re-timing of layoffs that would have occurred anyways and for which we provide supporting evidence in Section 1.3.3.6.

We operationalize this identification strategy following standard bunching techniques, e.g. Saez (2010), Chetty, Friedman, Olsen, and Pistaferri (2011), Kleven and Waseem (2013). First, we group all layoffs into two-week bins based on the workers' age at layoff. Second, we determine the lower bound of the missing region z_L by visual inspection, in our case three bins or six weeks. Last, we iteratively try different upper bounds for the excess region z_U until we balance the missing and excess "mass", that is, the estimated number of manipulators on either side of the threshold. We estimate the number of manipulators by fitting a second order polynomial to the observed layoff frequency, including a full set of dummies for bins in the manipulation region, and retrieving the relevant regression coefficients. In practice, we estimate the following specification:

$$c_j = \alpha + \sum_{p=0}^{P} \beta_p \cdot a_j^p + \sum_{k=z_L}^{z_U} \gamma_k \cdot \mathbb{I}[a_j = k] + \nu_j, \tag{1.13}$$

where c_j denotes the absolute frequency of layoffs in headcounts in bin j, a_j is the mid-point age in bin j, P denotes the order of the polynomial. The coefficients γ_k recover the differences between the observed data and the counterfactual frequency in the manipulation region $[z_L, z_U]$. Using hat-notation to denote regression coefficients, our estimate for the number of manipulators in the missing and excess region, respectively, is given by:

$$N_{\text{mani}}^{\text{missing}} = \sum_{k \in \text{missing}} |\hat{\gamma}_k| \quad \text{and} \quad N_{\text{mani}}^{\text{excess}} = \sum_{k \in \text{missing}} \hat{\gamma}_k. \tag{1.14}$$

Note that $\hat{\gamma}_k < 0$ if k belongs to the missing region, while $\hat{\gamma}_k > 0$ if it belongs to the excess region. We repeat the above procedure for different values of z_U until $N_{\text{mani}}^{\text{missing}} \approx N_{\text{mani}}^{\text{excess}}$. In our application we estimate a manipulation region consisting of three bins (six weeks) for the missing and two bins (four weeks) for the excess region.

Because they will be useful in the next steps, let us define estimates for the number of non-manipulators, which is an observable quantity, and the number of individuals in the excess regions who are not manipulators, respectively, as:

$$N_{\text{non-mani}}^{\text{missing}} = \sum_{k \in \text{missing}} c_k \quad \text{and} \quad N_{\text{w/o mani}}^{\text{excess}} = \sum_{k \in \text{excess}} c_k - \hat{\gamma}_k. \tag{1.15}$$

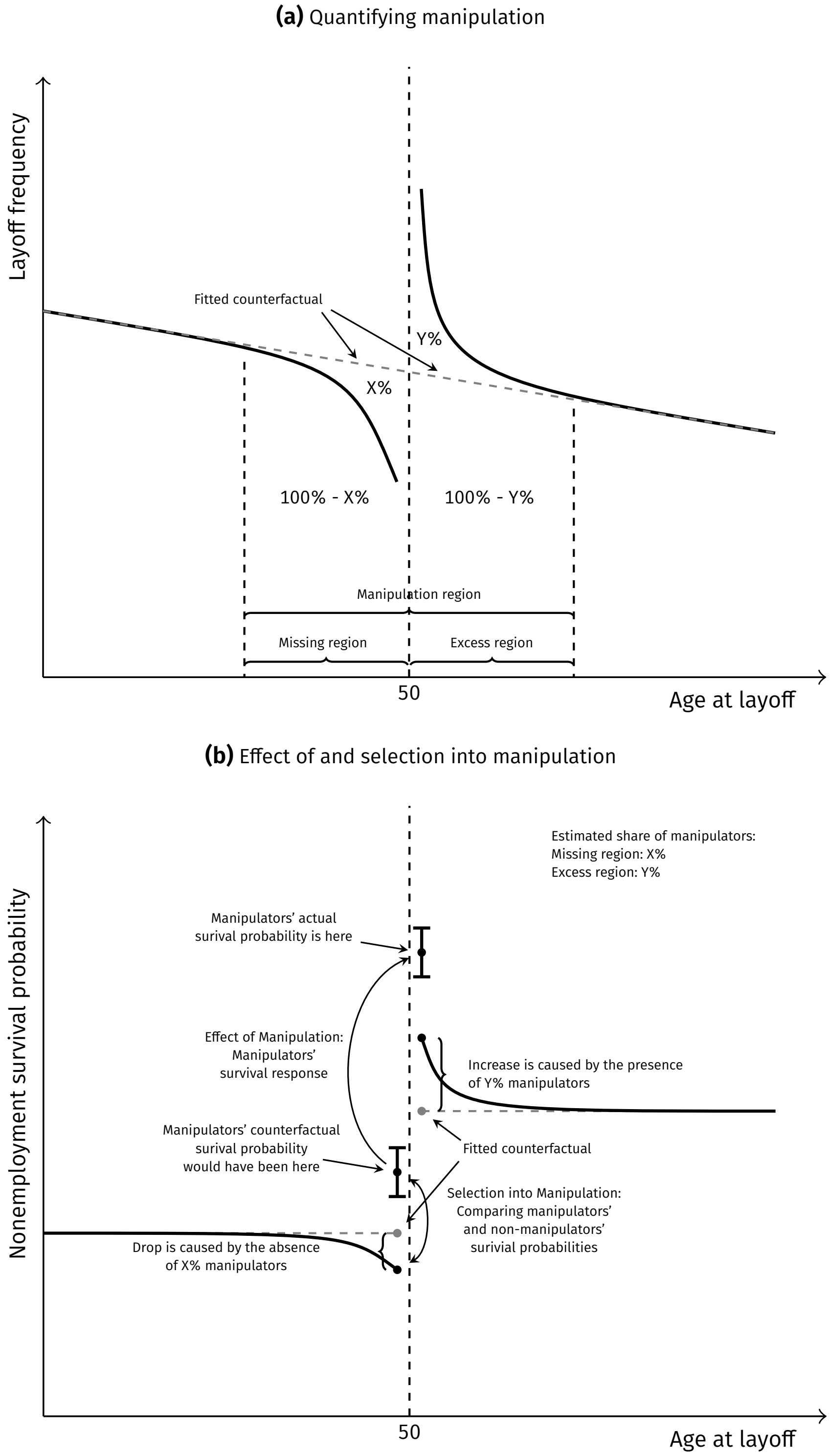
Note that we deliberately reserve the term “non-manipulator” for individuals in the missing region who at least in principle could have engaged in manipulation but did not. Given the total headcounts, it is straightforward to compute the share of manipulators in the missing and excess region, respectively, as follows:

$$s^{\text{missing}} = \frac{N_{\text{mani}}^{\text{missing}}}{N_{\text{mani}}^{\text{missing}} + N_{\text{non-mani}}^{\text{missing}}} \quad \text{and} \quad s^{\text{excess}} = \frac{N_{\text{mani}}^{\text{excess}}}{N_{\text{mani}}^{\text{excess}} + N_{\text{w/o mani}}^{\text{excess}}}. \tag{1.16}$$

Analogously, we define the share of manipulators in age bin k by:

$$s_k^{\text{missing}} = \frac{|\hat{\gamma}_k|}{|\hat{\gamma}_k| + c_k} \text{ for } k \in \text{missing} \quad \text{and} \quad s_k^{\text{excess}} = \frac{\hat{\gamma}_k}{c_k} \text{ for } k \in \text{excess}. \tag{1.17}$$

Equipped with a measure of the size of manipulation, we now turn to studying affected outcomes.



Note: The figure visualizes our identification strategy. Panel (a) illustrates how we estimate the number and respective share of manipulators in both the missing and excess region. Panel (b) constructs manipulators' survival response and illustrates the relevant comparison when studying selection into manipulation. Section 1.3.2 lays out how we estimate the fitted counterfactuals in practice.

Figure 1.2. Illustration of Identification Strategy

1.3.2.2 Effects of manipulation

This section outlines our empirical strategy for studying outcome variables that are not directly manipulated but could potentially be affected by manipulation. Figure 1.2b illustrates the idea for one of our outcomes of interest: nonemployment survival rates. Manipulation provides workers with additional UI coverage from month eight to twelve. Thus, it is likely that nonemployment survival rates respond to the increase in coverage. Consider a hypothetical statistical relationship between nonemployment survival and age at layoff, as in Figure 1.2b. In order to estimate how manipulators' survival rate responds, we take the difference between two quantities: manipulators' actual survival probability and manipulators' counterfactual survival probability had they not been able to manipulate. As illustrated in Figure 1.2b, we obtain these quantities by separately studying the missing and excess region. First, we fit a flexible counterfactual on the right-hand side of the threshold and estimate the difference between the observed and predicted survival rates to assess manipulators' actual survival probability. Intuitively, survival rates in the excess region are higher than predicted by the un-manipulated region to the right only due to manipulation. The extent to which observed and predicted nonemployment survival rates differ, together with an estimate of how many manipulators are causing this difference, let us recover manipulators' actual nonemployment survival probability. We use analogous arguments to back out manipulators' counterfactual nonemployment survival probability on the left-hand side of the threshold.

In practice, we start by running the following regression on individual-level data:

$$\begin{aligned} y_i = \ & \alpha + \sum_{p=1}^{P} \beta_p^{\leq 50} \cdot a_i^p \cdot \mathbb{I}[a_i \leq 50] + \sum_{p=0}^{P} \beta_p^{>50} \cdot a_i^p \cdot \mathbb{I}[a_i > 50] + \\ & + \sum_{k=z_U}^{z_L} \delta_k \cdot \mathbb{I}[a_i = k] + \xi_i, \end{aligned} \tag{1.18}$$

where y_i is the outcome of interest, e.g. weeks of UI benefit receipt or probability of still being nonemployed eight months after the layoff, $\beta_p^{\leq 50}$ and $\beta_p^{>50}$ are coefficients of two P-th degree polynomials in age, that are estimated based on information from the left-hand side and right-hand side, respectively. Due to the inclusion of $\mathbb{I}[a_i = k]$ indicator variables, the counterfactual polynomial is estimated as if we were excluding observations from the manipulation region $[z_L, z_U]$. The coefficients δ_k capture the difference in average outcomes between the observed data and the estimated counterfactual in the manipulation region.

Specification (1.18) allows for a treatment effect of longer PBD on outcomes, i.e. $\beta_0^{>50}$. We refer to $\beta_0^{>50}$ as the "donut" regression discontinuity (RD) coefficient. This coefficient captures the treatment effect of four additional months of PBD for the average individual in the population, as in Barreca, Guldi, Lindo, and Waddell (2011) and Scrutinio (2018).[22] We use it to benchmark our results for the response of manipulators (more on this below). Graphically, $\beta_0^{>50}$ recovers the difference between the two grey dots in Figure 1.2b.

The central idea of our estimation strategy is the re-scaling of the estimated differences ($\hat{\delta}_k$) by the respective share of manipulators. Formally, let Y denote our outcome of interest and $\bar{Y}_l^j$ its average over individuals l in region j. For each bin k in the missing region, we may calculate the difference in average outcomes between manipulators and non-manipulators as:[23]

$$\bar{Y}^{\text{missing}}_{\text{non-mani},k} - \bar{Y}^{\text{missing}}_{\text{mani},k} = \frac{\hat{\delta}_k}{s_k^{\text{missing}}}. \tag{1.19}$$

Note that the average outcome of non-manipulators in bin k is observable and given by

$$\bar{Y}^{\text{missing}}_{\text{non-mani},k} = \frac{\sum_{i=1}^{N} y_i \cdot \mathbb{I}[a_i = k]}{c_k}, \tag{1.20}$$

which allows us to recover manipulators' counterfactual outcome in bin k as

$$\bar{Y}^{\text{missing}}_{\text{mani},k} = \frac{\sum_{i=1}^{N} y_i \cdot \mathbb{I}[a_i = k]}{c_k} - \frac{\hat{\delta}_k}{s_k^{\text{missing}}} \tag{1.21}$$

and manipulators average counterfactual outcome over the entire missing region as

$$\bar{Y}^{\text{missing}}_{\text{mani}} = \frac{1}{N^{\text{missing}}_{\text{mani}}} \sum_k |\hat{\gamma}_k| \cdot \bar{Y}^{\text{missing}}_{\text{mani},k}. \tag{1.22}$$

The logic behind this re-scaling is straightforward: if we found that the absence of 10% of individuals in the missing region, namely the manipulators, resulted in a 100 unit drop starting from a predicted counterfactual of 1000 units, we could infer that the now missing individuals must have had an outcome of $\frac{1000-0.9\times(1000-100)}{0.1} =$ 1900 units on average.

22. Alternatively one could derive bounds on the average treatment effect following the method of Gerard, Rokkanen, and Rothe (2020). Because manipulation is clearly visible and locally confined in our setting we use a "donut" regression discontinuity design.

23. Indeed, we can write the coefficient $\hat{\delta}_k$ as:

$$\hat{\delta}_k = \bar{Y}^{\text{missing}}_{\text{non-mani},k} - \left(s_k \bar{Y}^{\text{missing}}_{\text{mani},k} - (1 - s_k)\bar{Y}^{\text{missing}}_{\text{non-mani},k}\right)$$

which after some rearrangement leads to our equation 1.19.

Following an analogous argument on the right-hand side of the age cutoff, we first re-scale the regression coefficient for bin k to obtain

$$\bar{Y}^{\text{excess}}_{\text{mani},k} - \bar{Y}^{\text{excess}}_{\text{w/o mani},k} = \frac{\hat{\delta}_k}{s^{\text{excess}}_k}. \tag{1.23}$$

Notice that the observable average outcome in bin k in the excess region has to satisfy

$$\bar{Y}^{\text{excess}}_{\text{observed},k} = \frac{\sum_{i=1}^{N} y_i \cdot \mathbb{I}[a_i = k]}{c_k} = \frac{\hat{\gamma}_k \cdot \bar{Y}^{\text{excess}}_{\text{mani},k} + (c_k - \hat{\gamma}_k) \cdot \bar{Y}^{\text{excess}}_{\text{w/o mani},k}}{c_k}. \tag{1.24}$$

Combining the two expressions above and rearranging terms gives us an estimate of manipulators' actual outcome in the form of

$$\bar{Y}^{\text{excess}}_{\text{mani},k} = \frac{\sum_{i=1}^{N} y_i \cdot \mathbb{I}[a_i = k]}{c_k} + (1 - s^{\text{excess}}_k) \cdot \frac{\hat{\delta}_k}{s^{\text{excess}}_k}, \tag{1.25}$$

for bin k in the excess region. We again calculate manipulators' average actual outcome over the entire excess region by

$$\bar{Y}^{\text{excess}}_{\text{mani}} = \frac{1}{N^{\text{excess}}_{\text{mani}}} \cdot \sum_k \hat{\gamma}_k \cdot \bar{Y}^{\text{excess}}_{\text{mani},k}, \tag{1.26}$$

which, together with equation (1.22) lets us define manipulators' response (or treatment effect) as

$$Y^{TE}_{\text{mani}} \equiv \bar{Y}^{\text{excess}}_{\text{mani}} - \bar{Y}^{\text{missing}}_{\text{mani}}. \tag{1.27}$$

Note that this strategy identifies the average response of a manipulator without recovering by how many weeks each individual manipulator delayed their layoff.

1.3.2.3 Recovering Responses of Non-manipulators

Having obtained an estimate of manipulators' response, we benchmark these results against the implied response of non-manipulators. As noted above, $\hat{\beta}_0^{>50}$ is an estimate of the effect of four additional months of PBD for an average individual who is moved over the threshold exogenously, i.e. without manipulation. Assuming that manipulators would have shown the same response to additional PBD coverage had they been moved over the threshold exogenously, instead of through manipulation, we can decompose the response for the average individual as follows:

$$s^{\text{missing}} \cdot Y^{TE}_{\text{mani}} + (1 - s^{\text{missing}}) \cdot Y^{TE}_{\text{non-mani}} = \hat{\beta}_0^{>50}. \tag{1.28}$$

A fraction of s^{missing} of the estimated jump in the polynomial $\hat{\beta}_0^{>50}$ is due to the response of manipulators, the remaining $(1 - s^{\text{missing}})$ has to be due to the response of non-manipulators. Rearranging thus gives us an estimate for non-manipulators' response:

$$Y^{TE}_{\text{non-mani}} = \frac{\hat{\beta}_0^{>50} - s^{\text{missing}} \cdot Y^{TE}_{\text{mani}}}{1 - s^{\text{missing}}}. \tag{1.29}$$

1.3.2.4 Selection into manipulation.

The procedure illustrated in Figure 1.2b also lets us study selection into manipulation by comparing manipulators' counterfactual outcomes to non-manipulators realized outcomes. Figure 1.2b highlights this comparison and would suggest that even absent manipulation, manipulators would have had a higher nonemployment survival rate than non-manipulators due to the drop in the outcome variable to the left of the cutoff. This is indeed what we show in Section 1.3.3.4. We now turn to our empirical findings and illustrate how they relate to the theoretical results from Section 1.2.

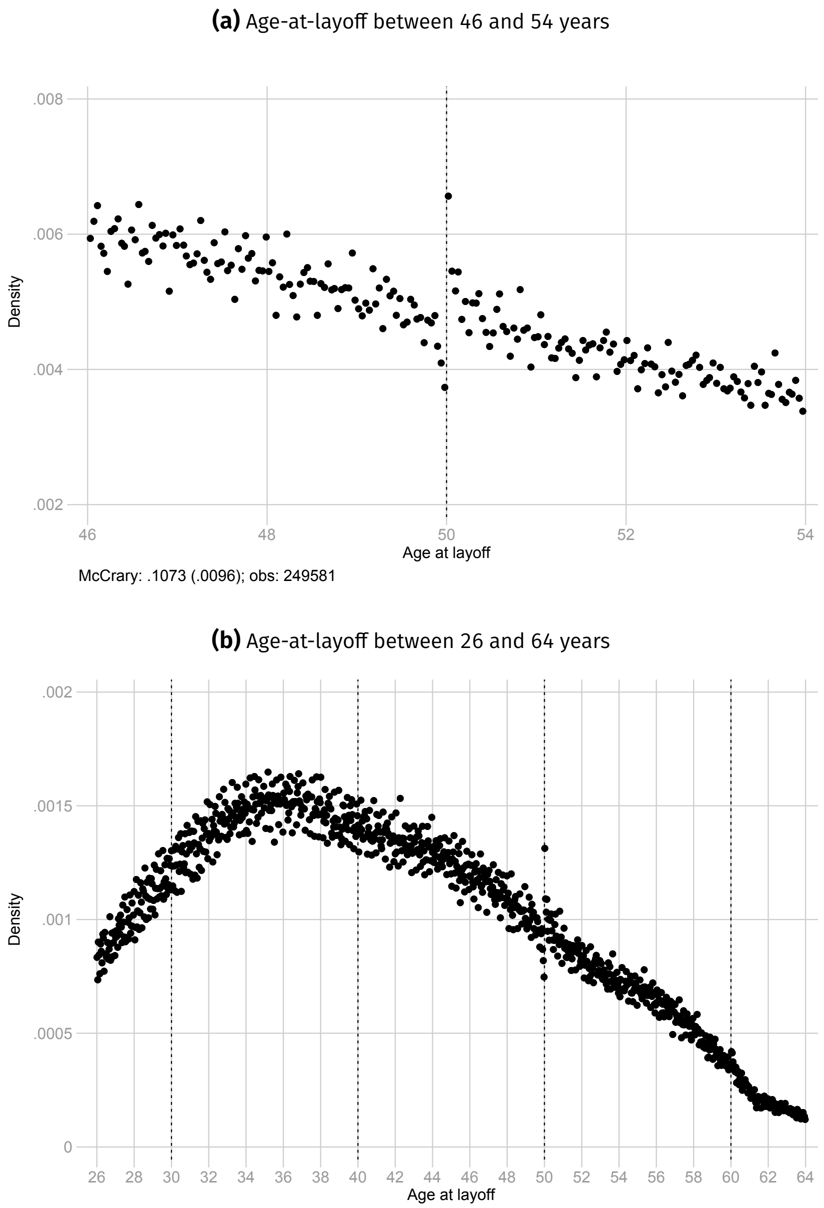
1.3.3 Results

In this section we examine the main findings. We start by presenting graphical evidence of manipulation in the form of strategic delays in the timing of layoffs around the fiftieth birthday threshold. After quantifying the magnitude of manipulation, we estimate the additional increase in UI receipt and nonemployment duration that arises from the change in manipulators' job search behavior. We highlight that most of the increase is mechanically the result of higher coverage due to relatively high long-term nonemployment risk on which manipulators are adversely selected. The implied responsiveness to UI is modest and, in particular, not higher than for non-manipulators. Last, we probe the robustness of our findings and examine observable characteristics on which manipulators are selected.

1.3.3.1 Evidence of manipulation

To provide graphical evidence of manipulation, Figure 1.3 plots the relative frequency of layoffs against workers' age at layoff. Figure 1.3b covers the entire age range from 26 to 64 years of age, while Figure 1.3a zooms into a narrower, four year window around the age-fifty threshold.[24] Both figures show a clear drop in the frequency of layoffs just before, and a pronounced spike after, the age-fifty threshold.

24. By plotting the layoff frequency over the entire age range in Figure 1.3b, we already rule out that manipulation is caused by other mechanisms like (round-) birthday effects. All our estimates for the counterfactual density and counterfactual outcomes are based on the narrower (46-54) window. Section 1.3.3.6 presents additional robustness checks.



Note: The figure shows the density of layoffs in the private sector, for individuals working on a permanent contract and claiming regular UI (OUB). The data cover the period from Feb 2009 to Dec 2012. Panel (a) plots the density for the age range from 46 to 54 years, while Panel (b) does so for the entire age range from 26 to 64 years of age. In both panels each dot represents a two-week bin. The underlying data in Panel (a) consists of 249,581 layoffs.

Figure 1.3. Layoff frequency for permanent contract private sector workers

Following our estimation strategy outlined in Section 1.3.2.1, we find the manipulation region to consist of all age bins from six weeks before (missing region),

Table 1.2. Headcount and Share Estimates

(1) Headcount manipulators missing region	(2) Headcount non-manipulators missing region	(3) Headcount manipulators excess region	(4) Headcount all other ind. excess region	(5) Share estimate missing	(6) Share estimate excess
571.2	3038.0	608.6	2390.4	0.158	0.203
(458.5, 680.0)	(2931.0, 3150.0)	(496.0, 718.5)	(2379.4, 2401.3)	(0.127, 0.188)	(0.172, 0.231)

Note: The table reports estimates of the total number of individuals in four groups: manipulators in the missing region (column 1), non-manipulators in the missing region (column 2), manipulators in the excess region (column 3) and all other individuals in the excess region (column 4). Columns 5 and 6 contain estimates for the share of manipulators in the missing and excess region, respectively. We formally define all quantities in Section 1.3.2. All results are based on our main sample consisting of 249,581 observations. Bootstrapped 95% confidence intervals are in parentheses.

up to four weeks after the threshold (excess region). Table 1.2 reports our estimates for the respective headcounts for the four groups of interest: manipulators in the missing region, non-manipulators in the missing region, manipulators in the excess region and all individuals in the excess region who are not manipulators, as well as share estimates for the missing and excess region. We estimate that a total of 571 layoffs are strategically delayed corresponding to 15.8% of layoffs in the missing region. The counterfactual relationship appears almost perfectly linear and is robust to the choice of the order of the polynomial. The estimated number of manipulators in the excess region, 609, deviates slightly from that in the missing region due to measurement error and corresponds to approximately 20.3% of layoffs in the excess region.

Relating these findings to the theoretical analysis in Section 1.2, we provide clear evidence of the presence of manipulation in our context. It is straightforward to translate the estimated number of manipulators into a share estimate once one decides on the definition of the relevant group. If one, for instances, took six weeks prior to the age threshold as the cutoff for the group definition of the young, the share M would correspond to the above estimate of 15.8% (see our discussion in Section 1.2.4 on this point). Unfortunately, we lack sufficient policy variation to credibly estimate the share *elasticities* in Proposition 3. Due to the nature of our manipulation mechanism, namely worker-firm bargaining, one can only speculate about plausible values. It also appears likely that manipulation elasticities are not constant in our setting, e.g. due to non-financial incentives such as warm-glow or reputation concerns playing a role. Importantly, the theory does not require pinning down the exact mechanism as long as one has credible estimates for the share elasticities (or is willing to make additional assumptions).

Table 1.3. UI Benefit Receipt Estimates (in Euro)

(1) Benefit receipt manipulators missing region	(2) Benefit receipt non-manipulators missing region	(3) Benefit receipt manipulators excess region	(4) Benefit receipt all other ind. excess region	(5) Benefit receipt response manipulators	(6) Benefit receipt response non-manipulators
5814.2 (5178.5, 6459.2)	5223.5 (5125.0, 5325.7)	8053.6 (7326.9, 8836.5)	7044.2 (6974.5, 7112.4)	2239.4 (1276.7, 3261.6)	1636.9 (1410.9, 1849.6)

Note: The table reports estimates of the mean UI benefit receipt (in Euro) of individuals in four groups: manipulators in the missing region (column 1), non-manipulators in the missing region (column 2), manipulators in the excess region (column 3) and all other individuals in the excess region (column 4). Columns 5 and 6 contain estimates of the UI benefit receipt response of manipulators and non-manipulators, respectively. We formally define all quantities in Section 1.3.2. All results are based on our main sample consisting of 249,581 observations. Bootstrapped 95% confidence intervals are in parenthesis.

Table 1.4. Benefit Duration Estimates (in weeks)

(1) Benefit duration manipulators missing region	(2) Benefit duration non-manipulators missing region	(3) Benefit duration manipulators excess region	(4) Benefit duration all other ind. excess region	(5) Benefit duration response manipulators	(6) Benefit duration response non-manipulators
27.8 (25.2, 30.6)	24.8 (24.4, 25.2)	41.8 (38.3, 45.6)	35.8 (35.5, 36.2)	13.9 (9.4, 18.7)	9.9 (8.9, 10.9)

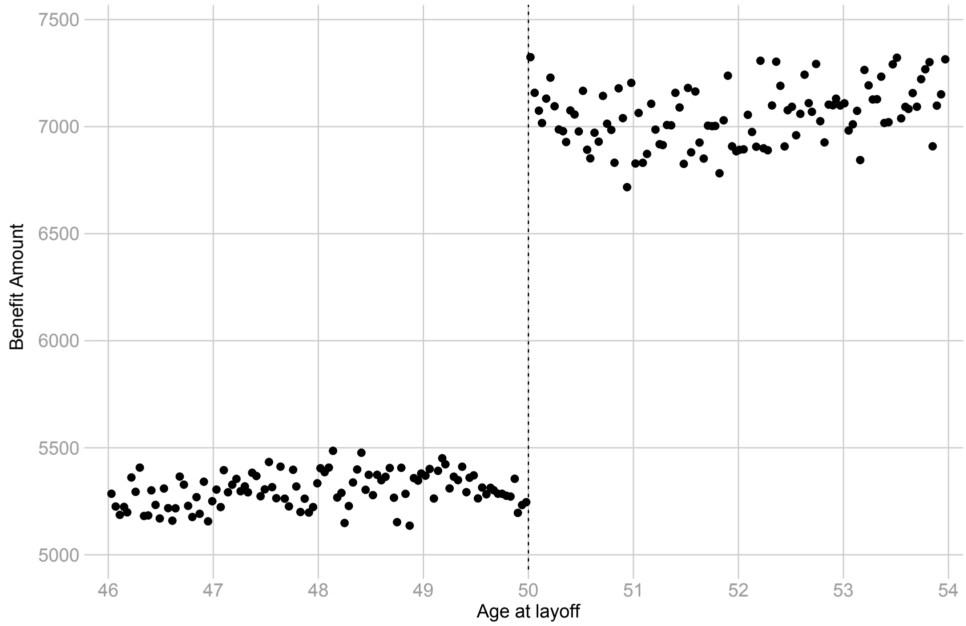
Note: The table reports estimates of the mean benefit duration (in weeks) of individuals in four groups: manipulators in the missing region (column 1), non-manipulators in the missing region (column 2), manipulators in the excess region (column 3) and all other individuals in the excess region (column 4). Columns 5 and 6 contain estimates of the benefit duration response of manipulators and non-manipulators, respectively. We formally define all quantities in Section 1.3.2. All results are based on our main sample consisting of 249,581 observations. Bootstrapped 95% confidence intervals are in parenthesis.

1.3.3.2 Effects of manipulation: UI benefit receipt and duration

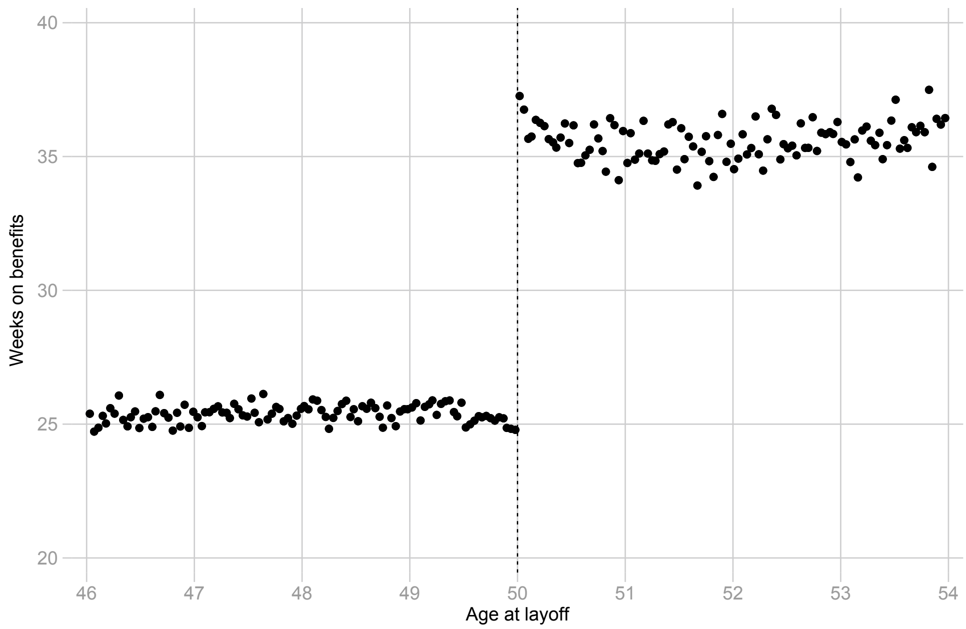
Manipulation provides workers with four additional months of UI coverage. To study the effect of extra coverage on manipulators' benefit receipt and nonemployment duration we begin by plotting these outcomes against workers' age at layoff in Figure 1.4. For each outcome we see visible changes around the age threshold indicating that both respond to manipulation. As outlined in Section 1.3.3.2 we combine these changes with the share estimate from the previous section to retrieve manipulators' as well as non-manipulators' responses. We report all estimates with associated 95% confidence intervals in Tables 1.3 and 1.4.[25]

25. All confidence intervals in the paper are obtained by simple non-parametric bootstrapping: we operationalize this by resampling layoff events and re-estimating the entire procedure, including the share of manipulators, 5000 times.

(a) Average UI receipt (in Euro)



(b) Average UI benefit duration (in weeks)



Note: The figure displays the average UI receipt in Euro (Panel (a)) and average UI benefit duration in weeks (Panel (b)) by age-at-layoff. In both panels each dot represents a two week bin. The sample includes all individuals working on a permanent contract and claiming regular UI (OUB). The data cover the period from Feb 2009 to Dec 2012. The underlying data consists of 249,581 layoffs.

Figure 1.4. Benefit Receipt and Duration

Our results indicate that manipulators would have collected 5814.2 Euro and spent 27.8 weeks on UI benefits, had they not manipulated (column 1 in Tables 1.3 and 1.4). Through manipulation these numbers increase to 8053.6 Euro and 41.8 weeks (column 3), resulting in an additional cost of 2239 Euro per manipulator (column 5). In order to benchmark these estimates, we compute the same numbers for non-manipulators following the strategy outlined in Section 1.3.2.3. We find that non-manipulators generate a total cost of 1636.9 Euro (column 6) when receiving additional coverage.

As highlighted in Section 1.2, these numbers alone are not directly welfare relevant, because they reflect both the mechanical transfer as well as possible distortions in job search. The next section provides a decomposition into these two components.[26]

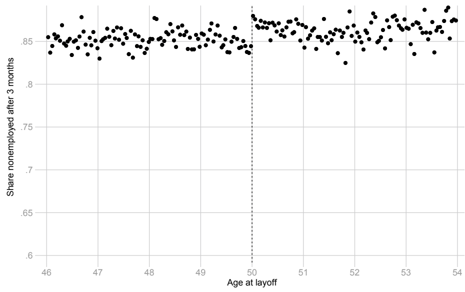
1.3.3.3 Distinguishing behavioral responses from mechanical effects

The key insight to decomposing behavioral and mechanical cost increases, is to repeat the preceding estimation procedure at different months after layoff to trace out *when* manipulators and non-manipulators respond to additional coverage. We start by plotting nonemployment survival rates against age at layoff at various months after layoff in Figure 1.5. Qualitatively, we observe bigger jumps around the thresholds precisely during the months with extra coverage. Similarly to before, we combine these changes with the estimated share of manipulators causing them to trace out monthly survival curves for both manipulators and non-manipulators.

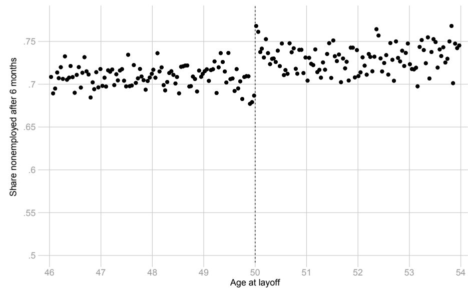
Figure 1.6a presents our estimated nonemployment survival curves of manipulators under the eight and twelve months PBD schemes. Figure 1.6b reports the difference between the two curves at any point, with associated bootstrapped 95% confidence intervals. The difference between the two curves reveals the effect of longer PBD along manipulators' survival curve which appears concentrated precisely in the months of extra UI coverage. We replicate the same analysis for non-manipulators and report its findings in Figure 1.7. The qualitative picture is similar, although confidence bands are much narrower in large part due to the fact that non-manipulators' survival curve under the eight month PBD scheme is observable rather than estimated.

26. It is worth noticing that the cost estimates are relevant for calculating cost-weighted elasticities given in equation (1.8) because they relate to the fiscal externality defined in equation (1.6).

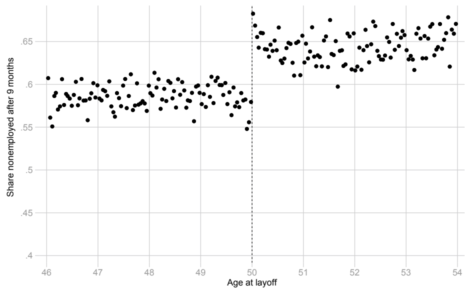
(a) Probability of still not being in employment at 3 months



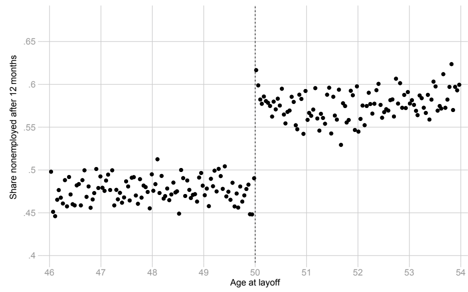
(b) Probability of still not being in employment at 6 months



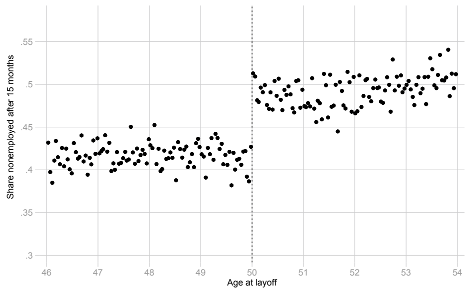
(c) Probability of still not being in employment at 9 months



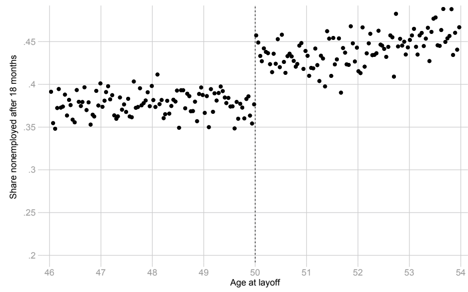
(d) Probability of still not being in employment at 12 months



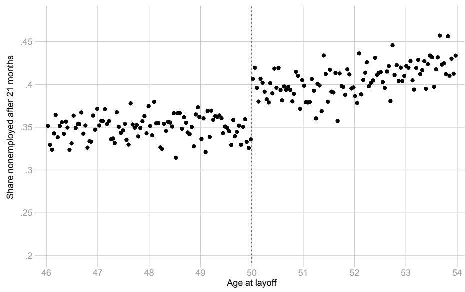
(e) Probability of still not being in employment at 15 months



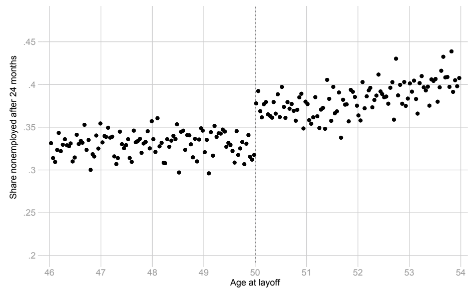
(f) Probability of still not being in employment at 18 months



(g) Probability of still not being in employment at 21 months



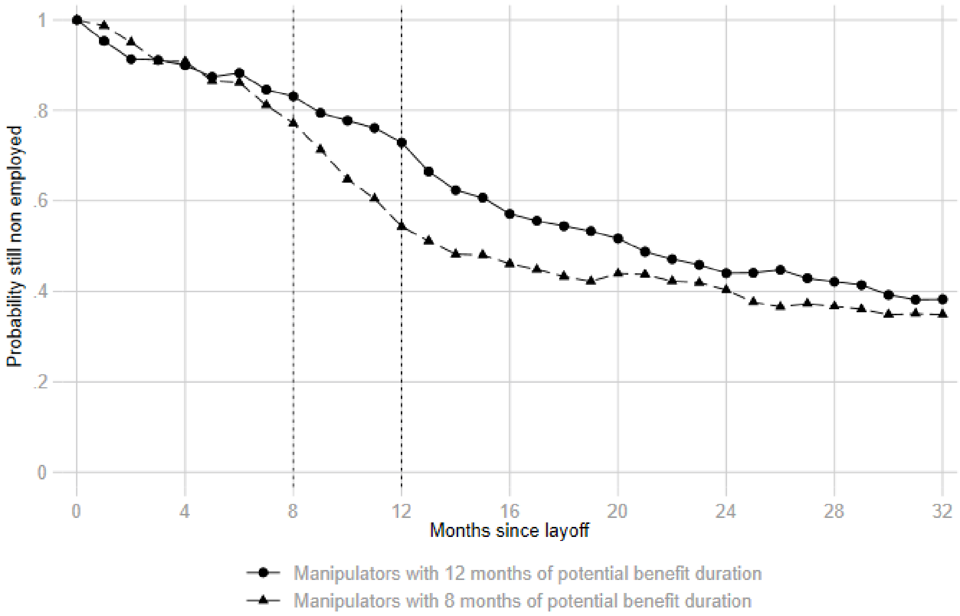
(h) Probability of still not being in employment at 24 months



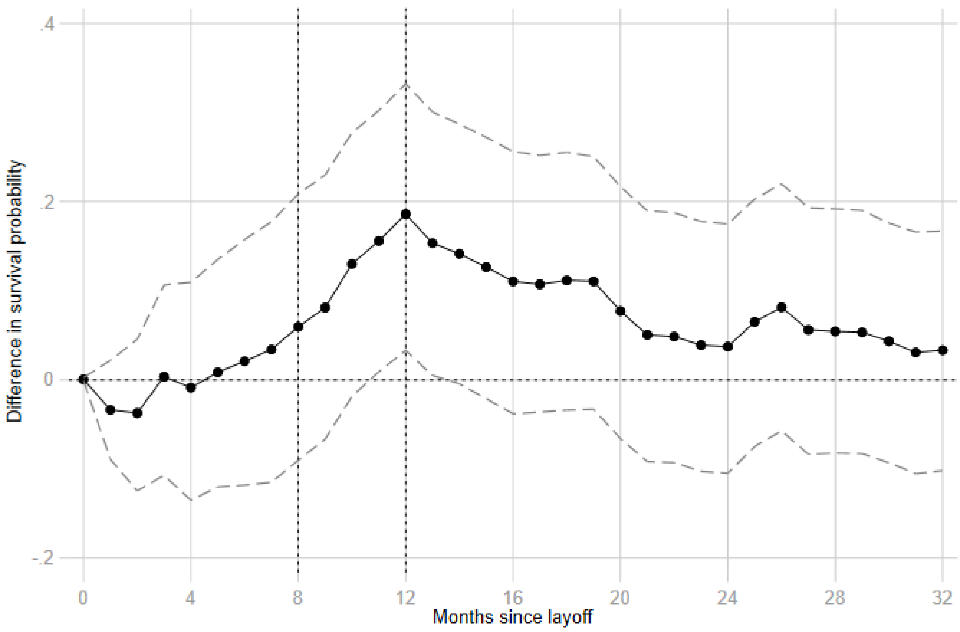
Note: The figures show the share of laid off workers, who are still not in employment after 3, 6, ..., 24 months. In all panels each dot represents a two week bin. The sample includes all individuals working on a permanent contract and claiming regular UI (OUB). The data cover the period from Feb 2009 to Dec 2012. The underlying data consists of 249,581 layoffs.

Figure 1.5. Nonemployment Survival Probabilities

(a) Nonemployment survival rates



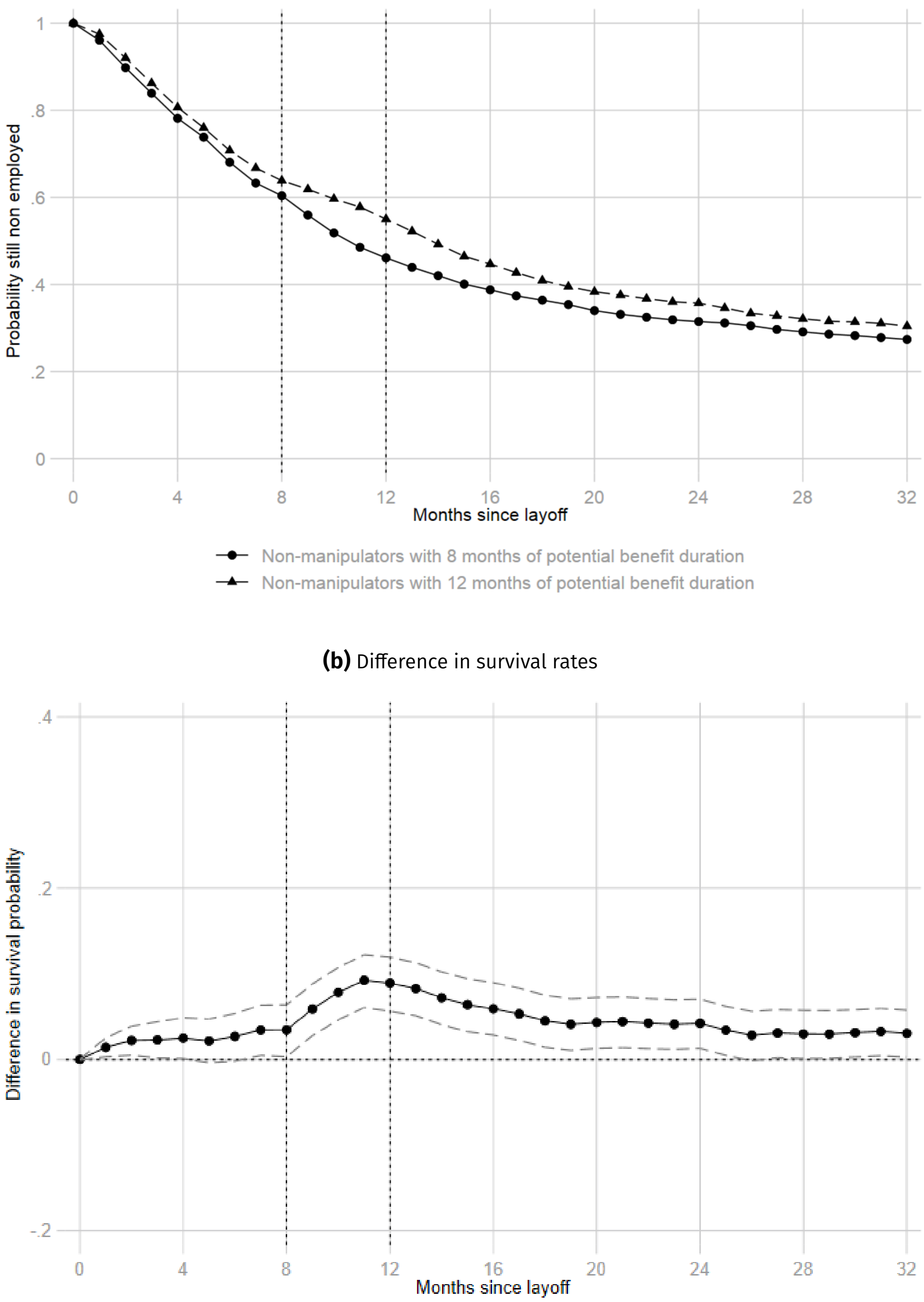
(b) Difference in survival rates



Note: Panel (a) plots point estimates of manipulators' actual and counterfactual nonemployment survival for the first 32 months after layoff. Our estimation strategy is outlined in Section 1.3.2. Panel (b) shows the difference between the two survival curves and contains bootstrapped 95% confidence intervals testing against zero difference.

Figure 1.6. Manipulators with 8 and 12 Months of PBD

(a) Nonemployment survival rates



(b) Difference in survival rates

Note: Panel (a) plots point estimates of non-manipulators' actual and counterfactual nonemployment survival for the first 32 months after layoff. Our estimation strategy is outlined in Section 1.3.2. Panel (b) shows the difference between the two survival curves and contains bootstrapped 95% confidence intervals testing against zero difference.

Figure 1.7. Manipulators with 8 and 12 Months of PBD

Table 1.5. BC/MC Ratio Estimates

	(1) without taxes ($\tau = 0\%$)	(2) with taxes ($\tau = 3\%$)
(a) Manipulators	0.24	0.32
	(0.02, 0.89)	(0.03, 1.13)
(b) Non-manipulators	0.26	0.32
	(0.12, 0.41)	(0.15, 0.50)

Note: The table reports BC/MC ratio estimates for (a) manipulators and (b) non-manipulators. BC/MC ratios are defined in equation (1.2). Bootstrapped 95% confidence intervals in parentheses.

We translate the survival rate responses into BC/MC ratio estimates for manipulators and non-manipulators following equation (1.2). To do so, we rely on numerical integration and weight responses by statutory benefit rates.[27] We report our BC/MC ratio estimates in Table 1.5. Because there is some disagreement in the literature as to what the appropriate tax rate is this context, columns 1 and 2 provide BC/MC ratios for a no tax $\tau = 0$ and a commonly used UI tax of $\tau = 3\%$, see e.g. Schmieder and von Wachter (2016) and Lawson (2017). As discussed in Section 1.2 an estimate of 0.24 for manipulators in column 1 of Table 1.5 implies that the government pays an additional 24 cents for each euro of UI transfer. The estimated BC/MC ratios for manipulators and non-manipulators are strikingly similar suggesting that there is no selection on moral hazard which links directly to equation (1.10) in Proposition 3.[28] From a positive perspective this finding also mitigates concerns that anticipated moral hazard is a prime motive to engage in manipulation.

1.3.3.4 Selection on long-term nonemployment risk

The remainder of our empirical analysis provides additional evidence to shed light on the drivers behind manipulation in our context. The previous section ruled out anticipated moral hazard as a key motivation to engage in manipulation. In this section we show that alleviated exhaustion risk is a strong predictor of manipulation.

27. We perform integration using the midpoint rule and impose a non-negativity constraint on the behavioral cost at any point in time. Note that in the first few months the point estimates of the survival rate response is negative for manipulators which would imply that longer PBD increases job finding rates. However, this finding is likely due to noise. As these negative contributions to the overall integral leads us to underestimate BC/MC ratios for manipulators, our estimates are conservative. Results are qualitatively unaltered without imposing the non-negativity constraint.

28. The reported BC/MC ratios are in the lower range of estimates in the previous literature, see Schmieder and von Wachter (2016) for an overview.

To do so, Figure 1.8 combines manipulators' and non-manipulators' eight months PBD survival curves from Section 1.3.3.3. A clear difference emerges and manipulators exhibit an almost 20 p.p. higher (counterfactual) exhaustion risk under the less generous eight months PBD scheme. This finding provides compelling evidence that anticipated exhaustion risk is a strong motive for manipulation. Note that these estimates also directly relate to the selection of risk scale factor in equation 1.10 in Proposition 3. The large exhaustion risk is also (partly) responsible for making most of the increase in benefit receipt mechanical, thus lowering the BC/MC ratio, in Section 1.3.3.3.

1.3.3.5 Characterizing manipulators

This last section of our analysis, provides some suggestive evidence on the underlying manipulation mechanism by documenting observable characteristics that are correlated with manipulation. In Figure 1.9 we start by visually inspecting the age distribution of layoffs for different types of contracts (permanent and temporary) and sectors (private and public). Manipulation is entirely confined to private sector permanent contract workers motivating the choice of our main sample.

Turning to observable worker and firm characteristics for our main sample, Table 1.6 reports a selection on observables analysis.[29] Columns 1 and 2 of Table 1.6 report estimated mean characteristics for manipulators and non-manipulators, respectively. Column 3 calculates their difference together with bootstrapped 95% confidence intervals. We find that manipulators are 18 p.p. more likely than non-manipulators to be female, 17 p.p. more likely to be employed in white-collar jobs and 7 p.p. less likely to have full-time contracts. Manipulators' wages are 6% lower, although estimates are relatively imprecise. Firm size plays an important role for manipulation: manipulators come from firms that are about 40% smaller. Overall, these findings suggest that adjustment costs, bargaining power and proximity to managers play a role in workers' ability to engage in manipulation. A full investigation into the underlying worker-firm bargaining mechanism is beyond the scope of this paper but we deem it an interesting avenue for future work.

Although more tentative, we view the selection patterns document in this section as evidence consistent with our main conclusion that manipulators are not adversely selected. If anything the findings suggest that manipulators might have higher marginal utilities, e.g. due to part-time work arrangements and lower wages.

1.3.3.6 Robustness

This section probes the robustness of two identifying assumptions underlying our empirical analysis and its link to the theoretical results from Section 1.2. First, we

29. The analysis closely follows Section 6.2 of Diamond and Persson (2016).

Table 1.6. Selection on Observables

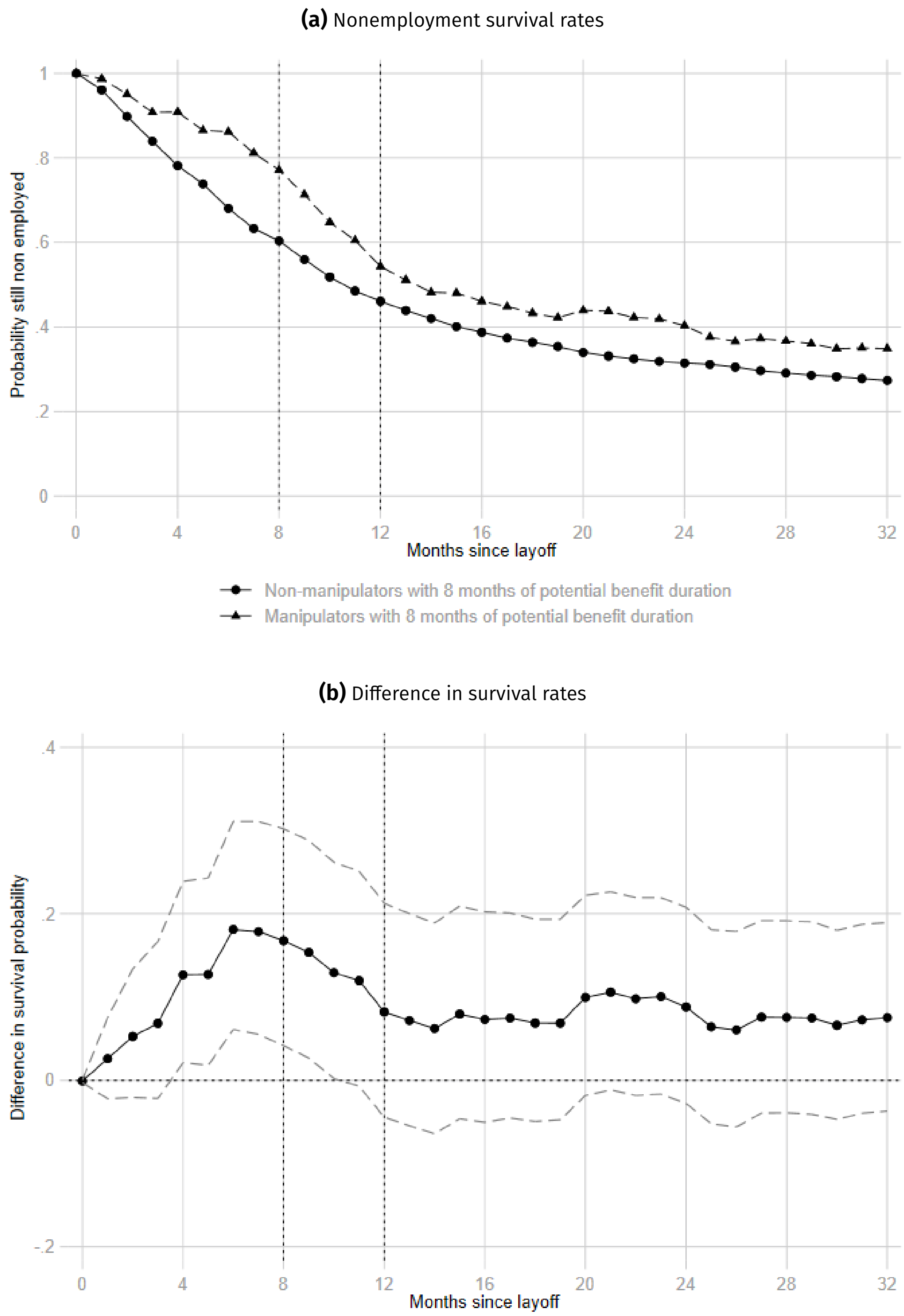
	(1) Manipulators	(2) Non-Manipulators	(3) Difference (1)-(2)
Female (share)	0.450	0.270	0.180
			(0.100, 0.281)
White-collar (share)	0.351	0.180	0.170
			(0.101, 0.239)
Southern Region (share)	0.483	0.471	0.012
			(-0.072, 0.098)
Full-time (share)	0.754	0.822	-0.067
			(-0.134, -0.000)
Tenure (in years)	6.577	5.718	0.859
			(-0.142, 1.853)
Daily Wage (in logs)	4.115	4.176	-0.0610
			(-0.142, 0.023)
Firm Age (in years)	14.546	14.335	0.211
			(-1.945, 2.320)
Firm Size (in logs)	1.862	2.258	-0.395
			(-0.640, -0.155)

Note: The table reports differences in observable characteristics between manipulators and non-manipulators in our main sample. Columns 1 and 2 report estimated means of observable characteristics for manipulators and non-manipulators, respectively. Column 3 reports their difference and associated 95% bootstrapped confidence intervals in parentheses.

provide evidence that manipulation is indeed the result of additional UI coverage around the age at layoff threshold. Second, the empirical analysis assumes that the discontinuity in PBD around the age threshold affects layoff decisions in exactly one way, namely, through a delay in an otherwise earlier occurring layoff.

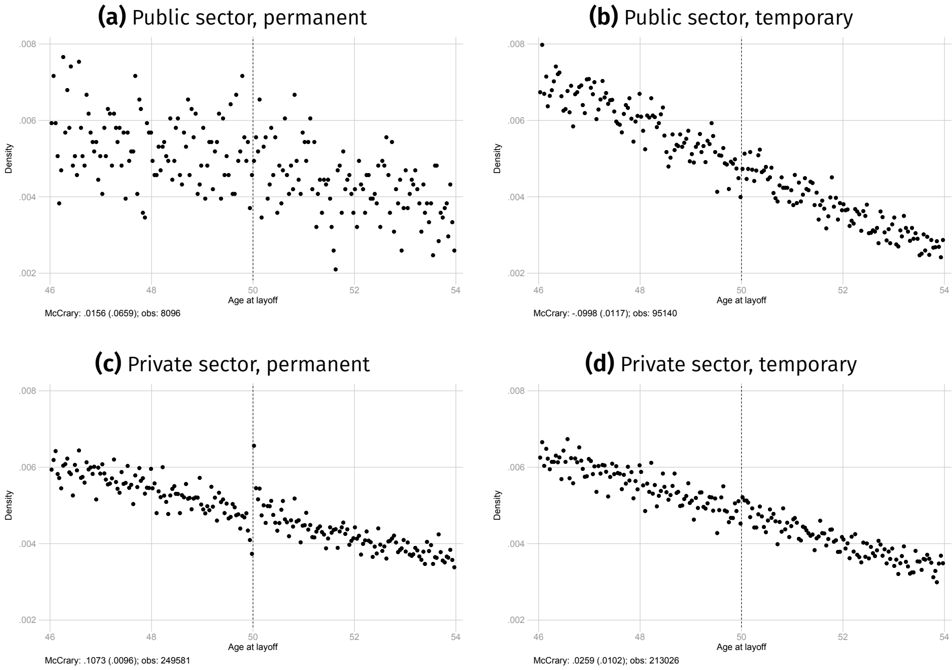
By plotting layoffs across the entire age distribution Figure 1.3b already ruled out several alternative explanations such as e.g. round birthday effects. To provide further supporting evidence Figure 1.10 plots layoff densities for two Italian UI schemes which replaced the OUB scheme after January 2013 and did not feature any discontinuity in generosity at the age fifty threshold.[30] Reassuringly, we find no evidence of manipulation under any of the these alternative schemes.

30. For institutional details regarding both UI schemes see Appendix 1.B.



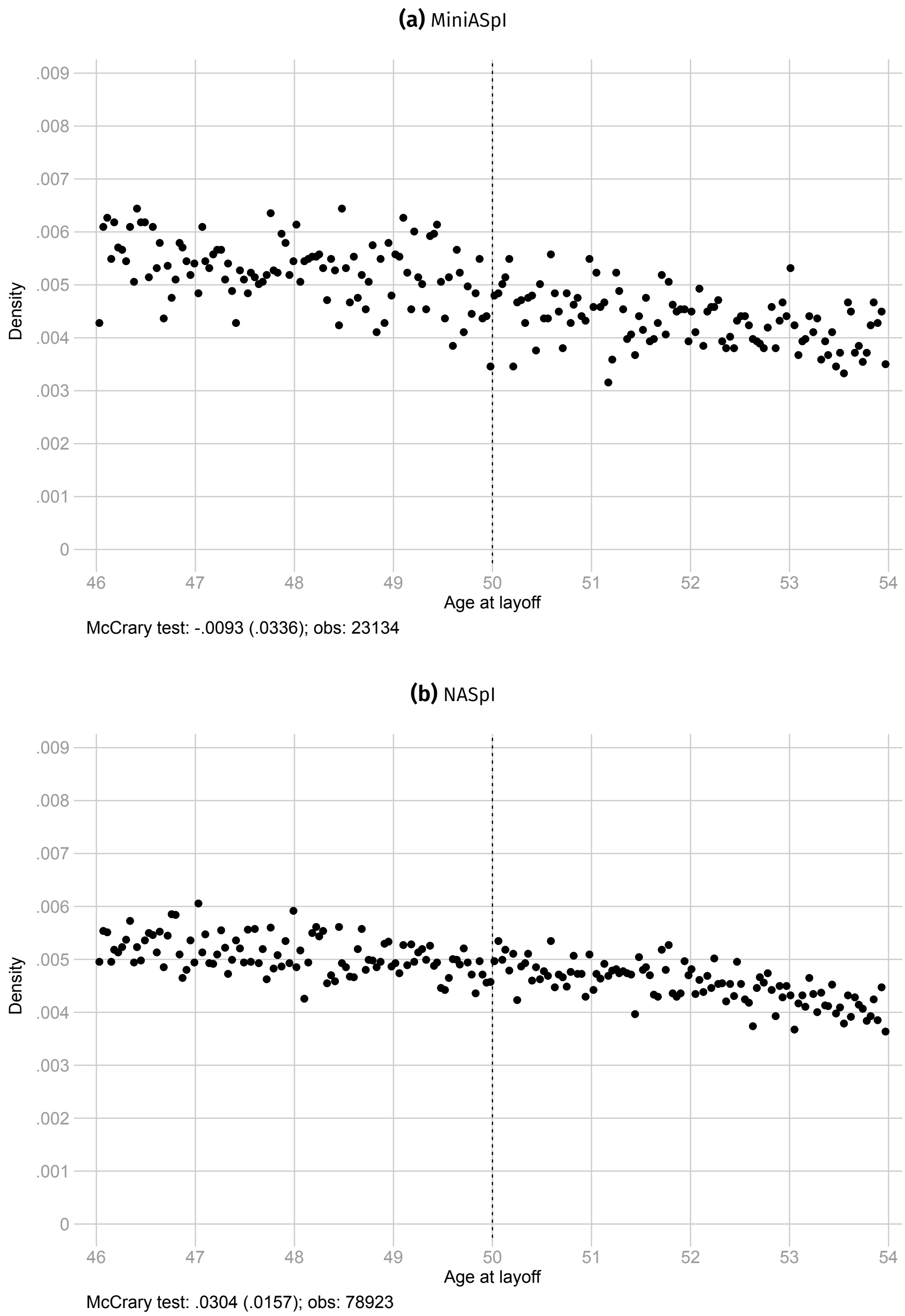
Note: Panel (a) plots point estimates of manipulators' and non-manipulators' nonemployment survival over the first 32 months after layoff under eight months of PBD. The estimation of the former is outlined in Section 1.3.2. The latter represents the observed mean survival rate in the missing region. Panel (b) shows the difference between the two survival curves and contains bootstrapped 95% confidence intervals testing against zero difference.

Figure 1.8. Manipulators and Non-manipulators with 8 Months of PBD



Note: The figure shows the density of layoffs by contract type. The data cover the period from Feb 2009 to Dec 2012. In all panels each dot represents a two-week bin. Individuals are classified as "public sector" workers if they cannot be matched to an employment spell in the private sector database (UNIEMENS).

Figure 1.9. Layoff Frequencies by Sector and Contract Type



Note: The figure shows the density of layoffs for workers laid off in the private sector and receiving MiniASpI (Mar 2013 to Apr 2015) or NASpI (from Jan 2016). In both panels each dot represents a two-week bin. The sample has been restricted to workers coming from permanent contracts in the private sector.

Figure 1.10. Placebo Checks: Layoff Frequencies under MiniASpI and NASpI

The second concern is related to the possible presence of *extensive margin* job separation effects of UI and merits special attention in the light of recent evidence by Albanese, Picchio, and Ghirelli (2020) and Jäger, Schoefer, and Zweimüller (2019). The former documents layoff responses at the eligibility threshold (52 weeks of contributions) in the same Italian OUB scheme we study. Although theoretically possible, we find no empirical evidence of any extensive margin job separation responses in our context through a series of robustness tests presented in detail in Appendix 1.C. Intuitively, the layoff density shown in Figure 1.3, shows no indication of any additional layoffs to the right of the cutoff that are not explained by missing layoffs in the missing region. We discuss this point as well as a series of other robustness tests exhaustively in Appendix 1.C and find no evidence for a violation of our identification assumption.

1.4 Concluding Remarks

This work lays out a simple, yet robust theoretical framework to guide the design of differentiated social insurance under manipulation. We identify a set of sufficient statistics and illustrate how key moments in the data can be estimated in practice. Our empirical strategy builds on and extends recently proposed bunching techniques which do not require rich policy variation for estimation.

We are optimistic that our empirical methodology might be fruitfully applied in other contexts and, although a full welfare assessment is beyond the scope of this paper, we deem it an interesting area for future research. As pointed out by Spinnewijn (2020) there remains important work to be done in understanding, analyzing and justifying frequently used tags in social insurance. We hope that our framework and methodology provide an important first step.

Although the theoretical results hold more generally, our empirical analysis focuses on the case where group membership is defined by a threshold rule in an underlying continuous variable, age-at-layoff. While there are many such cases in practice, another prevalent case is that of discrete variable group membership, e.g. based on gender or the number of children. Developing empirical methodologies for such settings is thus of first-order policy interest.

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Appendix 1.A Proofs

This appendix lays out the formal derivation of Proposition 3, which implies Proposition 1 for $M \equiv 0$. We further illustrate how to derive equation (1.4) as well as Proposition 2.

The government problem parameterized with baseline coverage P and extra coverage ΔP, such that $P_y = P$ and $P_o = P + \Delta P$, reads:

$$\max_{P,\Delta P,\tau} W \;=\; (1-G)\cdot V^o(P+\Delta P) + G\cdot \mathbb{E}^y\left[\tilde{V}^i(P)\right] + G\cdot M\cdot \mathbb{E}^m\left[\tilde{V}^i(P+\Delta P) - \tilde{V}^i(P) - q^i\right]$$

subject to the budget constraint:

$$\begin{aligned} &\tau\cdot\left[(1-G)\cdot\left(T - D^o(P+\Delta P)\right) + G\cdot\left(T - D^y(P)\right) + G\cdot M\cdot\left(D^m(P) - D^m(P+\Delta P)\right)\right] \\ =\;& b\cdot\left[(1-G)\cdot B^o(P+\Delta P) + G\cdot B^y(P) + G\cdot M\cdot\left(B^m(P+\Delta P) - B^m(P)\right)\right] + R. \end{aligned}$$

When considering small changes in extra coverage ΔP we may, by the envelope theorem, ignore all direct welfare effects of changes in job search intensities or manipulation choices.[31] Thus, small budget-neutral changes in ΔP have a welfare effect of:

$$\begin{aligned} \frac{dW}{d\Delta P} \;=\;& (1-G)\cdot\frac{dV^o(P_o)}{d\Delta P} + G\cdot M\cdot\mathbb{E}^m\left[\frac{d\tilde{V}^i(P_o)}{d\Delta P}\right] - \bar{u}'\cdot L\cdot\frac{d\tau}{d\Delta P} &(1.A.1)\\ =\;& (1-G)\cdot S^o_{P_o}\cdot\left(u^o(c_u+b) - u^o(c_u)\right) \\ +\;& G\cdot M\cdot\mathbb{E}^m\left[S^i_{P_o}\cdot\left(u^i(c_u+b) - u^i(c_u)\right)\right] \\ -\;& \bar{u}'\cdot\left[(1-G)\cdot\left(BC^o_{P_o} + MC^o_{P_o}\right) + G\cdot M\cdot\left(BC^m_{P_o} + MC^m_{P_o}\right)\right] \\ +\;& \bar{u}'\cdot G\cdot b\cdot(1-M)\cdot\epsilon_{1-M,\Delta P} &(1.A.2)\\ =\;& (1-G)\cdot\left(MC^o_{P_o}\cdot\tilde{u}'_o - \left(BC^o_{P_o} + MC^o_{P_o}\right)\cdot\bar{u}'\right) \\ +\;& G\cdot M\cdot\left(\mathbb{E}^m\left[MC^i_{P_o}\cdot\tilde{u}'_i\right] - \left(BC^m_{P_o} + MC^m_{P_o}\right)\cdot\bar{u}'\right) \\ +\;& G\cdot(1-M)\cdot MC^n_{P_y}\cdot\bar{u}'\cdot\epsilon_{1-M,\Delta P}, &(1.A.3) \end{aligned}$$

where we used the implicit differentiation of the government budget constraint $\tau\cdot L = b\cdot B + R$ and Leibniz rule to obtain:

31. These changes matter only to the extent that they operate through the government budget constraint.

$$
\begin{aligned}
L \cdot \frac{d\tau}{d\Delta P} &= b \cdot \frac{dB}{d\Delta P} - \tau \cdot \frac{dL}{d\Delta P} && (1.A.4)\\
&= (1-G) \cdot \left(b \cdot \frac{dB^o}{d\Delta P} + \tau \cdot \frac{dD^o}{d\Delta P} \right)\\
&+ G \cdot \frac{d}{d\Delta P} \int_i \underbrace{\left(b \cdot \left(B^i(P_o) - B^i(P_y) \right) + \tau \cdot \left(D^i(P_o) - D^i(P_y) \right) \right)}_{= FE^i \text{ by equation (1.6)}} \cdot \mathbb{I}_{q^i \leq \bar{q}^i} \; df(u^i, \psi^i, q^i)\\
& && (1.A.5)\\
&= (1-G) \cdot \left(BC^o_{P_o} + MC^o_{P_o} \right) + G \cdot \int_i \frac{dFE^i}{d\Delta P} \cdot \mathbb{I}_{q^i \leq \bar{q}^i} \; df(u^i, \psi^i, q^i)\\
&+ G \cdot \int_{u^i, \phi^i} FE^i \cdot \frac{d}{d\Delta P} \underbrace{\int_0^{\bar{q}^i} f(q|u_i, \phi_i) \; dq}_{= M^i \text{ by equation (1.7)}} \; df(u^i, \phi^i) && (1.A.6)\\
&= (1-G) \cdot \left(BC^o_{P_o} + MC^o_{P_o} \right) + G \cdot M \cdot \left(BC^m_{P_o} + MC^m_{P_o} \right)\\
&- G \cdot MC^n_{P_y} \cdot \int_{u^i, \phi^i} \frac{(1-M^i) \cdot FE^i}{MC^n_{P_y} \cdot \Delta P} \cdot \epsilon_{1-M^i, \Delta P} \; df(u^i, \phi_i) && (1.A.7)\\
&= (1-G) \cdot \left(BC^o_{P_o} + MC^o_{P_o} \right) + G \cdot M \cdot \left(BC^m_{P_o} + MC^m_{P_o} \right)\\
&- G \cdot (1-M) \cdot MC^n_{P_y} \cdot \epsilon_{1-M, \Delta P}, && (1.A.8)
\end{aligned}
$$

by the definition in equation (1.8). Exploiting assumptions 1 and 2, we rewrite (1.A.3) as:

$$
\begin{aligned}
\frac{1}{\bar{u} \cdot b} \cdot \frac{dW}{d\Delta P} &= (1-G) \cdot S^o_{P_o} \left(\frac{\tilde{u}'_o - \bar{u}'}{\bar{u}'} - \frac{BC^o}{MC^o} \right)\\
&+ G \cdot M \cdot S^m_{P_o} \left(\frac{\tilde{u}'_m - \bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m} \right)\\
&+ G \cdot (1-M) \cdot S^n_{P_y} \cdot \epsilon_{1-M, \Delta P}, && (1.A.9)
\end{aligned}
$$

which proves equation (1.5) in the main text.

Similarly, small budget-neutral changes in baseline coverage P have a welfare effect of:

$$\begin{aligned}\frac{dW}{dP} &= (1-G)\cdot\frac{dV^o(P_o)}{dP} + G\cdot\mathbb{E}^y\left[\frac{d\tilde{V}^i(P_o)}{dP}\right] \\ &+ G\cdot M\cdot\mathbb{E}^m\left[\frac{d\tilde{V}^i(P_o)}{dP} - \frac{d\tilde{V}^i(P_y)}{dP}\right] - \bar{u}'\cdot L\cdot\frac{d\tau}{dP} \qquad (1.A.10)\\ &= (1-G)\cdot\left(MC^o_{P_o}\cdot\tilde{u}'_o - \left(BC^o_{P_o}+MC^o_{P_o}\right)\cdot\bar{u}'\right)\\ &+ G\cdot\left(MC^y_{P_y}\cdot\tilde{u}'_y - \left(BC^y_{P_y}+MC^y_{P_y}\right)\cdot\bar{u}'\right)\\ &+ G\cdot M\cdot\left(\mathbb{E}^m\left[MC^i_{P_o}\cdot\tilde{u}'_i\right] - \left(BC^m_{P_o}+MC^m_{P_o}\right)\cdot\bar{u}'\right)\\ &- G\cdot M\cdot\left(\mathbb{E}^m\left[MC^i_{P_y}\cdot\tilde{u}'_i\right] - \left(BC^m_{P_y}+MC^m_{P_y}\right)\cdot\bar{u}'\right)\\ &+ G\cdot(1-M)\cdot MC^n_{P_y}\cdot\bar{u}'\cdot\epsilon_{1-M,P}, \qquad (1.A.11)\end{aligned}$$

where, again, we used the implicit differentiation of the government budget constraint $\tau\cdot L = b\cdot B + R$ and Leibniz rule to obtain:

$$\begin{aligned}L\cdot\frac{d\tau}{dP} &= b\cdot\frac{dB}{dP} - \tau\cdot\frac{dL}{dP} \qquad (1.A.12)\\ &= (1-G)\cdot\left(b\cdot\frac{dB^o}{dP}+\tau\cdot\frac{dD^o}{dP}\right) + G\cdot\left(b\cdot\frac{dB^y}{dP}+\tau\cdot\frac{dD^y}{dP}\right)\\ &+ G\cdot\frac{d}{dP}\int_i FE^i\cdot\mathbb{I}_{q^i\le\bar{q}^i}\ df(u^i,\psi^i,q^i) \qquad (1.A.13)\\ &= (1-G)\cdot\left(BC^o_{P_o}+MC^o_{P_o}\right) + G\cdot\left(BC^y_{P_y}+MC^y_{P_y}\right)\\ &+ G\cdot\int_i\frac{dFE^i}{dP}\cdot\mathbb{I}_{q^i\le\bar{q}^i}\ df(u^i,\psi^i,q^i) + G\cdot\int_{u^i,\phi^i} FE^i\cdot\frac{dM^i}{dP}\ df(u^i,\phi^i) \qquad (1.A.14)\\ &= (1-G)\cdot\left(BC^o_{P_o}+MC^o_{P_o}\right) + G\cdot\left(BC^y_{P_y}+MC^y_{P_y}\right)\\ &+ G\cdot M\cdot\left[\left(BC^m_{P_o}+MC^m_{P_o}\right)-\left(BC^m_{P_y}+MC^m_{P_y}\right)\right] - G\cdot(1-M)\cdot MC^n_{P_y}\cdot\epsilon_{1-M,P}, \\ &\qquad (1.A.15)\end{aligned}$$

and define

$$\epsilon_{1-M,P} := \mathbb{E}^n\left[\frac{FE^i}{MC^n_{P_y}\cdot P}\cdot\epsilon_{1-M^i,P}\right]. \qquad (1.A.16)$$

Under assumptions 1 and 2, we may rewrite (1.A.11) to:

$$\begin{aligned}\frac{1}{\bar{u}\cdot b}\cdot\frac{dW}{dP} &= (1-G)\cdot S^o_{P_o}\left(\frac{\tilde{u}'_o-\bar{u}'}{\bar{u}'} - \frac{BC^o}{MC^o}\right) + G\cdot S^y_{P_y}\left(\frac{\tilde{u}'_y-\bar{u}'}{\bar{u}'} - \frac{BC^y}{MC^y}\right)\\ &+ G\cdot M\cdot\left(S^m_{P_o}-S^m_{P_y}\right)\cdot\left(\frac{\tilde{u}'_m-\bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m}\right) + G\cdot(1-M)\cdot S^n_{P_y}\cdot\epsilon_{1-M,P}, \\ &\qquad (1.A.17)\end{aligned}$$

which proves equation (1.9) in the main text.

To prove equation (1.10) in Proposition 3, we substitute equation (1.5) into (1.9), which gives:

$$S^y_{P_y} \cdot \left(\frac{\tilde{u}'_y - \bar{u}'}{\bar{u}'} - \frac{BC^y}{MC^y} \right) - M \cdot S^m_{P_y} \cdot \left(\frac{\tilde{u}'_m - \bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m} \right)$$
$$+ \; (1-M) \cdot S^n_{P_y} \cdot \left(\epsilon_{1-M,P} - \epsilon_{1-M.\Delta P} \right) \; = \; 0. \tag{1.A.18}$$

Noting that,

$$S^y_{P_y} \cdot \left(\frac{\tilde{u}'_y - \bar{u}'}{\bar{u}'} - \frac{BC^y}{MC^y} \right) = M \cdot S^m_{P_y} \cdot \left(\frac{\tilde{u}'_m - \bar{u}'}{\bar{u}'} - \frac{BC^m}{MC^m} \right)$$
$$+ \; (1-M) \cdot S^n_{P_y} \cdot \left(\frac{\tilde{u}'_n - \bar{u}'}{\bar{u}'} - \frac{BC^n}{MC^n} \right), \tag{1.A.19}$$

we rewrite (1.A.18) to obtain:

$$\frac{\tilde{u}'_n - \bar{u}'}{\bar{u}'} - \frac{BC^n}{MC^n} \; = \; \epsilon_{1-M,\Delta P} - \epsilon_{1-M,P}. \tag{1.A.20}$$

For expositional ease we define

$$s \; = \; \frac{S^m_{P_y} - S^n_{P_y}}{S^n_{P_y}}, \tag{1.A.21}$$

and introduce shorthand notation for the social surplus from insurance for group $j \in \{n, m, y, o\}$:

$$SSP^j \; = \; \left(\frac{\tilde{u}'_j - \bar{u}'}{\bar{u}'} - \frac{BC^j}{MC^j} \right). \tag{1.A.22}$$

Finally, we rewrite (1.A.19) as follows:

$$\begin{aligned}
S^y_{P_y} \cdot SSP^y &= S^n_{P_y} \cdot SSP^n + M \cdot \left[S^m_{P_y} \cdot SSP^m - S^n_{P_y} \cdot SSP^n \right] \\
&= S^n_{P_y} \cdot SSP^n + M \cdot \left[S^m_{P_y} \cdot SSP^m - S^n_{P_y} \cdot SSP^n + S^n_{P_y} \cdot SSP^m - S^n_{P_y} \cdot SSP^m \right] \\
&= S^n_{P_y} \cdot SSP^n + M \cdot \left[S^n_{P_y} \cdot \left(SSP^m - SSP^n \right) + \left(S^m_{P_y} - S^n_{P_y} \right) \cdot SSP^m \right] \\
&= S^n_{P_y} \cdot \left(SSP^n + M \cdot \left(SSP^m - SSP^n \right) + s \cdot M \cdot SSP^m \right) \\
&= S^n_{P_y} \cdot \left((1 + s \cdot M) \cdot SSP^n + (1+s) \cdot M \cdot \left(SSP^m - SSP^n \right) \right),
\end{aligned} \tag{1.A.23}$$

which, since $S^y_{P_y} = S^n_{P_y} \cdot (1 + s \cdot M)$ and $\frac{1+s}{1+s \cdot M} = \frac{S^m_{P_y}}{S^y_{P_y}}$, implies

$$SSP^y = SSP^n + M \cdot \frac{S^m_{P_y}}{S^y_{P_y}} \cdot \left(SSP^m - SSP^n\right). \qquad (1.A.24)$$

Substituting (1.A.20) and (1.A.22) completes the proof of equation (1.10) in Proposition 3.

Last, we derive equation (1.11) in Proposition 3 by rewriting (1.5) as:

$$\begin{aligned}(1-G) \cdot S^o_{P_o} \cdot SSP^o &= -G \cdot \left[M \cdot S^m_{P_o} \cdot SSP^m + (1-M) \cdot S^n_{P_y} \cdot \epsilon_{1-M,\Delta P}\right] \\ &= -G \cdot \left[S^y_{P_o} \cdot SSP^y - (1-M) \cdot S^n_{P_o} \cdot SSP^n + (1-M) \cdot S^n_{P_y} \cdot \epsilon_{1-M,\Delta P}\right],\end{aligned}$$

which with equation (1.A.20) implies:

$$\begin{aligned}(1-G) \cdot S^o_{P_o} \cdot SSP^o + G \cdot S^y_{P_o} \cdot SSP^y &= G \cdot (1-M) \cdot \left[S^n_{P_o} \cdot SSP^n - S^n_{P_y} \cdot \epsilon_{1-M,\Delta P}\right] \\ &= G \cdot (1-M) \cdot \left[\left(S^n_{P_o} - S^n_{P_y}\right) \cdot \epsilon_{1-M,\Delta P} - S^n_{P_o} \cdot \epsilon_{1-M,P}\right],\end{aligned}$$

and concludes the proof.

Appendix 1.B Additional Institutional Details

This section provides additional information about the Italian unemployment insurance schemes in place from 2009. Our main sample covers the period from February 2009 until December 2012. There were two alternative UI schemes in place simultaneously to the main OUB scheme which we study in our analysis.

1.B.1 Alternative UI Schemes in Italy from 2009 to 2012

During the years from 2009 to 2012 two other UI schemes were in place: the Reduced Unemployment Benefits (RUB) and the Mobility Indemnity (MI).[32]

The RUB scheme targeted similar workers as OUB albeit different contribution requirements. While still requiring the first contribution to social security to have happened at least two years before, the RUB scheme only required 13 weeks (78 days) of contributions over the past year (instead of 52 weeks within the last two years as in OUB). The milder eligibility requirements went hand in hand with less generous benefits. Potential benefit duration was proportional to the days worked in the previous year (up to 180 days), while the replacement rate granted 35% of the average wage earned in the previous year for the first 120 days and 40% for the following 60 days. Because RUB is significantly less generous it is unlikely to interfere with our analysis of the OUB.[33]

The MI scheme (active until 2017) and was targeted to workers fired during mass layoffs or business re-organizations. It provided long and generous income support with active labor market reintegration and retraining programs. During the period under study the potential duration of this scheme depended on the worker's age at layoff and geography, with a maximum PBD of 48 months in the south and of 36 months in northern regions. UI benefits amounted to 80% of the salary for the first 12 months (with a cap annually set by law) and 64% during the following months. MI benefits represented a particularly attractive alternative for individuals involved in mass layoffs and could be responsible for an under-representation of these types of workers in our sample. What is more relevant for our analysis however is that selection into MI is largely beyond the control of the worker. Indeed, eligible firms needed to be undergoing significant economic restructuring and have a minimum size, while workers needed to meet additional tenure requirements.

32. *Indennità di Disoccupazione Ordinaria a Requisiti Ridotti* and *Indennità di Mobilità* in Italian, respectively.

33. For additional information, please refer to Anastasia, Mancini, and Trivellato (2009).

1.B.2 UI Schemes in Italy after 2012

The Italian welfare system underwent significant reform after 2012 all aiming at reducing the fragmentation of benefit schemes. In January 2013, both the OUB and the RUB were replaced respectively by the ASpI and MiniASpI.[34]

The ASpI mimicked many aspects of the OUB both in terms of requirements and structure. Eligibility requirements of the ASpI followed those of the OUB scheme. Potential benefit duration was also identical initially, however, it was reformed several times in 2014 and 2015 which makes it difficult to include the ASpI in our analysis. Benefit levels differed with a replacement rate of 75% for the first six month, 60% for month seven to twelve and 45% thereafter (all as fractions of the average wage in the preceding two years before layoff).

The MiniASpI was aimed at workers who did not meet the requirement for the ASpI, but had accumulated at least thirteen weeks of work in the last year. Potential benefit duration was equal to half of the weeks worked over that time period. Benefit receipt was proportional to past wages: workers received 75% of the average wage received during the two previous years.

Since April 2015, both measures are replaced by a single UI scheme which provides homogeneous coverage to workers from all types of layoffs. The new scheme, the NASpI, is based on the structure of the MiniASpI. To qualify, workers need at least 78 days of contributions in the year before layoff. Potential benefit duration is equal to half of the weeks worked over the previous four years. Benefit levels are proportional to past wages following a declining profile starting at 75% replacement rate with a 3 p.p. reduction for every month after the first four. Importantly for our analysis, there is no longer a discontinuity is potential benefit duration thus removing incentives for workers to delay their layoff.

Appendix 1.C Additional Robustness Tests

This section provides additional evidence in support of the identifying assumptions. Concretely, our analysis assumes that the discontinuity in PBD around the age threshold affects layoff decisions only through the delay of otherwise earlier occurring layoffs. The main threat to this assumption is the possibility of *extensive margin responses*, i.e. increases in the rate of job separations due to the incentives generated by the UI system. This is worrisome for two reasons. First we would be mismeasuring the upper bound of the manipulation region (z_U). Second, if the extra layoffs are systematically different, we would be altering the composition of layoffs in the manipulation region for reasons other than manipulation, introducing bias.

Extensive margin responses to UI have been studied both theoretically, see e.g. early work by Feldstein (1976), Feldstein (1978) and Topel (1983), as well as in re-

34. *Assicurazione Sociale per l'Impiego* in Italian.

cent empirical work e.g. Albanese, Picchio, and Ghirelli (2020) and Jäger, Schoefer, and Zweimüller (2019).

Albanese, Picchio, and Ghirelli (2020) find alleviated job separation rates as a response to the same Italian OUB scheme that we study but exploit the eligibility discontinuity of 52 contribution weeks within the last two years after which a worker qualifies for *any* UI. Although closely related there are several reasons why we might not find job separation effects in our context. Their variation is from zero to some PBD, whereas we study a PBD extension from a nonzero level. Because we are exploiting intensive rather than extensive margin incentives, extensive margin responses are likely significantly smaller. This is especially true because all workers in our sample are eligible for UI and have thus already "survived" the eligibility threshold Albanese, Picchio, and Ghirelli (2020) exploit.

The work by Jäger, Schoefer, and Zweimüller (2019) documents job separation effects of a large PBD reform in Austria which raised PBD from one to four years. They exploit this large variation to form a test for the efficiency of job separations by studying differences in separation rates of surviving job cohorts that were differentially treated by the reform. Again, there are several reasons to caution against extrapolating from their setting to ours. First, the sheer size of the PBD extension in Austria was unusually large. Second, it was targeted at relatively old workers who, as Jäger, Schoefer, and Zweimüller (2019) document, used it (in part) as a gateway into early retirement. Last, their setting is likely to produce larger extensive margin responses because the Austrian UI scheme covers voluntary quits and not just layoffs as in Italy.

Although there exists recent important evidence on the extensive margin job separation effects of UI programs we see reason to believe that such effects are significantly smaller or entirely absent in our context. Of course, the presence of job separation effects is ultimately an empirical question. In the following we provide three tests all of which support the absence of extensive margin responses in our setting.

1.C.1 Testing for Shifts in the Layoff Density

The first test is based on the shape of the layoff density. Concretely, we investigate whether there is a persistent increase in layoffs after the age fifty threshold. One might expect a persistent increase in the density if, for instance, firms that experience negative productivity shocks, dis-proportionally lay off workers above fifty due to the extended UI coverage. We operationalize this approach by estimating versions of a classical regression discontinuity design and estimate the following specification once for the entire sample and by excluding (an extended version of) the manipulation region:

$$d_j = \alpha + \lambda \cdot a_j + \gamma \cdot \mathbb{I}[a_j \geq 50] + \delta \cdot \mathbb{I}[a_j \geq 50] \cdot a_j + \nu_j, \tag{1.C.1}$$

where d_j denote the density of layoffs in two-week age bin j, a_j denotes the mid-point age and ν_j is an error term. The coefficient of interest γ is indicative of any discontinuity in the density at the age fifty threshold. While we expect a positive γ coefficient when estimating specification (1.C.1) capturing the presence of manipulation, once we (successfully) exclude the manipulation region, γ should be close to zero in the absence of extensive margin responses. This is precisely what we find with results of all three regressions presented in Table 1.D.1. Column 1 presents estimates from the full sample where we do find a positive and significant γ coefficient of 0.027, consistent with the visual evidence in Figure 1.3. More importantly, once we exclude the manipulation region in column 2, the estimated γ becomes indistinguishable from zero lending support to our identifying assumption. Column 3 repeats the previous analysis but with a modified definition of the manipulation region. Concretely, we extend the manipulation region to nine age bins prior to age fifty and four age bins after the threshold. The choice of this extended region is motivated by a simple quantitative heuristic. For the missing (excess) region we include the longest sequence of age bins from the threshold that are associated with negative (positive) regression coefficients in a simple OLS regression that allows for a separate effect of each age bin on the layoff frequency.[35] Reassuringly, the estimated γ coefficient in Table 1.D.1 remains quantitatively small and insignificant.

1.C.2 Testing for the Presence of Extra Excess Mass

In this section we provide a second test based on the empirical layoff density. This time we investigate the possibility that extensive margin responses are concentrated right after the threshold. Rather than leading to a persistent increase in the density, which we tested for in the preceding section, we are concerned with the presence of additional layoffs just after the threshold that are not due to re-timing. Indeed such additional layoffs might occur if there are jobs that "mature" into negative surplus and such separate precisely when the worker crosses the eligibility threshold for higher UI coverage. We probe this concern with the following analysis. First, in the absence of such additional layoffs missing and excess "mass", or numbers of manipulators, should balance exactly. If there are more excess manipulators one might be worried that these are the result of an extensive margin response thus violating our identifying assumption. We thus test the extent to which missing and excess mass balance around the threshold. To do so, we rely on the same definition of an extended manipulation region as in Section 1.C.1. Concretely, we estimate the following specification

35. In order to reduce the influence of very small coefficients, we ignore the sign of a coefficient if its absolute value is smaller or equal to 1/1000 of the average density across all bins. This is roughly equal to a deviation of three workers from the predicted counterfactual.

$$c_j = \alpha + \beta \cdot a_j + \sum_{k=A}^{50^-} \tilde{\gamma}_k \cdot \mathbb{I}[a_j = k] + \sum_{k=50^+}^{B} \tilde{\delta}_k \cdot \mathbb{I}[a_j = k] + \zeta_j, \tag{1.C.2}$$

where c_j corresponds to the number of layoffs in age bin j and a_j refers to the mid-point age in bin j. The set of $\tilde{\gamma}_k$ and $\tilde{\delta}_k$ coefficients capture the estimated number of manipulators in the respective bin k in the missing and excess region, respectively. The lower and upper bounds $A < z_L$ and $B > z_U$ are set to eighteen weeks (nine bins) and four eight weeks (four bins) as in the previous section. We calculate the difference between the sum of all $\tilde{\gamma}$ coefficients and the sum of all $\tilde{\delta}$ coefficients and re-scale it by the latter. The estimated 1.3% represents the share of the estimated manipulators in the excess region which is not explained by manipulators in the missing regions. Reassuringly, this number is very small lending further support to our main identification assumption.

1.C.3 Testing for Discontinuities in Observable Characteristics

Last we turn to a set of robustness tests based on observable characteristics around the age threshold. Intuitively, observable characteristics around the age cutoff should also differ due to manipulation. Similar to the density test in Section 1.C.1 we investigate if individuals differ based on their observable characteristics outside of the manipulation region. Concretely and for comparison, we run two regression models. The first is a standard regression discontinuity specification run on the full sample:

$$x_i = \alpha + \sum_{p=1}^{P} \lambda_p^{\leq 50} \cdot a_i^p \cdot \mathbb{I}[a_i < 50] + \sum_{p=0}^{P} \lambda_p^{>50} \cdot a_i^p \cdot \mathbb{I}[a_i \geq 50] + \xi_i, \tag{1.C.3}$$

where x_i denotes individual i's characteristic, a_i denotes age and P refers to the degree of the polynomial, in our case 2. In this standard RD specification the coefficient $\lambda_0^{>50}$ captures the jump at the threshold and is thus the coefficient of interest. The second model adds indicator variables for each age bin in the manipulation region and is specified as follows:

$$\begin{aligned} x_i = \kappa + \sum_{p=1}^{P} \theta_p^{\leq 50} \cdot a_i^p \cdot \mathbb{I}[a_i < 50] + \sum_{p=0}^{P} \theta_p^{>50} \cdot a_i^p \cdot \mathbb{I}[a_i \geq 50] \\ + \sum_{k=z_U}^{z_L} \delta_k \cdot \mathbb{I}[a_i = k] + \nu_i, \end{aligned} \tag{1.C.4}$$

where we use the main definition of the manipulation region, namely six weeks prior and four weeks after the age cutoff.

Each row of Table 1.D.2 reports the estimated $\lambda_0^{>50}$ coefficients from specification (1.C.3) and $\theta_0^{>50}$ coefficients from specification (1.C.4) for a given observable characteristics. Consistent with our main identifying assumption we find no significant estimates of $\theta_0^{>50}$ coefficients despite several of the estimates for $\lambda_0^{>50}$ being significant. Together these results show that once manipulation is taken into account, observable characteristics appear similar on either side of the age threshold, again consistent with the absence of extensive margin job separation effects.

Appendix 1.D Additional Tables

Table 1.D.1. Test for Discontinuity in Layoff Density

	(1) Whole sample	(2) Without manipulation region	(3) Without manipulation region (alternative definition)
Age	-0.0366***	-0.0335***	-0.0319***
	(0.0027)	(0.0023)	(0.0026)
$\mathbb{I}[\text{age} \geq 50] \times \text{Age}$	-0.0000	0.00029	0.0002
	(0.0042)	(0.0032)	(0.0033)
$\mathbb{I}[\text{age} \geq 50]$	0.0270**	0.0100	0.0015
	(0.0105)	(0.0075)	(0.0079)
Mean	0.48	0.48	0.48
R^2	0.866	0.898	0.904
N	208	203	195

Note: The table reports a parametric test to detect any discontinuity in the density of layoff around the 50 years of age threshold. Column 1 includes all age bins. Column 2 excludes the manipulation region which encompasses the three bins before the cutoff and the two bins after the cutoff. Column 3 excludes an extended manipulation defined in Section 1.C.1. Robust standard errors are reported in parentheses.

Table 1.D.2. Test for Discontinuity in Observables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Simple RD model			"Donut" RD model			Baseline
Variable	$\lambda_0^{>50}$	s.e.	T-stat	$\theta_0^{>50}$	s.e.	T-stat	mean
Female	0.011	0.005	**2.43**	0.000	0.005	-0.03	0.31
Experience	0.177	0.095	1.85	0.093	0.107	0.87	27.34
White-collar	0.017	0.005	**3.71**	0.005	0.005	0.86	0.20
Southern Region	-0.003	0.006	-0.56	-0.005	0.007	-0.74	0.47
Full-time	0.001	0.005	0.26	0.005	0.005	1.09	0.81
Tenure (in years)	-0.040	0.063	-0.63	-0.095	0.078	-1.22	5.85
Daily Wage (in logs)	0.000	0.006	0.03	0.005	0.007	0.69	4.17
Firm Age (in years)	-0.116	0.130	-0.89	-0.122	0.137	-0.89	14.269
Firm Size (in logs)	-0.038	0.014	**-2.72**	-0.015	0.016	-0.94	2.02

Note: The table reports results for the robustness test outlined in Section 1.C.3. Columns 1 to 3 report estimates of $\lambda_0^{>50}$ with associated standard error and t-stat from the RD specification (1.C.3). Columns 4 through 6 present the corresponding results for $\theta_0^{>50}$ from the "donut" RD model of specification (1.C.4). Each row represents a separate observable characteristic. T-stats are highlighted in bold if coefficients are significantly different from zero at the 5% level. Column 7 reports baseline averages for individuals fired between 49 and 50 years of age. The analysis is based on 249,581 spells of individuals laid off from a permanent contract from Feb 2009 to Dec 2012. Standard Errors clustered at the local labor market level.

Chapter 2

Immigration and Productivity: Evidence from US Labor Markets*

2.1 Introduction

The economic literature on the impact of immigration has largely focused on labor market outcomes, especially on wages and employment (see e.g. Card (2009), Ottaviano and Peri (2012), Manacorda, Manning, and Wadsworth (2012), Borjas (2014) and Dustmann, Schönberg, and Stuhler (2016) for recent surveys). There are some but not many papers about the impact of immigration on economic output and productivity. A notable exception is Peri (2012) who documents positive impacts of immigration on productivity, in particular total factor productivity, at the US state level. Exploiting the same source data, Borjas (2019) correlates GSP with immigration and concludes that there is no strong evidence of sizable effects of immigration on GSP per capita. Focusing on a historical context, Sequeira, Nunn, and Qian (2019) find that immigration causes long-run economic growth during the age of mass migration 1850-1920. Fulford, Petkov, and Schiantarelli (2020) document a positive impact of local diversity on prosperity in US counties between 1850 and 2010. There is a larger literature documenting that immigration raises innovation which might be expected to raise productivity.

The relative dearth of papers about the impact of immigration on productivity is perhaps surprising because one could argue that the primary impact of migrant workers is to produce goods and services which makes the study of the effect of immigration on GDP and GDP per capita a first order question. The impact on wages is then perhaps a subsequent question about the distribution of the extra output produced as this determines the distribution of the benefits (or costs) or immigration. For example, it could be that immigrants themselves capture the extra output they

* We thank seminar audiences at the LSE for valuable feedback and comments. Funding from the ERC grant #834455 "LPIGMANN" is gratefully acknowledged.

produce in which case any benefits to natives may be rather small, driven by the extent to which the migrants are complements or substitutes. On the other hand, it may be that migrants are paid less than their marginal product either because they are exploited or because they produce externalities. In this case some of the output gains from migration will be captured by natives.

This paper uses recently released, spatially dis-aggregated county by sector GDP data from the Bureau of Economic Activity (BEA) to provide new evidence on the impact of immigration on output per worker. Building on a newly assembled county by sector GDP per worker panel, we estimate production functions differentiating labor inputs along two dimensions: native vs. immigrant and high vs. low skill. We address concerns about the selection of workers into areas and sectors using a shift-share instrumental variable approach.

We find robust evidence that increasing the share high-skilled immigrants while reducing the share of low-skilled natives raises output per worker, with estimates that are generally larger, although not statistically different, than for the impact of increasing the share of high-skilled natives. On the other hand, shifting from lower-skilled natives to low-skilled immigrants does not seem to have a significant impact on productivity. When probing the robustness of these findings we find support in favor of these main conclusions.

We also compare the impact of immigrants on output with their impact on wages. This allows us to assess whether the impact on productivity is in line with the impact on wages and whether there is an impact on the labor share. Although more tentative, our estimates suggest that it is mostly workers themselves who reap the benefits of increased productivity through higher wages. We find no evidence of significant spillovers, at least in the short-run.

The remainder of the paper is organized as follows. Section 2.2 introduces the empirical setting and data, Section 2.3 describes the conceptual framework, Section 2.4 and 2.5 present the empirical strategy and our results and Section 2.6 concludes.

2.2 Empirical Setting and Data

Our empirical analysis studies the period 2000-2019 in the US. Our unit of observation is an industry (approximately two-digit) by commuting zone by year. We leverage newly released, spatially dis-aggregated real GDP data from the Bureau of Economic Activity (BEA) by county and two digit NAICS sector code and merge it with private employment information from the County Business Pattern database (CBP). For the composition of employment, e.g. the native and immigrant share, we use information from the 2000 Census and the American Community Survey (ACS). A summary description of our data sources follows: for a full documentation of the data sources used in this work see Appendix 2.B.

2.2.1 Primary Data Sources

GDP. Our measure of local output comes from the newly released county by sector GDP data provided by the BEA.[1] The data are part of the bureau's recent efforts to significantly dis-aggregate national and state-level statistics which have been available for decades. As with the state level figures, the BEA uses an income approach to measuring GDP at the county level. It builds on information from the Quarterly Census of Employment and Wages (QCEW) for wages and salaries of employees and IRS tax filing for proprietor's income to construct personal income estimates. These are complemented with information from the Economic Census, the National Establishment Time Series (NETS) sales data and several industry-specific data sources in an attempt to provide an accurate measure of local economic activity. All estimates are re-scaled to match state-level estimates and are thus consistent with the more aggregate figures by construction. All estimates are deflated to chained 2012 USD using national chain-type price indexes. For more details on the exact methodology see Panek, Rodriguez, and Baumgardner (2019).

We use GDP by county and sector information from 2001 to 2019, the maximum period presently available. Because the BEA suppresses information for small cells to protect confidentiality we use two digit 2012 NAICS sectors and in several cases aggregations thereof. Our final sample comprises 11 sectors: Construction (23), Manufacturing (31-33), Wholesale Trade (42), Retail Trade (44-45), Transportation, Warehousing (48-49), Information (51), Finance, Insurance, Real Estate and Rental and Leasing (52-53), Professional, Scientific, and Technical Services, Management of Companies and Enterprises and Administrative and Support and Waste Management and Remediation Services (54-56), Education Services, Health Care and Social Assistance (61-62), Arts, Entertainment and Recreation, and Accommodation and Food Services (71-72) and Other Services (81). These sectors do not cover the whole economy: for reasons explained below we exclude Agriculture, Forestry, Fishing and Hunting (11), Mining, Quarrying and Oil and Gas Extraction (21), Utilities(22) and Public Services (92).

The GDP by county information is place-of-work based rather than residence based. One caveat with our measure of GDP is that - similar to the distortion of national accounts due to profit shifting and transfers by multinational firms - the local GDP data may not accurately ascribe profits to counties in multi-county firms. However, assessing the extent and potential remedies of this concern is beyond the scope of this work.

Employment. Our measure for employment comes from the County Business Pattern (CBP) database from the US Census Bureau. Concretely, we use recently published data by Eckert, Fort, Schott, and Yang (2021) which combines hierarchical

1. The BEA released the first official version of the dataset on Dec 12, 2019. A prototype dataset was released on Dec 12, 2018.

constraints implicit in the official CBP figures to impute information for suppressed employment cells. Eckert et al. (2021)'s data provide a measure of headcount employment by county and six digit 2012 NAICS code which we aggregate up to the same two digit level as the GDP information. We devote some care to matching GDP and employment information because NAICS code classifications generally do not differentiate between private and public ownership. Since the CBP data covers only private non-farm employment we exclude farming as well as several other sectors that are likely to contain significant fraction of public employment. Specifically, we exclude the following sectors from the analysis: agricultural, forestry, fishing and hunting (11), mining, quarrying and oil and gas extraction (21), utilities (22) and public administration (92). Luckily, the BEA's GDP estimates do explicitly exclude public contributions to GDP for several sectors which insures a close link between the BEA and CBP data.[2] While raw CBP data is available until and including 2019, the imputed data by Eckert et al. (2021) covers only the years until and including 2016. This is because the US Census Bureau significantly altered it's reporting and suppression guidelines from 2017 onward. Our main sample therefore restricts attention to the years until and including 2016. We replicate our main findings in Appendix Table 2.A.15 and Table 2.A.16 for a subsample of the data unaffected by the reporting change.

Employment Shares. The information on the composition of employment comes from the 2000 Census and the American Community Survey (ACS) waives 2005-2019 available via the Integrated Public Use Microdata Series (IPUMS) Ruggles, Flood, Foster, Goeken, Pacas, et al. (2021). From 2001 until 2004 the ACS does not provide adequately fine geographic information. We construct estimates of the total number of workers by industry, education and country of birth at the place-of-work puma level which we then distribute to counties using a probabilistic crosswalk based on 2000 population estimates. For our IV construction explained in detail in Section 2.4.2, we differentiate 36 countries of birth. We classify high-skill education as having at least some college education, while low-skill refers to no years of college education. We provide details of the exact construction of employment share estimates in Appendix 2.B.

2.2.2 Main Sample and Summary Statistics

For our main sample we first combine the real GDP, employment and employment shares into a county by sector year panel covering 3079 counties and 11 industries over the years 2005 to 2016. The BEA suppresses GDP information to protect confidentiality and we use interpolation to deal with suppressed GDP information. We

2. Specifically, the BEA explicitly excludes public enterprises from the following sectors' GDP estimates: Management of Companies and Enterprises (55), Administrative and Support and Waste Management and Remediation Services (56), Education Services (61), Hospitals (622), Other Services (81).

describe the interpolation procedure in detail in Appendix 2.B and probe the robustness of the procedure in Appendix Table 2.A.9 and Table 2.A.10. For our main sample, we rely only on county-sectors with non-missing GDP information for all years from 2005 to 2016.

We aggregate all data at the commuting zone by sector level. Commuting zones (CZs) are collections of counties that are characterized by strong within and relatively weak across commuting ties Tolbert and Sizer (1996). There are 722 CZs in the mainland US. The motivation for conducting the main analysis at CZ, rather than county level, is twofold. First and foremost, commuting zones offer a reasonable approximation of small local economies and thus naturally lend themselves to a production function approach. Second, because we are relying on ACS's place-of-work PUMAs to construction employment shares the level of variation more naturally maps to larger aggregation rather than individual counties. We nevertheless provide estimates at the county level in Appendix Table 2.A.13 and 2.A.14. Third, estimating at CZ level allows for the possibility that there are spill-over effects that operate at the labor market level.

Apart from the restrictions imposed by missing information or data suppression, we exclude very small employment cells and (weakly) balance the sample. Concretely, we keep only CZ-sectors that have at least five industries each with a minimum headcount employment of ten across all years. We probe robustness to this restriction in Appendix Table 2.A.7 and Table 2.A.8.

The main dataset covers 701 CZs each with at least five and a maximum of eleven industries and spans the years 2005-2016. In Table 2.1 we present summary statistics of the main sample with 88,932 observations. Mean GDP per worker amounts to 128,151 USD with a considerably lower median of 86,254 USD. Headcount employment is even more right-skewed with a mean of around 15,000, and a median of around 2,300 workers. We work with a log specification of these variables in our main analysis. The average CZ sector employs 7% immigrant and around 50% high-skill (at least some college education) labor. High-skill immigrants make up 3%, low-skill immigrants 4% on average. Panel B of Table 2.1 shows changes in our main variables between 2005 and 2016. GDP and employment of the average CZ-sector rose by 13% and 1%. GDP per worker increased by 16% over the same time period. These changes were accompanied by changes in the employment composition. The share of high-skill employment rose by 5.4 p.p., driven by an increase of 4.6 p.p. in native high-skill employment and 0.8 p.p. increase in immigrant high-skill employment. These summary statistics provide insight into an average CZ sector. To square these numbers with national trends, we provide employment-weighted summary statistics in Appendix Table 2.A.2. In particular, as larger CZ sectors tend to employ more high-skill and more immigrant labor the share of immigrants in employment is around 18% and high-skill labor makes up around 56%. Table 2.A.3 in the Appendix provides summary statistics by industry.

Table 2.1. Summary Statistics

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	1,731	7,794	0.4	360,953	210	88,932
GDP per Worker (in USD)	128,151	140,186	1,953.1	5,611,095	86,254	88,932
Employment (headcount)	14,993	51,016	12.0	1,281,598	2,348	88,932
Pre-Employment (headcount)	14,589	48,887	8.8	1,249,510	2,304	88,932
Share immigrants	0.07	0.09	0.00	1.00	0.04	88,932
Share high-skill	0.49	0.18	0.00	1.00	0.47	88,932
Share high-skill immigrants	0.03	0.04	0.00	1.00	0.01	88,932
Share low-skill immigrants	0.05	0.07	0.00	0.74	0.02	88,932
Share high-skill natives	0.46	0.17	0.00	1.00	0.44	88,932
Share low-skill natives	0.47	0.17	0.00	1.00	0.47	88,932
Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.13	0.51	−0.85	17.33	0.07	88,932
GDP per Worker (in %)	0.16	0.55	−0.88	18.12	0.07	88,932
Employment (in %)	0.01	0.38	−0.93	16.80	−0.02	88,932
Share immigrants (in p.p.)	0.01	0.05	−0.61	0.33	0.01	88,932
Share high-skill (in p.p.)	0.05	0.09	−0.46	0.79	0.05	88,932
Share high-skill immigrants (in p.p.)	0.01	0.03	−0.14	0.33	0.01	88,932
Share low-skill immigrants (in p.p.)	0.00	0.04	−0.59	0.30	0.00	88,932
Share high-skill natives (in p.p.)	0.05	0.09	−0.41	0.76	0.04	88,932
Share low-skill natives (in p.p.)	−0.06	0.09	−0.78	0.75	−0.06	88,932

Note: This table reports summary statistics of GDP, GDP per worker, employment and employment shares for the main sample. Panel A presents levels and Panel B changes over the time period 2005-2016. In Panel B growth rates for GDP, GDP per worker and employment are constructed as arithmetic annual growth rates between 2005/7 to 2014/16. Pre-employment refers to average employment over the years 2000-2004.

2.3 Conceptual Framework

This section presents a production function approach that guides our empirical analysis in Section 2.4. Suppose we have a production function that is homogeneous of degree $\alpha \in \mathbb{R}_+$ in its $n \in \mathbb{N}$ inputs $L_1, \ldots, L_n$ representing the different types of labor used in production.[3] Output may thus be written as

$$Y = A \cdot F(L_1, \ldots, L_n)^\alpha, \qquad (2.1)$$

where Y denotes total output, A captures total factor productivity and $F(\cdot)$ is homogeneous of degree 1. By Euler's theorem, we may rewrite (2.1) as follows:

3. Because we restrict attention to labor inputs in production, our framework should be interpreted as a long-run production function with capital inputs in perfectly elastic supply.

$$
\begin{aligned}
Y &= A \cdot \left(\sum_{i=1}^{n} F_i \cdot L_i \right)^{\alpha} \\
&= A \cdot L^{\alpha} \cdot \left(\sum_{i=1}^{n} F_i \cdot s_i \right)^{\alpha} \\
&= A \cdot L^{\alpha} \cdot \left(F_n + \sum_{i=1}^{n-1} (F_i - F_n) \cdot s_i \right)^{\alpha} \\
&= A \cdot L^{\alpha} \cdot F_n^{-\alpha} \cdot \left(1 + \sum_{i=1}^{n-1} \frac{F_i - F_n}{F_n} \cdot s_i \right)^{\alpha} \\
&= A \cdot L^{\alpha} \cdot F_n^{-\alpha} \cdot \left(1 + \sum_{i=1}^{n-1} \frac{MPL_i - MPL_n}{MPL_n} \cdot s_i \right)^{\alpha}, \qquad (2.2)
\end{aligned}
$$

where $F_i = \frac{\partial F}{\partial L_i}$ denotes the partial derivative of F w.r.t. L_i, $L = \sum_i L_i$ denotes total employment, $s_i = \frac{L_i}{L}$ denotes the share of type L_i in total employment and $MPL_i = \frac{\partial Y}{\partial L_i}$ denotes the marginal product of labor of type L_i.

Equation (2.2) permits the following log-linear approximation

$$
log\left(\frac{Y}{L}\right) \approx log(A) + (1-\alpha) \cdot log(L) - \alpha \cdot log(F_n) + \alpha \cdot \sum_{i=1}^{n-1} \frac{MPL_i - MPL_n}{MPL_n} \cdot s_i. \qquad (2.3)
$$

Our main parameters of interest θ_i are the re-scaled (divided by α) coefficients on the s_i's and are given by

$$
\theta_i = \frac{MPL_i - MPL_n}{MPL_n}. \qquad (2.4)
$$

Each θ_i captures the relative productivity difference between labor type L_i and the omitted type L_n (in percent). We estimate specifications akin to equation (2.3) using OLS and 2SLS. We employ a two skill-type version differentiating high (with some college) and low (without any college) education, of the model in the empirical implementation. For a justification of a two skill model see e.g. Card (2009).

2.4 Empirical Strategy

This section lays out our empirical strategy to study the effects of immigration on productivity. We first present our main estimating equations before describing our shift-share instrumental variable approach.

2.4.1 Estimating Equation

We estimate several specifications motivated by equation (2.3). Concretely, we model the effect of the high- and low-skill immigrant labor shares $s_{ijt}^{imm,h}$ and $s_{ijt}^{imm,l}$, the high-skill native labor share $s_{ijt}^{nat,h}$ and log employment $log(l)_{ijt}$ in CZ i, industry j and year t on log productivity $log(y/l)_{ijt}$ as follows:

$$log(y/l)_{ijt} \; = \; \lambda_{it} + \delta_{r(i)jt} + \beta_1 \cdot s_{ijt}^{imm,h} + \beta_2 \cdot s_{ijt}^{imm,l} + \beta_3 \cdot s_{ijt}^{nat,h} + \beta_4 \cdot log(l)_{ijt} + \epsilon_{ijt}, \tag{2.5}$$

where y is real CZ sector GDP and l measures headcount employment, i.e. the number of workers. The coefficients β_1, β_2 and β_3 measure the productivity of the respective type of labor relative to the omitted category of low-skill native employment. We flexibly control for several contemporaneous changes that might influence productivity through a set of fixed effects. These include a full set of CZ year fixed effects λ_{it} which control for local economic conditions affecting all industries in a CZ, such as e.g. demand side, political or environmental factors. We further include a set of (regional) industry trends $\delta_{r(i)jt}$ that capture industry-specific productivity trends, e.g. due to technological change or trade which might affect industries differently. In our most demanding specification we allow these trends to be state-specific. The exhaustiveness of these fixed effects is a key strength of our approach. While previous studies often worked at the national or state level, our analysis exploits within state variation in productivity and relates it to the various employment shares and the size of the labor force. Because the latter effect will turn out to be rather small in many regressions (but only when we instrument for it), we also run specifications that omit the effect of log employment. Specifically, we estimate the following model:

$$log(y/l)_{ijt} \; = \; \lambda_{it} + \delta_{r(i)jt} + \beta_1 \cdot s_{ijt}^{imm,h} + \beta_2 \cdot s_{ijt}^{imm,l} + \beta_3 \cdot s_{ijt}^{nat,h} + \epsilon_{ijt}, \tag{2.6}$$

where all variables are defined as in equation (2.5).

Section 2.5.1 presents results from running regressions of equation (2.5) and (2.6) using OLS. Although we include a variety of fixed effects, the OLS estimates are likely to be biased for several reasons. First, there might be unobserved local characteristics that affect productivity and that correlate with the number and mix of workers in the area or industry; there is a long tradition in estimating production functions of worrying about the endogeneity of factor inputs - see e.g. Ackerberg, Caves, and Frazer (2015). Second, as we rely in part on interpolated data, we might have measurement error in our share estimates. Motivated by these concerns we turn to a shift-share instrumental variable approach to lend further support to the causal interpretation of the effect of immigration on productivity.

2.4.2 Shift-share Instrumental Variable

Given the likely bias of the OLS estimates, our goal is to exploit variation in the various types of labor used in production that is more plausibly exogenous and uncorrelated with local economic factors. The ideal instrument is a variable that shifts the supply of labor but is not driven by shifts to the production function (which will affect the demand for labor). In line with a long tradition in the literature on the economic effects of immigration Altonji and Card (1991) and Card (2001) we use shift-share instruments.

Specifically we construct separate shift-share instruments for all four endogenous regressors in specification (2.5). Concretely, we build predictors of the number of high- and low-skill immigrants, high- and low-skill natives and, by adding these up, a predictor of the size of the total work force for each CZ sector in each year. Our strategy exploits national trends in the size of the workforce of the respective group interacted with its geographical and industry distribution in the year 2000. Formally, let $L_{ijt}^{c,e}$ denote the number of workers from origin country c with skill level e, in CZ i, industry j and year t. Analogously, let $POP_{it}^{c,e}$ be the population (aged 15 to 64) from origin c with education e in CZ i in year t.[4] The omission of sub- or superscripts encodes the summation over the excluded indices , e.g. $L_{it}^{c,e} = \sum_j L_{ijt}^{c,e}$ refers to the total number of workers from country c, education e, in CZ i and year t across all industries. We denote with ˆ the respective predicted values of these variables which we construct as follows:

First, we define the share of individuals from origin c with education e in CZ i in the year 2000 as a share of their national total as

$$w_{i,2000}^{c,e} = \frac{POP_{i,2000}^{c,e}}{POP_{2000}^{c,e}}.$$

We use these origin- and skill-specific weights to distribute the national growth in the population of individuals from origin c with education e across CZs and predict the population of this group in each CZ as

$$P\hat{O}P_{i,t}^{c,e} = POP_{i,2000}^{c,e} + w_{i,2000}^{c,e} \cdot \left(POP_{t}^{c,e} - POP_{2000}^{c,e}\right).$$

Second, we distribute the predicted population according to the national industry distribution of all workers from origin c and with education e. Concretely, let

$$w_{j,2000}^{c,e} = \frac{L_{j,2000}^{c,e}}{L_{2000}^{c,e}}$$

denote the share of workers from origin c with education e who work in industry j in the year 2000 as a share of the national total. We predict the number of workers from origin o with education e, in CZ i, sector j and year t by multiplying the predicted

4. We take county population estimates from the US Census website, see Appendix 2.B for details.

population with the national industry shares. Formally, we have

$$\hat{L}^{c,e}_{ijt} = w^{c,e}_{j,2000} \cdot \hat{POP}^{c,e}_{i,t}.$$

Lastly, we construct the predicted high- and low-skill native and immigrant employment shares by aggregating the predicted values for the respective groups and dividing by the size of the predicted total labor force. Formally, we define the predicted shares as

$$\hat{s}^{nat,e}_{ijt} = \frac{\hat{L}^{USA,e}_{ijt}}{\hat{L}_{ijt}} \quad \text{and} \quad \hat{s}^{imm,e}_{ijt} = \frac{\sum_{c \neq USA} \hat{L}^{c,e}_{ijt}}{\hat{L}_{ijt}}. \tag{2.7}$$

Together with the log size of the total labor force, $log(\hat{L}_{ijt})$, these predicted shares form our instruments for the analysis in Section 2.5.2.

Intuitively, our instruments exploit two forces that help to predict and isolate exogenous variation in employment shares. First, new immigrants tend to settle in locations where previous immigrants from the same origin country settled.[5] Second immigrants from different origin countries bring different skill-sets and as a consequence tend to be concentrated in certain occupations and industries. The combination of these two forces leads to variation in the immigrant employment share that is driven by these historical settlement patterns, the industry / occupation specialization of previous immigrants and the national growth of immigrants from a specific origin country. If the national growth of immigrants from a certain origin country is not driven by local or industry specific labor demand shocks, the shift-share instruments are valid and provide exogenous variation. Shift-share instrumental variables are popular because they tend to have adequate power and are readily constructible (often) within sample. There is a recent literature that discusses identification and inference in shift-share IV designs in more detail, see Adao, Kolesár, and Morales (2019), Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2021). However, most of these recent contributions apply to a single cross-section or a panel in which the base shares change over time. Because we use time and cross-section fixed effects, there cannot be any endogeneity problem with the two components of our shift-share instrument; the baseline shares and the time variation. Our identification is based on the interaction between the two.

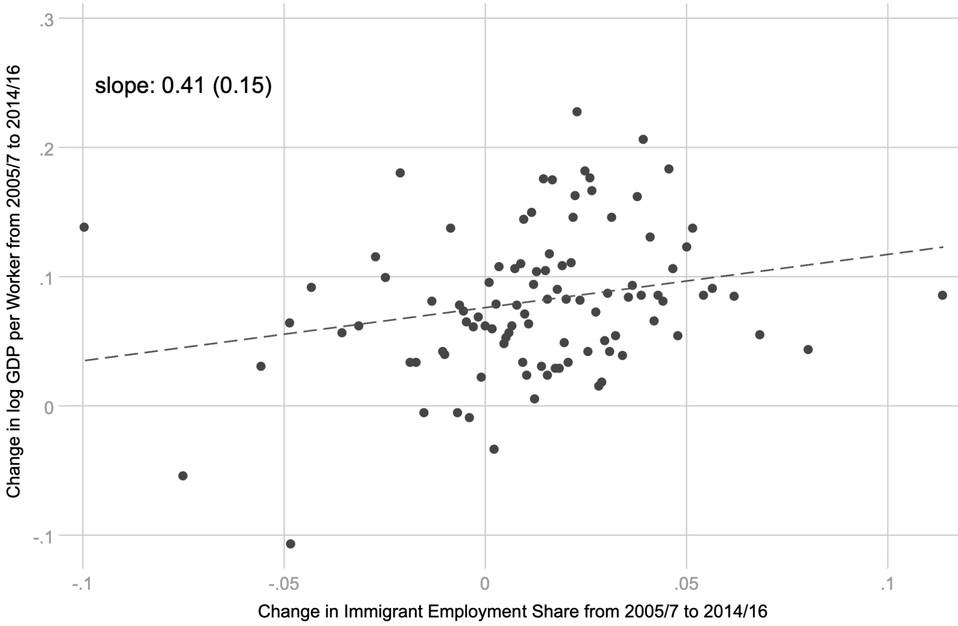
2.5 Results

Before turning to our main regression analysis, we present three sets of descriptive figures to provide visual evidence of the impacts of immigration on productivity. Fig-

5. The observation that new arriving immigrants tend to dis-proportionally settle in enclaves established by earlier immigrants dates back to Bartel (1989).

ure 2.1 plots changes in productivity, as measured by real GDP per worker, against changes in the immigrant employment share across CZ sectors between the years 2005/2007 and 2014/2016. There is a significant positive correlation of 0.41 (se 0.15) indicating that CZ sectors that saw a larger rise in the share of immigrants in employment also experienced larger gains in productivity.[6] Figure 2.2 repeats this analysis but splits the immigrant employment share into high- (at least some college education) and low-skill immigrant employment. The aggregate positive correlation from Figure 2.1 is due to the change in high-skill immigrant employment which depicts a strong positive correlation with changes in productivity of 2.25 (se 0.58). Contrary, changes in low-skill immigrant employment shares are associated with relatively smaller negative changes in productivity of -0.43 (se 0.19). We probe the robustness of these descriptive patterns in Figure 2.3 in which we residualize changes in productivity and immigrant employment shares on a set of industry fixed effects, changes in log employment, changes in high-skill native employment and changes in the opposite-skill immigrant share in employment. We find that the positive correlation between changes in the high-skill immigrant employment share decreases but remains significant at 0.80 (se 0.40). Contrary, once we include controls there is no longer any meaningful or significant relationship between productivity growth and the change in low-skill immigration with a correlation of -0.06 (se 0.14). These descriptive pattern provide clear graphical evidence and are suggestive of a positive effect of high-skill immigration on productivity. They also suggest a modest or nonexistent effect of low-skill immigration on productivity. Furthermore, Figure 2.1 through Figure 2.3 show that these conclusions are not driven by a small number of observations but hold more broadly. We now turn to the results of our main regression analysis.

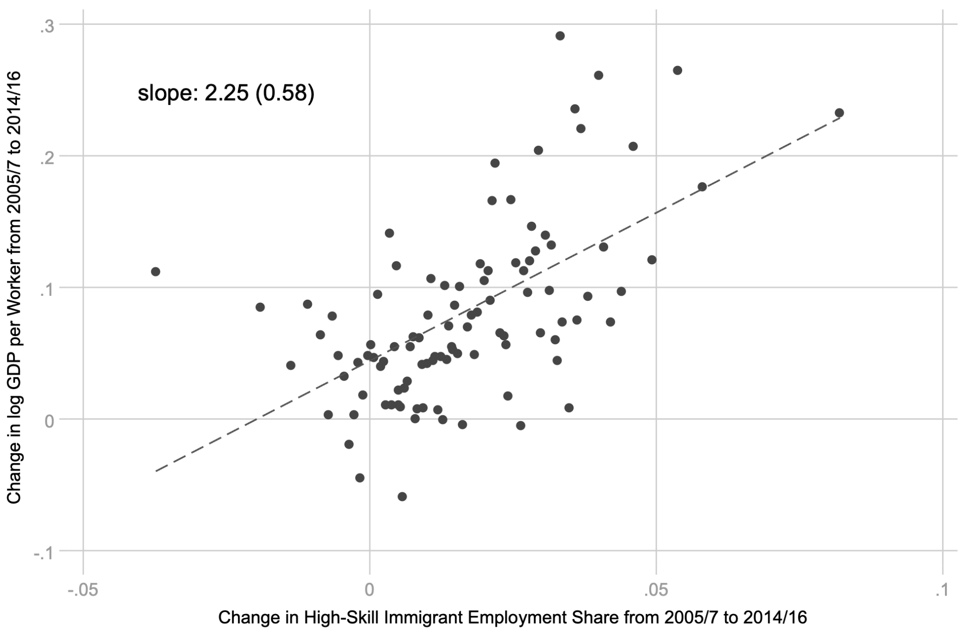
6. All figures are weighted by CZ sector pre-employment size and the reported standard errors are clustered at the state level.



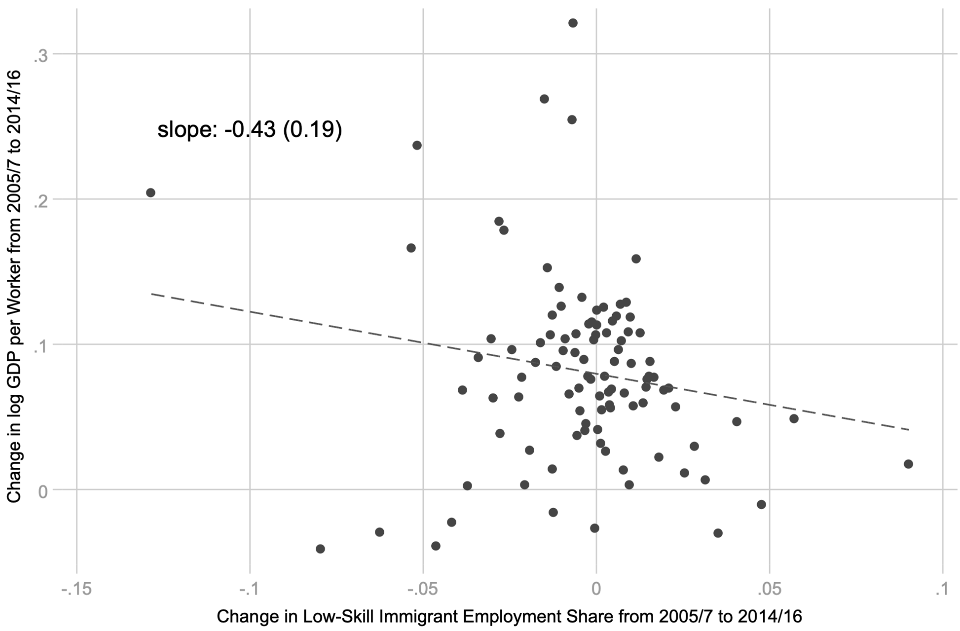
Note: This figure shows the relationship between changes in GDP per worker on the vertical axis and changes in the immigrant employment share on the horizontal axis between 2005/7 and 2014/16. Each bin represents one percent of CZ sector cells. The dashed line depicts the best linear fit estimated on the underlying CZ by sector level data using OLS.

Figure 2.1. Correlation between the Change in Productivity and the Change in the Immigrant Employment Share between 2005/7 and 2014/16

(a) High-Skill Immigration



(b) Low-Skill Immigration

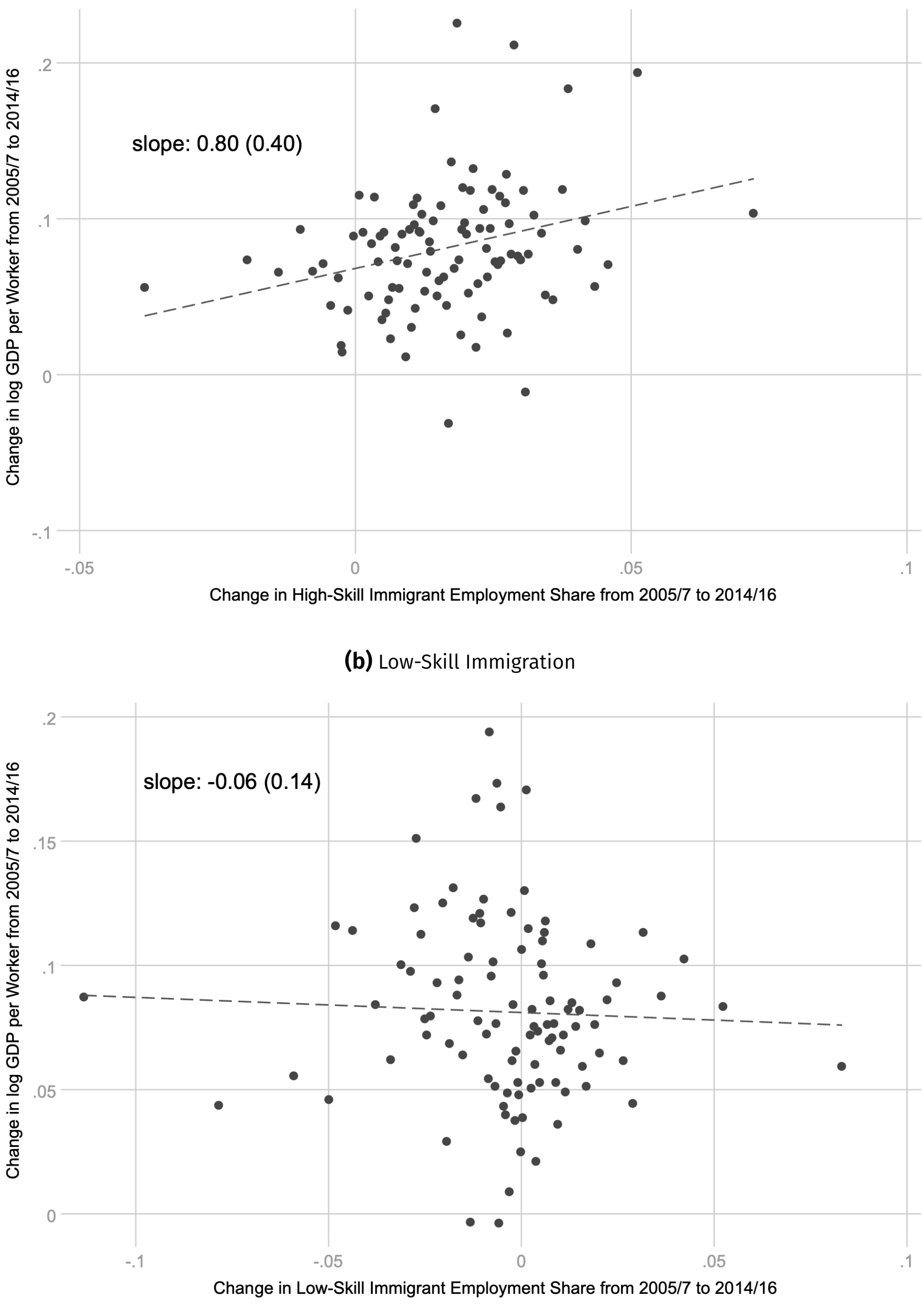


Note: This figure shows the relationship between changes in GDP per worker on the vertical axis and changes in the high-skill (Panel (a)) and the low-skill (Panel (b)) immigrant employment share on the horizontal axis between 2005/7 and 2014/16. Each bin represents one percent of CZ sector cells. The dashed line depicts the best linear fit estimated on the underlying CZ by sector level data using OLS.

Figure 2.2. Correlation between the Change in Productivity and the Change in the High- and Low-Skill Immigrant Employment Share between 2005/7 and 2014/16

(a) High-Skill Immigration

(b) Low-Skill Immigration



Note: This figure shows the relationship between changes in GDP per worker on the vertical axis and changes in the high-skill (Panel (a)) and the low-skill (Panel (b)) immigrant employment share on the horizontal axis between 2005/7 and 2014/16. All variables are residualized on a set of industry sector fixed effects and changes in log employment, changes in the high-skill native employment share and changes in the opposite-skill immigrant employment share. Each bin represents one percent of CZ sector cells. The dashed line depicts the best linear fit estimated on the underlying CZ by sector level data using OLS.

Figure 2.3. Correlation between the Change in Productivity and the Change in the High- and Low-Skill Immigrant Employment Share between 2005/7 and 2014/16 with Controls

2.5.1 OLS Results

We begin our analysis by estimating an aggregated version of our main specification, that is, without distinguishing between high- vs. low-skill within immigrant and native employment.[7] As before, and unless otherwise stated all regressions are weighted by CZ sector pre-employment size. Table 2.2 presents the results from OLS regressions of real GDP per worker on various employment shares and the size of the work force, log employment, on the CZ sector year level. The immigrant employment share is strongly negatively associated -0.33 (se 0.14) with the level of productivity even when including several layers of fixed effects in column 4.[8] Once we control for the educational composition and include the share of high-skill employment in the CZ sector the coefficient on the immigrant share falls substantially and becomes insignificant indicating the important interaction between immigration and the skill composition. A larger share of high-skill employment is strongly associated with high levels of productivity as one might expect.

Table 2.2. The Effect of Immigration on Productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log GDP per Worker							
Share immigrants	−0.286	−0.322	−0.245**	−0.332**	−0.103	−0.128	−0.054	−0.155
	(0.188)	(0.199)	(0.120)	(0.135)	(0.177)	(0.192)	(0.103)	(0.113)
Share high-skill					0.760***	0.832***	0.750***	0.729***
					(0.107)	(0.115)	(0.112)	(0.125)
Log employment	−0.074***	−0.068***	−0.076***	−0.128***	−0.080***	−0.076***	−0.091***	−0.145***
	(0.024)	(0.025)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)	(0.023)
R^2	0.90	0.91	0.92	0.94	0.91	0.91	0.93	0.95
N	88,932	88,932	88,932	88,656	88,932	88,932	88,932	88,656
CZ FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓		✓	✓	✓
Industry x Year FE		✓	✓	✓		✓	✓	✓
Region x Industry x Year FE			✓	✓			✓	✓
State x Industry x Year FE				✓				✓

Note: This table reports coefficients from an OLS regression of specification (2.8). The dependent variable is log GDP per worker and the endogenous variables are the immigrant employment share, the high-skill employment share and log employment. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

7. Concretely, we estimate versions of the following specification by OLS

$$log(GDP)_{ijt} = \lambda_{it} + \delta_{r(i)jt} + \beta_1 \cdot share^{imm}_{ijt} + \beta_2 \cdot share^{h}_{ijt} + \beta_3 \cdot log(EMP)_{ijt} + \epsilon_{ijt} \tag{2.8}$$

8. Some specifications contain "region" or "region by industry" fixed effects. Regions refer to Census divisions throughout. There are a total of nine divisions representing collections of neighboring states, e.g. East North Central or New England. See the Census website for details.

Motivated by these findings we split the immigrant and native employment share into high- and low-skill and report OLS estimates in Table 2.3. Concretely we estimates models of log real GDP per worker on the high- and low-skill immigrant and high-skill native employment shares and on log employment. All effect sizes are measured relative to the omitted category of low-skill native employment. Table 2.3 confirms the findings from Figures 2.2 and 2.3 that differentiating immigrants by skill is essential. We find that the high-skill immigrant employment share is strongly associated 0.94 (se 0.26) with higher productivity especially when controlling for the remainder of the employment composition in column 8. The effect of the low-skill immigrant employment share turns insignificant in this specification -0.13 (se 0.12) although we find strong negative univariate correlations in columns 3 and 4 of Table 2.3. Column 8 of Table 2.3 also shows a large and positive effect of the high-skill native employment share of 0.69 (se 0.08). The coefficient appears significantly lower than the point estimate for the high-skill immigrant employment share although we cannot reject the null of equal coefficients at conventional significant levels. We now turn to our main results.

Table 2.3. The Effect of High- and Low-Skill Immigration on Productivity (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log GDP per Worker							
Share high-skill immigrants	0.865***	0.754**			0.635**	0.551*	1.039***	0.935***
	(0.211)	(0.321)			(0.261)	(0.284)	(0.228)	(0.263)
Share low-skill immigrants			−0.546***	−0.493***	−0.446**	−0.400***	−0.209	−0.131
			(0.175)	(0.181)	(0.188)	(0.146)	(0.185)	(0.120)
Share high-skill natives							0.673***	0.690***
							(0.114)	(0.082)
Log employment	−0.084***	−0.085***	−0.080***	−0.083***	−0.086***	−0.088***	−0.086***	−0.094***
	(0.024)	(0.026)	(0.024)	(0.024)	(0.024)	(0.026)	(0.024)	(0.025)
R^2	0.90	0.92	0.90	0.92	0.90	0.92	0.91	0.93
N	88,932	88,932	88,932	88,932	88,932	88,932	88,932	88,932
CZ FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓		✓		✓		✓
Region x Industry x Year FE		✓		✓		✓		✓

Note: This table reports coefficients from an OLS regression of specification (2.5). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

2.5.2 2SLS Results

As outlined in Section 2.4.2 we complement our OLS estimates with 2SLS estimates from our shift-share instrumental variable approach. To this end we instrument all four endogenous variables in specification (2.5) by the predicted employment shares constructed in equation (2.7) and predicted log employment. The first stage regression coefficients reported in Appendix Table 2.A.4 indicate sufficient power to separately predict all four variables. Table 2.4 reports the results of our IV analysis in three parts. Panel A of Table 2.4 provides OLS estimates for comparison, Panel B instruments the three employment shares but leaves log employment endogenous and Panel C instruments all three employment shares *and* log employment.

Table 2.4 shows three main findings. First, we robustly find a large positive impact of increasing the high-skill immigrant and high-skill native employment share at the expense of low-skill natives employment. Our estimates imply that a one percent increase in the share of high-skill immigrants accompanied by a one percent reduction in the share of low-skill natives increases real GDP per worker by between 1 to 3 percent. [To benchmark these results ...] Second we consistently find small, mostly insignificant, sometimes positive impacts of the low-skill immigrant employment share, implying that substituting between low-skill immigrant and native employment doesn't meaningfully affect productivity. Third, these conclusions are robust to the exact inclusion of fixed effects. The reported Kleibergen Paap first stage F-statistics in Table 2.4 indicate that the instruments are strong and have sufficient power with values above conventional thresholds.[9]

Panel C of Table 2.4 further suggests that scale effects, as captured by estimates of β_4 in specification (2.5), are relatively small. Constant returns to scale seems a reasonable approximation to the data. This motivates investigating specification (2.6) which omits log employment. Table 2.5 reports results of estimating specification (2.6) with Panel A showing OLS and Panel B presenting 2SLS estimates using the predicted shares from equation (2.7) as instruments. The findings in Table 2.5 confirm the previous conclusion. Larger high-skill immigrant and native employment shares (at the expense of low-skill native employment) increase productivity markedly, while low-skill immigration has smaller, mostly insignificant impacts. Again, these conclusions are robust to the choice of fixed effects and the instruments appear sufficiently powerful.

9. Our results are (mostly) based on F-statistics that far exceed conventional levels. This is reassuring in the light of recent concerns about possible overstatements of statistical significance in single IV specifications based on conventional F-statistic levels, see e.g. Lee, McCrary, Moreira, and Porter (2021).

Table 2.4. The Effect of High- and Low-Skill Immigration on Productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	1.039***	1.095***	0.995***	0.924***	0.935***	0.957***
	(0.228)	(0.236)	(0.237)	(0.244)	(0.263)	(0.251)
Share low-skill immigrants	−0.209	−0.205	−0.205	−0.126	−0.131	−0.313**
	(0.185)	(0.200)	(0.201)	(0.112)	(0.120)	(0.143)
Share high-skill natives	0.673***	0.746***	0.765***	0.671***	0.690***	0.622***
	(0.114)	(0.121)	(0.120)	(0.074)	(0.082)	(0.073)
Log employment	−0.086***	−0.087***	−0.080***	−0.095***	−0.094***	−0.150***
	(0.024)	(0.024)	(0.025)	(0.025)	(0.025)	(0.023)
R^2	0.91	0.91	0.91	0.93	0.93	0.95
N	88,932	88,932	88,932	88,932	88,932	88,656
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	3.520***	3.526***	3.354***	2.880***	2.864***	3.936***
	(0.886)	(0.943)	(0.928)	(0.562)	(0.576)	(0.779)
Share low-skill immigrants	0.543	0.544	0.516	0.930***	0.929***	1.117***
	(0.566)	(0.591)	(0.595)	(0.225)	(0.226)	(0.392)
Share high-skill natives	1.920***	1.957***	1.965***	1.392*	1.384*	1.830
	(0.649)	(0.638)	(0.648)	(0.744)	(0.757)	(1.142)
Log employment	−0.102***	−0.104***	−0.097***	−0.110***	−0.109***	−0.185***
	(0.024)	(0.024)	(0.025)	(0.031)	(0.031)	(0.033)
KP F-stat	27.24	28.18	28.51	30.01	30.01	22.41
N	88,932	88,932	88,932	88,932	88,932	88,656
Panel C: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.449***	2.412***	2.429***	1.862**	1.845**	2.626***
	(0.831)	(0.861)	(0.842)	(0.725)	(0.747)	(0.590)
Share low-skill immigrants	0.274	0.263	0.285	0.824***	0.823***	0.992***
	(0.634)	(0.646)	(0.628)	(0.216)	(0.218)	(0.358)
Share high-skill natives	2.455***	2.475***	2.386***	1.856**	1.845**	2.309*
	(0.611)	(0.592)	(0.591)	(0.804)	(0.816)	(1.270)
Log employment	0.057*	0.052	0.032	0.046	0.046	−0.006
	(0.034)	(0.035)	(0.037)	(0.029)	(0.029)	(0.027)
KP F-stat	18.54	19.33	19.79	25.48	25.39	20.78
N	88,932	88,932	88,932	88,932	88,932	88,656
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓	✓	✓
Industry x Year FE			✓	✓	✓	✓
Region x Industry FE				✓	✓	✓
Region x Industry x Year FE					✓	✓
State x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.5. The Effect of High- and Low-Skill Immigration on Productivity (w/o log employment)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	0.891***	0.939***	0.849***	0.732***	0.737***	0.660**
	(0.218)	(0.224)	(0.227)	(0.229)	(0.246)	(0.258)
Share low-skill immigrants	−0.191	−0.187	−0.188	−0.096	−0.099	−0.295*
	(0.174)	(0.188)	(0.190)	(0.116)	(0.124)	(0.150)
Share high-skill natives	0.673***	0.744***	0.762***	0.636***	0.656***	0.549***
	(0.118)	(0.126)	(0.124)	(0.077)	(0.085)	(0.078)
R^2	0.91	0.91	0.91	0.92	0.93	0.94
N	88,932	88,932	88,932	88,932	88,932	88,656
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.831***	2.785***	2.656***	2.161***	2.147***	2.581***
	(0.863)	(0.909)	(0.900)	(0.572)	(0.590)	(0.580)
Share low-skill immigrants	0.370	0.357	0.342	0.855***	0.854***	0.987***
	(0.626)	(0.648)	(0.648)	(0.215)	(0.217)	(0.362)
Share high-skill natives	2.264***	2.302***	2.283***	1.720**	1.708**	2.325*
	(0.653)	(0.641)	(0.655)	(0.827)	(0.838)	(1.302)
KP F-stat	26.13	26.68	26.80	26.47	26.31	23.33
N	88,932	88,932	88,932	88,932	88,932	88,656
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓	✓	✓
Industry x Year FE			✓	✓	✓	✓
Region x Industry FE				✓	✓	✓
Region x Industry x Year FE					✓	✓
State x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.6. Robustness

	(1)	(2)	(3)	(4)	(5)
Sample excludes:	-	California	Texas	-	-
IV excludes:	-	-	-	China & India	Mexico
Panel A: OLS	Log GDP per Worker				
Share high-skill immigrants	0.935	0.747***	0.917***	0.935***	0.935***
	[0.345,1.385]	(0.266)	(0.280)	(0.263)	(0.263)
Share low-skill immigrants	−0.131	−0.043	−0.172	−0.131	−0.131
	[−0.419,0.124]	(0.117)	(0.139)	(0.120)	(0.120)
Share high-skill natives	0.690	0.652***	0.661***	0.690***	0.690***
	[0.484,0.823]	(0.079)	(0.086)	(0.082)	(0.082)
Log employment	−0.095	−0.087***	−0.092***	−0.095***	−0.095***
	[−0.158,−0.052]	(0.026)	(0.027)	(0.025)	(0.025)
R^2	0.93	0.92	0.93	0.93	0.93
N	88,932	86,712	81,216	88,932	88,932
Panel B: 2SLS	Log GDP per Worker				
Share high-skill immigrants	2.860	2.468**	2.547***	2.474**	5.091***
	[1.547,5.780]	(0.974)	(0.545)	(1.165)	(0.733)
Share low-skill immigrants	0.927	1.036***	0.780***	0.775***	1.858***
	[0.507,1.807]	(0.302)	(0.176)	(0.266)	(0.299)
Share high-skill natives	1.382	0.579	1.354	1.388	2.223***
	[−0.327,3.028]	(0.432)	(0.832)	(0.893)	(0.474)
Log employment	−0.109	−0.090***	−0.105***	−0.106***	−0.130***
	[−0.187,−0.527]	(0.031)	(0.032)	(0.033)	(0.029)
KP F-stat	30.05	29.08	29.22	8.05	38.35
N	88,932	86,712	81,216	88,932	88,932
Panel C: 2SLS	Log GDP per Worker				
Share high-skill immigrants	1.844	0.803	1.572*	2.217*	3.791***
	[−0.513,3.085]	(0.976)	(0.795)	(1.248)	(0.843)
Share low-skill immigrants	0.823	0.877***	0.665***	0.830***	1.670***
	[0.270,1.470]	(0.291)	(0.183)	(0.275)	(0.258)
Share high-skill natives	1.846	0.834**	1.734*	1.964**	2.347***
	[0.966,3.517]	(0.367)	(0.887)	(0.927)	(0.620)
Log employment	0.046	0.078**	0.042	0.037	0.014
	[−0.126,0.117]	(0.031)	(0.029)	(0.030)	(0.034)
KP F-stat	25.41	21.16	23.97	8.04	24.78
N	88,932	86,712	81,216	88,932	88,932
CZ x Year FE	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Column 1 reports 95% bootstrapped confidence intervals for each coefficient. Columns 2 and 3 exclude California and Texas, respectively. Columns 4 and 5 leave out China and India, and Mexico from the IV construction, respectively. Columns 2-5 report standard errors (in parentheses) clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.7. Robustness (w/o log employment)

	(1)	(2)	(3)	(4)	(5)
Sample excludes:	-	California	Texas	-	-
IV excludes:	-	-	-	China & India	Mexico
Panel A: OLS			Log GDP per Worker		
Share high-skill immigrants	0.737	0.524**	0.720***	0.737***	0.737***
	[0.161,1.102]	(0.224)	(0.261)	(0.246)	(0.246)
Share low-skill immigrants	−0.099	0.001	−0.137	−0.099	−0.099
	[−0.413,0.156]	(0.110)	(0.144)	(0.124)	(0.124)
Share high-skill natives	0.656	0.618***	0.632***	0.656***	0.656***
	[0.441,0.794]	(0.081)	(0.091)	(0.085)	(0.085)
R^2	0.93	0.92	0.93	0.93	0.93
N	88,932	86,712	81,216	88,932	88,932
Panel B: 2SLS			Log GDP per Worker		
Share high-skill immigrants	2.146	1.575*	1.851***	2.283*	3.913***
	[0.591,3.402]	(0.818)	(0.605)	(1.182)	(0.644)
Share low-skill immigrants	0.854	0.950***	0.698***	0.816***	1.688***
	[0.340,1.546]	(0.282)	(0.176)	(0.272)	(0.231)
Share high-skill natives	1.708	0.716*	1.625*	1.816*	2.335***
	[−0.094,3.439]	(0.391)	(0.909)	(0.990)	(0.613)
KP F-stat	26.28	23.34	25.18	8.01	33.06
N	88,932	86,712	81,216	88,932	88,932
CZ x Year FE	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Column 1 reports 95% bootstrapped confidence intervals. Columns 2 and 3 exclude California and Texas, respectively. Columns 4 and 5 leave out China and India, and Mexico from the IV construction, respectively. Columns 2-5 report standard errors (in parentheses) clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

2.5.3 Robustness

In this section we probe the robustness of our main results along several dimensions. First, we begin by providing bootstrapped 95% confidence intervals in column 1 of Table 2.6 and Table 2.7 to guide against concerns about non-normality or leverage - the sensitivity of the estimates and standard errors to a small set of observations, see Young (2021). The estimates are based on 1000 bootstrap samples clustered at the state-level. Although confidence intervals are sometimes considerably larger, especially for the high-skill employment shares, the broad conclusions seem robust. We complement this analysis with a worst-case cluster (state) leave-out strategy in which we drop two states that have the largest effect on the main estimates and standard errors.[10] Columns 2 and 3 in Table 2.6 and Table 2.7 omit the states of California and Texas respectively. For both states one might also be concerned about very particular productivity and/or immigration pattern. Reassuringly the results seem relatively robust to excluding either state. The exclusion of California does affect several estimates, in particular when we instrument for all four endogenous variables in Panel C of Table 2.6. This is likely due to California's disproportional role and importance for immigrant settlements both historically and today.

Columns 5 and 6 of Tables 2.6 and 2.7 probe the sensitivity to certain origin countries, namely, China and India as well as Mexico in the construction of our instrumental variable. Mexican immigrants make up the fast majority of all immigrants in the US and immigrants from China and India tend to have exceptionally highly levels of education, see Card (2009). We in turn, exclude those countries from the construction of the IV and report the results in Panels B and C of Tables 2.6 and 2.7. The exclusion of China and India as origin counties, significantly weakens the IV with an F-statistics of around 8 instead of 20-30, so weak instrumental variables concerns might be warranted. This leads to substantially less precise estimates, however and reassuringly the point estimates remain relatively stable. Exclusion of Mexican immigrants in the IV leads to larger estimates in column 6. This might be explained by the relative low levels of education of Mexican immigrants, see e.g. Table 2 in Card (2009).

We probe the robustness of our estimates to various regression weights in Appendix Tables 2.A.5 and 2.A.6. Until now, all results are weighted by CZ sector pre-employment size and thus can interpreted as the productivity effect affecting the average worker. Columns 3 and 4 of Tables 2.A.5 and 2.A.6 use the square root of pre-employment size as weights, while columns 5 and 6 report unweighted regression results. The coefficients of interest become significantly smaller under the alternative weighting schemes. This might be driven by two factors. First, the employment shares are measured with more noise in small CZ sector cells leading to less precise estimates. Second, there might be heterogeneity in the impact of employment shares on productivity and larger CZ sectors have larger treatment effects. While weighting does affect the size and precision of point estimates it does not lead to qualitatively opposite conclusions.

To investigate the sensitivity of our estimates to the industry composition we report results on a balanced panel of CZ with data on all eleven industries in columns 2 of Tables 2.A.7 and 2.A.8. The results are virtually identical to our main estimates. Columns 3 to 5 of Tables 2.A.7 and 2.A.8 exclude the construction, manufacturing and information industry, respectively. The average construction and manufacturing CZ sector employs a relatively high share of immigrant workers ,see Table 2.A.3 and the former has significant impact on the strength of the IV. The information industry

10. The cluster leave-out results are available from the authors upon request.

has seen the largest growth in productivity over the sample period, see Table 2.A.3. However, we find that the exclusion of neither of these sectors meaningful alters our conclusions.

Last we explore a modified measure of employment, namely hours of work instead of headcount employment. To this end, we use the ACS data to construct estimates of the number of hours worked per worker in each county sector year and multiply it by headcount employment data from the CBP. We also adjust the employment share estimates to a per hour worked rather than per worker basis. Tables 2.A.11 and 2.A.12 provide the estimates of this analysis which are very close to our main results. If anything, the change to hours worked brings estimates of the impact of high-skill immigrant and native employment closer together.

2.5.4 Additional Results

In a final step, we investigate the connection between our productivity effects and potential wage effects. We are interested in how much, if any, of the productivity increases are captured by workers and if so by whom. Although a full investigation of these effects is beyond the scope of this work we show suggestive evidence that suggests it is the workers themselves who capture most of the productivity gains. We do so by providing two pieces of evidence.

First, we study the effects of the various employment shares on the average compensation per worker. The BEA provides such estimates together with the GDP data. In order to make the GDP and compensation data directly comparison we use nominal, that is non-inflated, GDP figures.[11] Columns 1 and 2 of Table 2.8 replicate the previous analysis with nominal GDP per worker as the outcome variable. The estimated effects are very similar. Columns 3 and 4 provide estimates of the impacts of employment shares on the average compensation per worker. We find slightly larger effects on compensation compared to output for high-skill, and slightly lower for low-skill, implying that all of the impact on productivity is captured by wages. In columns 5 and 6 of Table 2.8 we estimate the effect on the labor share, as defined by compensation over GDP. Although imprecisely estimated we again find that high-skill immigrant and employment are causing a higher labor shares, while low-skill immigrant employment causes a lower labor share, all compared to native low-skill employment.

The advantage of the BEA's compensation data is that they are directly comparable to the GDP estimates. However, they do allow to investigate which workers benefit through higher compensation. We thus turn to the ACS data which is underlying our share estimates and which contains, until now unused, information on wages. This part of the analysis is somewhat more descriptive but we try and mimic the previous specifications as close as possible. Concretely, we construct estimates of

11. For more information on the variables and the data sources see Appendix 2.B.

the share of high- and low-skill immigrant and high-skill native employment as well as log headcount employment at the place-of-work puma (PWPUMA) by sector year level. Additionally, we construct indicator variables which encode to which group a given individual belongs. We then regress log wages on these variables at the individual level and report the results in Table 2.9. In column 1 which is closest to our main specification for the productivity estimates, we find that the high-skill immigrant and native employment shares are associated with larger wages while the low-skill immigrant share tend to depress wages relative to low-skill native employment. In columns 2 to 4 we unpack these effects into the direct effect of an individual belonging to one of said employment groups (captured by the coefficients on the indicator variables) and the remaining indirect spillover effects from the types of other workers (coefficients on the shares). We find that the inclusion of (rich enough) fixed effects all but eliminates the spillover effects and leaves only the direct effects.[12] These findings suggest that spillover effects are rather small and that most of the impact appears to be captured by the individual workers themselves.

12. Some of the share coefficients in column 4 are statistically significant, however they are small in magnitude. Also, because results reported in Table 2.9 cluster standard errors at the PWPUMA level, precision is likely overstated.

Table 2.8. GDP, Earnings and Labor Share

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker		Log Comp. per Worker		Log Labor Share	
Share high-skill immigrants	0.760***	0.922***	1.304***	1.233***	0.485***	0.257*
	(0.253)	(0.270)	(0.266)	(0.275)	(0.116)	(0.130)
Share low-skill immigrants	−0.077	−0.116	−0.287***	−0.270***	−0.210**	−0.154**
	(0.124)	(0.123)	(0.104)	(0.099)	(0.092)	(0.066)
Share high-skill natives	0.702***	0.718***	0.707***	0.700***	−0.003	−0.025
	(0.086)	(0.084)	(0.075)	(0.074)	(0.041)	(0.043)
Log employment		−0.079***		0.035*		0.112***
		(0.025)		(0.019)		(0.015)
R^2	0.93	0.93	0.92	0.92	0.88	0.89
N	83,525	83,525	83,516	83,516	83,516	83,516
Panel B: 2SLS	Log GDP per Worker		Log Comp. per Worker		Log Labor Share	
Share high-skill immigrants	2.164***	1.881***	2.841***	2.406***	0.670**	0.517
	(0.467)	(0.553)	(0.323)	(0.379)	(0.297)	(0.337)
Share low-skill immigrants	0.895***	0.878***	0.390**	0.365**	−0.513***	−0.522***
	(0.207)	(0.209)	(0.159)	(0.156)	(0.182)	(0.177)
Share high-skill natives	1.503**	1.661**	1.966***	2.208***	0.497	0.583
	(0.708)	(0.719)	(0.385)	(0.445)	(0.453)	(0.407)
Log employment		0.046*		0.070**		0.025
		(0.027)		(0.027)		(0.020)
KP F-stat	46.72	32.71	46.72	32.71	46.72	32.71
N	83,525	83,525	83,516	83,516	83,516	83,516
CZ x Year FE	✓	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specifications (2.6) (odd columns) and specification (2.5) (even columns). The dependent variable is log nominal GDP per worker (columns 1-2), log compensation per worker (columns 3-4) and log labor share (columns 5-6). The labor share is defined as the ratio of compensations over nominal GDP (see Section 2.4 for details). The endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which all endogenous variables are instrumented includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.9. Individual-Level Wages Analysis

	(1)	(2)	(3)	(4)	(5)
			Log Wages		
Share high-skill immigrants	0.716***		0.323***	−0.054***	
	(0.075)		(0.071)	(0.020)	
Share low-skill immigrants	−0.331***		−0.274***	−0.023	
	(0.032)		(0.032)	(0.015)	
Share high-skill natives	0.637***		0.228***	−0.078***	
	(0.020)		(0.018)	(0.007)	
Indicator high-skill immigrant		0.483***	0.479***	0.479***	0.482***
		(0.008)	(0.008)	(0.008)	(0.008)
Indicator low-skill immigrant		−0.083***	−0.073***	−0.073***	−0.071***
		(0.007)	(0.007)	(0.007)	(0.007)
Indicator high-skill native		0.545***	0.542***	0.540***	0.541***
		(0.004)	(0.004)	(0.004)	(0.004)
Log employment	0.148***	0.152***	0.144***	−0.012***	
	(0.008)	(0.009)	(0.008)	(0.003)	
R^2	0.15	0.20	0.20	0.21	0.22
N	17,667,847	17,667,847	17,667,847	17,667,840	17,667,388
PWPUMA x Year FE	✓	✓	✓	✓	✓
Industry x Year FE	✓	✓	✓	✓	✓
PWPUMA x Industry FE				✓	✓
PWPUMA x Industry x Year FE					✓

Note: This table reports coefficients from OLS wage regressions described in Section 2.5.4. The dependent variable is log wages and the endogenous variables are indicator variables for high- and low-skill immigrant and high-skill native status. Columns 1 and 3 additionally include log CZ by sector employment. The sample is constructed by distributing observations from the ACS's place-of-work pumas (PWPUMA) to the corresponding CZ according to a probabilistic cross-walk. Each observation is weighted by the product of the ACS sampling weight (*perwt*) and the probability weight for each CZ. Columns 3-4 additionally weight observations by CZ sector pre-employment size. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

2.6 Conclusion

In summary our work provides novel direct evidence on the productivity effects of immigration. We employ a production function approach and study variation in productivity within US state sectors over time. Our findings point to large impacts of high-skill immigrants on productivity and small or zero effects of low-skill immigrants at least in the short run. Most of the productivity impacts appear to be captured by workers themselves although this conclusion is more tentative.

One caveat of our study is that we rely on a relatively short time period and thus can only study short run responses. If the benefits and/or costs of immigration only materialize over longer periods our estimates might miss those long-term effects. Such concerns would also pose a challenge from an identification perspective as we are not exploiting a structural break in immigration trends Jaeger, Ruist, and Stuhler (2018).

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Appendix 2.A Additional Tables

Table 2.A.1. Data Sources

		Year(s)			
Variable	Unit	2000	2001-2004	2005-2016	2017-2019
GDP	2012 USD thous.	n.a.	BEA	BEA	BEA
Employment	Headcount	CBP from Eckert et al. (2021)	CBP from Eckert et al. (2021)	CBP from Eckert et al. (2021)	raw CBP
Shares	-	CENSUS	n.a.	ACS	ACS

Note: This table illustrates the data sources for GDP, employment and employment shares for the years 2000-2019. For more details see Section 2.2 and Appendix 2.B. The abbreviations are as follows:
BEA - Bureau of Economic Activity
CBP - County Business Pattern
CENSUS - 2000 Census (5% sample)
ACS - American Community Survey (yearly samples)

Table 2.A.2. Summary Statistics (emp. weighted)

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	22,225	37,808	0.4	360,953	8,041	88,932
GDP per Worker (in USD)	121,398	104,716	1,953.1	5,611,095	84,415	88,932
Employment (headcount)	183,472	248,360	12.0	1,281,598	87,912	88,932
Pre-Employment (headcount)	178,407	239,532	8.8	1,249,510	84,799	88,932
Share immigrants	0.18	0.14	0.00	1.00	0.14	88,932
Share high-skill	0.56	0.16	0.00	1.00	0.54	88,932
Share high-skill immigrants	0.09	0.07	0.00	1.00	0.07	88,932
Share low-skill immigrants	0.10	0.10	0.00	0.74	0.06	88,932
Share high-skill natives	0.48	0.15	0.00	1.00	0.46	88,932
Share low-skill natives	0.34	0.16	0.00	1.00	0.31	88,932
Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.11	0.23	−0.85	17.33	0.11	88,932
GDP per Worker (in %)	0.10	0.23	−0.88	18.12	0.06	88,932
Employment (in %)	0.02	0.17	−0.93	16.80	0.01	88,932
Share immigrants (in p.p.)	0.01	0.03	−0.61	0.33	0.01	88,932
Share high-skill (in p.p.)	0.06	0.04	−0.46	0.79	0.06	88,932
Share high-skill immigrants (in p.p.)	0.02	0.02	−0.14	0.33	0.01	88,932
Share low-skill immigrants (in p.p.)	−0.00	0.03	−0.59	0.30	−0.00	88,932
Share high-skill natives (in p.p.)	0.04	0.04	−0.41	0.76	0.04	88,932
Share low-skill natives (in p.p.)	−0.05	0.04	−0.78	0.75	−0.05	88,932

Note: This table reports pre-employment weighted summary statistics of GDP, GDP per worker, employment and employment shares for the main sample. Panel A presents levels and Panel B changes over the time period 2005-2016. In Panel B growth rates for GDP, GDP per worker and employment are constructed as arithmetic annual growth rates between 2005/7 to 2014/16. Pre-employment refers to average employment over the years 2000-2004.

Table 2.A.3. Summary Statistics by Industry Sector

NAICS 23: Construction

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	887	2,642	1.1	49,485	170	8,244
GDP per Worker (in USD)	103,333	38,629	4,970.8	1,239,259	96,583	8,244
Employment (headcount)	8,639	23,669	15.0	436,418	1,694	8,244
Pre-Employment (headcount)	9,142	24,715	17.2	343,064	1,772	8,244
Share immigrants	0.10	0.11	0.00	0.66	0.06	8,244
Share high-skill	0.32	0.10	0.00	0.77	0.32	8,244
Share high-skill immigrants	0.02	0.03	0.00	0.25	0.00	8,244
Share low-skill immigrants	0.08	0.10	0.00	0.62	0.05	8,244
Share high-skill natives	0.30	0.10	0.00	0.70	0.30	8,244
Share low-skill natives	0.60	0.13	0.12	1.00	0.60	8,244

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	−0.05	0.62	−0.83	8.83	−0.15	8,244
GDP per Worker (in %)	0.03	0.27	−0.59	1.65	0.01	8,244
Employment (in %)	−0.07	0.46	−0.70	5.51	−0.14	8,244
Share immigrants (in p.p.)	0.02	0.05	−0.23	0.19	0.01	8,244
Share high-skill (in p.p.)	0.03	0.07	−0.23	0.21	0.04	8,244
Share high-skill immigrants (in p.p.)	0.00	0.02	−0.07	0.07	0.00	8,244
Share low-skill immigrants (in p.p.)	0.02	0.05	−0.21	0.18	0.01	8,244
Share high-skill natives (in p.p.)	0.03	0.07	−0.23	0.21	0.03	8,244
Share low-skill natives (in p.p.)	−0.05	0.08	−0.27	0.25	−0.05	8,244

NAICS 31-33: Manufacturing

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	2,921	8,190	1.0	115,532	620	8,040
GDP per Worker (in USD)	134,852	116,024	21,787.2	4,402,123	111,615	8,040
Employment (headcount)	17,655	41,931	17.0	828,883	5,702	8,040
Pre-Employment (headcount)	21,953	54,417	20.6	904,629	6,737	8,040
Share immigrants	0.11	0.11	0.00	0.81	0.07	8,040
Share high-skill	0.39	0.12	0.00	0.94	0.39	8,040
Share high-skill immigrants	0.03	0.04	0.00	0.43	0.02	8,040
Share low-skill immigrants	0.08	0.09	0.00	0.71	0.05	8,040
Share high-skill natives	0.36	0.11	0.00	0.94	0.36	8,040
Share low-skill natives	0.53	0.14	0.06	1.00	0.54	8,040

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.09	0.50	−0.70	7.33	0.01	8,040
GDP per Worker (in %)	0.27	0.63	−0.70	9.01	0.18	8,040
Employment (in %)	−0.12	0.22	−0.80	1.75	−0.13	8,040
Share immigrants (in p.p.)	0.01	0.06	−0.61	0.29	0.01	8,040
Share high-skill (in p.p.)	0.06	0.07	−0.22	0.37	0.06	8,040
Share high-skill immigrants (in p.p.)	0.01	0.02	−0.10	0.15	0.01	8,040
Share low-skill immigrants (in p.p.)	0.00	0.05	−0.59	0.30	0.00	8,040
Share high-skill natives (in p.p.)	0.05	0.06	−0.19	0.35	0.05	8,040
Share low-skill natives (in p.p.)	−0.07	0.07	−0.37	0.36	−0.06	8,040

Table 2.A.3. Summary Statistics by Industry Sector (continued)

NAICS 42: Wholesale Trade

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	1,444	5,218	1.9	81,103	171	7,848
GDP per Worker (in USD)	153,311	72,272	22,512.1	1,941,533	143,516	7,848
Employment (headcount)	8,301	28,489	18.0	478,523	1,184	7,848
Pre-Employment (headcount)	8,491	29,685	25.2	446,969	1,266	7,848
Share immigrants	0.07	0.11	0.00	0.92	0.03	7,848
Share high-skill	0.46	0.16	0.00	1.00	0.47	7,848
Share high-skill immigrants	0.02	0.05	0.00	0.57	0.00	7,848
Share low-skill immigrants	0.05	0.08	0.00	0.73	0.01	7,848
Share high-skill natives	0.43	0.16	0.00	1.00	0.44	7,848
Share low-skill natives	0.49	0.17	0.00	1.00	0.48	7,848

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.23	0.46	−0.71	4.14	0.13	7,848
GDP per Worker (in %)	0.20	0.45	−0.81	3.90	0.12	7,848
Employment (in %)	0.06	0.29	−0.79	2.22	0.02	7,848
Share immigrants (in p.p.)	0.00	0.07	−0.40	0.20	0.00	7,848
Share high-skill (in p.p.)	0.05	0.12	−0.46	0.79	0.05	7,848
Share high-skill immigrants (in p.p.)	0.01	0.04	−0.12	0.19	0.00	7,848
Share low-skill immigrants (in p.p.)	−0.00	0.06	−0.47	0.18	0.00	7,848
Share high-skill natives (in p.p.)	0.04	0.12	−0.41	0.68	0.04	7,848
Share low-skill natives (in p.p.)	−0.05	0.12	−0.45	0.75	−0.04	7,848

NAICS 44-45: Retail Trade

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	1,334	3,961	1.5	69,826	288	8,412
GDP per Worker (in USD)	54,239	34,043	25,048.4	1,589,948	51,863	8,412
Employment (headcount)	21,572	54,156	29.0	811,659	5,584	8,412
Pre-Employment (headcount)	21,123	52,118	62.6	717,113	5,782	8,412
Share immigrants	0.06	0.07	0.00	0.54	0.04	8,412
Share high-skill	0.42	0.09	0.07	0.80	0.42	8,412
Share high-skill immigrants	0.02	0.03	0.00	0.26	0.01	8,412
Share low-skill immigrants	0.03	0.04	0.00	0.37	0.02	8,412
Share high-skill natives	0.40	0.09	0.07	0.79	0.40	8,412
Share low-skill natives	0.54	0.10	0.19	0.93	0.55	8,412

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.03	0.25	−0.43	3.80	−0.01	8,412
GDP per Worker (in %)	0.05	0.25	−0.42	4.26	0.02	8,412
Employment (in %)	−0.01	0.11	−0.45	0.93	−0.03	8,412
Share immigrants (in p.p.)	0.01	0.03	−0.17	0.18	0.01	8,412
Share high-skill (in p.p.)	0.06	0.06	−0.13	0.26	0.06	8,412
Share high-skill immigrants (in p.p.)	0.01	0.02	−0.05	0.07	0.01	8,412
Share low-skill immigrants (in p.p.)	0.00	0.02	−0.18	0.16	0.00	8,412
Share high-skill natives (in p.p.)	0.05	0.06	−0.15	0.24	0.05	8,412
Share low-skill natives (in p.p.)	−0.06	0.06	−0.27	0.14	−0.06	8,412

Table 2.A.3. Summary Statistics by Industry Sector (continued)

NAICS 48-49: Transportation, Warehousing

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	676	2,170	1.5	31,257	121	7,128
GDP per Worker (in USD)	133,346	179,223	10,995.2	5,611,095	100,639	7,128
Employment (headcount)	6,135	18,276	15.0	282,780	1,160	7,128
Pre-Employment (headcount)	5,466	17,116	8.8	234,169	884	7,128
Share immigrants	0.06	0.09	0.00	0.63	0.03	7,128
Share high-skill	0.37	0.13	0.00	0.98	0.37	7,128
Share high-skill immigrants	0.02	0.04	0.00	0.48	0.00	7,128
Share low-skill immigrants	0.04	0.07	0.00	0.52	0.01	7,128
Share high-skill natives	0.35	0.13	0.00	0.98	0.35	7,128
Share low-skill natives	0.59	0.15	0.00	1.00	0.59	7,128

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.10	0.61	−0.63	11.08	0.02	7,128
GDP per Worker (in %)	0.05	0.57	−0.75	9.64	−0.03	7,128
Employment (in %)	0.15	0.86	−0.93	16.80	0.05	7,128
Share immigrants (in p.p.)	0.02	0.05	−0.21	0.23	0.01	7,128
Share high-skill (in p.p.)	0.05	0.10	−0.30	0.41	0.04	7,128
Share high-skill immigrants (in p.p.)	0.01	0.03	−0.12	0.21	0.00	7,128
Share low-skill immigrants (in p.p.)	0.01	0.04	−0.16	0.18	0.00	7,128
Share high-skill natives (in p.p.)	0.04	0.09	−0.32	0.41	0.03	7,128
Share low-skill natives (in p.p.)	−0.06	0.10	−0.39	0.39	−0.05	7,128

NAICS 51: Information

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	1,163	5,942	1.2	120,022	77	7,824
GDP per Worker (in USD)	151,164	77,034	3,689.5	1,722,596	137,317	7,824
Employment (headcount)	4,960	18,926	16.0	348,357	585	7,824
Pre-Employment (headcount)	5,376	19,259	20.4	246,672	670	7,824
Share immigrants	0.04	0.08	0.00	1.00	0.00	7,824
Share high-skill	0.62	0.19	0.00	1.00	0.64	7,824
Share high-skill immigrants	0.03	0.07	0.00	1.00	0.00	7,824
Share low-skill immigrants	0.01	0.04	0.00	0.63	0.00	7,824
Share high-skill natives	0.59	0.19	0.00	1.00	0.61	7,824
Share low-skill natives	0.36	0.19	0.00	1.00	0.34	7,824

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.32	0.67	−0.78	10.04	0.21	7,824
GDP per Worker (in %)	0.57	1.02	−0.88	18.12	0.42	7,824
Employment (in %)	−0.10	0.30	−0.81	2.24	−0.14	7,824
Share immigrants (in p.p.)	0.01	0.06	−0.22	0.33	0.00	7,824
Share high-skill (in p.p.)	0.08	0.15	−0.38	0.77	0.07	7,824
Share high-skill immigrants (in p.p.)	0.01	0.04	−0.14	0.33	0.00	7,824
Share low-skill immigrants (in p.p.)	0.00	0.04	−0.21	0.19	0.00	7,824
Share high-skill natives (in p.p.)	0.07	0.14	−0.38	0.76	0.07	7,824
Share low-skill natives (in p.p.)	−0.08	0.14	−0.78	0.40	−0.07	7,824

Table 2.A.3. Summary Statistics by Industry Sector (continued)

NAICS 52-53: Finance, Insurance, Real Estate						
Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	4,417	17,978	8.9	360,953	652	8,412
GDP per Worker (in USD)	430,224	182,710	90,987.5	3,636,101	398,400	8,412
Employment (headcount)	11,591	38,986	23.0	601,191	1,542	8,412
Pre-Employment (headcount)	11,772	40,836	34.4	603,889	1,516	8,412
Share immigrants	0.05	0.06	0.00	0.53	0.02	8,412
Share high-skill	0.63	0.12	0.10	1.00	0.64	8,412
Share high-skill immigrants	0.03	0.05	0.00	0.45	0.01	8,412
Share low-skill immigrants	0.02	0.03	0.00	0.36	0.00	8,412
Share high-skill natives	0.60	0.12	0.10	1.00	0.61	8,412
Share low-skill natives	0.35	0.12	0.00	0.90	0.34	8,412
Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.22	0.24	−0.49	2.87	0.19	8,412
GDP per Worker (in %)	0.31	0.25	−0.47	1.70	0.29	8,412
Employment (in %)	−0.05	0.19	−0.58	1.60	−0.08	8,412
Share immigrants (in p.p.)	0.01	0.03	−0.16	0.15	0.01	8,412
Share high-skill (in p.p.)	0.07	0.08	−0.22	0.53	0.06	8,412
Share high-skill immigrants (in p.p.)	0.01	0.03	−0.13	0.16	0.01	8,412
Share low-skill immigrants (in p.p.)	0.00	0.02	−0.10	0.16	0.00	8,412
Share high-skill natives (in p.p.)	0.05	0.08	−0.22	0.53	0.05	8,412
Share low-skill natives (in p.p.)	−0.07	0.08	−0.53	0.22	−0.07	8,412

NAICS 54-56: Services, Management, Administrative						
Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	2,740	10,605	0.4	152,794	211	8,064
GDP per Worker (in USD)	96,052	53,586	1,953.1	801,905	84,712	8,064
Employment (headcount)	26,989	91,983	12.0	1,276,370	2,614	8,064
Pre-Employment (headcount)	26,104	91,405	11.4	1,249,510	2,457	8,064
Share immigrants	0.08	0.08	0.00	0.79	0.06	8,064
Share high-skill	0.59	0.13	0.01	1.00	0.60	8,064
Share high-skill immigrants	0.04	0.05	0.00	0.44	0.02	8,064
Share low-skill immigrants	0.04	0.06	0.00	0.74	0.02	8,064
Share high-skill natives	0.55	0.12	0.01	1.00	0.56	8,064
Share low-skill natives	0.37	0.13	0.00	0.99	0.36	8,064
Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.37	0.88	−0.85	17.33	0.24	8,064
GDP per Worker (in %)	0.35	0.90	−0.75	17.87	0.22	8,064
Employment (in %)	0.09	0.49	−0.84	5.06	0.03	8,064
Share immigrants (in p.p.)	0.02	0.05	−0.16	0.18	0.02	8,064
Share high-skill (in p.p.)	0.03	0.08	−0.24	0.32	0.03	8,064
Share high-skill immigrants (in p.p.)	0.01	0.03	−0.13	0.14	0.01	8,064
Share low-skill immigrants (in p.p.)	0.01	0.03	−0.12	0.17	0.00	8,064
Share high-skill natives (in p.p.)	0.02	0.08	−0.30	0.34	0.02	8,064
Share low-skill natives (in p.p.)	−0.04	0.08	−0.34	0.25	−0.04	8,064

Table 2.A.3. Summary Statistics by Industry Sector (continued)

NAICS 61-62: Education, Health Care

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	1,922	6,054	0.8	93,731	315	8,304
GDP per Worker (in USD)	50,454	14,866	4,670.5	193,045	51,253	8,304
Employment (headcount)	29,806	85,268	47.0	1,281,598	6,337	8,304
Pre-Employment (headcount)	24,834	70,872	69.4	1,003,276	5,534	8,304
Share immigrants	0.06	0.06	0.00	0.53	0.04	8,304
Share high-skill	0.70	0.07	0.40	0.94	0.71	8,304
Share high-skill immigrants	0.04	0.04	0.00	0.36	0.03	8,304
Share low-skill immigrants	0.02	0.03	0.00	0.26	0.01	8,304
Share high-skill natives	0.66	0.07	0.34	0.87	0.67	8,304
Share low-skill natives	0.28	0.07	0.03	0.60	0.27	8,304

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.18	0.19	−0.62	1.97	0.17	8,304
GDP per Worker (in %)	0.08	0.19	−0.77	2.10	0.06	8,304
Employment (in %)	0.11	0.19	−0.72	2.03	0.10	8,304
Share immigrants (in p.p.)	0.01	0.02	−0.09	0.10	0.01	8,304
Share high-skill (in p.p.)	0.05	0.04	−0.12	0.15	0.05	8,304
Share high-skill immigrants (in p.p.)	0.01	0.02	−0.04	0.08	0.01	8,304
Share low-skill immigrants (in p.p.)	0.00	0.01	−0.07	0.06	0.00	8,304
Share high-skill natives (in p.p.)	0.04	0.04	−0.13	0.16	0.04	8,304
Share low-skill natives (in p.p.)	−0.05	0.04	−0.17	0.12	−0.05	8,304

NAICS 71-72: Entertainment, Accommodation

Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	873	3,133	0.4	53,605	132	8,340
GDP per Worker (in USD)	33,300	12,854	5,523.5	232,428	30,790	8,340
Employment (headcount)	19,871	54,983	19.0	977,864	4,309	8,340
Pre-Employment (headcount)	16,952	45,317	29.4	672,620	3,828	8,340
Share immigrants	0.10	0.10	0.00	0.56	0.07	8,340
Share high-skill	0.37	0.11	0.00	0.80	0.37	8,340
Share high-skill immigrants	0.03	0.03	0.00	0.27	0.02	8,340
Share low-skill immigrants	0.07	0.08	0.00	0.54	0.05	8,340
Share high-skill natives	0.34	0.11	0.00	0.72	0.34	8,340
Share low-skill natives	0.56	0.13	0.16	1.00	0.57	8,340

Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	0.08	0.28	−0.72	3.15	0.06	8,340
GDP per Worker (in %)	0.01	0.18	−0.66	1.39	−0.01	8,340
Employment (in %)	0.08	0.19	−0.59	1.61	0.07	8,340
Share immigrants (in p.p.)	0.01	0.05	−0.25	0.22	0.00	8,340
Share high-skill (in p.p.)	0.06	0.07	−0.21	0.27	0.06	8,340
Share high-skill immigrants (in p.p.)	0.00	0.02	−0.10	0.09	0.00	8,340
Share low-skill immigrants (in p.p.)	0.00	0.04	−0.28	0.26	0.00	8,340
Share high-skill natives (in p.p.)	0.05	0.07	−0.18	0.26	0.05	8,340
Share low-skill natives (in p.p.)	−0.06	0.07	−0.30	0.24	−0.06	8,340

Table 2.A.3. Summary Statistics by Industry Sector (continued)

NAICS 81: Other Services						
Panel A: Levels 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in mil. USD)	507	1,589	1.4	26,133	100	8,316
GDP per Worker (in USD)	69,474	20,657	8,366.4	242,025	64,824	8,316
Employment (headcount)	7,535	21,114	19.0	284,599	1,506	8,316
Pre-Employment (headcount)	7,582	21,022	21.0	279,164	1,518	8,316
Share immigrants	0.08	0.10	0.00	0.71	0.05	8,316
Share high-skill	0.46	0.12	0.00	0.90	0.47	8,316
Share high-skill immigrants	0.03	0.04	0.00	0.46	0.01	8,316
Share low-skill immigrants	0.06	0.08	0.00	0.71	0.03	8,316
Share high-skill natives	0.44	0.13	0.00	0.90	0.44	8,316
Share low-skill natives	0.48	0.13	0.09	0.98	0.48	8,316
Panel B: Changes 2005-2016	Mean	SD	Min	Max	Median	Obs.
GDP (in %)	−0.13	0.15	−0.50	1.98	−0.14	8,316
GDP per Worker (in %)	−0.08	0.16	−0.67	0.93	−0.10	8,316
Employment (in %)	−0.03	0.14	−0.64	0.97	−0.04	8,316
Share immigrants (in p.p.)	0.02	0.05	−0.27	0.16	0.02	8,316
Share high-skill (in p.p.)	0.05	0.09	−0.31	0.40	0.05	8,316
Share high-skill immigrants (in p.p.)	0.01	0.03	−0.14	0.10	0.01	8,316
Share low-skill immigrants (in p.p.)	0.01	0.04	−0.27	0.16	0.01	8,316
Share high-skill natives (in p.p.)	0.04	0.09	−0.32	0.39	0.04	8,316
Share low-skill natives (in p.p.)	−0.06	0.09	−0.34	0.26	−0.06	8,316

Note: This table reports summary statistics of GDP, GDP per worker, employment and employment shares by industry. Panels A present levels and Panels B changes over the time period 2005-2016. In Panels B growth rates for GDP, GDP per worker and employment are constructed as arithmetic annual growth rates between 2005/7 to 2014/16. Pre-employment refers to average employment over the years 2000-2004.

Table 2.A.4. First Stage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome: Employment share of	High imm.	Low imm.	High nat.	log emp.	High imm.	Low imm.	High nat.	log emp.
Inst. share high-skill immigrants	0.889***	−0.359***	0.235*	2.381*	1.047***	−0.534***	0.143	2.609**
	(0.116)	(0.123)	(0.131)	(1.216)	(0.193)	(0.190)	(0.150)	(1.122)
Inst. share low-skill immigrants	0.033	0.736***	0.188*	−0.639	0.086	0.760***	0.039	−0.941*
	(0.025)	(0.113)	(0.097)	(0.447)	(0.061)	(0.109)	(0.060)	(0.491)
Inst. share high-skill natives	0.017	0.106**	0.732***	−0.839	0.114**	−0.023	0.697***	−0.866
	(0.030)	(0.043)	(0.080)	(0.708)	(0.052)	(0.075)	(0.076)	(0.829)
Inst. log employment	0.008	−0.026***	0.005	1.327***	0.005	−0.032***	0.014*	1.312***
	(0.006)	(0.006)	(0.010)	(0.085)	(0.007)	(0.007)	(0.008)	(0.089)
addlinespaceR^2	0.91	0.88	0.87	0.97	0.93	0.92	0.90	0.98
N	88,932	88,932	88,932	88,932	88,932	88,932	88,932	88,932
CZ FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
CZ x Year FE					✓	✓	✓	✓
Region x Industry x Year FE					✓	✓	✓	✓

Note: This table reports coefficients from a first stage OLS regression of the four instruments on the respective endogeneous variables. The dependent variables are the employment share of high and low skill immigrants, high skill natives and log employment in columns 1 through 4, and 5 through 8. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.5. Robustness Regression Weights

Regression Weights:	(1) emp.	(2) emp.	(3) sqrt. emp.	(4) sqrt. emp.	(5) unweighted	(6) unweighted
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	1.039***	0.935***	0.726***	0.636***	0.333***	0.307***
	(0.228)	(0.263)	(0.138)	(0.146)	(0.065)	(0.061)
Share low-skill immigrants	−0.209	−0.131	−0.254	−0.180**	−0.076	−0.025
	(0.185)	(0.120)	(0.158)	(0.074)	(0.126)	(0.051)
Share high-skill natives	0.673***	0.690***	0.257***	0.259***	0.084***	0.070***
	(0.114)	(0.082)	(0.037)	(0.027)	(0.019)	(0.013)
Log employment	−0.086***	−0.094***	−0.121***	−0.137***	−0.132***	−0.153***
	(0.024)	(0.025)	(0.015)	(0.014)	(0.017)	(0.014)
R^2	0.91	0.93	0.87	0.89	0.80	0.83
N	88,932	88,932	88,932	88,932	88,932	88,932
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	3.520***	2.864***	3.253***	3.191***	3.781***	3.669***
	(0.886)	(0.576)	(1.077)	(0.911)	(0.832)	(0.940)
Share low-skill immigrants	0.543	0.929***	0.527	0.843**	0.687	0.670
	(0.566)	(0.226)	(0.517)	(0.336)	(0.755)	(0.559)
Share high-skill natives	1.920***	1.384*	0.714	0.691	0.635	0.373
	(0.649)	(0.757)	(0.512)	(0.508)	(0.849)	(0.685)
Log employment	−0.102***	−0.109***	−0.136***	−0.155***	−0.141***	−0.162***
	(0.024)	(0.031)	(0.018)	(0.018)	(0.019)	(0.017)
KP F-stat	27.24	30.01	23.59	35.22	15.22	29.31
N	88,932	88,932	88,932	88,932	88,932	88,932
Panel C: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.449***	1.845**	1.245	0.743	0.901	0.297
	(0.831)	(0.747)	(0.885)	(0.846)	(0.570)	(0.733)
Share low-skill immigrants	0.274	0.823***	0.248	0.514	0.314	0.101
	(0.634)	(0.218)	(0.560)	(0.360)	(0.801)	(0.604)
Share high-skill natives	2.455***	1.845**	0.748	0.440	−0.455	−0.670
	(0.611)	(0.816)	(0.704)	(0.624)	(0.827)	(0.593)
Log employment	0.057*	0.046	0.046**	0.038*	0.038*	0.029
	(0.034)	(0.029)	(0.021)	(0.020)	(0.019)	(0.020)
KP F-stat	18.54	25.39	17.72	29.06	10.89	24.35
N	88,932	88,932	88,932	88,932	88,932	88,932
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓		✓		✓
Region x Industry x Year FE		✓		✓		✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. For comparison, columns 1-2 replicate columns 1 and 5 in Table 2.4 and are pre-employment size weighted. Pre-employment refers to average employment from 2000-2004. Columns 3-4 weight by the square root of pre-employment and columns 5-6 are unweighted. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.6. Robustness Regression Weights (w/o log employment)

Regression Weights:	(1) emp.	(2) emp.	(3) sqrt. emp.	(4) sqrt. emp.	(5) unweighted	(6) unweighted
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	0.891***	0.737***	0.545***	0.405***	0.256***	0.207***
	(0.218)	(0.246)	(0.134)	(0.129)	(0.061)	(0.054)
Share low-skill immigrants	−0.191	−0.099	−0.247	−0.169**	−0.101	−0.054
	(0.174)	(0.124)	(0.149)	(0.073)	(0.132)	(0.061)
Share high-skill natives	0.673***	0.656***	0.241***	0.220***	0.071***	0.048***
	(0.118)	(0.085)	(0.037)	(0.027)	(0.017)	(0.012)
R^2	0.91	0.93	0.86	0.88	0.80	0.82
N	88,932	88,932	88,932	88,932	88,932	88,932
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.831***	2.147***	1.751**	1.223*	1.508***	0.812
	(0.863)	(0.590)	(0.858)	(0.714)	(0.507)	(0.603)
Share low-skill immigrants	0.370	0.854***	0.318	0.579*	0.393	0.188
	(0.626)	(0.217)	(0.550)	(0.342)	(0.780)	(0.570)
Share high-skill natives	2.264***	1.708**	0.739	0.489	−0.225	−0.511
	(0.653)	(0.838)	(0.642)	(0.579)	(0.758)	(0.562)
KP F-stat	26.13	26.31	23.98	38.61	15.76	34.36
N	88,932	88,932	88,932	88,932	88,932	88,932
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓		✓		✓
Region x Industry x Year FE		✓		✓		✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. For comparison, columns 1-2 replicate columns 1 and 5 in Table 2.4 and are pre-employment size weighted. Pre-employment refers to average employment from 2000-2004. Columns 3-4 weight by the square root of pre-employment and columns 5-6 are unweighted. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.7. Robustness Sample Restrictions

	(1) baseline sample	(2) balanced sample	(3) excl. Construction	(4) excl. Manufacturing	(5) excl. Information
Panel A: OLS	Log GDP per Worker				
Share high-skill immigrants	0.935***	0.951***	0.931***	0.543***	1.007***
	(0.263)	(0.265)	(0.266)	(0.167)	(0.311)
Share low-skill immigrants	−0.131	−0.121	−0.133	0.145	−0.053
	(0.120)	(0.121)	(0.150)	(0.119)	(0.101)
Share high-skill natives	0.690***	0.718***	0.694***	0.500***	0.722***
	(0.082)	(0.085)	(0.091)	(0.077)	(0.088)
Log employment	−0.094***	−0.092***	−0.085***	−0.085***	−0.109***
	(0.025)	(0.026)	(0.026)	(0.019)	(0.027)
R^2	0.93	0.93	0.93	0.95	0.93
N	88,932	71,544	80,688	80,892	81,108
Panel B: 2SLS	Log GDP per Worker				
Share high-skill immigrants	2.864***	2.819***	2.713**	2.275***	2.807***
	(0.576)	(0.577)	(1.046)	(0.684)	(0.663)
Share low-skill immigrants	0.929***	0.914***	0.946***	0.986***	1.152***
	(0.226)	(0.227)	(0.324)	(0.195)	(0.251)
Share high-skill natives	1.384*	1.414*	1.317	1.350**	1.034
	(0.757)	(0.757)	(0.944)	(0.626)	(0.748)
Log employment	−0.109***	−0.106***	−0.097***	−0.130***	−0.117***
	(0.031)	(0.032)	(0.036)	(0.033)	(0.033)
KP F-stat	30.01	29.74	16.03	25.93	30.10
N	88,932	71,544	80,688	80,892	81,108
Panel C: 2SLS	Log GDP per Worker				
Share high-skill immigrants	1.845**	1.865**	1.496	0.737	1.763**
	(0.747)	(0.741)	(1.251)	(0.881)	(0.765)
Share low-skill immigrants	0.823***	0.812***	0.779**	0.669***	0.960***
	(0.218)	(0.219)	(0.319)	(0.227)	(0.247)
Share high-skill natives	1.845**	1.849**	1.681	1.645**	1.652**
	(0.816)	(0.809)	(1.053)	(0.696)	(0.796)
Log employment	0.046	0.042	0.037	0.094**	0.051*
	(0.029)	(0.030)	(0.028)	(0.038)	(0.028)
KP F-stat	25.39	25.49	17.06	27.91	23.95
N	88,932	71,544	80,688	80,892	81,108
CZ x Year FE	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. Columns 1 replicates column 5 in Table 2.4 for comparison. Column 2 restricts the sample to CZ with information on all eleven industries. Column 3-5 exclude the construction, manufacturing and the information sector, respectively. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.8. Robustness Sample Restrictions (w/o log employment)

	(1) baseline sample	(2) balanced sample	(3) excl. Construction	(4) excl. Manufacturing	(5) excl. Information
Panel A: OLS	Log GDP per Worker				
Share high-skill immigrants	0.737***	0.759***	0.748***	0.294*	0.775**
	(0.246)	(0.247)	(0.248)	(0.174)	(0.299)
Share low-skill immigrants	−0.099	−0.090	−0.093	0.149	−0.031
	(0.124)	(0.125)	(0.158)	(0.110)	(0.107)
Share high-skill natives	0.656***	0.684***	0.661***	0.405***	0.690***
	(0.085)	(0.088)	(0.094)	(0.086)	(0.091)
R^2	0.93	0.93	0.93	0.95	0.93
N	88,932	71,544	80,688	80,892	81,108
Panel B: 2SLS	Log GDP per Worker				
Share high-skill immigrants	2.147***	2.134***	1.836*	1.381**	2.082***
	(0.590)	(0.590)	(1.045)	(0.606)	(0.648)
Share low-skill immigrants	0.854***	0.841***	0.826**	0.802***	1.018***
	(0.217)	(0.218)	(0.314)	(0.192)	(0.244)
Share high-skill natives	1.708**	1.726**	1.580	1.522**	1.463*
	(0.838)	(0.835)	(1.057)	(0.691)	(0.816)
KP F-stat	26.31	26.06	18.21	28.74	23.75
N	88,932	71,544	80,688	80,892	81,108
CZ x Year FE	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. Columns 1 replicates column 5 in Table 2.5 for comparison. Column 2 restricts the sample to CZ with information on all eleven industries. Column 3-5 exclude the construction, manufacturing and the information sector, respectively. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.9. Robustness GDP Interpolation

	(1)	(2)	(3)	(4)	(5)	(6)
Interpolation never exceeds:	5 tot. yrs.	5 tot. yrs.	2 tot. yrs.	2 tot. yrs.	1 tot. yr.	0 tot. yrs.
Interpolation never exceeds:	5 cons. yrs.	2 cons. yrs.	2 cons. yrs.	1 cons. yr.	1 cons. yr.	0 cons. yrs.
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	0.935***	0.905***	0.907***	0.908***	0.898***	0.932***
	(0.263)	(0.269)	(0.270)	(0.269)	(0.271)	(0.306)
Share low-skill immigrants	−0.131	−0.132	−0.130	−0.125	−0.125	−0.113
	(0.120)	(0.120)	(0.121)	(0.121)	(0.121)	(0.121)
Share high-skill natives	0.690***	0.697***	0.700***	0.702***	0.699***	0.718***
	(0.082)	(0.083)	(0.083)	(0.084)	(0.085)	(0.087)
Log employment	−0.094***	−0.090***	−0.090***	−0.088***	−0.086***	−0.080***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.023)
R^2	0.93	0.93	0.93	0.93	0.93	0.93
N	88,932	87,648	87,276	86,520	86,376	84,444
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.864***	2.547***	2.517***	2.488***	2.278***	1.947**
	(0.576)	(0.674)	(0.673)	(0.658)	(0.727)	(0.948)
Share low-skill immigrants	0.929***	0.876***	0.872***	0.881***	0.831***	0.729***
	(0.226)	(0.224)	(0.222)	(0.219)	(0.226)	(0.222)
Share high-skill natives	1.384*	1.183	1.182	1.142	1.023	1.102
	(0.757)	(0.775)	(0.783)	(0.766)	(0.776)	(0.768)
Log employment	−0.109***	−0.100***	−0.099***	−0.096***	−0.092***	−0.084**
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.032)
KP F-stat	30.01	22.67	22.46	25.76	27.96	31.99
N	88,932	87,648	87,276	86,520	86,376	84,444
Panel C: 2SLS	Log GDP per Worker					
Share high-skill immigrants	1.845**	1.431*	1.443*	1.411*	1.219	0.905
	(0.747)	(0.845)	(0.832)	(0.830)	(0.892)	(0.965)
Share low-skill immigrants	0.823***	0.748***	0.752***	0.761***	0.711***	0.609***
	(0.218)	(0.225)	(0.221)	(0.222)	(0.234)	(0.208)
Share high-skill natives	1.845**	1.667*	1.665*	1.618*	1.498*	1.358*
	(0.816)	(0.830)	(0.832)	(0.822)	(0.826)	(0.784)
Log employment	0.046	0.064**	0.059**	0.062**	0.061**	0.047**
	(0.029)	(0.026)	(0.025)	(0.023)	(0.023)	(0.023)
KP F-stat	25.39	20.63	19.98	23.28	25.61	27.48
N	88,932	87,648	87,276	86,520	86,376	84,444
CZ x Year FE	✓	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. Columns 1 replicates column 5 in Table 2.4 for comparison. Column 2-5 alter the interpolation of suppressed county by sector GDP information in the construction of the sample: The baseline sample (column 1) interpolates GDP information but never over more than five consecutive years, and excludes county sectors with more than five total years of suppressed data all together. Column 2 reports results for the subsample if the interpolation is restricted to two consecutive and five total years, column 3 to two consecutive and two total years, and so on. The Appendix 2.B for details about the interpolation methodology. The column header states the interpolation restrictions. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.10. Robustness GDP Interpolation (w/o log employment)

	(1)	(2)	(3)	(4)	(5)	(6)
Interpolation never exceeds:	5 tot. yrs.	5 tot. yrs.	2 tot. yrs.	2 tot. yrs.	1 tot. yr.	0 tot. yrs.
Interpolation never exceeds:	5 cons. yrs.	2 cons. yrs.	2 cons. yrs.	1 cons. yr.	1 cons. yr.	0 cons. yrs.
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	0.737***	0.718***	0.719***	0.724***	0.719***	0.751**
	(0.246)	(0.252)	(0.252)	(0.252)	(0.254)	(0.282)
Share low-skill immigrants	−0.099	−0.100	−0.097	−0.092	−0.092	−0.086
	(0.124)	(0.124)	(0.124)	(0.124)	(0.124)	(0.124)
Share high-skill natives	0.656***	0.665***	0.668***	0.672***	0.670***	0.691***
	(0.085)	(0.086)	(0.086)	(0.087)	(0.087)	(0.089)
R^2	0.93	0.93	0.93	0.93	0.93	0.93
N	88,932	87,648	87,276	86,520	86,376	84,444
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.147***	1.866***	1.845***	1.831***	1.644**	1.278
	(0.590)	(0.663)	(0.660)	(0.657)	(0.718)	(0.820)
Share low-skill immigrants	0.854***	0.798***	0.797***	0.808***	0.759***	0.652***
	(0.217)	(0.218)	(0.215)	(0.214)	(0.224)	(0.204)
Share high-skill natives	1.708**	1.479*	1.484*	1.433*	1.307	1.266
	(0.838)	(0.844)	(0.850)	(0.835)	(0.842)	(0.803)
KP F-stat	26.31	20.05	19.80	22.67	24.34	29.56
N	88,932	87,648	87,276	86,520	86,376	84,444
CZ x Year FE	✓	✓	✓	✓	✓	✓
Region x Industry x Year FE	✓	✓	✓	✓	✓	✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. Columns 1 replicates column 5 in Table 2.5 for comparison. Column 2-5 alter the interpolation of suppressed county by sector GDP information in the construction of the sample: The baseline sample (column 1) interpolates GDP information but never over more than five consecutive years, and excludes county sectors with more than five total years of suppressed data all together. Column 2 reports results for the subsample if the interpolation is restricted to two consecutive and five total years, column 3 to two consecutive and two total years, and so on. The Appendix 2.B for details about the interpolation methodology. The column header states the interpolation restrictions. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.11. GDP per Hour Worked

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Hour Worked					
Share high-skill immigrants	0.789***	0.831***	0.738***	0.690***	0.709***	0.728***
	(0.195)	(0.203)	(0.203)	(0.180)	(0.197)	(0.181)
Share low-skill immigrants	−0.244	−0.236	−0.238	−0.172*	−0.181	−0.341**
	(0.159)	(0.168)	(0.170)	(0.098)	(0.108)	(0.130)
Share high-skill natives	0.479***	0.542***	0.551***	0.503***	0.519***	0.480***
	(0.096)	(0.102)	(0.101)	(0.064)	(0.069)	(0.058)
Log Hours Worked	−0.107***	−0.108***	−0.101***	−0.116***	−0.116***	−0.170***
	(0.023)	(0.023)	(0.024)	(0.024)	(0.024)	(0.022)
R^2	0.89	0.89	0.90	0.91	0.91	0.93
N	88,932	88,932	88,932	88,932	88,932	88,656
Panel B: 2SLS	Log GDP per Hour Worked					
Share high-skill immigrants	3.575***	3.513***	3.316***	2.895***	2.876***	3.821***
	(0.855)	(0.908)	(0.891)	(0.528)	(0.539)	(0.721)
Share low-skill immigrants	0.539	0.527	0.496	0.850***	0.848***	0.968***
	(0.510)	(0.535)	(0.536)	(0.218)	(0.219)	(0.329)
Share high-skill natives	1.852**	1.892**	1.868**	1.332*	1.323*	1.744
	(0.724)	(0.714)	(0.727)	(0.725)	(0.737)	(1.177)
Log Hours Worked	−0.124***	−0.124***	−0.118***	−0.132***	−0.131***	−0.204***
	(0.023)	(0.023)	(0.024)	(0.029)	(0.029)	(0.032)
KP F-stat	20.23	20.84	21.26	36.46	36.53	24.55
N	88,932	88,932	88,932	88,932	88,932	88,656
Panel C: 2SLS	Log GDP per Hour Worked					
Share high-skill immigrants	2.274***	2.162**	2.119**	1.756**	1.740**	2.289***
	(0.831)	(0.862)	(0.840)	(0.679)	(0.699)	(0.548)
Share low-skill immigrants	0.236	0.210	0.218	0.739***	0.738***	0.821***
	(0.600)	(0.613)	(0.593)	(0.205)	(0.208)	(0.299)
Share high-skill natives	2.475***	2.494***	2.380***	1.900**	1.884**	2.338*
	(0.717)	(0.697)	(0.699)	(0.806)	(0.816)	(1.331)
Log Hours Worked	0.058*	0.054	0.038	0.040	0.040	−0.003
	(0.032)	(0.034)	(0.035)	(0.026)	(0.026)	(0.027)
KP F-stat	13.48	14.03	14.27	23.43	23.33	20.84
N	88,932	88,932	88,932	88,932	88,932	88,656
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓	✓	✓
Industry x Year FE			✓	✓	✓	✓
Region x Industry FE				✓	✓	✓
Region x Industry x Year FE					✓	✓
State x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5). The dependent variable is log GDP per hour worked and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.12. GDP per Hour Worked (w/o log employment)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Hour Worked					
Share high-skill immigrants	0.620***	0.653***	0.567***	0.481***	0.493***	0.420**
	(0.185)	(0.192)	(0.194)	(0.165)	(0.181)	(0.181)
Share low-skill immigrants	−0.213	−0.204	−0.207	−0.121	−0.127	−0.304**
	(0.147)	(0.155)	(0.157)	(0.108)	(0.117)	(0.144)
Share high-skill natives	0.482***	0.543***	0.551***	0.470***	0.485***	0.407***
	(0.098)	(0.105)	(0.103)	(0.066)	(0.072)	(0.059)
R^2	0.88	0.89	0.89	0.90	0.91	0.93
N	88,932	88,932	88,932	88,932	88,932	88,656
Panel B: 2SLS	Log GDP per Hour Worked					
Share high-skill immigrants	2.690***	2.573***	2.411***	2.021***	2.007***	2.268***
	(0.857)	(0.900)	(0.890)	(0.558)	(0.576)	(0.522)
Share low-skill immigrants	0.333	0.307	0.286	0.765***	0.764***	0.819***
	(0.588)	(0.610)	(0.607)	(0.202)	(0.204)	(0.302)
Share high-skill natives	2.276***	2.311***	2.255***	1.768**	1.752**	2.346*
	(0.748)	(0.736)	(0.753)	(0.815)	(0.825)	(1.346)
KP F-stat	19.64	19.95	20.10	30.13	29.96	25.17
N	88,932	88,932	88,932	88,932	88,932	88,656
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓	✓	✓
Industry x Year FE			✓	✓	✓	✓
Region x Industry FE				✓	✓	✓
Region x Industry x Year FE					✓	✓
State x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). The dependent variable is log GDP per hour worked and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.13. County-Level Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	0.440***	0.467***	0.420***	0.422***	0.407***	0.465***
	(0.080)	(0.086)	(0.107)	(0.109)	(0.103)	(0.107)
Share low-skill immigrants	−0.180*	−0.165	−0.118	−0.117	−0.212***	−0.286***
	(0.103)	(0.111)	(0.079)	(0.080)	(0.073)	(0.095)
Share high-skill natives	0.225***	0.262***	0.249***	0.252***	0.226***	0.204***
	(0.028)	(0.033)	(0.033)	(0.034)	(0.030)	(0.034)
Log employment	−0.199***	−0.192***	−0.211***	−0.211***	−0.228***	−0.240***
	(0.017)	(0.018)	(0.017)	(0.017)	(0.016)	(0.016)
R^2	0.81	0.82	0.83	0.83	0.84	0.87
N	292,723	292,315	292,315	292,315	292,315	281,107
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	3.240***	3.148***	3.123***	3.135***	3.338***	3.692***
	(0.725)	(0.760)	(0.705)	(0.708)	(0.757)	(0.840)
Share low-skill immigrants	0.790***	0.792***	0.967***	0.973***	0.982***	1.097***
	(0.271)	(0.294)	(0.218)	(0.219)	(0.214)	(0.375)
Share high-skill natives	−0.126	−0.124	0.520	0.538	0.551	0.871
	(0.577)	(0.629)	(0.536)	(0.542)	(0.660)	(0.965)
Log employment	−0.207***	−0.199***	−0.219***	−0.219***	−0.239***	−0.256***
	(0.019)	(0.019)	(0.020)	(0.020)	(0.019)	(0.019)
KP F-stat	19.26	20.14	25.38	25.33	16.13	7.40
N	292,723	292,315	292,315	292,315	292,315	281,107
Panel C: 2SLS	Log GDP per Worker					
Share high-skill immigrants	1.245*	1.215	1.761*	1.774*	1.836*	1.519
	(0.709)	(0.757)	(0.995)	(1.006)	(1.072)	(1.141)
Share low-skill immigrants	0.422	0.424	0.961***	0.970***	1.027***	1.125***
	(0.400)	(0.382)	(0.250)	(0.253)	(0.273)	(0.397)
Share high-skill natives	1.709***	1.443***	1.807***	1.837***	2.128***	3.206**
	(0.479)	(0.480)	(0.610)	(0.624)	(0.789)	(1.502)
Log employment	0.024	−0.002	−0.047	−0.046	−0.066	−0.061
	(0.077)	(0.078)	(0.064)	(0.064)	(0.063)	(0.055)
KP F-stat	9.26	9.12	8.80	8.62	4.31	1.76
N	292,723	292,315	292,315	292,315	292,315	281,107
County FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
County x Year FE		✓	✓	✓	✓	✓
Industry x Year FE		✓	✓	✓	✓	✓
Region x Industry FE			✓	✓	✓	✓
Region x Industry x Year FE				✓	✓	✓
State x Industry x Year FE					✓	✓
CZ x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5) at the county-sector-year level. For consistency, only county-sector cells that (i) underlie the CZ-sector main analysis panel and (ii) have at least ten headcount employment in all years are included. The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.14. County-Level Analysis (w/o log employment)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	0.304***	0.328***	0.231***	0.230***	0.184**	0.194**
	(0.068)	(0.073)	(0.078)	(0.080)	(0.077)	(0.082)
Share low-skill immigrants	−0.080	−0.057	−0.024	−0.021	−0.134	−0.201*
	(0.100)	(0.108)	(0.101)	(0.103)	(0.093)	(0.110)
Share high-skill natives	0.248***	0.286***	0.244***	0.247***	0.204***	0.162***
	(0.029)	(0.035)	(0.033)	(0.034)	(0.030)	(0.032)
R^2	0.79	0.80	0.81	0.81	0.83	0.85
N	292,723	292,315	292,315	292,315	292,315	281,107
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	1.449**	1.194	1.394	1.415	1.264	0.838
	(0.714)	(0.757)	(0.838)	(0.847)	(1.029)	(1.198)
Share low-skill immigrants	0.459	0.420	0.959***	0.970***	1.044***	1.134***
	(0.452)	(0.472)	(0.266)	(0.269)	(0.313)	(0.421)
Share high-skill natives	1.522**	1.460**	2.154***	2.180***	2.730**	3.938**
	(0.578)	(0.635)	(0.783)	(0.797)	(1.057)	(1.726)
KP F-stat	19.74	20.45	23.00	22.76	15.65	6.01
N	292,723	292,315	292,315	292,315	292,315	281,107
County FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
County x Year FE		✓	✓	✓	✓	✓
Industry x Year FE		✓	✓	✓	✓	✓
Region x Industry FE			✓	✓	✓	✓
Region x Industry x Year FE				✓	✓	✓
State x Industry x Year FE					✓	✓
CZ x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6). For consistency, only county-sector cells that (i) underlie the CZ-sector main analysis panel and (ii) have at least ten headcount employment in all years from 2005-2016 are included. The dependent variable is log GDP per hour worked and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.15. Robustness Long Panel

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	1.270***	1.327***	1.165***	1.101***	1.105***	1.064***
	(0.221)	(0.231)	(0.231)	(0.226)	(0.240)	(0.268)
Share low-skill immigrants	−0.207	−0.184	−0.202	−0.110	−0.117	−0.328**
	(0.184)	(0.196)	(0.199)	(0.113)	(0.120)	(0.130)
Share high-skill natives	0.717***	0.795***	0.801***	0.689***	0.710***	0.636***
	(0.122)	(0.132)	(0.129)	(0.081)	(0.088)	(0.086)
Log employment	−0.086***	−0.088***	−0.078***	−0.089***	−0.088***	−0.133***
	(0.022)	(0.023)	(0.023)	(0.023)	(0.023)	(0.022)
R^2	0.91	0.91	0.92	0.93	0.93	0.95
N	103,402	103,402	103,402	103,402	103,402	103,057
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	3.811***	3.761***	3.407***	3.208***	3.190***	4.109***
	(0.770)	(0.911)	(0.883)	(0.484)	(0.491)	(1.001)
Share low-skill immigrants	0.642	0.647	0.574	1.019***	1.021***	1.167***
	(0.505)	(0.550)	(0.558)	(0.238)	(0.238)	(0.427)
Share high-skill natives	1.611**	1.641***	1.635**	1.183*	1.180	1.412
	(0.630)	(0.605)	(0.612)	(0.696)	(0.707)	(1.156)
Log employment	−0.102***	−0.103***	−0.092***	−0.103***	−0.101***	−0.162***
	(0.022)	(0.022)	(0.023)	(0.028)	(0.028)	(0.031)
KP F-stat	32.26	34.08	34.33	30.41	29.94	24.34
N	103,402	103,402	103,402	103,402	103,402	103,057
Panel C: 2SLS	Log GDP per Worker					
Share high-skill immigrants	2.711***	2.564***	2.366***	2.345***	2.327***	2.926***
	(0.801)	(0.871)	(0.830)	(0.492)	(0.506)	(0.711)
Share low-skill immigrants	0.373	0.348	0.317	0.996***	0.997***	1.176***
	(0.618)	(0.646)	(0.627)	(0.230)	(0.230)	(0.389)
Share high-skill natives	2.408***	2.419***	2.275***	1.910**	1.897**	2.261*
	(0.526)	(0.504)	(0.502)	(0.765)	(0.774)	(1.268)
Log employment	0.076***	0.074**	0.057*	0.049**	0.049**	0.020
	(0.027)	(0.027)	(0.029)	(0.023)	(0.023)	(0.022)
KP F-stat	22.49	23.00	22.91	16.88	16.65	15.72
N	103,402	103,402	103,402	103,402	103,402	103,057
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓	✓	✓
Industry x Year FE			✓	✓	✓	✓
Region x Industry FE				✓	✓	✓
Region x Industry x Year FE					✓	✓
State x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B and Panel C) regressions of specification (2.5) for the long panel from 2005-2019 described in detail in Appendix 2.B. The sample excludes county-sector cells which have suppressed employment information between 2017-2019 when aggregating to the CZ-sector level. For consistency, only CZ-sector cells with at least ten headcount employment are included. The dependent variable is log GDP per worker and the endogenous variables are the high- and low-skill immigrant employment shares, the high-skill native employment share and log employment. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented. Panel C additionally instruments log employment. Panel B and C include the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Table 2.A.16. Robustness Long Panel (w/o log employment)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS	Log GDP per Worker					
Share high-skill immigrants	1.124***	1.174***	1.023***	0.920***	0.920***	0.800***
	(0.215)	(0.225)	(0.226)	(0.212)	(0.224)	(0.261)
Share low-skill immigrants	−0.180	−0.157	−0.179	−0.074	−0.079	−0.300**
	(0.173)	(0.183)	(0.188)	(0.117)	(0.123)	(0.143)
Share high-skill natives	0.726***	0.802***	0.805***	0.665***	0.686***	0.583***
	(0.125)	(0.135)	(0.132)	(0.083)	(0.090)	(0.089)
R^2	0.90	0.91	0.91	0.93	0.93	0.94
N	103,402	103,402	103,402	103,402	103,402	103,057
Panel B: 2SLS	Log GDP per Worker					
Share high-skill immigrants	3.182***	3.064***	2.763***	2.622***	2.608***	3.054***
	(0.773)	(0.876)	(0.850)	(0.426)	(0.438)	(0.714)
Share low-skill immigrants	0.488	0.473	0.415	1.003***	1.005***	1.175***
	(0.572)	(0.611)	(0.610)	(0.227)	(0.227)	(0.391)
Share high-skill natives	2.067***	2.094***	2.031***	1.677**	1.663**	2.168*
	(0.580)	(0.559)	(0.571)	(0.763)	(0.771)	(1.261)
KP F-stat	31.61	32.38	32.42	22.53	22.21	21.35
N	103,402	103,402	103,402	103,402	103,402	103,057
CZ FE	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
CZ x Year FE		✓	✓	✓	✓	✓
Industry x Year FE			✓	✓	✓	✓
Region x Industry FE				✓	✓	✓
Region x Industry x Year FE					✓	✓
State x Industry x Year FE						✓

Note: This table reports coefficients from OLS (Panel A) and 2SLS (Panel B) regressions of specification (2.6) for the long panel from 2005-2019 described in detail in Appendix 2.B. The sample excludes county-sector cells which have suppressed employment information between 2017-2019 when aggregating to the CZ-sector level. For consistency, only CZ-sector cells with at least ten headcount employment are included. The dependent variable is log GDP per hour worked and the endogenous variables are the high- and low-skill immigrant employment shares and the high-skill native employment share. Panel B reports coefficients from 2SLS regressions in which the three share variables are instrumented and includes the first-stage Kleibergen Paap F-statistics on the excluded instruments. The IV construction is described in Section 2.4.2. All regressions are weighted by pre-employment size, that is, average employment between 2000-2004. Standard errors in parentheses are clustered at the (48) state level, and, ***, **, * denote statistical significance at the 1%, 5% and 10% levels, respectively.

Appendix 2.B Data

In this appendix we outline the variable and sample construction, including the handling of missing and suppressed information.

2.B.1 GDP Data

We obtain county by sector real GDP estimates from the BEA.[13] For a description of the construction of the estimates see Section 2.2.1 and Panek, Rodriguez, and Baumgardner (2019). The raw data contains chained 2012 USD estimates of local GDP at roughly the two digit NAICS code sector level and aggregations thereof for the years 2001-2019. Industry classification is based on the 2012 NAICS code system. Because the BEA suppresses information to protect confidentiality we use several aggregations of two digit NAICS sectors. For reasons explained below we exclude Agriculture, Forestry, Fishing and Hunting (11), Mining, Quarrying and Oil and Gas Extraction (21), Utilities(22) and Public Services (92), leaving us with the following industries: Construction (23), Manufacturing (31-33), Wholesale Trade (42), Retail Trade (44-45), Transportation, Warehousing (48-49), Information (51), Finance, Insurance, Real Estate and Rental and Leasing (52-53), Professional, Scientific, and Technical Services, Management of Companies and Enterprises and Administrative and Support and Waste Management and Remediation Services (54-56), Education Services, Health Care and Social Assistance (61-62), Arts, Entertainment and Recreation, and Accommodation and Food Services (71-72) and Other Services (81).

On the geographical level, we restrict attention to the mainland United States, dropping Alaska and Hawaii, as well as Washington D.C. from the analysis. For the state of Virginia the BEA uses an aggregated delineation of counties which group together independent cities with their surrounding county in several but not all instances.[14] We adopt this aggregation throughout when working at the county level.

The final county by sector GDP dataset contains 643,511 observations for 3079 counties, 11 sectors and 19 years (2001-2019). Out of these, approximately 13% are suppressed due to confidentiality. The suppression is roughly balanced across years and amounts to 12.8% for our main sample period from 2005-2016. We reduce the number of missing/suppressed cells via interpolation. Our interpolation relies on employment information, which is never suppressed, and is outlined in Section 2.B.6.1 below.

13. Data was downloaded from the BEA's website at https://apps.bea.gov/regional/downloadzip.cfm, on June 21, 2021.

14. For example, Albemarle County (fips code: 51003) and Charlottesville (fips code: 51540) form "Albemarle + Charlottesville" (fips code: 51901). All 519xx fips codes refer to such combinations of independent cities and surrounding counties.

2.B.2 Employment Data

Our measure for headcount employment comes from the County Business Pattern (CBP) database from the US Census Bureau. Specifically, we use data published by Eckert et al. (2021) who impute suppressed employment cells in the CBP data.[15] We use the yearly native NAICS code data and aggregate it up to the same two digit level as the GDP information. We devote some care to matching GDP and employment information because NAICS code classifications do not differentiate between private and public ownership. Since the CBP data covers only private non-farm employment we exclude NAICS sector Agriculture, Forestry, Fishing and Hunting (11) as well as several other sectors that are likely to contain significant fraction of public employment. Specifically, we exclude the following sectors from the analysis: Agricultural, Forestry, Fishing and Hunting (11), Mining, Quarrying and Oil and Gas Extraction (21), Utilities (22) and Public Administration (92). Fortunately, the BEA's GDP estimates do explicitly exclude public contributions to GDP for several sectors which insures a close link between the BEA and CBP data. The BEA explicitly exclude public enterprises from the following sectors' GDP estimates: Management of Companies and Enterprises (55), Administrative and Support and Waste Management and Remediation Services (56), Education Services (61), Hospitals (622), Other Services (81).

While raw CBP data is available until and including 2019, the imputed data by Eckert et al. (2021) covers only the years until and including 2016. This is because the US Census Bureau significantly altered its reporting and suppression guidelines from 2017 onward. Our main sample therefore restricts attention to the years until and including 2016. We replicate our main findings in Appendix Table 2.A.15 and Table 2.A.16 for a subsample of the data unaffected by the reporting change. We describe how we construct our *long panel* in Section 2.B.8 below.

2.B.3 Employment Shares

The information on the composition of employment comes from the 2000 Census and the American Community Survey (ACS) waives 2005-2019 available via the Integrated Public Use Microdata Series (IPUMS) Ruggles et al. (2021). From 2001 until 2004 the ACS does not provide adequately fine geographic information.

We restrict the sample to working-age individuals aged 15 to 64 with known place-of-work in the mainland United States (excl. Washington D.C.). Because BEA's GDP data is place-of-work, rather than place-of-residence based we adopt this concept when constructing our employment share estimates in the ACS / Census data. Concretely, we construct estimates of the total number of workers (as well as the total number of hours worked for our hours measure), in a place-of-work public

15. Eckert et al. (2021)'s data is publicly available at https://fpeckert.me/cbp and was downloaded on November 5, 2019.

use micro area (PWPUMA) by industry, education and country of birth. We use the same eleven two-digit native NAICS code industries and aggregations thereof as in the BEA and CBP data. Our definition of high-skill encompasses all individual with at least some years of college education, and low-skill correspondingly covers individual with no college education. For the construction of our shift share instrumental variable (see Section 2.4.2) we reply on estimates of the total number of workers for the 36 foreign counties that make up the largest share of the immigrant workforce in the US. Specifically, we construct estimates of the number of high- and low-skill workers in each PWPUMA by industry year for the following countries of birth: Brazil, Canada, China, Colombia, Cuba, Dominican Republic, Ecuador, El Salvador, Ethiopia, Germany, Guatemala, Guyana, Haiti, Honduras, India, Iran, Italy, Jamaica, Japan, North Korea, South Korea, Mexico, Nicaragua, Nigeria, Pakistan, Peru, Philippines, Poland, Puerto Rico, Russia, Thailand, Trinidad and Tobago, United Kingdom, Venezuela, Vietnam and Yugoslavia.

Census changed its PWPUMA codes from 2012 onward. Prior to 2012, there are 1237 unique PWPUMAs, post 2012 there are 974. For each coding scheme we have eight years of data (2000, 2005-11 and 2012-2019). We aggregate industries to the same eleven sectors as in the BEA data and differentiate a total of 38 countries of birth (36 countries listed above plus USA and “others”). The PWPUMA industry by country of birth panel has a total of 7,393,584 cells.

2.B.4 Missing and Suppressed Employment Share Information

There are a few instances (approx. 3%) in which the ACS does not contain a single observations for a PWPUMA industry cell and our employment share estimates are thus missing. We use interpolation and extrapolation to fill in these missing cells. To reduce noise in the procedure we proceed as follows. We set share estimates to missing throughout if a PWPUMA industry has less than four (out of possible eight) years with non-missing information. We fill in all intermediate years by linear interpolation between non-missing year observations. For the extrapolation of share estimates we have to ensure that they fall within $[0, 1]$. Because natives make up the fast majority in the sample we extrapolate the native share in employment and truncate the extrapolation at 0 or 1 whenever it exceeds these boundaries. We then calculate the implied share of the foreign-born employment share and distribute it to the individual foreign countries based on the average foreign country distribution within PWPUMA industry cell over the years with non-missing data. We proceed analogously and construct education-specific share estimates by using the average education of native and foreign-born labor in a PWPUMA industry cell to extrapolate.

2.B.5 Other Data Sources

We use several other data sources in this work. In particular, the BEA also provides estimates of nominal GDP and nominal worker compensation by county sector year, which we use in Table 2.8. The data is available at BEA's website at the same address at the real GDP data above. We also rely on county population estimates from the Census Bureau for the construction of our instrumental variable.[16] For this we restrict attention to individuals between 15 and 64 years of age as in the employment share construction.

2.B.6 Main Sample

For our main sample we combine the real GDP, employment and employment shares into a county by sector year panel covering 3079 counties and 11 industries over the years 2005 to 2016. For an overview on data availability by year see Table 2.A.1. Before aggregating all variables at the CZ by sector level, we use interpolation to deal with suppressed GDP information.

2.B.6.1 GDP Suppression

As mentioned, approximately 13% of county sector cells have suppressed GDP data. We reduce the number of suppressed cells via interpolation. In doing so we rely on employment data from the CBP which is never subject to suppression (until 2016). We thus interpolate on a GDP per worker basis. This is important due to the non-random nature of suppression, e.g. due to firm exist.

For our main sample we proceed as follows. We first exclude all county sector cells with more than a total of five years of suppressed GDP information between 2005-2016. We calculate GDP per worker for all non-missing years. We then use linear interpolation of GDP per worker for intermediate years of missing GDP per worker and multiply employment counts with the interpolated GDP per worker estimate to do obtain interpolated GDP data. When doing so we never interpolate for more than five consecutive years. Lastly we only keep county sectors with non-missing GDP (raw and interpolated) information for all years between 2005-2016. We probe the robustness of our findings w.r.t. the exact choice of interpolation restrictions in Appendix Table 2.A.9 and Table 2.A.10 in which we repeat the interpolation for more stringent exclusion criteria.

16. We downloaded Census county population data by age at https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-counties.html for 2000-2010 and https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-detail.html for 2010-2019 on January 21, 2021.

2.B.7 Sample Restrictions

Apart from the restrictions imposed by data availability, see Section 2.B.6.1, we restrict the sample as follows. First, we impose a minimum number of employment headcount across all years. That is, we keep only CZ sectors with headcount employment of at least ten in all years between 2005 and 2016. Second, to insure that we have sufficient variation within CZ across sectors we restrict attention to CZ with data on at least five different industries (of the eleven above). We probe robustness to this restriction in Appendix Table 2.A.7 and Table 2.A.8.

2.B.8 Long Panel

As mentioned above, we probe the robustness of our findings on a longer panel spanning 2005-2019, which is not affected by the change in suppression protocol in the CBP employment data. To this end, we repeat the construction of our main sample (incl. the sample restrictions above) but additionally require there to be no suppressed or omitted employment information after 2016 before collapsing the panel to the CZ sector level. This implies that a CZ sector might contain slightly different county sectors in the main vs. the long panel even for the overlapping years from 2005 to 2016. We report our results for the long panel in Appendix Table 2.A.15 and Table 2.A.16.

Chapter 3

Ranking Mechanisms for Coupled Binary Decisions*

3.1 Introduction

Almost all collective decisions in society – be it in committees, parliaments or referenda – are made by means of (simple) Majority Rule. We base decisions on how *many* individuals favor or oppose a reform rather than how *much* everyone cares. This blindness to preference intensities casts doubt on the efficiency of voting as an aggregation mechanism. Consider a scenario in which 49% of individuals oppose a proposed reform with drastic consequences for each individual. A majority of 51% of people marginally benefits and therefore supports the reform. Nevertheless it seems sensible to decide in favor of the minority. This inherent weakness of direct democracy based on Majority Rule has long been recognized as the *Tyranny of the Majority* (De Tocqueville (1835)).

Advocates of Majority Voting point out several desirable properties. First, Majority Voting takes everyone's opinion into account and treats them equally. Second, Majority Voting respects consensus. Third, Majority Voting provides individuals with an incentive to reveal their preferences truthfully. For instance, if one were to naively ask how much everyone cares about a given reform, individuals would certainly like to exaggerate their feelings to sway the decision in their favor regardless of how much they actually cared. So is it at all possible to elicit preference intensities truthfully while maintaining all desirable properties of Majority Voting?

This paper gives an affirmative answer to this question for the practically relevant class of coupled binary decisions. Consider a set of agents who face a fixed agenda of several reforms that have to be approved or rejected. We study a class of Rank-

* We thank Albin Erlanson, Thomas Gräber, Rafael Hortala-Vallve, Andreas Kleiner, Benny Moldovanu, Balazs Szentes as well as seminar audiences at University Bonn, LSE, the 13th Meeting of the Society for Social Choice and Welfare in Lund and at the 10th Conference on Economic Design in York. Financial support through the Bonn Graduate School of Economics is gratefully acknowledged.

ing Mechanisms which are sensitive to preference intensities while maintaining all desirable properties mentioned above. Agents communicate which alternative they prefer in each decision problem. Additionally, they report a priority ranking over decision problems by ranking each problem according to the absolute difference in utilities between the reform and the status quo. These rankings are then used to assign weights to agents' votes in a voting mechanism. In each decision problem the reform is implemented if and only if the sum of weighted votes in favor of implementation outweighs the one supporting the status quo. Any Ranking Mechanism is thus implementable as a weighted voting procedure. Rather than deciding upon each reform separately a Ranking Mechanism makes use of the linkage of problems by eliciting cardinal information of preferences. In particular, the approval of any reform depends on *both* the number of agents in favor and their relative preference intensity towards the issue (as reflected by the rank they assigned to that particular problem).

This paper establishes two sets of results. For the case of identical decision problems we prove that the sincere strategy is a Bayes-Nash equilibrium of any Ranking Mechanism. Agents find it optimal to rank problems according to the absolute difference in utilities between the two alternatives as long as all other agents do the same. We then maximize over the class of Ranking Mechanisms and derive a closed form solution for the ex-ante efficient weight vector. The optimal Ranking Mechanism ex-ante Pareto dominates Separate Majority Voting for arbitrary number of agents and decision problems. Further, it achieves full efficiency in the limit as the number of decision problems tends to infinity.

We then extend our idea of ranking to non-identical decision problems. We propose a generalized class of Randomized Ranking Mechanisms all of which induce sincere equilibrium behavior. Intuitively, randomization is such that from the perspective of all other agents each agent reports every priority ranking with equal probability. We derive the ex-ante efficient Randomized Ranking Mechanism and provide a closed form solution for the optimal weight vector. The optimal Randomized Ranking Mechanism ex-ante Pareto dominates Separate Majority Voting for any number of agents and decision problems.

The optimal (Randomized) Ranking Mechanism respects both anonymity and unanimity. Moreover, under mild conditions it allows for strong minorities to overturn weak majorities and therefore mitigates the *Tyranny of the Majority*. Our proposed mechanism is the first to successfully link both identical and non-identical decision problem for any number of agents and problems.

Further we document that the picture changes under a different equilibrium concept. Building on a result by Hortala-Vallve (2010) we show that under mild conditions Separate Majority Voting is ex-ante Pareto efficient in the class of strategy-proof mechanisms. In other words, the requirement that agents find truth-telling a dominant strategy makes it impossible to exploit the coupled structure and precludes any use of cardinal information.

The rest of the paper is organized as follows. Section 3.2 reviews the existing literature. The formal model is presented in Section 3.3. Section 3.4 presents two impossibility results and may be seen as a theoretical justification for our interest in the topic. In Section 3.5 we study the class of Ranking Mechanisms linking identical decision problems. We generalize our results to non-identical decision problems in Section 3.6. Section 3.7 concludes.

3.2 Related Literature

The conceptual idea of evaluating efficiency of voting rules in terms of ex-ante expected welfare goes back to Rae (1969). Our work adds to a series of recent papers studying the ex-ante welfare properties of voting schemes in environments with cardinal preferences (Gershkov, Moldovanu, and Shi (2017), Kim (2017) among others).

The traditional literature on social choice has focused on environments with ordinal preferences over alternatives. Classical impossibility results include the famous *Gibbard-Satterthwaite-Theorem* (Gibbard (1973), Satterthwaite (1975)) and subsequent work demonstrating its robustness on cardinal type spaces with respect to randomization (Hylland (1980)) and Bayesian implementation of ordinal mechanisms (Majumdar and Sen (2004)).

Coupling multiple decisions alone is not sufficient to overcome impossibility results. Barberà, Sonnenschein, and Zhou (1991) study a setting in which agents have separable, ordinal preferences over subsets of objects. In our terminology, an object is a decision problem which is contained in the subset if and only if the reform in that decision problem is implemented. Their main result characterizes the set of strategy-proof mechanisms and implies that only the most preferred subset of each voter can be elicited truthfully. In a cardinal framework with a finite number of binary decisions Hortala-Vallve (2010) shows that any strategy-proof mechanism cannot be both unanimous and sensitive to preference intensities. As shown in Section 3.4 his results imply that (i) Separate Majority Rule is ex-ante efficient in the class of strategy-proof mechanisms and (ii) full efficiency remains unachievable among incentive compatible mechanisms for any finite number of decisions.

We are not the first to show that coupling decision problems may improve efficiency under Bayesian implementation. There exist voting mechanisms that are sensitive to cardinal intensities and Pareto improve upon ordinal mechanisms such as Separate Majority Voting. Most notable examples thereof are a *Rationing Procedure* by Jackson and Sonnenschein (2007), a *Simple Scheme* by Casella and Gelman (2008) and *Qualitative Voting* by Hortala-Vallve (2012).

Jackson and Sonnenschein (2007) demonstrate that as the number of identical decision problems tends to infinity full efficiency is achievable. Their Rationing Procedure works as follows. For any number of decision problems an agent announces his utility type directly, but he has to ration his reported type so as to match the underlying distribution as best as possible. The mechanism then picks the alternative that maximizes reported welfare. However, their Rationing Procedure crucially relies on identical type distributions across problems. It does not readily extend to a finite number of decision problems or continuous type spaces and exact equilibrium strategies are unknown. Our Ranking Mechanism also achieves full efficiency in the limit while simultaneously admitting intuitive equilibrium behavior and welfare improvements for any finite number of decision problems.

In Casella and Gelman (2008), agents are endowed with a single bonus vote, which can be cast in addition to regular votes. The decision is made according to the sum of votes cast for each alternative. Their main result proves that in large populations the Simple Scheme improves upon Separate Majority Voting for small enough bonus votes. Although they restrict attention to large populations our Proposition 6 implies that casting the bonus vote on the decision problem with highest difference in utilities remains an equilibrium for any number of agents. Casella and Gelman (2008) generalize their results to non-identical type distributions across problems but not agents.

Hortala-Vallve (2012) proposes another intuitive voting procedure. Agents are endowed with a fixed number of votes that can be distributed freely among alternatives and problems. A reform is accepted if the total number of votes supporting the reform is larger than the number of votes against it. The main result of the paper shows that in settings with 2 or 3 agents with 4 possible valuations and 2 decision problems Qualitative Voting is ex-ante efficient. Another mechanism motivating much of the recent literature on coupled binary decisions is the Storable Votes procedure by Casella (2005), which applies to a dynamic setup of a committee meeting regularly over time.

While there has been considerable effort the literature has not yet proposed a mechanism which is *both* intuitive and predictable – at least for the practically relevant case of finitely many problems and agents. Simplicity as well as predictability are prerequisites for any real world application. Our paper fills this gap and applies the idea of ranking to a social choice setting without monetary transfers, namely coupled binary decisions.[1]

Our results for the optimal (Randomized) Ranking Mechanism identify expected order statistics as important moments of the underlying type distribution. In this spirit our work is related to a recent paper by Kim (2017), who studies a social choice problem with K alternatives. Kim (2017) proposes a mechanism based on expected order statistics which improves upon Majority Voting by partly eliciting cardinal information on preferences. However, Kim's mechanism is not applicable

1. The idea of ranking alternatives or objects has also been studied in the multidimensional cheap talk literature, for example in the context of coordination in auctions Campbell (1998) and Pesendorfer (2000) or biased expert advise Chakraborty and Harbaugh (2007) among others.

in our setting due to the impossibility result by Majumdar and Sen (2004). Relatedly, Apesteguia, Ballester, and Ferrer (2011) rely on expected order statistics to characterize the ordinal mechanism that maximizes ex-ante expected utility in a social choice problem with cardinal preferences. In contrast to our work, Apesteguia, Ballester, and Ferrer (2011) abstract from incentive considerations.

3.3 The Model

There are $n \in \mathbb{N}$ agents, who have to decide on $d \in \mathbb{N}$ binary decisions. Each decision problem $k \in D = \{1, \ldots, d\}$ consists of two alternatives $\{0, 1\}$. We interpret 0 as maintaining the status quo and 1 as implementing a reform. The overall outcome is a vector $x \in X = [0, 1]^d$ where the kth component x_k represents the probability of implementing the reform in decision $k \in D$.

We normalize the utility of maintaining the status quo to 0 for every agent and every decision problem. Each agent $i \in N = \{1, \ldots, n\}$ draws a private von Neumann-Morgenstern utility vector (or type) $u_i = (u_i^1, \ldots, u_i^d)$ representing his cardinal utility if the reform is implemented in each of the different decision problems. We refer to the sign of u_i^k as agent i's ordinal type and to $|u_i^k|$ as his preference intensity in decision k. Throughout the paper we refer to u_i^k as the random variable and its realization interchangeably. The random variable u_i^k takes on values in $U_i^k \subset \mathbb{R}$ and is independently distributed between agents and across problems. Formally, u_i^k is independent of u_j^l for all $i, j \in N$ with $i \neq j$ and all $k, l \in D$ with $k \neq l$. It has a finite first absolute moment and its continuous pdf ρ_i^k is symmetric around zero. For notational convenience let $\mathcal{U}_i = (U_i^1, ..., U_i^d)$, $\mathcal{U} = (\mathcal{U}_i)_{i \in N}$ and $\mathcal{U}_{-i} = (\mathcal{U}_1, ..., \mathcal{U}_{i-1}, \mathcal{U}_{i+1}, ..., \mathcal{U}_n)$.

The distribution of types is common knowledge among agents. We assume that agents' utility is separable across problems and write the overall utility of agent i with utility type $u_i \in \mathcal{U}_i$ for outcome $x \in X$ as $V_i(x) = \sum_{k=1}^d u_i^k \cdot x_k$.[2] The above environment is entirely separable implying that there is no a priori reason to link decision problems at all.

An indirect mechanism $G = (\mathcal{M}, g(\cdot))$ consists of a message space $\mathcal{M} = M^{\otimes n}$, which encompasses a message or action set M for each agent and a decision rule $g : \mathcal{M} \to X$, which maps into the set of possible outcomes. Again, we refer to g_k as the random outcome in decision k as well as to its realization. Unless made explicit all expectation operators are meant to include the randomness of the mechanism. We restrict attention to mechanisms that treat all agents equally.

Definition 1. An indirect mechanism $G = (\mathcal{M}, g)$ is anonymous if for all permutations σ on N and all $m \in \mathcal{M}$ it holds that $g(m_1, ..., m_n) = g(m_{\sigma(1)}, ..., m_{\sigma(n)})$.

2. We follow most of the literature by assuming that preferences are additively separable across problems. Ahn and Oliveros (2012) demonstrate the importance of the separability assumption for equilibrium predictions even under Separate Majority Voting.

Agent i's strategy $s_i : \mathscr{U}_i \to M$ maps i's utility vector into a message in his action set. A collection of strategies for all agents $s = (s_1, ..., s_n)$ is called a strategy profile and the strategy profile of all but agent i is denoted by s_{-i}. Agent i evaluates a strategy s_i given an indirect mechanism $(\mathscr{M}, g)$ and a strategy profile of the other agents s_{-i} by taking expectations over all other agents' utility types (and the potentially random mechanism), i.e. according to $\mathbb{E}_{-i}[V_i(g(s_i, s_{-i}))]$.[3]

Definition 2. A strategy profile $\hat{s}$ is a Bayes-Nash equilibrium of $(\mathscr{M}, g)$ if for every agent i the strategy $\hat{s}_i$ is in expectation a best response to the strategy profile $\hat{s}_{-i}$ of the other agents. Formally, $\mathbb{E}_{-i}[V_i(g(\hat{s}_i, \hat{s}_{-i}))] \geq \mathbb{E}_{-i}[V_i(g(s_i, \hat{s}_{-i}))]$ for all i and s_i.

A mechanism is direct if $\mathscr{M} = \mathscr{U}$, i.e. agents report their utility type directly.

Definition 3. A direct mechanism $(\mathscr{U}, g)$ is

(1) strategy-proof, if for every agent i with type u_i the truthful strategy is a best response to any strategy profile of all other agents. Formally, $V_i(g(u_i, u_{-i})) \geq V_i(g(\tilde{u}_i, u_{-i}))$ for all i, u_i, $\tilde{u}_i$ and u_{-i}.
(2) incentive compatible, if for every agent i with type u_i the truthful strategy is in expectation a best response to the truthful strategy profile of all other agents. Formally, $\mathbb{E}_{-i}[V_i(g(u_i, u_{-i}))] \geq \mathbb{E}_{-i}[V_i(g(\tilde{u}_i, u_{-i}))]$ for all i, u_i and $\tilde{u}_i$.

While the revelation principle guarantees that there is theoretically no loss in restricting attention to direct mechanisms, it might still be simpler to communicate indirect mechanisms in practice. The Ranking Mechanisms we introduce below are examples for which an indirect representation facilitates understanding and offers an intuitive implementation.

Throughout the paper we measure efficiency at the ex-ante stage. Agent i's ex-ante expected utility under a mechanism $(\mathscr{M}, g)$ and strategy profile s is $\mathbb{E}[V_i(g(s))]$ where the expectation is taken w.r.t. to all random variables.

Definition 4. A mechanism (ex-ante Pareto) dominates another mechanism if it generates at least as high levels of ex-ante expected utility for all agents. A mechanism is (ex-ante Pareto) efficient if it is not dominated.

Full efficiency refers to the highest ex-ante utility level achievable under any (not necessarily incentive compatible) mechanism. Ex-ante expected welfare is the sum over all agents' ex-ante expected utility levels. A necessary requirement for ex-ante efficiency is unanimity.

Definition 5. A mechanism is unanimous if in every decision problem it implements the alternative preferred by all agents whenever such alternative exists.

3. Throughout $\mathbb{E}_i$ and $\mathbb{E}_{-i}$ denote expectations taken with respect to all random variables with subscript i and subscripts $j \neq i$ (including the randomness of the mechanism), respectively.

One unanimous mechanism is Separate Majority Voting, which serves as a benchmark throughout this work. Every agent casts a single vote on every problem and the decision is made by simple Majority Rule or in case of a tie by a fair coin toss separately for each problem. Separate Majority Voting is strategy-proof but makes no use of the fact that there are multiple problems.

3.4 Impossibility Results

The first result of this section shows that if one restricts attention to strategy-proof mechanisms Separate Majority Voting is ex-ante Pareto efficient. This result is a consequence of an impossibility result by Hortala-Vallve (2010). We borrow the following definition.

Definition 6. (Hortala-Vallve (2010)) The preference domain is unrestricted if there exists $\epsilon > 0$ such that $(-\epsilon, \epsilon) \subseteq U_i^k$ for all $i \in N$ and all $k \in D$.

With this definition we have the following proposition.

Proposition 4. Among anonymous, strategy-proof mechanisms Separate Majority Voting is efficient in an unrestricted domain.

Proposition 4 follows from the impossibility result established in Hortala-Vallve (2010): Among strategy-proof mechanisms unanimity implies non-sensitivity and separability. A mechanism is separable on d coupled decision problems if the outcome implemented in each decision problem only depends on agents' utilities for that problem. A mechanism is sensitive if there exist two utility profiles of the same ordinal type but with different intensities, which result yet in a different outcome for at least one decision problem. In other words, any strategy-proof and unanimous mechanism elicits only *ordinal* types and cannot *link* decision problems. Proposition 4 follows because on a single decision problem (Separate) Majority Voting is ex-ante efficient among all anonymous, strategy-proof mechanisms in symmetric environments.[4]

Proposition 4 implies that from an ex-ante welfare perspective there is no advantage in *linking* decision problems in the class of strategy-proof mechanisms. Moreover the efficient mechanism elicits only ordinal types. Our environment with cardinal utility and randomization allows us to work with the different implementation concept of incentive compatibility. The weaker requirement of incentive compatibility does not make the problem trivial. Incentive constraints still present a non-negligible restriction as full efficiency remains unachievable.

Proposition 5. Full efficiency is unachievable among incentive compatible mechanisms.

4. For a general proof of the optimality of majority voting see Schmitz and Tröger (2012).

Proof. See Appendix. □

Incentive compatibility implies that only proportional types can be elicited which prevents full efficiency. Together the above results raise the following question: Is it at all possible to find an incentive compatible mechanism that improves upon Separate Majority Voting? In the remainder of this paper we give an affirmative answer to this question.

3.5 Ranking Identical Decision Problems

Our improvement upon Separate Majority Voting is centered around the intuitive idea of *ranking* decision problems. Concretely, we would like agents to not only communicate which alternative they prefer in each decision problem – as in Separate Majority Voting – but also express which problem they care most about, which second, and so on.

To formalize the idea we define the following message space.

Definition 7. The (ranking) message space is defined as $M = \{(a, \pi) \mid a \in \{0,1\}^d, \pi \in \sigma(D)\}$, where $\sigma(D)$ denotes the set of all permutations over D. We denote the profile of message spaces for all agents by $\mathcal{M} = M^{\otimes n}$.

Note that any message $m \in M$ can canonically be separated across problems, i.e. $m = (m^k)_{k=1,\dots,d}$. For decision problem $k \in D$ we interpret message $m^k = (a^k, \pi^k)$ in two parts. The ordinal part a^k encodes whether an agent is in favor of the reform $a^k = 1$ or prefers the status quo $a^k = 0$. The cardinal part $\pi^k \in D$ corresponds to the rank an agent assigns to problem k. Importantly, an agent can assign every rank exactly once.

We are interested in eliciting *one particular* ranking over decision problems, namely, the one in which an agent ranks each decision problem according to the absolute difference in utilities between the two proposed alternatives. Using Definition 7 of the message space we formulate the following strategy.

Definition 8. A strategy $\overset{*}{s}_i : \mathcal{U}_i \to M$ is *sincere* if agent i reports his favored alternative for every problem k and a ranking $\overset{*}{\pi}_i$ which sorts all problems by their preference intensities. Formally, $\overset{*}{a}{}_i^k = 1$ if and only if $u_i^k > 0$ and $\overset{*}{\pi}{}_i^k > \overset{*}{\pi}{}_i^l$ only if $\left|u_i^k\right| \geq \left|u_i^l\right|$.[5]

Our goal is to induce sincere equilibrium behavior. The motivation to focus attention on the sincere strategy is twofold. First, it is intuitive and easy to understand from the perspective of an agent thereby making it a likely equilibrium outcome in practice. This is especially important because we work with the weaker Bayes-Nash equilibrium concept. Second, the sincere strategy contains *strictly* more information

5. Since types are continuously distributed the sincere strategy is unique with probability one.

than what is elicited by Separate Majority Voting. Therefore the sincere strategy is a promising starting point both from a practical as well as theoretical perspective.

However, it is not obvious how to construct (non-trivial) mechanisms for which the sincere strategy profile is a Bayes-Nash equilibrium. We first present our main idea under the following simplifying assumption.

Assumption 3. The random variable u_i^k is identically and independently distributed between agents and across problems.

Section 3.6 generalizes our results to settings with different type distributions between agents and across problems. The next section introduces a class of simple mechanisms all of which induce sincere equilibrium behavior under Assumption 3.

3.5.1 Ranking Mechanisms

In this section we introduce the class of *Ranking Mechanisms*. Ranking Mechanisms correspond to a generalization of standard voting procedures like Separate Majority Voting. For every decision problem an agent communicates whether or not he is in favor of implementing the reform. A Ranking Mechanism then assigns a weight to every vote of an agent. For each decision problem the weight assigned to an agent's vote *solely* depends on the agent's reported rank of that particular problem. Therefore two agents may be assigned different weights in the same decision problem if they rank it differently. However, weights are not agent-specific and since every agent gets to report every rank exactly once a Ranking Mechanism remains anonymous.

Formally, we define a Ranking Mechanism $(\mathcal{M}, g^{RM,w})$ with $\mathcal{M}$ defined in Definition 7 as follows. Every agent reports an ordinal type as well as a priority ranking. The decision rule $g^{RM,w} : \mathcal{M} \to X$ is parametrized by a weight vector $w = (w^1, ..., w^d) \in W$, where $W \subset \mathbb{R}^d_{++}$ denotes the set of strictly positive weight vectors with d non-decreasing entries. For every decision problem $k \in D$ and every agent $i \in N$ the Ranking Mechanism $(\mathcal{M}, g^{RM,w})$ translates the report $m_i^k = (a_i^k, \pi_i^k)$ into a signed weight $(2 \cdot a_i^k - 1) \cdot w^{\pi_i^k}$. The ordinal part maps into the sign of the weight such that $a_i^k = 0, 1$ corresponds to a negative and a positive sign, respectively. The cardinal part $\pi_i^k \in D$ determines the entry of the weight vector $w \in W$. In particular, higher reported ranks map into (weakly) higher weights. Formally, we define Ranking Mechanisms as the maximization of the resulting sum of signed weights.

Definition 9. The Ranking Mechanism $(\mathcal{M}, g^{RM,w})$ with weight vector $w \in W$ implements the outcome that maximizes the sum of signed weights. Ties are broken by a fair coin toss. Formally, the decision rule is defined as

$$g^{RM,w}(m) \in \underset{x \in \{0, \frac{1}{2}, 1\}^d}{\arg\max} \left\{ \sum_{i=1}^{n} \sum_{k=1}^{d} \left(2 \cdot a_i^k - 1\right) \cdot w^{\pi_i^k} \cdot x_k \right\}.$$

Note that $g^{RM,w}$ is identical for multiples of w, i.e. $g^{RM,w} \equiv g^{RM,\lambda \cdot w}$ for all $\lambda > 0$.

The class of Ranking Mechanisms has several desirable properties. First, Ranking Mechanisms are both anonymous and unanimous. Second, as we show in Section 3.5.3 all Ranking Mechanisms induce sincere equilibrium behavior. Third, any Ranking Mechanism corresponds to a simple voting procedure: Every agent is endowed with d votes of pre-specified weights $w^1, ..., w^d$. Agents are allowed to cast one weighted vote in each decision problem. For every problem the alternative with the higher sum of weighted votes is implemented. Ties are broken by a fair coin toss. This interpretation offers a simple implementation of any Ranking Mechanism in practice. Further it identifies Separate Majority Voting as belonging to the class of Ranking Mechanisms with weights $(1, ..., 1)$.[6] Lastly, from a theoretical perspective the results of Section 3.5.4 imply that on the ranking message space there is no loss in restricting attention to Ranking Mechanisms. If agents report sincerely the ex-ante efficient outcome is implementable by a Ranking Mechanism. The next section illustrates the class of Ranking Mechanisms by means of an example.

3.5.2 Example

Distribution of Types. There are three agents, who have to decide on two binary decisions. For every decision problem we normalize every agent's utility to 0 if the status quo is maintained. We denote by u_i^k the utility of agent $i \in \{1, 2, 3\}$ in decision problem $k \in \{I, II\}$ if the corresponding reform is implemented. Utility u_i^k is drawn from a standard normal distribution. It may thus be positive or negative implying that an agent is either in favor or against the proposed reform, respectively. Further the absolute value of u_i^k encodes his preference intensity towards the decision.

Sincere Strategies. Suppose agents 1, 2 and 3 draw utility vectors $u_1 = (4, -1)$, $u_2 = (3, -2)$ and $u_3 = (1, 4)$, respectively. Assume further that all agents find it optimal to report sincerely. Agents 1's sincere report $\overset{*}{s}_1$ is given by $(\overset{*}{a}_1, \overset{*}{\pi}_1) = (10, 21)$. Agent 1 is in favor of the reform in the first decision problem and against it in the second $\overset{*}{a}_1 = (10)$. By reporting $\overset{*}{\pi}_1 = (21)$ agent 1 assigns a higher rank to his vote in decision problem I and a lower priority to problem II. The sincere reports of agent 2 and 3 are given by $\overset{*}{s}_2 = (10, 21)$ and $\overset{*}{s}_3 = (11, 12)$, respectively.

Ranking Mechanism. We illustrate the Ranking Mechanism with weight vector $w = (1, 3)$. For decision problem I the Ranking Mechanism translates agent 1's report $m_1^1 = (a_1^1, \pi_1^1) = (1, 2)$ into the signed weight $(2 \cdot a_1^1 - 1) \cdot w^{\pi_1^1} = +3$. Intuitively, agent 1 is in favor of the reform (positive sign) and indicates a high priority (weight 3) in decision problem I. For decision problem II agent 1 reports $(a_1^2, \pi_1^2) = (0, 1)$ and the assigned weight equals $(2 \cdot a_1^2 - 1) \cdot w^{\pi_1^2} = -1$. The assigned weights for decision problem I and II for agent 1 are summarized in column 2 in the table below.

6. Note that the *Simple Scheme* by Casella and Gelman (2008) also belongs to the class of Ranking Mechanisms with weights $(1, ..., 1, 1 + \theta)$.

Analogously the Ranking Mechanism assigns signed weights to agent 2 and 3 as summarized in column 3 and 4. After translating all agents' reports into signed weights the Ranking Mechanism calculates the problem wise sum of signed weights (column 5) and implements the reform if and only if the sum is positive. The resulting outcome of the Ranking Mechanism is illustrated in column 6. For comparison column 7 contains the outcome under Separate Majority Voting.

Decision problem	Agent 1 $(10, 21)$	Agent 2 $(00, 21)$	Agent 3 $(11, 12)$	Sum of weights	Outcome RM	Outcome SMV
I	+3	+3	+1	7	1	1
II	−1	−1	+3	1	1	0

A few points are worth noting. First, the Ranking Mechanism respects unanimity in decision problem I. Second, by overturning the majority of agents the Ranking Mechanism deviates from Separate Majority Voting in decision problem II. Agent 3 ranks problem II highest and thereby sways the decision in his favor albeit being a minority. In our case this is indeed a desirable outcome. Utility vectors are drawn such that the sum of utilities increases from 8 under Separate Majority Voting to 9 under the Ranking Mechanism. Third, the sincere strategy is not a dominant strategy for every agent. Agent 1, for example, prefers to deviate to report $(10, 12)$ thereby changing the outcome of problem II while not affecting that of problem I. Although it is not a dominant strategy, the next section proves that the sincere strategy profile constitutes a Bayes-Nash equilibrium.

3.5.3 Sincere Equilibrium

This section establishes the most important property of the class of Ranking Mechanisms, namely that agents find it optimal to report sincerely. Apart from its theoretical appeal the existence and characterization of an equilibrium is indispensable to any further efficiency analysis.

Proposition 6. Under Assumption 3, the sincere strategy profile is a Bayes-Nash equilibrium of any Ranking Mechanism.

Proof. See Appendix. □

The proof consists of two parts essentially separating ordinal and cardinal incentives. For every agent the sincere ordinal report is weakly optimal independently of the reported priority ranking and the message profile of all other agents. Having reported sincere ordinal type an agent finds it optimal to rank decision problems sincerely. Since all reports by the other agents are equally probable, an agent has no incentive to strategically rank decision problems.

Importantly, Proposition 6 allows us to make precise welfare predictions and to compare the performance of different Ranking Mechanisms. In the remainder of this section we assume that agents report sincerely whenever we evaluate the performance of a Ranking Mechanism.

3.5.4 The Optimal Ranking Mechanism

This section compares the ex-ante welfare of different Ranking Mechanisms. For any fixed number of agents and decision problems we solve for the ex-ante efficient Ranking Mechanism. In particular, we derive a closed form solution for the ex-ante efficient weight vector. A consequence of our derivation is that the optimal Ranking Mechanism ex-ante dominates Separate Majority Voting.

What is the best outcome a mechanism can implement given that agents report sincerely? Intuitively, the efficient mechanism should decide in favor of a reform if the sum of expected utilities from doing so is positive. Therefore it should assign to each agent's vote a weight that corresponds to that agent's expected utility from implementing the reform. More precisely, the signed weight should equal the agent's expected utility conditional on all information contained in his report. By Definition 8 the ordinal part of an agent's message is informative about the sign of his utility and should therefore only determine the sign of the weight. The cardinal part - i.e. the rank assigned to a problem - contains information about an agent's preference intensity. Concretely, an agent ranks a problem at position $l \in D$ if he has his l-th highest preference intensity in that problem. Therefore the l-th weight should correspond to the expected value of an agent's l-th order statistic of his preference intensity. Building on this logic we define the following weight vector.

Definition 10. The efficient weight vector $\overset{*}{w} \in W$ is given by

$$\overset{*}{w} = \left(\mathbb{E}_i\left[\left|u_i^k\right|_{(1:d)}\right], \ldots, \mathbb{E}_i\left[\left|u_i^k\right|_{(d:d)}\right]\right)$$

for some $i \in N$ and $d \in D$, where $\left|u_i^k\right|_{(k:d)}$ denotes the k-th (out of d) order statistic of the preference intensity $\left|u_i^k\right|$.[7] Under Assumption 3, the above definition is independent of the choice of $i \in N$ and $k \in D$ which justifies the notation. We refer to $(\mathcal{M}, g^{RM,\overset{*}{w}})$ as the optimal Ranking Mechanism.

The next proposition justifies Definition 10.

Proposition 7. Under Assumption 3, the optimal Ranking Mechanism is ex-ante Pareto efficient in the class of Ranking Mechanisms.

Proof. See Appendix. □

7. Since u_i^k is Lebesgue-integrable the weights $\overset{*}{w}$ are well-defined, see Ahsanullah, Nevzorov, and Shakil (2013), page 76.

In the Appendix we prove a stronger result. The optimal Ranking Mechanism is ex-ante Pareto efficient among *all* indirect mechanisms that are defined on the ranking message space and induce sincere equilibrium behavior. Put differently, there is no better way to make use of the information elicited through sincere equilibrium behavior than to assign weights to agents' votes. For any sincere message profile the Ranking Mechanism maximizes ex-ante expected welfare conditional on all agents' reports.

Definition 10 characterizes the efficient weight vector in terms of agents' type distributions. For $u_i^k \sim ii\mathcal{N}(0,1)$ as in the example in Section 3.5.2 the efficient weights are approximately $(0.467, 1.128)$.[8] We round all numbers to three digits throughout this paper. A consequence of Proposition 7 is that the optimal Ranking Mechanism ex-ante dominates Separate Majority Voting.

Corollary 1. Under Assumption 3, the optimal Ranking Mechanism ex-ante dominates Separate Majority Voting.

The optimal Ranking Mechanism dominates Separate Majority Voting in the weak sense of Definition 4. Inspection of the proof of Proposition 7 shows that the optimal Ranking Mechanism generates at least as high levels of conditional ex-ante expected welfare message profile by message profile. It is thus sufficient to ensure the existence of one message profile that results in different outcomes to guarantee a strict improvement. Note that the two mechanisms differ if there exists a message profile such that a strong minority overturns a weak majority (see Section 3.5.2). This occurs if the largest minority of $\lfloor \frac{n}{2} \rfloor$ agents all with the highest assigned weight of $\overset{*}{w}{}^d = \mathbb{E}_i\left[\left|u_i^k\right|_{(d:d)}\right]$ overturn the smallest majority of $\lceil \frac{n}{2} \rceil$ agents all with the smallest assigned weight $\overset{*}{w}{}^1 = \mathbb{E}_i\left[\left|u_i^k\right|_{(1:d)}\right]$. The following condition is sufficient for the optimal Ranking Mechanism to strictly increase ex-ante expected utility upon Separate Majority Voting.

Remark 1. The optimal Ranking Mechanism strictly increases ex-ante expected welfare over Separate Majority Voting if the number of agents $n \in \mathbb{N}$, the number of decision problems $d \in \mathbb{N}$ and the distribution of types is such that

$$\left\lfloor \frac{n}{2} \right\rfloor \cdot \mathbb{E}_i\left[\left|u_i^k\right|_{(d:d)}\right] > \left\lceil \frac{n}{2} \right\rceil \cdot \mathbb{E}_i\left[\left|u_i^k\right|_{(1:d)}\right]. \tag{3.1}$$

Ceteris paribus Condition (3.1) is more likely to hold the higher the number of agents or problems or the more dispersed the type distribution. If the number of agents is even and there are at least two decision problems $d \geq 2$ the existence of some cardinal information - i.e. $Var\left(\left|u_i^k\right|\right)$ is nonzero - is sufficient for Condition

8. $\mathbb{E}\left[\left|u_i^k\right|_{(l:d)}\right] = \frac{d!}{(l-1)!\cdot(d-l)!} \int_{-\infty}^{\infty} |x| \cdot (F(x))^{l-1} \cdot (1-F(x))^{d-l} \mathrm{d}F(x)$, see for example chapter 7 in Ahsanullah, Nevzorov, and Shakil (2013)

(3.1) to be satisfied. Condition (3.1) in Remark 1 ensures that the optimal Ranking Mechanism dominates Separate Majority Voting not merely by more efficient resolution of ties, but also the more substantive change of allowing strong minorities to overturn weak majority. Put differently, the optimal Ranking Mechanism strictly improves upon Separate Majority Voting whenever it mitigates the *Tyranny of the Majority*. Note that in the example in Section 3.5.2 both the weight vector $(1, 3)$ and the efficient weight vector $(0.467, 1.128)$ satisfy Condition (1) for three agents and two decision problems.

In the remainder of this section we provide a limiting result reminiscent of Jackson and Sonnenschein (2007). As the number of decision problems goes to infinity, the optimal Ranking Mechanism achieves full efficiency.

Proposition 8. Under Assumption 3, if the support of the type distribution is bounded, the ex-ante utility levels under the optimal Ranking Mechanism converge to full efficiency as the number of decision problems tends to infinity.

Proof. See Appendix. □

Proposition 8 is driven by the insight that as the number of decision problems becomes arbitrarily large agents are able to perfectly communicate their underlying utility vector. Apart from being theoretically appealing the above result offers a strong rationale for linking decision problems. Note that by symmetry of the environment any Ranking Mechanism trivially converge to full efficiency as the number of agents tends to infinity.

3.6 Ranking Non-Identical Decision Problems

In this section we relax Assumption 3 and allow for different type distributions between agents and across problems. We impose that utility types are independently but not necessarily identically distributed between agents and across problems.

We first show that the sincere strategy profile is - in general - no longer a Bayes-Nash equilibrium. However, there exist special cases for which it is. Motivated by this observation we propose a shuffling procedure based on randomization which restores sincere equilibrium behavior of all agents. We then derive the ex-ante efficient Randomized Ranking Mechanism and prove that it ex-ante dominates Separate Majority Voting.

3.6.1 Strategic Ranking

Consider a modified version of our example from Section 3.5.2. Suppose agent 1 draws his utility type in problem II from a uniform distribution with support $[-1, 1]$ instead of from a standard normal distribution. Formally, all $u_i^k \sim ii\mathcal{N}(0, 1)$ with the exception of u_1^2 which is independently drawn from Uniform[-1,1].

Under these conditions agent 1 no longer reports every priority ranking with the same probability when following the sincere strategy. Agent 1 is more likely to rank problem I as his first ranked problem, i.e. report priority ranking $\pi_1 = (21)$. Concretely, the probability that agent 1 reports priority ranking $\pi_1 = (21)$ under the sincere strategy is $\mathbb{P}_1[\overset{*}{\pi}_1 = (21)] = \mathbb{P}_1\left[\left|u_1^1\right| > \left|u_1^2\right|\right] = 0.631 \neq 0.5$. So agent 1 ranks problem I over problem II with probability 63.1% when reporting sincerely.

So, if agent 1 and 2 were to report sincerely, agent 3 would anticipate that agent 1 is likely to rank problem I highest and thus might have an incentive to strategically misreport his priority ranking. Since agent 1 is more likely to prioritize problem I agent 3 might prefer ranking $\pi_3 = (12)$ in order to influence the decision in problem II with higher probability. Agent 3 will find such deviations desirable if he has similar preference intensities for problem I and II. Straightforward calculations show that this is indeed the case in our example and agent 3 deviates from the sincere strategy.[9] Therefore the sincere strategy profile is no longer a Bayes-Nash equilibrium.

The example above demonstrates that Proposition 6 does not hold when we allow for differently distributed types between agents and across problems. Agent 3 deviates from the sincere ranking, because agent 1 is more likely to rank problem I over problem II when following the sincere strategy. Conversely, as long as agent 1 reports every priority ranking with the same probability, agent 3 has no incentive to strategically rank problems. This implies that it is not necessary that agent 1 has the same distribution of types across all problems. It is merely necessary that all agents have type distributions which result in a uniform distribution over all possible priority rankings under the sincere strategy. Formally, we define the following property of an agent's type distribution.

Assumption 4. For every agent i the type distribution is Ranking Uniform, i.e. $\mathbb{P}_i[\overset{*}{\pi}_i = \pi_i] = \mathbb{P}_i[\overset{*}{\pi}_i = \pi_i']$ for all $\pi_i, \pi_i' \in \sigma(D)$ and all $i \in N$.

Assumption 4 is violated in the example above. But suppose agent 1 drew his utility in decision problem II from a uniform distribution with support $[-c, c]$ for some $c \in \mathbb{R}_{++}$. Then for $c \approx 1.470$ it holds that $\mathbb{P}_1\left[\left|u_1^1\right| > \left|u_1^2\right|\right] = \frac{1}{2}$. Agent 1 reports each priority ranking with equal probability and type distributions are Ranking Uniform. As this example illustrates there exist Ranking Uniform type distributions that are not identical across problems. For these the following corollary generalizes Proposition 6.

Corollary 2. Under Assumption 4, the sincere strategy profile is a Bayes-Nash equilibrium of any Ranking Mechanism.

9. W.l.o.g consider the case of $u_3^k > 0$ for $k = 1, 2$, i.e. agent 3 is in favor of implementing the reform in both decision problems. Let $p := \mathbb{P}_1\left[\left|u_1^1\right| > \left|u_1^2\right|\right]$. It is straightforward to verify that

$$\mathbb{E}_{-3}\left[V_3\left(g^{RM,w}\left(\overset{*}{s}_3, \overset{*}{s}_{-3}\right)\right)\right] = \mathbb{E}_{-3}\left[V_3\left(g^{RM,w}\left((11), (21), \overset{*}{s}_{-3}\right)\right)\right] < \mathbb{E}_{-3}\left[V_3\left(g^{RM,w}\left((11), (12), \overset{*}{s}_{-3}\right)\right)\right]$$

for all $u_3 \in \left\{(u_3^1, u_3^2) \in \mathbb{R}_{++}^2 \,\middle|\, \frac{u_3^1}{u_3^2} < \frac{1+p}{2-p}\right\}$.

The corollary follows from inspection of the proof of Proposition 6. The next section builds on the above insight and defines a shuffling procedure based on randomization. Motivated by Corollary 2 the procedure guarantees that from the perspective of every agent all reports of the other agents are equally probable.

3.6.2 Shuffling Rankings

To illustrate the idea of our shuffling procedure consider the example from the previous Section 3.6.1. Recall that all $u_i^k \sim \mathcal{N}(0,1)$ with the exception of $u_1^2 \sim$ Uniform$[-1,1]$. Under the sincere strategy agent 1 is more likely to rank problem I over problem II, i.e. $\overset{*}{\pi}_1 = (21)$ with probability 0.631 and $\overset{*}{\pi}_1 = (12)$ with probability $1 - 0.631 = 0.369$.

Suppose agent 1 reported sincerely and consider the following shuffling procedure that turns every reported ranking of agent 1 into a shuffled ranking as follows. With probability 0.208 the reported ranking is changed to the less probable ranking (12) and with probability $(1 - 0.208)$ the reported ranking remains unchanged. Then, the probability that agent 1's shuffled ranking equals ranking (21) is given by $0.631 \cdot (1 - 0.208) = 0.500$ and the probability for it to be (12) equals $0.369 + 0.631 \cdot 0.208 = 0.500$. If the mechanism were to use the shuffled ranking of agent 1 there would be no incentive for agent 2 and 3 to strategically rank decision problems. From their point of view all shuffled rankings of agent 1 are equally likely. Further, agent 1 has no incentive to strategically rank decision problems since shuffling occurs with equal probability after any report. In the remainder of this section we generalize the above shuffling procedure to an arbitrary number of agents and problems.

A shuffling procedure is a (random) mapping from agents' reported rankings into the set of all possible rankings. It is characterized by two parts. First, for every agent i we define a shuffling probability $\alpha_i \in [0,1]$ which corresponds to the probability with which every reported ranking of agent i is shuffled. Second, for every agent i we specify the shuffling lottery $\beta_i \in \Delta(\sigma(D))$ where $\beta_i^{\pi_i} \in [0,1]$ is the probability with which the reported ranking is changed to ranking π_i in case it does get shuffled. Formally, we define a shuffling procedure as follows.

Definition 11. A shuffling procedure for agent i is a random mapping $\gamma_i : \sigma(D) \to \sigma(D)$ defined as

$$\gamma_i(\pi_i) = \begin{cases} \pi_i & \text{with probability } 1 - \alpha_i \\ \pi_i' & \text{with probability } \alpha_i \cdot \beta_i^{\pi_i'} \end{cases}$$

for $\pi_i, \pi_i' \in \sigma(D)$, where $\alpha_i \in [0,1]$ and $\beta_i \in \Delta(\sigma(D))$ are referred to as agent i's shuffling probability and shuffling lottery, respectively. We refer to the image $\gamma_i(\pi_i)$ as agent i's shuffled ranking.

The goal is to construct a shuffling procedure – that is choose α and β – such that every agent's shuffled ranking is uniformly distributed under the sincere strategy profile. We formalize this point in the following remark.

Remark 2. For any agent i the choice of α_i and β_i is such that it leads to a uniform distribution of shuffled rankings under the sincere strategy. Formally, we choose $\alpha_i \in [0,1]$ and $\beta_i \in \Delta(\sigma(D))$ such that

$$\mathbb{P}_i\left[\gamma_i(\overset{*}{\pi}_i) \;=\; \pi_i\right] \;=\; (1-\alpha_i)\cdot p_i^{\pi_i} + \alpha_i \cdot \beta_i^{\pi_i} \;=\; \frac{1}{d!} \text{ for all } \pi_i \;\in\; \sigma(D), \tag{3.2}$$

where $p_i^{\pi_i} := \mathbb{P}_i\left[\overset{*}{\pi}_i = \pi_i\right]$ is agent i's probability of ranking π_i under the sincere strategy.

The intuition behind equation (3.2) is straightforward. There are two ways a shuffled ranking takes on one particular ranking: either the agent sincerely reports that ranking and it does not get shuffled, or the agent's reported ranking does get shuffled in which case the shuffling lottery picks the ranking.

Equation (3.2) immediately places a lower bound on the shuffling probabilities α_i. To see this, consider the ranking that an agent is most likely to report under the sincere strategy and suppose the shuffling lottery β_i places probability zero on this ranking. Plugging this into equation (3.2) gives the lower bound for the shuffling probability α_i. Intuitively, even if the shuffling lottery places probability zero on the most probable sincerely reported ranking the shuffling procedure still needs to bring down its probability to $\frac{1}{d!}$. Since all other rankings are by definition less likely the minimal level of shuffling is pinned down by the probability of an agent's most probable reported ranking under the sincere strategy profile. Formally, we define the shuffling probabilities for all agents as follows.

Definition 12. The (minimal) shuffling probability for agent i is given by

$$\alpha_i \;=\; 1 - \frac{1}{d!\cdot p_i^{\max}},$$

where $p_i^{\max} := \max_{\pi_i \in \sigma(D)} \mathbb{P}_i\left[\overset{*}{\pi}_i = \pi_i\right]$ is the probability of the ranking which agent i is most likely to reported under the sincere strategy.[10] Let $\alpha = (\alpha_i)_{i\in N}$ correspond to the collection of shuffling probabilities for all agents.

Note that if (and only if) an agent's type distribution is Ranking Uniform in the sense of Assumption 4 his shuffling probability is zero. The shuffling procedure does not introduce randomization if an agent already reports all rankings with equal

10. While our shuffling procedure also works for larger choices of α_i the next section shows that in the context of our Ranking Mechanisms the minimal choice in Definition 12 is desirable from an ex-ante welfare perspective.

probability. For nonzero shuffling probabilities equation (3.2) implies the following choice for the shuffling lottery.

Definition 13. The shuffling lottery of agent i with nonzero shuffling probability α_i (defined in Definition 12) is given by

$$\beta_i^{\pi_i} = \frac{1}{\alpha_i}\left(\frac{1}{d!} - (1-\alpha_i)\cdot p_i^{\pi_i}\right) \text{ for } \pi_i \in \sigma(D),$$

where $p_i^{\pi_i} := \mathbb{P}_i\left[\overset{*}{\pi}_i = \pi_i\right]$ is the probability with which agent i reports ranking π_i under the sincere strategy. For consistency we choose $\beta_i^{\pi_i} = p_i^{\pi_i}$ for all $\pi_i \in \sigma(D)$ if agent i's shuffling probability is zero in Definition 12. Let $\beta = (\beta_i)_{i\in N}$ denote the collection of shuffling lotteries for all agents.

A shuffling procedure with shuffling probabilities and shuffling lotteries as in Definition 12 and Definition 13 – henceforth referred to as *the* shuffling procedure – leads to a uniform distribution of shuffled rankings by all agents. From the perspective of any one agent all other agents' shuffled rankings are equally likely and there is no incentive to strategically rank decision problems. In the next section we integrate the shuffling procedure into our Ranking Mechanism.

3.6.3 Randomized Ranking Mechanisms

Equipped with the shuffling procedure from the previous section, we define the new class of Randomized Ranking Mechanisms. A Randomized Ranking Mechanism corresponds to a Ranking Mechanism on the shuffled message profile. It uses the message space from Definition 7 and its decision rule $g^{RRM,w} : \mathcal{M} \to \Delta(X)$ is parametrized by a weight vector $w = (w^1, ..., w^d) \in W$, where $W \subset \mathbb{R}^d_{++}$ denotes the set of strictly positive weight vectors with non-decreasing components. Formally, we define a Randomized Ranking Mechanism as follows.

Definition 14. The Randomized Ranking Mechanism $(\mathcal{M}, g^{RRM,w})$ with weight vector $w \in W$ implements the same outcome as the Ranking Mechanism $g^{RM,w}$ on the shuffled message profile. Formally,

$$g^{RRM,w}(m) = \left(g^{RM,w} \circ \gamma\right)(m)$$

where $\gamma(m) = (a_i, \gamma_i(\pi_i))_{i\in N}$ denotes the profile of shuffled messages of all agents and γ_i is the shuffling procedure defined in the previous section (Definition 11, 12 and 13).

Every Randomized Ranking Mechanism is a composition of the corresponding Ranking Mechanism (with the same weight vector) and the shuffling procedure. Definition 14 immediately implies that for any strategy profile the distribution over outcomes under the Randomized Ranking Mechanism is identical to that of the corresponding Ranking Mechanism under the shuffled strategy profile. Formally, we have the following remark.

Remark 3. For any strategy profile $\hat{s}$, the corresponding shuffled strategy profile $\gamma(\hat{s}) = \big(\hat{a}, \gamma(\hat{\pi})\big)$ and any $w \in W$ we have

$$g^{RRM,w}(\hat{s}) \sim g^{RM,w}(\gamma(\hat{s})).$$

Definition 14 and Remark 3 allow Randomized Ranking Mechanisms to inherit many of the properties of Ranking Mechanisms. In particular, we have the following proposition analogous to Proposition 6.

Proposition 9. The sincere strategy profile is a Bayes-Nash equilibrium of any Randomized Ranking Mechanism.

Proof. See Appendix. □

The logic of the proof is as follows. First, every agent finds it optimal to sincerely report his ordinal type because shuffling only affects the reported ranking. Second, neither the shuffling probability nor the shuffling lottery depend on an agent's reported ranking. Therefore every agent only considers the case in which his reported ranking is not shuffled. But in expectation the shuffled report profile of the sincere rankings of all other agents is uniformly distributed and an agent has no incentive to deviate from the sincere strategy by the same logic as in the proof of Proposition 6.

It is straightforward to see that Proposition 9 continues to hold for choices of shuffling probabilities larger than the minimal choice defined in Definition 12, as long as we also adjust the shuffling lotteries as in Definition 13. The following remark illustrates the optimality of the minimal choice in Definition 12 from an ex-ante welfare perspective.

Remark 4. To illustrate the optimality of a minimal choice of α (together with corresponding shuffling lottery defined in Definition 13) rewrite ex-ante expected welfare as

$$\sum_i \mathbb{E}_{u,\gamma}\left[V_i(g^{RRM,w}(\overset{*}{s}))\right] = \sum_i \mathbb{E}_{u,\gamma}\left[V_i(g^{RM,w}(\gamma(\overset{*}{s})))\right]$$

$$= \sum_i \mathbb{E}_{u_i}\left[(1-\alpha_i)\underbrace{\mathbb{E}_{-i}\left[V_i(g^{RM,w}(\overset{*}{s}_i, \tilde{s}_{-i}))\right]}_{(*)} + \alpha_i \sum_{\pi_i'} \beta_i^{\pi_i'} \underbrace{\mathbb{E}_{-i}\left[V_i(g^{RM,w}((\overset{*}{a}_i, \pi_i'), \tilde{s}_{-i}))\right]}_{(**)}\right],$$

where $\tilde{s}_{-i} = (\overset{*}{a}_i, \gamma_i(\overset{*}{\pi}_i))_{-i}$ denotes the shuffled strategy profile of all agents but agent i. For all i and $u_i \in \mathscr{U}_i$ expression $(*)$ is weakly larger than expression $(**)$ by Proposition 6 and both are independent of α_{-i} and β_{-i} as long as $\tilde{s}_{-i} \sim \text{Uniform}(\mathscr{M}_{-i})$. Thus

α chosen minimally (subject to achieving uniformity) maximizes ex-ante expected welfare for any weight vector.

The shuffling probabilities in Definition 12 are not only desirable in terms of ex-ante expected welfare, but also ensure that if an agent's type distribution is Ranking Uniform no randomization is introduced. In particular, we have the following remark.

Remark 5. Under Assumption 4, any Randomized Ranking Mechanism collapses to the corresponding Ranking Mechanism.

In the next section we turn to the optimal choice of the weight vector. We implicitly assume that agents report sincerely whenever we evaluate the performance of any Randomized Ranking Mechanism.

3.6.4 The Optimal Randomized Ranking Mechanism

Having established sincere equilibrium behavior this section compares the ex-ante welfare of different Randomized Ranking Mechanisms. For any fixed number of agents and decision problems we derive the ex-ante efficient Randomized Ranking Mechanism and provide a closed form solution for the associated weight vector. The optimal Randomized Ranking Mechanism ex-ante dominates Separate Majority Voting.

The intuition is analogous to that in Section 3.5.4. What weight should the mechanism assign to an agent's vote based on his shuffled ranking? Intuitively, the weight should correspond to an agent's expected utility from implementing the reform conditional on his report. However, the assigned weights can neither discriminate between agents or problems nor can they depend on the realization of the randomization or the choice of the shuffle lottery. The following definition generalizes Definition 10.

Definition 15. The efficient weight vector $\overset{**}{w} \in W$ is given by

$$\overset{**}{w}^l = \frac{1}{n} \cdot \sum_i \Big((1-\alpha_i) \cdot \sum_k \mathbb{P}_i \big[\overset{*}{\tilde{\pi}}{}_i^k = l \big] \cdot \mathbb{E}\Big[\big| u_i^k \big|_{(l:d)} \Big] + \alpha_i \cdot \sum_k \mathbb{P}_{\beta_i} \big[\tilde{\pi}_i^k = l \big] \cdot \mathbb{E}\big[\big| u_i^k \big| \big] \Big)$$

for $l = 1, \ldots, d$, where $\big|u_i^k\big|_{(l:d)}$ denotes the l-th (out of d) order statistic of the preference intensity $\big|u_i^k\big|$ and $\mathbb{P}_{\beta_i}\big[\tilde{\pi}_i^k = l\big] := \sum_{\pi_i : \pi_i^k = l} \beta_i^{\pi_i}$ is defined as the probability that problem k is ranked on l-th position through shuffling lottery β_i. We refer to $(\mathscr{M}, g^{RRM, \overset{**}{w}})$ as the optimal Randomized Ranking Mechanism.

Before providing intuition we justify Definition 15 by the following proposition.

Proposition 10. The optimal Randomized Ranking Mechanism is ex-ante Pareto efficient in the class of Randomized Ranking Mechanisms.

Proof. See Appendix. □

Proposition 10 follows from suitably rewriting ex-ante expected welfare. The intuition behind Proposition 10 and Definition 15 is as follows. For every agent i the efficient l-th weight trades-off two cases. First, with probability $1-\alpha_i$ agent i's report is sincere and did not get shuffled. In this case it is efficient to set the l-th weight for agent i to the expected value of his l-th highest preference intensity under the sincere strategy. Because we allow for different distributions across problems the expected value of the l-th highest order statistic for a fixed decision problem may vary across problems. The ex-ante expected value of the l-th highest preference intensity under the sincere strategy thus weights all expected l-th order statistics by their respective sincere probability, that is, by the probability that an agent sincerely ranks that problem at position l. Second, with probability α_i agent i's ranking gets shuffled. In this case – since the shuffle lottery is uninformative about the preference intensity – the efficient l-th weight corresponds to the unconditional expected preference intensity. Again, the expected preference intensity may vary across problems and needs to be weighted by the probability that a problem is ranked at the l-th position by the shuffling lottery β_i of agent i. Lastly, since we restrict attention to anonymous mechanism the efficient weight vector cannot depend on an agent's identity. It is therefore efficient to take the average over all "agent-specific" efficient weights outlined above.[11]

It is further instructive to consider the following special case. Under Assumption 4, the shuffling probabilities are zero and Definition 15 simplifies.

Remark 6. Under Assumption 4, the optimal Randomized Ranking Mechanism corresponds to the Ranking Mechanism with weight vector $\overset{**}{w} \in W$ given by

$$\overset{**}{w}^{l} = \frac{1}{n \cdot d} \cdot \sum_{i} \sum_{k} \mathbb{E}\left[\left| u_i^k \right|_{(l:d)} \right]$$

for $l = 1, ..., d$.

Remark 6 generalizes Definition 10 of the optimal weight vector in the identical case of Section 3.5 by allowing for different type distributions between agents and across problems as long as Assumption 4 is satisfied. In this case the efficient l-th weight corresponds to the expected value of the l-th highest preference intensity averaged across all agents and problems. By Definition 14 of the Randomized Ranking Mechanism the randomization procedure only shuffles the reported ranking. Thus

11. All our results readily extend to the case in which we drop the anonymity requirement and allow for agent-specific weights.

it has no effect for constant weight vectors for which the order is irrelevant. This implies that the Randomized Ranking Mechanism with weight vector $w = (1, ..., 1)$ implements the same outcome as Separate Majority Voting. Therefore Proposition 10 implies that the optimal Randomized Ranking Mechanism ex-ante dominates Separate Majority Voting.

Corollary 3. The optimal Randomized Ranking Mechanism ex-ante dominates Separate Majority Voting.

Analogously to Section 3.5.4 the optimal Randomized Ranking Mechanism dominates Separate Majority Voting in the weak sense of Definition 4. The following remark follows from the same logic as Remark 1 in Section 3.5.4 and guarantees the welfare improvement to be strict. The Randomized Ranking Mechanism and Separate Majority Voting differ if there exists a report profile such that a strong minority overturns a weak majority. Formally, we have the following remark.

Remark 7. The optimal Randomized Ranking Mechanism strictly increases ex-ante expected welfare over Separate Majority Voting if the number of agents $n \in \mathbb{N}$, the number of decision problems $d \in \mathbb{N}$ and the distribution of types is such that

$$\left\lfloor \frac{n}{2} \right\rfloor \cdot \overset{**}{w}^{d} > \left\lceil \frac{n}{2} \right\rceil \cdot \overset{**}{w}^{1}. \tag{3.3}$$

The intuition is analogous to Section 3.5.4. Condition (3.3) in Remark 7 ensures that the optimal Randomized Ranking Mechanism dominates Separate Majority Voting not merely by more efficient resolution of ties, but also by allowing strong minorities to overturn weak majorities thereby mitigating the *Tyranny of the Majority*.

Note that in our modified example in Section 3.6.1 the efficient weight vector equals $(0.455, 1.041)$. It allows for overturning by satisfying Condition (3.3) in Remark 7 for three agents and two decision problems and therefore strictly improves upon Separate Majority Voting.

3.7 Concluding Remarks

In this paper we show that among strategy-proof mechanisms Separate Majority Voting is ex-ante efficient and there is no benefit in coupling binary decisions. When moving to the class of incentive compatible mechanisms full efficiency remains unachievable for a finite number of decision problems but one can improve upon Separate Majority Voting.

In order to do so, we study a class of Ranking Mechanisms. A Ranking Mechanism corresponds to a simple weighted voting procedure, in which agents are free to distribute weights across problems and alternatives. For the case of identically distributed preferences over problems any Ranking Mechanism admits an intuitive equilibrium strategy. Agents rank problems according to the absolute difference in utilities between alternatives, i.e. by their preference intensities. We solve for the ex-ante efficient Ranking Mechanism and give a close-form solution for the corresponding optimal weight vector. The optimal Ranking Mechanism ex-ante dominates Separate Majority Voting and achieves full efficiency in the limit as the number of decision problems goes to infinity. In the case of non-identically distributed problems we introduce a randomization procedure which sustains sincere equilibrium behavior. Incentives are preserved by ensuring that from the perspective of every agent all priority rankings of all other agents are equally likely. We provide a closed-form solution for the ex-ante efficient weight vector and prove that the optimal Randomized Ranking Mechanism ex-ante dominates Separate Majority Voting.

All our results hold for an arbitrary number of agents and decisions thereby complementing mechanisms in the previous literature, which work well for an infinite number of decisions (Jackson and Sonnenschein (2007)) or a large enough number of agents (Casella and Gelman (2008)). Moreover the optimal (Randomized) Ranking Mechanism represents - to the best of our knowledge - the first mechanism which successfully couples non-identically distributed binary decision problems, induces intuitive equilibrium behavior and dominates Separate Majority Voting for any number of agents and problems.

Throughout this work we restricted attention to anonymous mechanisms. From an ex-ante welfare perspective it might be desirable to discriminate between agents. All of our analysis readily extends to the case of allowing for agent-specific weights. The optimal (Randomized) Ranking Mechanism is not without its weaknesses. In particular, it relies on a strong knowledge assumption regarding the underlying type distributions.

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Appendix 3.A Appendix: Proofs

Proof of Proposition 5. The following corollary is a straightforward adoption of Proposition 1 in Hortala-Vallve (2010) for the case of incentive compatibility.

Definition 16. The expected indirect utility function $\mathscr{V}_i : \mathscr{U}_i \to \mathbb{R}$ of agent i under mechanism $(\mathscr{U}, g)$ is defined by $\mathscr{V}_i(u_i) = \sum_{k=1}^{d} u_i^k \cdot \mathbb{E}_{-i}[g_k(u_i, u_{-i})]$.

Corollary 4 (Hortala-Vallve (2010))**.** A mechanism $(\mathscr{U}, g)$ is incentive compatible if and only if agents' expected indirect utilities are homogeneous of degree one and convex.
That is, $\mathscr{V}_i(\lambda \cdot u_i) = \lambda \cdot \mathscr{V}_i(u_i)$ for $\lambda \geq 0$, $u_i \in \mathscr{U}_i$ and is convex in u_i.

For any incentive compatible mechanism (U, g) it follows that

$$\mathbb{E}_{-i}[g_k(u_i, u_{-i})] = \mathbb{E}_{-i}[g_k(\lambda \cdot u_i, u_{-i})] \tag{3.A.1}$$

for every $i \in \{1, ..., n\}$, every $k \in \{1, ..., d\}$, every $u_i \in \mathscr{U}_i$ and every $\lambda \geq 0$.

Equation (3.A.1) states that from agent i's perspective the expected outcome of the mechanism is identical on proportional utility types. In other words, proportional types of agent i are bunched in expectation.

To prove Proposition 5 suppose for sake of contradiction that g is incentive compatible and achieves full efficiency. By the above g bunches proportional types in expectation. Consider two cases depending on whether or not Equation (3.A.1) holds pointwise:

Case 1: Equation (3.A.1) holds pointwise everywhere, that is, proportional types are bunched type by type. It is enough to consider the case of two agents and one decision problem. For one decision problem all possible types are proportional and hence g must be constant, which is not optimal. The same line of reasoning extends to settings with more agents and more decision problems.

Case 2: Equation (3.A.1) does not hold pointwise everywhere, implying that there exist $i \in \{1, ..., n\}$, $k \in \{1, ..., d\}$, $u_i \in \mathscr{U}_i$ with $u_i^k \neq 0$, $\lambda \in \mathbb{R}_{++} \setminus \{1\}$ and $u'_{-i} \in \mathscr{U}_{-i}$ such that $g_k(u_i, u'_{-i}) \neq g_k(\lambda \cdot u_i, u'_{-i})$. Consider the case $u_i^k > 0$ and $g_k(u_i, u'_{-i}) > g_k(\lambda \cdot u_i, u'_{-i})$. All other cases follow by an analogous argument. In order for Equation (3.A.1) to be satisfied, there must exist $u''_{-i} \in \mathscr{U}_{-i}$ such that $g_k(u_i, u''_{-i}) < g_k(\lambda \cdot u_i, u''_{-i})$. The fact that g achieves full efficiency necessitates that for fixed $u_{-i} \in \mathscr{U}_{-i}$ the function $g_k(\cdot, u_{-i})$ depends only on the value of u_i^k and not on the other components of u_i. Further $g_k(\cdot, u_{-i})$ has to be non-decreasing in $u_i^k > 0$. For $\lambda > 1$ this contradicts the first inequality, for $\lambda < 1$ the second. □

Proof of Proposition 6. Fix $w \in W$ and denote $g^{RM,w}$ by g. Formally, we need to show that for all agents $i \in N$, all $u_i \in \mathscr{U}_i$ and $\overset{*}{s}_{-i} = \left(\overset{*}{a}_{-i}, \overset{*}{\pi}_{-i}\right)$ it holds that

$$\overset{*}{s}_i(u_i) = \left(\overset{*}{a}_i, \overset{*}{\pi}_i\right)(u_i) \in \underset{(a_i,\pi_i)}{\arg\max} \left\{\mathbb{E}_{-i}\left[V_i(g((a_i,\pi_i),\overset{*}{s}_{-i}))\right]\right\}. \tag{3.A.2}$$

The proof consists of two parts.

Part 1: For any message profile of the other agents $m_{-i} = (a_{-i}, \pi_{-i})$ and any fixed priority ranking π_i agent i finds the strategy $s_i = (\overset{*}{a}_i, \pi_i)$ weakly optimal. Note that

$$V_i(g((a_i,\pi_i), m_{-i})) = \sum_k u_i^k \cdot g_k\left(\left(a_i^k, \pi_i^k\right), m_{-i}^k\right) \tag{3.A.3}$$

for $u_i \in \mathscr{U}_i$ and $(a_i, \pi_i) \in M$. Since for all $k \in D$, all $\pi_i^k \in D$ and all $m_{-i} \in \mathscr{M}_{-i}$

$$g_k\left(\left(1, \pi_i^k\right), m_{-i}^k\right) \geq g_k\left(\left(0, \pi_i^k\right), m_{-i}^k\right),$$

it follows that equation (3.A.3) is maximized for

$$a_i^k = \overset{*}{a}{}_i^k = \begin{cases} a_i^k = 1 & \text{if } u_i^k > 0 \\ a_i^k = 0 & \text{if } u_i^k \leq 0. \end{cases}$$

Part 2: For the sincere strategy profile of the other agents $\overset{*}{s}_{-i} = (\overset{*}{a}_{-i}, \overset{*}{\pi}_{-i})$ and the sincere $\overset{*}{a}_i$ agent i finds the sincere priority ranking $\overset{*}{\pi}_i$ weakly optimal. Exploiting uncorrelated types we have

$$\begin{aligned} &\mathbb{E}_{-i}\left[V_i(g((\overset{*}{a}_i,\pi_i),\overset{*}{s}_{-i}))|u_i\right] = \mathbb{E}_{-i}\left[V_i(g((\overset{*}{a}_i,\pi_i),\overset{*}{s}_{-i}))\right] \\ &= \sum_{k:u_i^k>0} u_i^k \cdot \mathbb{E}_{-i}\left[g_k\left(\left(1,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\right] + \sum_{k:u_i^k<0} u_i^k \cdot \mathbb{E}_{-i}\left[g_k\left(\left(0,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\right] \end{aligned} \tag{3.A.4}$$

for $u_i \in \mathscr{U}_i$ and $(\overset{*}{a}_i, \pi_i) \in M$. We decompose the message space $\mathscr{M}_{-i}$ of all other agents according to the outcome that would be implemented in the absence of agent i. Formally, we define

$$\mathscr{M}_{-i}^{k,q} := \left\{m_{-i} \in \mathscr{M}_{-i} \middle| g_k\left(\frac{1}{2}, \pi_i^k, m_{-i}^k\right) = q\right\} \text{ for } q = 0, \frac{1}{2}, 1.$$

The set $\mathscr{M}_{-i}^{k,q}$ encompasses all message profiles of the other agents such that without agent i outcome $q \in \{0, \frac{1}{2}, 1\}$ is implemented in problem k. Note that by definition of g_k the set $\mathscr{M}_{-i}^{k,q}$ is independent of π_i^k which justifies the notation. Using the fact that for all $k \in D$, all $\pi_i^k \in D$ and all $m_{-i} \in \mathscr{M}_{-i}$

$$g_k\left(\left(1, \pi_i^k\right), m_{-i}^k\right) \geq g_k\left(\left(\frac{1}{2}, \pi_i^k\right), m_{-i}^k\right) \geq g_k\left(\left(0, \pi_i^k\right), m_{-i}^k\right)$$

with strict inequalities if $g_k\left(\left(\frac{1}{2},\pi_i^k\right),m_{-i}^k\right)=\frac{1}{2}$. We write (3.A.4) as

$$\sum_{k:u_i^k>0} u_i^k\cdot\Big\{\mathbb{E}_{-i}\left[g_k\left(\left(1,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,0}\right]\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,0}\right] \tag{3.A.5}$$

$$+\overbrace{\mathbb{E}_{-i}\left[g_k\left(\left(1,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,1}\right]}^{=1}\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,1}\right]$$

$$+\underbrace{\mathbb{E}_{-i}\left[g_k\left(\left(1,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,\frac{1}{2}}\right]}_{=1}\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,\frac{1}{2}}\right]\Big\}$$

$$+\sum_{k:u_i^k<0} u_i^k\cdot\Big\{\mathbb{E}_{-i}\left[g_k\left(\left(0,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,1}\right]\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,1}\right] \tag{3.A.6}$$

$$+\overbrace{\mathbb{E}_{-i}\left[g_k\left(\left(0,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,0}\right]}^{=0}\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,0}\right]$$

$$+\underbrace{\mathbb{E}_{-i}\left[g_k\left(\left(0,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,\frac{1}{2}}\right]}_{=0}\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,\frac{1}{2}}\right]\Big\}$$

$$=\sum_{k:u_i^k>0} u_i^k\cdot\left\{\mathbb{E}_{-i}\left[g_k\left(\left(1,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,0}\right]\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,0}\right]\right\}$$

$$+\sum_{k:u_i^k<0} u_i^k\cdot\left\{\mathbb{E}_{-i}\left[g_k\left(\left(0,\pi_i^k\right),\overset{*}{s}{}_{-i}^k\right)\middle|\mathscr{M}_{-i}^{k,1}\right]\cdot\mathbb{P}_{-i}\left[\mathscr{M}_{-i}^{k,1}\right]\right\}+C, \tag{3.A.7}$$

with C independent of π_i. We further decompose the type space of all other agents depending on whether or not agent i with priority ranking π_i^k changes the outcome in decision problem k. We split $\mathscr{M}_{-i}^{k,0}$ into three disjoint sets of reports of other agents: the set $\mathscr{M}^{k,0}\left(\pi_i^k\right)$ such that the inclusion of agent i voting in favor of the reform with a priority ranking π_i^k does not change the outcome and 0 is still implemented in decision problem k and the sets $\mathscr{T}^{k,0}\left(\pi_i^k\right)$ and $\mathscr{P}^{k,0}\left(\pi_i^k\right)$ on which the outcome changes to $\frac{1}{2}$ and 1, respectively. Formally,

$$\mathscr{M}_{-i}^{k,0}=\underbrace{\left\{m_{-i}\in\mathscr{M}_{-i}\middle|0=g_k\left(0.5,\pi_i^k,m_{-i}^k\right)\wedge g_k\left(1,\pi_i^k,m_{-i}^k\right)=0\right\}}_{=:\mathscr{M}^{k,0}\left(\pi_i^k\right)}$$

$$\biguplus\underbrace{\left\{m_{-i}\in\mathscr{M}_{-i}\middle|0=g_k\left(0.5,\pi_i^k,m_{-i}^k\right)\wedge g_k\left(1,\pi_i^k,m_{-i}^k\right)=\frac{1}{2}\right\}}_{=:\mathscr{T}^{k,0}\left(\pi_i^k\right)}$$

$$\biguplus\underbrace{\left\{m_{-i}\in\mathscr{M}_{-i}\middle|0=g_k\left(0.5,\pi_i^k,m_{-i}^k\right)\wedge g_k\left(1,\pi_i^k,m_{-i}^k\right)=1\right\}}_{=:\mathscr{P}^{k,0}\left(\pi_i^k\right)}.$$

As made explicit by the notation the decomposition depends on π_i^k. Analogously, we define $\mathcal{M}^{k,1}\left(\pi_i^k\right)$, $T^{k,1}\left(\pi_i^k\right)$ and $P^{k,1}\left(\pi_i^k\right)$ by

$$\begin{aligned}\mathcal{M}_{-i}^{k,1} = &\underbrace{\left\{m_{-i} \in \mathcal{M}_{-i} \middle| 1 = g_k\left(0.5, \pi_i^k, m_{-i}^k\right) \wedge g_k\left(0, \pi_i^k, m_{-i}^k\right) = 1\right\}}_{=:\mathcal{M}^{k,1}\left(\pi_i^k\right)} \\ &\biguplus \underbrace{\left\{m_{-i} \in \mathcal{M}_{-i} \middle| 1 = g_k\left(0.5, \pi_i^k, m_{-i}^k\right) \wedge g_k\left(0, \pi_i^k, m_{-i}^k\right) = \frac{1}{2}\right\}}_{=:\mathcal{T}^{k,1}\left(\pi_i^k\right)} \\ &\biguplus \underbrace{\left\{m_{-i} \in \mathcal{M}_{-i} \middle| 1 = g_k\left(0.5, \pi_i^k, m_{-i}^k\right) \wedge g_k\left(0, \pi_i^k, m_{-i}^k\right) = 0\right\}}_{=:\mathcal{P}^{k,1}\left(\pi_i^k\right)}.\end{aligned}$$

Since for all $k \in D$, all $m_{-i} \in \mathcal{M}_{-i}$ and $\tilde{\pi}_i^k < \pi_i^k \in D$

$$g_k\left(1, \tilde{\pi}_i^k, m_{-i}^k\right) \leq g_k\left(1, \pi_i^k, m_{-i}^k\right) \text{ and } g_k\left(0, \tilde{\pi}_i^k, m_{-i}^k\right) \geq g_k\left(0, \pi_i^k, m_{-i}^k\right)$$

with strict inequalities if $g_k\left(0, \tilde{\pi}_i^k, m_{-i}^k\right) = \frac{1}{2}$. It follows that

$$\mathcal{T}^{k,q}\left(\tilde{\pi}_i^k\right) \subseteq \mathcal{P}^{k,q}\left(\pi_i^k\right) \text{ and } \mathcal{P}^{k,q}\left(\tilde{\pi}_i^k\right) \subseteq \mathcal{P}^{k,q}\left(\pi_i^k\right) \tag{3.A.8}$$

for all $k \in D$, all $\tilde{\pi}_i^k < \pi_i^k \in D$ and $q = 0, 1$. By definition of g we have for all $k, l, \pi_i^k \in D$:

$$\begin{aligned}&\left|\mathcal{P}^{k,1}\left(\pi_i^k\right)\right| = \left|\mathcal{P}^{l,1}\left(\pi_i^k\right)\right| = \left|\mathcal{P}^{l,0}\left(\pi_i^k\right)\right| \\ &\qquad \text{and } \left|\mathcal{T}^{k,1}\left(\pi_i^k\right)\right| = \left|\mathcal{T}^{l,1}\left(\pi_i^k\right)\right| = \left|\mathcal{T}^{l,0}\left(\pi_i^k\right)\right|.\end{aligned} \tag{3.A.9}$$

Using the above construction we write (3.A.7) as

$$\begin{aligned}
&\sum_{k:u_i^k>0} u_i^k \cdot \Big\{ \underbrace{\mathbb{E}_{-i}\Big[g_k\big((1,\pi_i^k),\overset{*}{s}{}_{-i}^k\big)\Big|\mathscr{P}^{k,0}\big(\pi_i^k\big)\Big]}_{=1} \cdot \mathbb{P}_{-i}\big[\mathscr{P}^{k,0}\big(\pi_i^k\big)\big] \\
&\qquad + \underbrace{\mathbb{E}_{-i}\Big[g_k\big((1,\pi_i^k),\overset{*}{s}{}_{-i}^k\big)\Big|\mathscr{M}^{k,0}\big(\pi_i^k\big)\Big]}_{=0} \cdot \mathbb{P}_{-i}\big[\mathscr{M}^{k,0}\big(\pi_i^k\big)\big] \\
&\qquad + \underbrace{\mathbb{E}_{-i}\Big[g_k\big((1,\pi_i^k),\overset{*}{s}{}_{-i}^k\big)\Big|\mathscr{T}^{k,0}\big(\pi_i^k\big)\Big]}_{=\frac{1}{2}} \cdot \mathbb{P}_{-i}\big[\mathscr{T}^{k,0}\big(\pi_i^k\big)\big] \Big\} \\
&+ \sum_{k:u_i^k<0} u_i^k \cdot \Big\{ \underbrace{\mathbb{E}_{-i}\Big[g_k\big((0,\pi_i^k),\overset{*}{s}{}_{-i}^k\big)\Big|\mathscr{P}^{k,1}\big(\pi_i^k\big)\Big]}_{=0} \cdot \mathbb{P}_{-i}\big[\mathscr{P}^{k,1}\big(\pi_i^k\big)\big] \\
&\qquad + \underbrace{\mathbb{E}_{-i}\Big[g_k\big((0,\pi_i^k),\overset{*}{s}{}_{-i}^k\big)\Big|\mathscr{M}^{k,1}\big(\pi_i^k\big)\Big]}_{=1} \qquad\qquad (3.A.10) \\
&\qquad\qquad \cdot \Big(1 - \mathbb{P}_{-i}\big[\mathscr{P}^{k,1}\big(\pi_i^k\big)\big] - \mathbb{P}_{-i}\big[\mathscr{T}^{k,1}\big(\pi_i^k\big)\big]\Big) \\
&\qquad + \underbrace{\mathbb{E}_{-i}\Big[g_k\big((0,\pi_i^k),\overset{*}{s}{}_{-i}^k\big)\Big|\mathscr{T}^{k,1}\big(\pi_i^k\big)\Big]}_{=\frac{1}{2}} \cdot \mathbb{P}_{-i}\big[\mathscr{T}^{k,1}\big(\pi_i^k\big)\big] \Big\} + C \\
&= \sum_{k:u_i^k>0} u_i^k \cdot \Big(\mathbb{P}_{-i}\big[\mathscr{P}^{k,0}\big(\pi_i^k\big)\big] + \frac{1}{2}\cdot \mathbb{P}_{-i}\big[\mathscr{T}^{k,0}\big(\pi_i^k\big)\big]\Big) \\
&\quad + \sum_{k:u_i^k<0} u_i^k \cdot (-1) \cdot \Big(\mathbb{P}_{-i}\big[\mathscr{P}^{k,1}\big(\pi_i^k\big)\big] + \frac{1}{2}\cdot \mathbb{P}_{-i}\big[\mathscr{T}^{k,1}\big(\pi_i^k\big)\big]\Big) + \tilde{C} \qquad (3.A.11)
\end{aligned}$$

with $\tilde{C}$ independent of π_i. Exploiting symmetry and independence assumptions the crucial step in the proof is to realize that every report profile of other agents is equally probable. Formally, the fact that ρ_i^k is centered around zero for all $k \in D$ and independence of $\{u_i^k\}_k$ imply that $\overset{*}{a}_i \sim \text{Uniform}\big(\{0,1\}^d\big)$ for all $i \in N$. From $\{u_i^k\}_k$ independent and identically distributed it follows that $\overset{*}{\pi}_i \sim \text{Uniform}\,(\sigma(D))$ for all $i \in N$. By Definition 8 we have $\overset{*}{a}_i \perp \overset{*}{\pi}_i$, which implies $\overset{*}{s}_i \sim \text{Uniform}\,(M)$ for all $i \in N$. Independence of the family $\{u_i^k\}_i$ guarantees $\overset{*}{s}_{-i} \sim \text{Uniform}\big(\mathscr{M}_{-i}\big)$ for all $i \in N$, which together with (3.A.9) allows us to rewrite (3.A.11) dropping superscripts

$$\sum_k \big|u_i^k\big| \cdot \Big(\mathbb{P}_{-i}\big[\mathscr{P}\big(\pi_i^k\big)\big] + \frac{1}{2}\cdot \mathbb{P}_{-i}\big[\mathscr{T}\big(\pi_i^k\big)\big]\Big) + \tilde{C}. \qquad (3.A.12)$$

From (3.A.8) it follows that for all $\tilde{\pi}_i^k < \pi_i^k \in D$

$$\mathbb{P}_{-i}\big[\mathscr{P}\big(\tilde{\pi}_i^k\big)\big] + \frac{1}{2}\cdot \mathbb{P}_{-i}\big[\mathscr{T}\big(\tilde{\pi}_i^k\big)\big] \le \mathbb{P}_{-i}\big[\mathscr{P}\big(\pi_i^k\big)\big] + \frac{1}{2}\cdot \mathbb{P}_{-i}\big[\mathscr{T}\big(\pi_i^k\big)\big]$$

which implies that (3.A.12) is maximized for

$$\pi_i = \overset{*}{\pi}_i \in \left\{ \pi_i \in \sigma(D) \,:\, \pi_i^k < \pi_i^l \text{ only if } \left|u_i^k\right| \leq \left|u_i^l\right| \text{ for all } k,l \in D \right\}.$$

□

Proof of Proposition 7. Let $\mathscr{M}$ be defined as in Definition 7. For any mechanism $(\mathscr{M}, g)$, not necessarily a Ranking Mechanism, ex-ante expected welfare is given by

$$\begin{aligned}
\mathbb{E}\left[\sum_i V_i\left(g(\overset{*}{s})\right)\right] &= \sum_{m \in \mathscr{M}^{RM}} \mathbb{P}[\overset{*}{s} = m] \cdot \mathbb{E}\left[\sum_i \sum_k u_i^k \cdot g_k(m) \middle| \overset{*}{s} = m\right] \\
&= \sum_m \mathbb{P}[\overset{*}{s} = m] \cdot \sum_i \sum_k \mathbb{E}_i\left[u_i^k \middle| \overset{*}{s}_i = m_i\right] \cdot g_k(m) \\
&= \sum_m \mathbb{P}[\overset{*}{s} = m] \cdot \sum_i \sum_k \left(2 \cdot a_i^k - 1\right) \cdot \mathbb{E}_i\left[\left|u_i^k\right| \middle| \overset{*}{\pi}_i = \pi_i\right] \cdot g_k(m) \\
&= \sum_m \mathbb{P}[\overset{*}{s} = m] \cdot \sum_i \sum_k \left(2 \cdot a_i^k - 1\right) \cdot \mathbb{E}_i\left[\left|u_i^k\right|_{(\pi_i^k : d)}\right] \cdot g_k(m),
\end{aligned}$$

which implies that the is no loss in restricting attention to separable mechanisms and $g \equiv g^{RM,\overset{*}{w}}$ from Definition 9 and 10 is efficient. □

Proof of Proposition 8. We rewrite the sum of ex-ante expected utilities in problem k under $g_k^{RM,\overset{*}{w}}$ as

$$\begin{aligned}
&\sum_i \mathbb{E}\left[u_i^k \cdot g_k^{RM,\overset{*}{w}}\left(\overset{*}{s}^k\right)\right] \\
&= \sum_{m^k} \left(\mathbb{P}\left[\overset{*}{s}^k = m^k\right] \cdot g_k^{RM,\overset{*}{w}}\left(m^k\right) \cdot \sum_i \mathbb{E}_i\left[u_i^k \mid \overset{*}{s}_i^k = m_i^k\right] \right) \\
&= \sum_{(a^k,\pi^k)} \left(\mathbb{P}\left[\overset{*}{s}^k = \left(a^k, \pi^k\right)\right] \cdot \max\left\{0, \sum_i \left(2a_i^k - 1\right) \cdot \mathbb{E}_i\left[\left|u_i^k\right|_{(\pi_i^k : d)}\right]\right\} \right) \\
&= \frac{1}{2^n \cdot d^n} \cdot \sum_{a^k \in \{0,1\}^n} \sum_{\pi_1^k = 1}^{d} \cdots \sum_{\pi_n^k = 1}^{d} \max\left\{0, \sum_i \left(2a_i^k - 1\right) \cdot \mathbb{E}_i\left[\left|u_i^k\right|_{(\pi_i^k : d)}\right]\right\} \\
&= \frac{1}{2^n} \cdot \sum_{a^k \in \{0,1\}^n} \int_0^1 \cdots \int_0^1 \max\left\{0, \sum_i \left(2a_i^k - 1\right) \cdot \mathbb{E}_i\left[\left|u_i^k\right|_{(\lceil d \cdot \pi_i^k \rceil : d)}\right]\right\} \mathrm{d}\pi_1^k \ldots \mathrm{d}\pi_n^k,
\end{aligned}$$

where we used the fact that $\overset{*}{s}^k \sim \text{Uniform}\left(\mathscr{M}^k\right)$. Exploiting boundedness of all integrals and continuity of the maximum-operator we obtain

$$
\begin{aligned}
&\lim_{d\to\infty}\frac{1}{2^n}\cdot\sum_{a^k\in\{0,1\}^n}\int_0^1\cdots\int_0^1 \max\left\{0,\sum_i\left(2a_i^k-1\right)\cdot\mathbb{E}_i\left[\left|u_i^k\right|_{(\lceil d\cdot\pi_i^k\rceil:d)}\right]\right\}\mathrm{d}\pi_1^k\ldots\mathrm{d}\pi_n^k\\
=&\frac{1}{2^n}\cdot\sum_{a^k\in\{0,1\}^n}\int_0^1\cdots\int_0^1 \max\left\{0,\sum_i\left(2a_i^k-1\right)\cdot\mathbb{E}_i\left[\lim_{d\to\infty}\left|u_i^k\right|_{(\lceil d\cdot\pi_i^k\rceil:d)}\right]\right\}\mathrm{d}\pi_1^k\ldots\mathrm{d}\pi_n^k\\
=&\frac{1}{2^n}\cdot\sum_{a^k\in\{0,1\}^n}\int_0^1\cdots\int_0^1 \max\left\{0,\sum_i\left(2a_i^k-1\right)\cdot\Phi^{-1}\left(\pi_i^k\right)\right\}\mathrm{d}\pi_1^k\ldots\mathrm{d}\pi_n^k\\
=&\mathbb{E}\left[\max\left\{0,\sum_{i=1}^n u_i^k\right\}\right], \qquad (3.A.13)
\end{aligned}
$$

where Φ^{-1} denotes the inverse cdf of the absolute value of agents' valuations. The crucial step in the proof makes use of the following result on the asymptotic convergence of order statistics. For any random variable X with cdf F and pdf f and any $p\in[0,1]$ it holds that $X_{(\lceil d\cdot p\rceil:d)}\sim AN\left(F^{-1}(p),\frac{p\cdot(1-p)}{d\cdot f(F^{-1}(p))^2}\right)$ at all points such that $f\left(F^{-1}(p)\right)\neq 0$, see Ahsanullah, Nevzorov, and Shakil (2013), page 111. Since (3.A.13) is the sum of ex-ante expected utility levels that correspond to full efficiency for problem k this concludes the proof.

□

Proof of Proposition 9. Fix $w\in W$. We need to show that for all agents $i\in N$, all $u_i\in\mathscr{U}_i$ and $\overset{*}{s}_{-i}=\left(\overset{*}{a}_{-i},\overset{*}{\pi}_{-i}\right)$ it holds that

$$\overset{*}{s}_i(u_i)\ \in\ \arg\max_{s_i}\left\{\mathbb{E}_\gamma\left[\mathbb{E}_{-i}\left[V_i(g^{RRM}(s_i,\overset{*}{s}_{-i}))\right]\right]\right\}.$$

We define the profile of shuffled sincere strategies of all other agents as $\tilde{s}_{-i}=(\overset{*}{a}_{-i},\gamma_{-i}(\overset{*}{\pi}_{-i}))$ and rewrite the above expression as

$$
\begin{aligned}
&\mathbb{E}_{\gamma_i}\left[\mathbb{E}_{u_{-i},\gamma_{-i}}\left[V_i(g^{RRM}(s_i,\overset{*}{s}_{-i}))\right]\right]\ =\ \mathbb{E}_{\gamma_i}\left[\mathbb{E}_{u_{-i},\gamma_{-i}}\left[V_i(g^{RM}(\gamma_i(s_i),\tilde{s}_{-i}))\right]\right]\\
=&(1-\alpha_i)\cdot\underbrace{\mathbb{E}_{u_{-i},\gamma_{-i}}\left[V_i(g^{RM}(s_i,\tilde{s}_{-i}))\right]}_{(*)}+\alpha_i\cdot\sum_{\pi_i'}\beta_i^{\pi_i'}\cdot\underbrace{\mathbb{E}_{u_{-i},\gamma_{-i}}\left[V_i(g^{RM}((a_i,\pi_i'),\tilde{s}_{-i}))\right]}_{(**)}.
\end{aligned}
$$

By construction $\tilde{s}_{-i}\sim\text{Uniform}(\mathscr{M}_{-i})$ and therefore expression $(*)$ is maximized by $\overset{*}{s}_i$ by Proposition 6. Further expression $(**)$ is independent of the reported π_i and maximized by $\overset{*}{a}_i$ by the same logic as Part 1 of Proposition 6.

□

Proof of Proposition 10. We write ex-ante expected welfare under the Randomized Ranking Mechanism $(\mathscr{M}, g^{RRM,w})$ as

$$\mathbb{E}\left[\sum_i V_i(g^{RRM,w}(\overset{*}{s}))\right] = \mathbb{E}\left[\sum_i V_i(g^{RM,w}(\tilde{s}))\right]$$
$$= \sum_{m\in\mathscr{M}} \mathbb{P}[\tilde{s} = m] \cdot \sum_i \sum_k \mathbb{E}\left[u_i^k | \tilde{s} = m\right] \cdot g_k^{RM,w}(m)$$
$$= \frac{1}{(2^d \cdot d!)^n} \cdot \sum_m \sum_k \sum_i \mathbb{E}\left[u_i^k | \tilde{s}_i^k = m_i^k\right] \cdot g_k^{RM,w}\left(m^k\right). \tag{3.A.14}$$

Let $\bar{M}$ denote the set of all possible report profiles of all agents for a single decision problem, i.e. $\bar{M} = \left(\{0,1\}, D\right)^{\otimes n}$. Further, we divide $\bar{M}$ into anonymous equivalence classes. Formally, for $\bar{m} \in \bar{M}$ define $[\bar{m}] = \left\{\tilde{m} \in \bar{M} | \left(\tilde{m}_{\sigma(1)}, \ldots, \tilde{m}_{\sigma(n)}\right) = \bar{m} \text{ for some } \sigma \in \sigma(N)\right\}$. We refer to $[\bar{m}]$ as the equivalence class and its representative interchangeably and denote by $[\bar{M}]$ the set of all equivalence classes. We write (3.A.14) as

$$\frac{1}{(2^d \cdot d!)^n} \cdot \sum_k \sum_{\bar{m}\in\bar{M}} \sum_i \mathbb{E}\left[u_i^k | \tilde{s}_i^k = \bar{m}_i\right] \cdot g_k^{RM,w}(\bar{m})$$
$$= \frac{1}{(2^d \cdot d!)^n} \cdot \sum_k \sum_{[\bar{m}]\in[\bar{M}]} \sum_{\bar{m}\in[\bar{m}]} \sum_i \mathbb{E}\left[u_i^k | \tilde{s}_i^k = \bar{m}_i\right] \cdot g_k^{RM,w}(\bar{m})$$
$$= \frac{1}{(2^d \cdot d!)^n} \cdot \sum_k \sum_{[\bar{m}]} g_k^{RM,w}\left([\bar{m}]\right) \cdot \left((n-1)! \cdot \sum_j \sum_i \mathbb{E}\left[u_i^k | \tilde{s}_i^k = [\bar{m}]_j\right]\right), \tag{3.A.15}$$

where we used that $g^{RM,w}$ is anonymous and that for all $i, j \in N$ there exist $(n-1)!$ permutations in $\sigma(N)$ sending i onto j. After suitably rearranging (3.A.15) Definition 9 gives us

$$
\begin{aligned}
&\frac{1}{(2^d \cdot d!)^n} \cdot \sum_k n! \cdot \sum_{[\bar m]} \sum_j \frac{1}{n} \cdot \sum_i \mathbb{E}\left[u_i^k | \tilde s_i^k = [\bar m]_j\right] \cdot g_k^{RM,w}\left([\bar m]\right) \\
=&\frac{1}{(2^d \cdot d!)^n} \cdot \sum_k \sum_{\bar m \in \bar M} \sum_j \left(\frac{1}{n} \cdot \sum_i \mathbb{E}\left[u_i^k | \tilde s_i^k = \bar m_j\right]\right) \cdot \left(\frac{1}{d} \cdot \sum_l g_l^{RM,w}(\bar m) \right) \\
=&\frac{1}{(2^d \cdot d!)^n} \cdot \sum_{\bar m \in \bar M} \sum_j \sum_l \left(\frac{1}{n} \cdot \sum_i \sum_k \frac{1}{d} \cdot \mathbb{E}\left[u_i^k | \tilde s_i^k = \bar m_j\right]\right) \cdot g_l^{RM,w}(\bar m) \\
=& \sum_{m \in \mathscr{M}} \mathbb{P}[\tilde s = m] \cdot \sum_j \sum_l \left(2 \cdot a_j^l - 1\right) \\
& \qquad \cdot \left(\frac{1}{n} \cdot \sum_i \sum_k \mathbb{P}\left[\tilde \pi_i^k = \pi_j^l\right] \cdot \mathbb{E}\left[\left|u_i^k\right| \middle| \tilde \pi_i^k = \pi_j^l\right]\right) \cdot g_l^{RM,w}\left(m^l\right) \\
\leq& \sum_{m \in \mathscr{M}} \mathbb{P}[\tilde s = m] \cdot \sum_j \sum_l \left(2 \cdot a_j^l - 1\right) \\
& \qquad \cdot \left(\frac{1}{n} \cdot \sum_i \sum_k \mathbb{P}\left[\tilde \pi_i^k = \pi_j^l\right] \cdot \mathbb{E}\left[\left|u_i^k\right| \middle| \tilde \pi_i^k = \pi_j^l\right]\right) \cdot g_l^{RM,\overset{**}{w}}\left(m^l\right) \\
=&\mathbb{E}\left[\sum_j V_j(g^{RM,\overset{**}{w}}(\tilde s)) \right] = \mathbb{E}\left[\sum_j V_j(g^{RRM,\overset{**}{w}}(\overset{*}{s})) \right],
\end{aligned}
$$

with weight vector $\overset{**}{w} \in W$ given by

$$
\begin{aligned}
\overset{**}{w}{}^r =& \frac{1}{n} \cdot \sum_i \sum_k \mathbb{P}\left[\tilde \pi_i^k = r\right] \cdot \mathbb{E}\left[\left|u_i^k\right| \middle| \tilde \pi_i^k = r\right] \\
=& \frac{1}{n} \cdot \sum_i \sum_k \left((1-\alpha_i) \cdot \mathbb{P}_i\left[\overset{*}{\pi}{}_i^k = r\right] \cdot \mathbb{E}\left[\left|u_i^k\right| | \overset{*}{\pi}{}_i^k = r\right] + \alpha_i \cdot \sum_{\hat\pi_i : \hat\pi_i^k = r} \beta_i^{\hat\pi_i} \cdot \mathbb{E}\left[\left|u_i^k\right|\right] \right) \\
=& \frac{1}{n} \cdot \sum_i \sum_k \left((1-\alpha_i) \cdot \mathbb{P}_i\left[\overset{*}{\pi}{}_i^k = r\right] \cdot \mathbb{E}\left[\left|u_i^k\right|_{(r:d)}\right] + \alpha_i \cdot \mathbb{P}_{\beta_i}\left[\tilde \pi_i^k = r\right] \cdot \mathbb{E}\left[\left|u_i^k\right|\right] \right)
\end{aligned}
$$

for $r = 1, \ldots, d$ as in Definition 15.

□