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Fellowship for NBER Summer Institute April 29, 2025
The Review of Economics and Statistics

Dear Selection Committee,

I am writing to apply for the Review of Economics and Statistics Fellowship at the NBER Summer Institute. I am an applied microeconomist and an Assistant Professor of Economics at the University of South Florida. My research focuses on labor and education, with particular emphasis on occupational licensing and peer effects. My work has been published in the *Review of Economics and Statistics, Journal of Public Economics, Journal of Economic Behavior and Organization, and Journal of Health Economics*.

My current research portfolio examines how institutions and environments shape individual labor market and educational outcomes. In the attached paper, "The Impact of Occupational Licensing on Unemployment and Inequality during Recessions," coauthored with Peter Blair, we investigate how occupational licensing affected employment outcomes during both the Great Recession and the COVID-19 recession. We find that licensed workers experienced significantly greater employment stability compared to unlicensed workers across both downturns, highlighting occupational licensing as a key but understudied institution influencing labor market resilience and inequality during economic shocks.

By presenting this paper in the Labor Studies/Public Economics session, I aim to highlight the growing importance of occupational licensing, which deserves more academic attention given its increasing role in labor market policy debates. Additionally, by attending the 'Economics of Education' and 'Gender in the Economy' sessions, I hope to further extend my pipeline on peer effects. My recent publication in the Journal of Economic Behavior and Organization on gender norms is closely related to work by Claudia Olivetti and Caroline Hoxby, and I am eager to build on these connections to explore broader questions about education, gender, and labor market dynamics.

My research perspective emphasizes the interplay between labor market institutions, inequality, and economic resilience, grounded in careful empirical identification. I hope to contribute to the Summer Institute by bringing my work on occupational licensing and peer effect to the attention of broader audiences. Attending the Summer Institute would provide a valuable opportunity to receive high-level feedback on my projects, connect with leading scholars, and further develop my empirical and policy-relevant research agenda.

Thank you for considering my application. I would be honored to participate in the Summer Institute under the REStat Fellowship and contribute to its vibrant research community.

Sincerely,
Dr. Bobby Chung

DR. BOBBY (WING YIN) CHUNG

May 2025

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FIELD OF INTEREST

Labor, Education, Health

EMPLOYMENT

Assistant Professor Fall 2023 - Present
University of South Florida, Department of Economics

Assistant Professor Fall 2021 - Spring 2023
St.Bonaventure University, Department of Finance

Postdoctoral Researcher Fall 2019 - Summer 2021
University of Illinois (Urbana-Champaign), School of Labor and Employment Relations

Adjunct Assistant Professor Summer 2019
The Open University of Hong Kong, School of Art and Social Science

Adjunct Lecturer Summer 2018
The Open University of Hong Kong, School of Art and Social Science

EDUCATION

Clemson University 2014 - 2019
Ph.D in Economics

Hong Kong Baptist University 2012 - 2013
Master of Science in Applied Economics, *Distinction*

The Open University of Hong Kong 2008 - 2011
Bachelor of Social Science, *First-class honors*

WORKING PAPERS

"Licensed Professionals and Corporate Board Performance: The Effect of the Sarbanes-Oxley Act on the Audit Committee" (w/ Ben Posmanick, Alex Obie)

"The Impact of Occupational Licensing on Unemployment and Inequality during Recessions," (w/ Peter Blair), Submitted to **AEJ: Policy**

- WP version: "Does Occupational Licensing Reduce Job Loss During Recessions?" *NBER (#32486)*

PUBLICATIONS

(* as Corresponding author)

"Composition of Peer Mothers and Gender Norms: Class Randomization and Short-run Effects" (w/ Liwen Chen, Guanghua Wang), 2025, **Journal of Economic Behavior and Organization**

* "Occupational Licensing in US Public Schools: Nationwide Implementation of Teacher Performance Assessment" (w/ Jian Zou), 2025, **Journal of Public Economics**

"Job market signaling through occupational licensing" (w/ Peter Blair), 2025, **Review of Economics and Statistics**

"The Effect of Expansion of Nurse Practitioner Scope of Practice on Early Covid-19 Deaths" (w/ Noah Trudeau), 2024, **Contemporary Economic Policy**

* "Effects of Occupational License Access on Undocumented Immigrants: Evidence from the California Reform", 2024, **Journal of Regulatory Economics**

* "Understanding peer parental spillover: Mechanisms and randomization evidence in China" (w/ Jian Zou), 2023, **Economic Inquiry**

"Exposure to socially influential peer parents: Evidence from Cadre Parents in China" (w/ Liwen Chen, Guanghua Wang), 2023, **China Economic Review**

* "The costs and potential benefits of occupational licensing: A case of real estate license reform", 2022, **Labour Economics**

" A model of occupational licensing and statistical discrimination" (w/ Peter Blair), 2021, **AEA Papers and Proceedings**

* "Peers' parents and educational attainment: The exposure effect", 2020, **Labour Economics**

"The effect of the National Kidney Registry on the kidney-exchange market" (w/ Roksana Ghanbariamin), 2020, **Journal of Health Economics**

"How much of a barrier to entry is occupational licensing?" (w/ Peter Blair), 2019, **British Journal of Industrial Relations** (top 10% download)

"Threats and promises in bargaining" (w/ Dan Wood), 2019, **Journal of Economic Behavior and Organization**

AFFILIATIONS

Research Affiliate, HCEO, University of Chicago — Fall 2018 -

Research Affiliate, Knee Center of Occupational Regulations, West Virginia University — Fall 2021 -

Visiting Scholar, Harvard University (Graduate School of Education) — Fall 2020 - Spring 2021

RECENT REFEREE SERVICE

AEJ Applied, AEJ Policy, Economics of Education Review, International Economic Review, Journal of Policy Analysis and Management, Journal of Economic Behavior and Organization, Journal of Health Economics, Journal of Human Resources, Journal of Labor Economics, Journal of Population Economics, ILR Review, Review of Economics and Statistics.

AWARDS

Graduate Assistantship, Clemson	2014-2019
Professional Enrichment Grant, Clemson	Summer 2019
Price Theory Scholarship, University of Chicago	Fall 2017
Best Second Year Paper Award, Clemson "Occupational licensing and racial wage differentials"	Summer 2016
MSc in Applied Economics Distinction Scholarship, HKBU	Summer 2013

PRESENTATIONS

2025	AEA
2024	AEA, SEA, CEA, WEA, St. Bonaventure University
2023	SOLE, University of South Florida, William & Mary
2022	SOLE, IHS Research Symposium, AEFP, RIDGE Labor Conference
2021	SEA, Carolina Region Empirical Economics Day
2020	CSOR Regulation Conference, WEA, EALE/SOLE
2019	CSOR Regulation Conference, EALE, AEA, SEA
2018	Wake Forest University, Hong Kong Baptist University, SEA, Fourth Annual Conference on Network Science and Economics, South Carolina Applied Micro Day
2017	SEA, Price Theory Summer Camp (UChicago)
2016	SEA, HCEO Summer Camp (UChicago)

The Impact of Occupational Licensing on Unemployment and Inequality during Recessions*

Peter Q. Blair†
Bobby W. Chung‡

April 28, 2025

Abstract

State occupational licenses are required for one-quarter of American jobs, yet their impact on unemployment and inequality during downturns is unknown. Leveraging state-occupation variation in licensing intensity, we assess the causal effect of licensure on unemployment during the Great Recession and COVID-19 recession. We find that licensed workers faced a 0.8-1.1 percentage point (27%-37%) smaller increase in unemployment than unlicensed workers. Calibrating a model of worker utility with our estimates shows that failing to account for these effects understates inequality between licensed and unlicensed workers by 3%-7%. Licensing increases inequality because it is a barrier to job exit.

Keywords: Occupational licensing, inequality, recessions, Great Recession, COVID-19.

JEL Classification: E02, E24, J08, J23, J24, J44, J64, K31, L31, and M51.

*This manuscript previously circulated as "Does Occupational Licensing Reduce Job Loss During Recessions?" We are thankful for the comments from Isaiah Andrews, David Autor, Desmond Ang, Jay Bhattacharaya, Michela Carlana, David Deming, Steven Durlauf, John Friedman, Matthew Gentzkow, Larry Katz, Bill Kerr, Erzo F. P. Luttmer, Jesse Shapiro, Mark Shepard, Evan Soltas, Eric Taylor, Emiliana Vegas, Ivan Werning and seminar participants at WEA, Harvard, UChicago, and the Cleveland Fed. We also received excellent research support from Anne Korte. All errors are ours.

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‡Bobby Chung is an Assistant Professor at the University of South Florida in the Economics Department. He is also a research affiliate of the HCEO and the Knee Regulatory Research Center (email: bobbywchung@usf.edu).

1 Introduction

Occupational licensing is one of the most pervasive labor market regulations in many economies. In the United States and the European Union, about one in four workers is subject to occupational license requirements that make it illegal to work for pay without a license (Gittleman et al., 2018; Koumenta and Pagliero, 2019). These licenses, intended to ensure quality and safety in professions ranging from medicine to cosmetology, also create barriers that can contribute to economic inequality. This paper explores a crucial but often overlooked aspect of occupational licensing: its ability to shield licensed workers from job loss during economic recessions and the way in which this increases inequality between licensed and licensed workers above and beyond the well-known licensing wage premium (Kleiner and Krueger, 2013; Gittleman et al., 2018).

Economists have long considered the institution of occupational licensure to be a contributing factor to inequality (Smith, 1776; Friedman and Kuznets, 1945; Friedman, 1962; Leland, 1979; Maurizi, 1974; Shapiro, 1986).[1] The empirical evidence on the inequality caused by licensing, however, has focused on inequality in wages between licensed and unlicensed workers, mirroring the traditional focus on wages when studying inequality by education attainment (Kleiner and Krueger, 2013; Pizzola and Tabarrok, 2017; Autor, 2014; Katz and Murphy, 1992). What is largely missing from the literature is an understanding of how licensing contributes to inequality by impacting the likelihood that a worker is employed (Kukaev and Timmons, 2024). Studying the extent to which licensing can cause inequality by creating a disparity in unemployment between licensed and unlicensed workers is important because we know from recent work on black-white inequality that ignoring differences in unemployment can result in underestimating both the level and time evolution of inequality between groups (Bayer and Charles, 2018).

In this paper, we provide the first causal estimates of the impact of occupational licensing on unemployment during recessions. We find that licensed workers experienced a 0.8-1.1 percentage point (27%-37%) smaller increase in unemployment than unlicensed workers during both recessions, suggesting that our findings are not driven by the peculiarities of a given recession. Moreover, we show that the differential job protection experienced by licensed workers during recessions is not offset by a negative compensating earnings differential (Rosen, 1974; Mortensen, 2003; Lang and Majumdar, 2004; Sorkin, 2018). While the literature to date has focused on wage inequality caused by licensing,

[1] For example, in *The Wealth of Nations*, Adam Smith, argued: "The policy of Europe, by obstructing the free circulation of labour and stock both from employment to employment, and from place to place, occasions in some cases a very inconvenient inequality in the whole of the advantages and disadvantages of their different employments."

we show that occupational licensing laws generate an additional source of inequality by reducing the extent to which licensed workers experience unemployment during times of economic uncertainty. Using a back-of-the-envelope calculation, we find that the inequality between licensed and unlicensed workers is 3%-7% higher than one would think based solely on the licensing wage premium.

At the height of the Great Recession, Larry Jacobson, then executive director of the National Society of Professional Engineers, lamented to the *New York Times*: *"What is missing are enough licensed professionals who have worked at least five years under experienced engineers..."* (Uchitelle, 2009). Occupational licensing potentially shields licensed workers from unemployment during recessions because licensing laws prohibit unlicensed workers from substituting for licensed workers. In a slack labor market, licensed workers are less expendable because they are more versatile. Second, as measured in Blair and Chung (2019), licensed workers are already scarce talent during normal times, i.e., the fraction of workers who sort into an occupation is 17%-27% lower if the occupation requires a license. Consequently, companies may be reluctant to layoff licensed workers during recessions if they anticipate competition to rehire them during recovery, consistent with models of labor hoarding (Biddle, 2014).

To measure the impact of occupational licensing on unemployment during recessions, we leverage cross-state variation in licensing laws and compare the difference in the unemployment rate between licensed and unlicensed workers in the same industry during each month in the two years before and after the COVID-19 recession and the Great Recession. In each recession, we have over 3 million worker-month observations. Our key outcome of interest is whether an individual reports being unemployed. We code an individual as being licensed if the individual reports having a government-issued occupational license that is required by their current job (if employed) or required by their previous job (if unemployed). We code a state-occupation pair as licensed if more than 50% of workers in the state-occupation pair report being licensed, following Blair and Chung (2019).

Our identification is analogous to a difference-in-differences approach, with the baseline license indicator capturing pre-shock selection. The key parameter of interest is the coefficient on the interaction term between the indicator for whether an individual has a license and an indicator for whether the observation comes from the period that follows the onset of the recession.[2] The parameter measures the shielding effect of licensing

[2]We control for a pre-labor market measure of worker ability, education, potential experience, demographics, regional time trends, interactions between worker ability, education, and union status, and the recession indicator, and fixed effects for industry, survey month, and state.

– how much occupational licensing differentially shields licensed workers from unemployment as compared to unlicensed workers during the recession as compared to non-recessionary times. We show that our results are quantitatively similar when we use the state-occupation definition of licensure, which mitigates against measurement error in individual self-reported licensure status.

The identifying assumptions for us to causally interpret our parameter measuring the shielding effect of licensing are: 1) the unemployment gap between unlicensed and licensed workers would have evolved similarly in the post-recession period as it had in the pre-recession period, had the recession not occurred, 2) the timing of the recession is uncorrelated with other treatments that could have shielded licensed workers from unemployment as compared to their unlicensed peers, and 3) our measure of pre-labor market ability is a valid proxy for controlling for selection. We test the first assumption by running a placebo test in which we split the two-year preperiod in half and re-estimate our model. We find no shielding effect for occupational licensing during this placebo recession. The second assumption seems plausible, given that the recession is a nationwide shock, whereas the licensing variation occurs at the state level. To test our third assumption, we show that our measure of average worker ability at the state-occupational level is economically meaningful for predicting wages, unemployment, licensure status, and college attainment, and our preferred treatment effects of licensing on unemployment during the recession are obtained by the specifications that control for pre-market ability.

Quantitatively, we find that licensing shields workers from a recession-induced increase in the unemployment rate of 0.82 percentage points (p.p.) during COVID-19 and 1.11 p.p. during the Great Recession. These effects are meaningful. To avoid a 1 p.p. increase in the state unemployment rate, Borgschulte and Martorell (2018) estimates that workers are willing to give up 1.5%-2% in earnings. Moreover, the 1 p.p. lower increase in unemployment represents 27% to 37% of the increase in the unemployment rate among unlicensed workers during COVID-19 and the Great Recession, respectively.

We find no evidence for a negative compensating differential, which economic theory would suggest (Rosen, 1974, 1986); the licensing earnings premium does not fall in the presence of the lower unemployment risk faced by licensed workers as compared to unlicensed workers — ruling out a scenario in which licensed workers and firms agree to trade off lower unemployment for lower earnings. A back-of-the-envelope calculation shows that overlooking the additional job loss protection licensed workers receive during recessions would understate inequality between licensed and unlicensed workers by 3% to 7% — a magnitude comparable to the welfare gains estimated by Finkelstein et al.

(2024) from the mortality impacts of the Great Recession.[3]

To check the robustness of our main results, we conducted a series of auxiliary tests. We find that our results are not driven by a single industry, but are similar across all industries. The relative selection of workers into licensed occupations does not change in recession years as compared to non-recession years. Moreover, selection on unobservables would need to be implausibly large to explain our findings (Altonji et al., 2005; Oster, 2019). Occupational licensing has the strongest shielding effect from recession-induced unemployment in places where labor demand was hardest hit by the recession, as measured using industry-level Bartik shocks (Great Recession), and states that mandated lockdowns (COVID-19). In both recessions, licensing shields workers from layoffs and not voluntary quits, casting doubt on labor supply responses as a mechanism.

Existing work demonstrates that licensing requirements generate income inequality by creating rents for incumbents and restricting entry for new workers (Friedman, 1962; Stigler, 1971; Kleiner and Krueger, 2013; Blair and Chung, 2019; Johnson and Kleiner, 2020a; Kleiner and Soltas, 2023). Licensed workers also experience shorter unemployment duration during non-recession periods, as shown by Kukaev and Timmons (2024). Although there is a robust literature that examines how macroeconomic shocks interact with other major labor market institutions such as unemployment insurance, collective bargaining, and employment protection laws (Nickell, 1997; Blanchard and Wolfers, 2000; Bertola et al., 2001; Giupponi and Landais, 2023),[4] this paper is the first to explore how licensing affects unemployment during recessions. Overlooking the shielding effect of licensing during recessions underestimates the extent to which licensing amplifies lifetime income inequality, because unemployment has lasting negative effects on career progression and earning potential and the incidence of recession-induced job loss varies significantly by worker characteristics, reinforcing the uneven impacts of economic contractions (Edin and Gustavsson, 2008; Jarosch, 2023; Neal, 1995; Schmieder et al., 2016; Cortes and Forsythe, 2023; Mian and Sufi, 2014; Mirer, 1973; Yagan, 2019). The license shielding during downturns also offers a novel angle to quantify economic rents captured by licensed workers, which is distinct from the conventional wage-related measures.

[3]The reduction in job loss for licensed workers during recessions that we document does not appear to come at the expense of greater job loss for unlicensed workers in the same state-industry pair.

[4]For example, unionized workers tend to be more vulnerable to cyclical downturns due to wage rigidity imposed by union contracts whereas minimum wage workers are more likely to be laid off during economic contractions (Guriev et al., 2019; **?**; Pearce, 1983; Yamane, 1993).

2 Data and Empirical Strategy

2.1 Employment and Licensing Data

The data used in the study are drawn from the monthly Current Population Survey (CPS), a nationally representative survey of US workers with rich labor market and demographic information. In 2015, the CPS became the first nationally representative survey to continuously record whether an individual has an occupational license. Prior to the CPS, a special module of the 2008 SIPP recorded a single cross-section mapping out which workers were licensed Gittleman et al. (2018). Gallop and Westat also conducted surveys that provided a snapshot of the prevalence of occupational licensing Kleiner and Krueger (2010, 2013). Fortuitously, the CPS allows us to measure the licensure status of workers whether they are employed or unemployed. Employed workers are asked if their current job requires a license and unemployed workers are asked if their previous job required a license. Having a measure of licensure for both employed and unemployed workers makes it possible for us to explore how licensure changes the probability of unemployment during recessions.

Our estimation sample consists of individuals between 18 and 65 who are in the labor force, excluding armed forces and unpaid family workers. For the COVID-19 recession, we use CPS licensing and unemployment data that span January 2018 to December 2022. In Table 1, we report the average unemployment rate separately for licensed and unlicensed workers before COVID-19 and after COVID-19, the difference in the unemployment rate between licensed and unlicensed workers in each time period, and the difference in this difference, which measures the extent to which licensed workers experience less job loss than unlicensed workers during the recession. Likewise, we report pre-COVID-19 and post-COVID-19 means for the characteristics of workers, e.g., sex, age, race, college, separately for licensed workers and unlicensed workers, the difference in the means for each period and the difference in this difference, which measures how much selection into licensing changed during the recession. The summary statistics in Table 1 suggest that occupational licensing may shield licensed workers from job loss during recessions beyond what observable worker characteristics can explain.

Table 1: Average Unemployment and Demographics by License Status Before and After COVID-19 Recession

	Pre-COVID-19			Post-COVID-19			
	Unlicensed	Licensed	Difference	Unlicensed	Licensed	Difference	Diff-in-Diff
Outcome							
unemployed	0.043	0.015	-0.0284***	0.065	0.027	-0.0379***	-0.00956***
			(0.000893)			(0.00127)	(0.00102)
Individual characteristics							
female	0.452	0.555	0.103***	0.449	0.559	0.109***	0.00619
			(0.00377)			(0.00350)	(0.00377)
age	40.206	43.174	2.968***	40.272	43.250	2.978***	0.0105
			(0.0982)			(0.117)	(0.0728)
black	0.133	0.112	-0.0216***	0.134	0.113	-0.0209***	0.000714
			(0.00594)			(0.00568)	(0.00241)
Hispanic	0.199	0.112	-0.0864***	0.205	0.119	-0.0860***	0.000357
			(0.0147)			(0.0140)	(0.00298)
Asian	0.066	0.056	- 0.0103***	0.069	0.059	-0.00970***	0.000646
			(0.00268)			(0.00282)	(0.00184)
union membership	0.242	0.268	0.0259***	0.235	0.264	0.0288***	0.00290**
			(0.00209)			(0.00264)	(0.00115)
college	0.335	0.569	0.234***	0.358	0.590	0.231***	-0.00260
			(0.00653)			(0.00575)	(0.00373)
govt	0.108	0.248	0.140***	0.108	0.249	0.140***	0.000272
			(0.00596)			(0.00617)	(0.00322)
self employed	0.084	0.119	0.0346***	0.088	0.125	0.0363***	0.00177
			(0.00443)			(0.00516)	(0.00207)
Observations	1,196,258	290,593		1,229,125	303,485		

Data: Monthly CPS (Jan 2018 to Dec 2022)

Note: 'Licensed' refers to individuals who require a government-issued credential to work in the current job (the previous job if unemployed). We utilize the individual attainment to show the raw statistics in this table. 'Pre-COVID-19' refers the period before March 2022. Sample weight apples. Standard errors are clustered at the state level in testing differences.

When we examine the difference-in-differences measure from Table 1, we find that licensed workers are on average 0.96 p.p. less likely to experience job loss during the recession than their unlicensed peers. Examining the difference-in-differences for the nine individual worker characteristics, we find that eight of the nine are statistically indistinguishable from zero and are each economically small.[5] The sole characteristic that has a statistically significant difference-in-difference is union membership. Licensed workers are 0.29 p.p. more likely to be union members (than unlicensed workers) during the recession than before, which represents an increase in unionization of 1% (26.8% of licensed workers are union members before COVID-19). By contrast, the change in the unemployment rate of 0.96 p.p. is 34% of the pre-COVID-19 gap in unemployment between licensed and unlicensed workers.

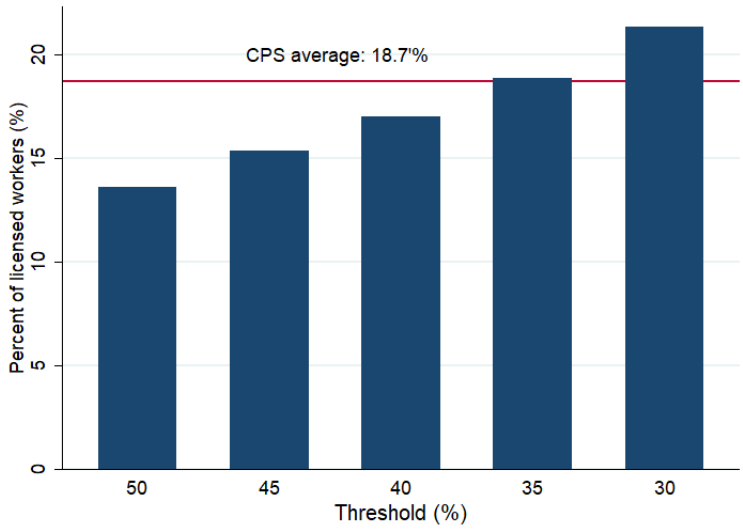
Because the license attainment variable in the CPS is self-reported, it may be susceptible to measurement error (Kleiner and Vorotnikov, 2017). In the regressions described in the next section, we adopt a threshold rule as an alternative way to define license requirements at the state-by-occupation level (Blair and Chung, 2019). For each 6-digit occupation (defined by the Standard Occupational Classification (SOC)) in each state, we tabulate (with sample weights) the proportion of workers who report requiring a government-issued license. The tabulation sample is limited to the pre-COVID-19 period to limit the sorting caused by the COVID-19 recession. We then define a state-occupation cell as licensed if more than x% of workers in that state-occupation cell report requiring a license to work. The treatment variable is then an intent-to-treat measure, assigning the license status to a worker based on the other workers' response in the same state-occupation cell.

We employ a data-driven approach to determine the appropriate threshold x in the regressions. To avoid mechanical in-sample correlation, we first use the CPS sample in 2016 and 2017 to construct out-of-sample license information for each state-occupation under varies thresholds. We then merge this out-of-sample information to our estimation sample and redefine the license status of workers. Figure 1 compares the redefined percent of licensed under different thresholds with the original raw mean in CPS (18.7%). The 50% threshold is restrictive since the redefined percent of licensed (13.6%) is much smaller than the raw mean, which could increase Type I error that falsely assigned an unlicensed status to licensed workers. On the less restrictive end at 30%, the redefined percent (21.3%) is much bigger, which could induce Type II error that falsely assigned a licensed status to unlicensed workers. In the main regressions, we employ the 35%

[5]For example, we find that the gap in the fraction of workers with a bachelor's degree who are licensed versus those who are unlicensed drops by 0.26 p.p., relative to the pre-COVID-19 value. The difference-in-difference here represents less than 1% of the pre-COVID-19 mean of 33.5% of unlicensed workers with bachelor's degrees and is, moreover, statistically indistinguishable from zero.

threshold since the redefined percent (18.8%) is the closest to the raw statistic. To address the possible Type I and Type II errors, we control for 'misreport' status if a licensed worker is reassigned as unlicensed or an unlicensed worker is reassigned as licensed. In this way, our state-by-occupation license indicator compares the 'truly' licensed with the 'truly' unlicensed.[6]

Figure 1: Comparing Raw License Statistic with Different Threshold Rules



Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: The figure tracks the percent of licensed workers under different threshold, with 50% being the most restrictive. In the main regressions, we define a worker as 'licensed' if a state-occupation has more than 35% of workers report requiring a government license. Under this rule, the percent of licensed matches closely with the raw sample statistic in the CPS.

2.2 Empirical Strategy

An ideal comparison is to randomize the attainment of occupational licenses of individuals before a recession and measure whether the gap in unemployment between licensed and unlicensed workers changes during the recession. There are two challenges to implementing the ideal experiment. First, it is impossible to forecast the timing of a recession. Second, randomly assigning licenses raises ethical concerns because licensed workers earn a wage premium (Kleiner and Krueger, 2010; Timmons and Thornton, 2010; Kleiner and Krueger, 2013; Pizzola and Tabarrok, 2017; Kleiner and Soltas, 2023; Blair and Chung, Forthcoming). Because we cannot foresee recessions or randomly assign occupational licenses to individuals, we make progress on the question that animates this paper by leveraging a natural experiment.

[6] In the working paper version, we find a similar shielding pattern using individual license attainment.

Since occupation definitions are national, the choice of individual states to disagree on whether an occupation is licensed creates a natural experiment in which there is plausibly exogenous variation in licensing across states. For example, an individual remodeling a bathroom in Massachusetts is required to have a license but an individual performing the same task in New Hampshire, a neighboring state, is not required to have a license (Blair and Fisher, 2022). We pair this across-state and within-state variation in licensing with variation in the timing of when the NBER declares that the economy is in recession to test whether licensing shields workers from job loss during recessions. Since the NBER's recession dating is retrospective, it is hard for workers to contemporaneously sort into occupations on account of the NBER's future designation of the recession period. The COVID-19 recession, in particular, was unexpected because it was driven by a global health shock rather than by a steady deterioration in macroeconomic conditions.

The plausible exogeneity of the state variation in licensing laws alone may not be enough for our natural experiment to yield causal estimates. We must overcome endogeneity due to ability bias. We, therefore, require a measure of worker ability at the state-occupation level to account for nonrandom selection within state into licensed occupations and differential shocks to unemployment by ability during the recession. Selection into licensed occupations within the state, for example, could introduce ability bias, as shown in the Blair and Chung (2021) model of statistical discrimination and occupational licensing. An occupation's market share also decreases when it is licensed by the state which is further reason to believe that licensing laws could induce selection by screening out low-ability workers (Shapiro, 1986; Blair and Chung, 2019). Furthermore, baseline differences in worker ability could also shape how workers experience an economic shock independently of occupational license.

Table 2: Measures of Pre-Labor market Ability by Licensure Status

	unlicensed	licensed	licensed-unlicensed
Math	0.4805 (0.0019)	0.5558 (0.0042)	0.0753 (0.0046)***
English	0.6694 (0.0017)	0.7623 (0.0036)	0.0929 (0.0040)***
Science	0.4669 (0.0018)	0.5735 (0.0042)	0.1066 (0.0046)***
N	71,831	13,699	

Source: Survey of Income and Program Participation (Panel 2008)

Note: Sample includes employed individuals who are between 18 and 65. Following Gittleman et al. (2018), individuals who have missing/imputed information in license/union/wage questions, and wage outliers (hourly wage below $5 or above $100) are dropped. 'License' refers to individuals who report having a government-issued license and is required by the job.

We follow the literature and take the fraction of workers in a state-occupation cell who report having taken advanced math, science, or English courses in high school as proxy measures of average worker ability at the state-occupation level (Blair and Chung,

Forthcoming). The data come from the topical module of the SIPP in 2012 and are advantageous for our use for three reasons. First, because the survey also asks workers if they have an occupational license, we can test whether licensed workers are on average more "able" than unlicensed workers. As reported in Online Appendix Table 2, licensed workers are more likely to have taken advanced math (7.5 p.p.), science (10.7 p.p.), and English (9.3 p.p.) courses in high school than their unlicensed peers. Second, the common occupation classification code enables us to link the external ability measures in SIPP to our main household CPS data and quantify the usefulness of our ability measure by exploring its correlations with educational attainment and labor market outcomes. As reported in Table A1, a one-unit increase in our ability proxy predicts a 2-4 p.p. increase in the probability that a worker is licensed, a 0.5 p.p. reduction in unemployment, wages that are 5-6 p.p. higher, and a 12 p.p. increase in bachelor's degree attainment. Third, because our ability measures come from data that precede the COVID-19 pandemic, they are predetermined, which rules out reverse causality. In our preferred empirical specification, we will include all three measures of worker ability as control variables. The inclusion of pre-market ability measure is analogous to the role of AFQT score in the estimation of education premium (Neal and Johnson, 1996).

In our baseline specification, the outcome 'Y_{istd}' measures whether worker 'i' living in state 's,' working in industry 'd' reports being unemployed at time 't.' We regress the unemployment indicator on an indicator variable '$license_{ist}$' that equals one if the worker reports having a state-issued license that is required for the worker's current job (if the worker is employed, or for the worker's previous job if the worker is unemployed). In the regression, we also include an interaction term between the worker's license status and an indicator '$post$' that is equal to one for all observations from time periods following the onset of the recession being studied. The interaction term 'license $\times$ post' is our coefficient of interest. To test whether our main effect is driven by selection on ability or differences in other observable features, in the regression, we also include control variables for average worker ability at the state-occupation level '$a_{s,p}$' and its interaction with the '$post$' recession indicator, worker demographics 'X_{ist},' and fixed effects for the worker's state of residence 'θ_s'. We additionally control for occupation-by-month fixed effect ('θ_p') to address systematic occupational differences in seasonality. In extended specifications, we also test the robustness of our results by controlling for the interaction effect of recession with education/union.

The formal regression is:

$$\begin{aligned} Y_{istd} =& \beta_0 + \beta_1 license_{ist} + \beta_2 post + \beta_3 license_{ist} \times post \\ &+ a_{s,p} + a_{s,p} \times post + \Gamma X_{ist} + \theta_s + \theta_p + e_{istp}. \end{aligned} \tag{1}$$

β_1 represents the baseline unemployment gap between licensed and unlicensed workers during non-recessionary times. The coefficient β_3 on the interaction term '$license_{ist} \times post$, our parameter of interest, measures how the unemployment gap between licensed and unlicensed workers changes after the recession compared to the value of the unemployment gap prior to the recession. If β_3 is negative, occupation license is "shielding" licensed workers from increases in unemployment during the recession (compared to their unlicensed peers) by an amount equal to the magnitude of the coefficient of interest. For example, if the estimated treatment effect from the model were -0.00957, this would suggest that licensing shields workers from a 0.96 p.p. increase in unemployment. We require three assumptions to hold for us to interpret β_3 as a causal parameter. First, we need to assume that in the absence of the recession the unemployment gap between unlicensed and licensed workers would have evolved similarly in the postperiod to its path in the preperiod. Second, we need to assume that the timing of the recession is orthogonal to other treatments that could have shielded licensed workers from unemployment compared to their unlicensed peers. Third, we need to assume that our measure of prelabor market ability is a valid proxy for controlling for selection.

3 Results from COVID-19 Recession

We begin our analysis by presenting the variation in the data transparently using an event study inspired by the difference-in-differences approach in Equation 1:

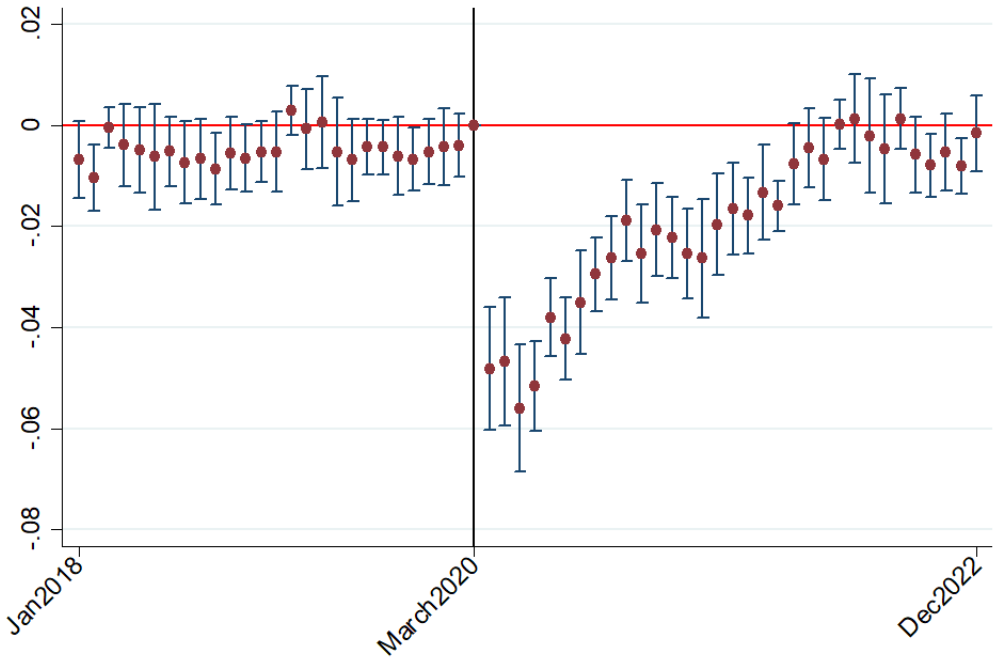
$$\begin{aligned} Y_{istp} =& \alpha_0 + \alpha_1 license_{ist} + \sum_{\tau \neq -1} \alpha_\tau \times \mathbb{1}(\tau = t - t^*) \times license_{ist} \\ &+ a_{s,p} + a_{s,p} \times post + \Gamma X_{ist} + \theta_s + \theta_t + \theta_p + e_{istp}, \end{aligned} \tag{2}$$

where the outcome remains the unemployment status of a worker and the parameters of interest are the α_τ, which capture the average unemployment difference between licensed and unlicensed workers in time 'τ,' relative to its value in the event month immediately preceding the recession $\tau = -1$, i.e., March 2020 (where t^* equals April 2020).

We present the result of the event study in Figure 2, where the y-axis measures the average difference in the probability of unemployment between licensed workers and

unlicensed workers in a given period of time, relative to its value in $\tau = -1$. We call this difference the relative unemployment gap. In the period before the recession, we did not see substantial differences in the relative unemployment gap. In fact, the unemployment gap bounces between zero and one percentage point, and all confidence intervals overlap. In contrast, when the COVID-19 recession hit in March 2020, we see an immediate and statistically significant decrease in the unemployment rate of licensed workers compared to that of unlicensed workers. Initially, licensed workers are 4 percentage points less likely to be unemployed than their unlicensed peers. Over the next 23 months licensed workers continue to be differentially shielded from the increase in unemployment from COVID-19. Following at 24-month mark, we return to the pre-recession baseline.

Figure 2: Licensing Workers Shielded from job loss during COVID-19 Recession



Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: Sample includes individuals between 18 and 65 who are in the labor force. The panel shows the difference between the unlicensed and the licensed in unemployment with a 95 percent confidence interval. The specification follows column 1 of Table 3. Sample weights apply. Standard errors are clustered at the state level.

In Table 3, we report the results of our analysis in which we estimate the difference in the average unemployment rate between licensed and unlicensed workers in the two years after the COVID-19 recession compared to its value in the two years before the recession, using the difference-in-difference regression from Equation 1. In column (1) of Table 3 we report results from a model that only includes control variables for worker de-

mographics and state-fixed effects and occupation-by-month fixed effects. The model in column (2) includes our measure of pre-labor market ability and an interaction between ability and the *post* recession indicator. In column (3), we add an interaction between an indicator for whether the worker i completed a four-year college degree and the '*post*' recession indicator since licensed workers are on average more educated than unlicensed workers and that workers with more education are protected from unemployment during COVID-19 as in Beuermann et al. (2024). In column (4), we add an interaction between the worker union status and the '*post*' recession indicator. In column (5) we drop observations from all universally licensed occupations since these occupations are licensed in all states and therefore do not contribute any identifying variation. Dropping universally licensed occupations also tests whether the shielding effect of licensing during COVID-19 was driven by an increase in demand for medical professionals since many professions in the medical field are universally licensed, e.g., physicians and nurses.

Leveraging cross state variation in licensing laws, in column (1), we find that licensing shields workers from a 1.37 p.p. increase in unemployment. Moreover, it compounds inequality between licensed and unlicensed workers, since licensed workers were already 0.66 p.p. less likely to be unemployed than unlicensed workers prior to the recession. The result is statistically significant at the level 1%, with a t-statistics of 8.9. Controlling for ability, we find a statistically significant shielding effect of 1.25 pp, which is roughly 9% smaller that what we found in the base case. Our ability measure matters, but can not explain away the main effect that we estimate. Adding an interaction between worker education and the COVID-19 indicator, we find that occupational licensing shields workers from a 0.78 p.p. increase in the unemployment rate above and beyond what could be explained by differences in education levels and the unemployment shielding effect of education during recessions as shown in Beuermann et al. (2024). When we add controls the interaction between union status and the COVID-19 indicator, we estimate a shielding effect of 0.72 p.p., which is also statistically significant at the 1% level. When we drop universally licensed occupations, our fully saturated model outputs a shielding effect of 1.01 p.p., which is also statistically significant at the 1% level. The estimates from the full sample in column (4) are therefore a conservative estimate of the shielding effect of licensing.

Taking the most conservative estimate in column (4), the shielding effect of licensing during the recession represents 19% of the raw gap in the post-COVID-19 unemployment rate between unlicensed and licensed workers or 25% of the pre-pandemic gap in unemployment rate (see Table 1 for the gaps in unemployment rates). Because unlicensed workers were already more likely to be unemployed than unlicensed workers prior to

COVID-19, the shielding effect of licensing during the recession further exacerbates labor market inequality by licensure status. In fact, in the saturated model with the full sample, we found that unlicensed workers were 1.01 p.p. more likely to be unemployed than licensed workers before COVID-19 and this gap nearly doubles to 1.73 p.p. in the aftermath of the COVID-19 recession. Another angle to interpret the shielding effect is to see by how much licensing shields workers against an unemployment shock. Using the unemployment impact of Covid as a comparison (the coefficient of 'Covid'), licensing shields workers from 21% (column 4) and 33% (column 5) of the unemployment shock induced by COVID-19.

Table 3: Licensure Shields Workers from Unemployment during COVID-19 Recession

	(1)	(2)	(3)	(4)	(5)
$license_{os}$ x covid	-0.0137***	-0.0125***	-0.00783***	-0.00719***	-0.0101***
	(0.00153)	(0.00131)	(0.00109)	(0.00108)	(0.00168)
$license_{os}$	-0.00656***	-0.00721***	-0.00972***	-0.0101***	-0.00592***
	(0.00157)	(0.00143)	(0.00143)	(0.00142)	(0.00186)
covid	0.0243***	0.0314***	0.0329***	0.0331***	0.0332***
	(0.00209)	(0.00317)	(0.00318)	(0.00321)	(0.00332)
Observations	3,003,290	3,003,290	3,003,290	3,003,290	2,637,141
R-squared	0.033	0.033	0.033	0.033	0.033
State FE	X	X	X	X	X
Occ x Month FE	X	X	X	X	X
Ability		X	X	X	X
College x Covid			X	X	X
Union x Covid				X	X
Drop Universal					X

Data: IPUMS Monthly Current Population Survey (2018 - 2022).

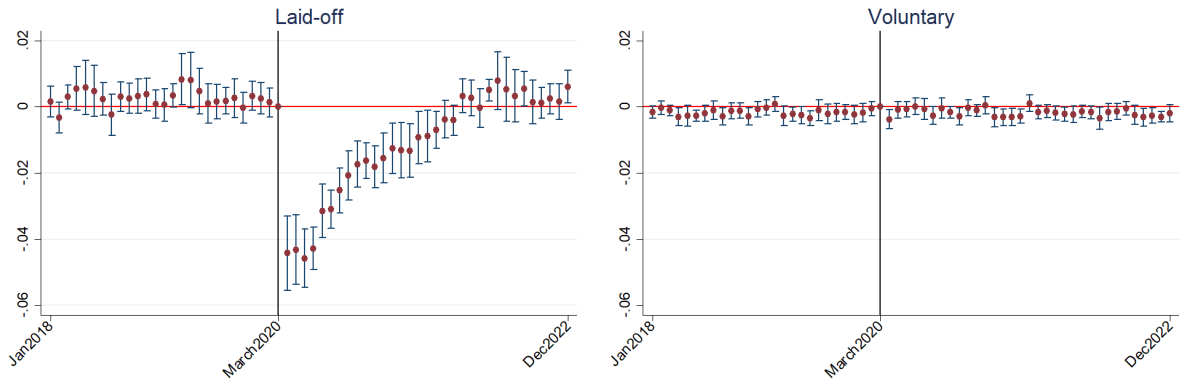
Note: Dependent variable in all regressions is an unemployment indicator. Sample includes individuals between 18 and 65 who are in the labor force. All regressions control for demographic characteristics (age, race and ethnicity, gender), a college indicator, a union indicator, a public sector indicator, a self-employed indicator, an indicator of whether the license is required by the job, an indicator of possessing a professional certification, and state fixed effects. The 22 universal defined by Johnson and Kleiner (2020b) include elementary/secondary school teacher, lawyer, barber/cosmetologist, real estate broker/agent, electrician, insurance agent, pharmacist, EMT/paramedic,real estate appraiser/assessor, pest control worker, chiropractor, nurse (RN/LPN), physician, social worker, occupational and physical therapist, psychologist, dental hygienist, dentist, physician assistant, veterinarian, optometrist, and podiatrist. Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

3.1 Testing Labor Supply and Labor Demand Responses as Mechanisms

The effect we estimate could be driven by the responses on the labor supply side or labor demand side. In this subsection, we offer two tests for which mechanism is operative. In Figure 3 we estimate our event study of changes in the relative unemployment gap separately by layoffs (which we consider to be more closely related to a negative labor

demand shock) and voluntary quits (which we consider to be more closely related to a labor supply decision), using the basic difference-in-difference approach (Equation 2). Here we find that licensing shields workers from job loss due to layoffs in states that implement lockdown, but there is no impact of licensing on voluntary quits.

Figure 3: Licensing Reduces Job Loss due to Layoffs in COVID-19



Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: Sample includes individuals between 18 and 65 who are in the labor force. This figure compares the time dummies of the shielding effect of licensing on laidoff (left) and voluntary separation (right) with a 95% confidence interval, using the DID full specification. Sample weights apply. Standard errors are clustered at the state level.

For the second test, we measure whether occupational licensing protects licensed workers more strongly in places that were more severely hit by the recession. In the beginning of COVID-19, 42 states plus the District of Columbia implemented a statewide lockdown order, while the rest of the eight did not. The eight states include Arkansas, Iowa, Nebraska, North Dakota, South Dakota, Oklahoma, Utah, and Wyoming. Although both sets of states experienced a common labor supply shock from COVID-19, states that imposed a lockdown experienced a more severe negative labor demand shock due to the government order (Alexander and Karger, 2023). The results in Brotherhood et al. (2020) suggest that the optimal lockdown policy in the US should have been stricter than it was.

To test whether licensing differentially protected licensed workers from job loss during COVID-19-induced recession in states that experienced a larger decline in labor demand, we augment Equation 1 with a triple differences design, comparing the shielding effect of licensing in states with and without lockdown orders (the base terms in a triple-differences model are absorbed by the fixed effects). We estimate the following regression:

$$\begin{aligned} Y_{istp} =& \delta_0 + \delta_1 license_{ist} + \delta_2 license_{ist} \times post \\ &+ \delta_3 lockdown_s \times post + \delta_4 license_{ist} \times lockdown_s \times post \\ &+ a_{s,p} + a_{s,p} \times lockdown_s \times post + \Gamma X_{ist} + \theta_s + \theta_t + \theta_p + e_{istp}, \end{aligned} \tag{3}$$

where $lockdown_s \times post$ is an interaction between an indicator for states that imposed a lockdown and the *post* indicator that equals one or all time periods following the onset of the recession. Our coefficient of interest is δ_4 which measures whether licensing differentially shielded licensed workers from unemployment during COVID-19 in states that implemented a lockdown compared to states that did not impose a lockdown.

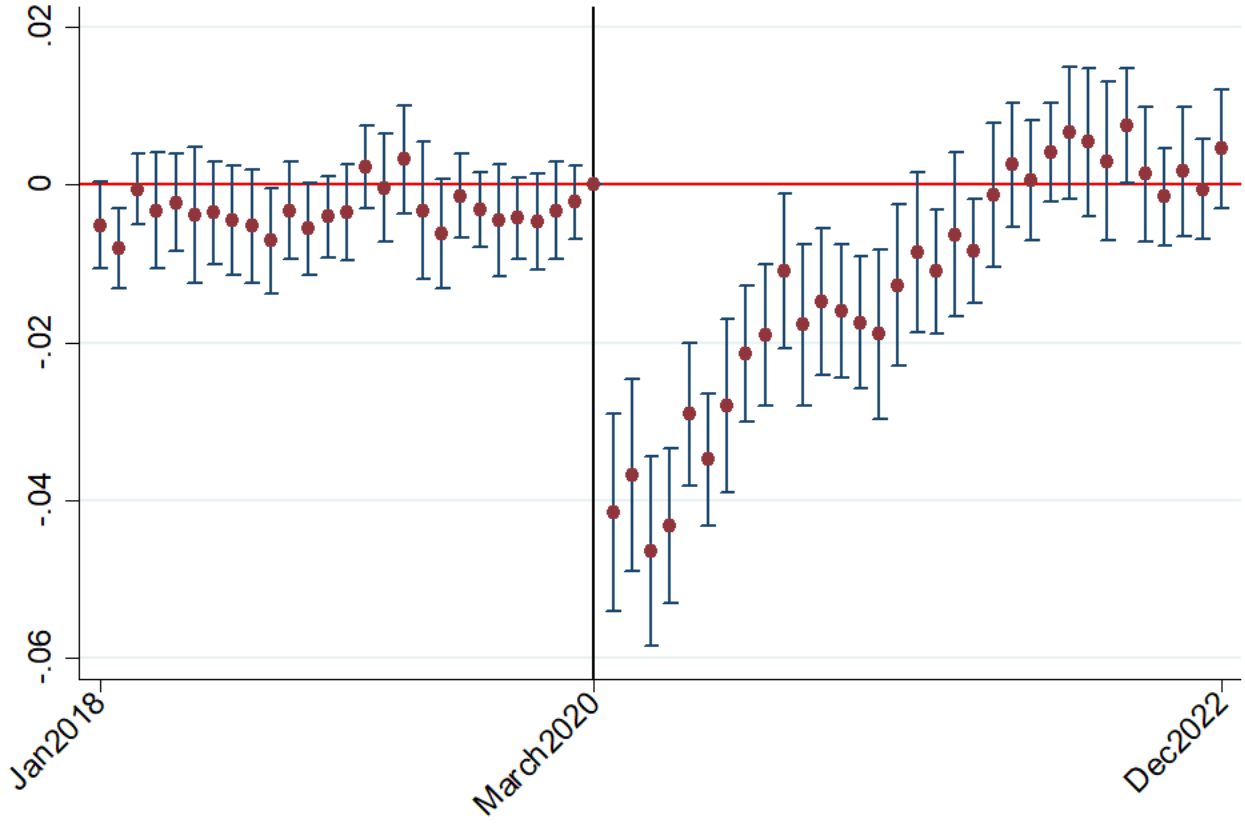
The identification of δ_4 as a causal parameter relies on the idiosyncratic timing of COVID-19 and the emergency reaction of the state governments to issue lockdown orders in response to COVID-19. We also assume that the unanticipated variation in lockdown decision by state is orthogonal to an individual's licensing decision; therefore, pre-lockdown selection is unlikely to bias the causal interpretation of δ_4. Pre-pandemic sorting by workers is further accounted for by the coefficient δ_2 on the base term $license_{ist}$, which allows for the natural level of unemployment to be different between licensed and unlicensed workers before the pandemic — consistent with the finding in Kukaev and Timmons (2024) that licensed workers experience lower levels of unemployment and shorter unemployment spells during non-recessionary times. One might still worry that post-lockdown sorting of workers into licensing could generate our results by reverse causality: individuals could choose to get a license because of the recession. Although this type of sorting is possible in theory, fulfilling all requirements is not instantaneous in practice, especially during a pandemic that resulted in the closure of most services. Another potential threat to identification is the endogeneity of lockdown decision to the state of the local economy.

We assess the possibility of post-lockdown sorting with two approaches. We first test whether the proportion of people who report a license changes around the time of the COVID-19 pandemic (Online Appendix Figure A1). There is no significant change or trend in individuals' license attainment before and after the shock. We perform a second set of tests, regressing observable characteristics of individuals, e.g., race, age, educational attainment, on the interaction between license status and event time dummies (Online Appendix Figure A2). We do not observe significant changes in the observable characteristics of licensed workers as a result of the pandemic. Both tests suggest that reverse causality is unlikely to drive any results that we find. We also test the orthogonality between the state unemployment rate in 2018 and 2019 and the state lockdown decision in 2020 (Online Appendix Table A2).[7] We do not find significant predictive power of these variables on whether a state adopts a stay-at-home order in 2020.

In Table 4, we report the results that we obtain by estimating Equation 3 with varying

[7] We also include the percent of workers in the state who have a license or professional certification, are self-employed, the mean hourly wage, and the racial composition of the state in both 2018 and 2019.

Figure 4: Event Study of Triple-Differences Estimate



Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: The figure traces the event dummies of the triple-differences coefficient with the 95% confidence interval. The specification corresponds to column 1 of Table 4. Sample weights apply. Standard errors are clustered at the state level.

levels of control variables, following the structure of Table 3. Focusing on the coefficient from the triple interaction term license × lockdown × covid, we find that occupational licensing reduces the negative impact of the recession 1.28 to 1.47 p.p. more in states that experienced the recession most severely.[8] Figure 4, we present the results of an event study in which we plot the coefficient on the triple interaction between license × lockdown × post. We find that in states with lockdowns, which are the states that experience the largest increase in unemployment during the recession, licensed workers are shielded from a 4 p.p. increase in unemployment at the onset of the COVID-19 recession and that this shielding eventually fades out after 20 months.

[8]Consistent with the notion that lockdowns were a negative shock to labor demand, we find that states that imposed lockdowns experienced a higher unemployment rate of 1.62 to 2.39 p.p. (see the coefficient on lockdown × post).

Table 4: Job Shielding Effect of Licensing during COVID-19 recession strongest in states imposing Lockdowns

	(1)	(2)	(3)	(4)	(5)
$license_{os}$ x lockdown x covid	-0.0147***	-0.0134***	-0.0130***	-0.0128***	-0.0141***
	(0.00244)	(0.00242)	(0.00239)	(0.00238)	(0.00301)
$license_{os}$ x covid	-0.000558	-0.000516	0.00117	0.00147	0.00141
	(0.00209)	(0.00219)	(0.00218)	(0.00220)	(0.00274)
$license_{os}$	-0.00528***	-0.00594***	-0.00701***	-0.00726***	-0.00412**
	(0.00148)	(0.00135)	(0.00135)	(0.00134)	(0.00176)
lockdown x covid	0.0162***	0.0239***	0.0227***	0.0227***	0.0225***
	(0.00276)	(0.00370)	(0.00358)	(0.00360)	(0.00359)
Observations	3,003,290	3,003,290	3,003,290	3,003,290	2,637,141
R-squared	0.041	0.041	0.042	0.042	0.041
Time FE	X	X	X	X	X
State FE	X	X	X	X	X
Occ x Month FE	X	X	X	X	X
Ability + Ability x covid		X	X	X	X
College x Covid			X	X	X
Union x Covid				X	X
Drop Universal					X

Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: Dependent variable in all regressions is an unemployment indicator. The sample includes individuals aged 18 to 65 years who are in the labor force. XX Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

In Table 5, we reproduce the DID and the lockdown specification by varying the threshold in which we used 35% as the main cutoff to define whether a state-occupation requires a license. From a stringent threshold of 50% in column (1) to a lenient threshold of 30% in column (5), the shielding estimates remain stable in effect sizes. The insensitivity to different cutoffs alleviate the concern that the threshold rule may assign inaccurate license status to workers.

Table 5: Results Consistent across Licensing Thresholds

	(1)	(2)	(3)	(4)	(5)
Threshold	0.5	0.45	0.4	0.35 (main)	0.3
$license_{os}$ x covid	-0.00660***	-0.00673***	-0.00724***	-0.00719***	-0.00742***
	(0.000965)	(0.000968)	(0.00106)	(0.00108)	(0.00105)
$license_{os}$	-0.0113***	-0.0120***	-0.0112***	-0.0101***	-0.00964***
	(0.00214)	(0.00211)	(0.00178)	(0.00142)	(0.00129)
covid	0.0332***	0.0332***	0.0332***	0.0331***	0.0331***
	(0.00319)	(0.00319)	(0.00320)	(0.00321)	(0.00323)
R-squared	0.033	0.033	0.033	0.033	0.033
$license_{os}$ x lockdown x covid	-0.0112***	-0.0117***	-0.0117***	-0.0128***	-0.0131***
	(0.00250)	(0.00234)	(0.00232)	(0.00238)	(0.00221)
$license_{os}$ x covid	-0.000397	0.000283	-3.80e-05	0.00147	0.00166
	(0.00241)	(0.00224)	(0.00228)	(0.00220)	(0.00198)
$license_{os}$	-0.00770***	-0.00875***	-0.00800***	-0.00726***	-0.00704***
	(0.00202)	(0.00200)	(0.00170)	(0.00134)	(0.00120)
lockdown	0.0225***	0.0226***	0.0225***	0.0227***	0.0228***
	(0.00355)	(0.00355)	(0.00356)	(0.00360)	(0.00362)
R-squared	0.042	0.042	0.042	0.042	0.042
Observations	3,003,290	3,003,290	3,003,290	3,003,290	3,003,290

Data: IPUMS Monthly Current Population Survey (2018 - 2022).

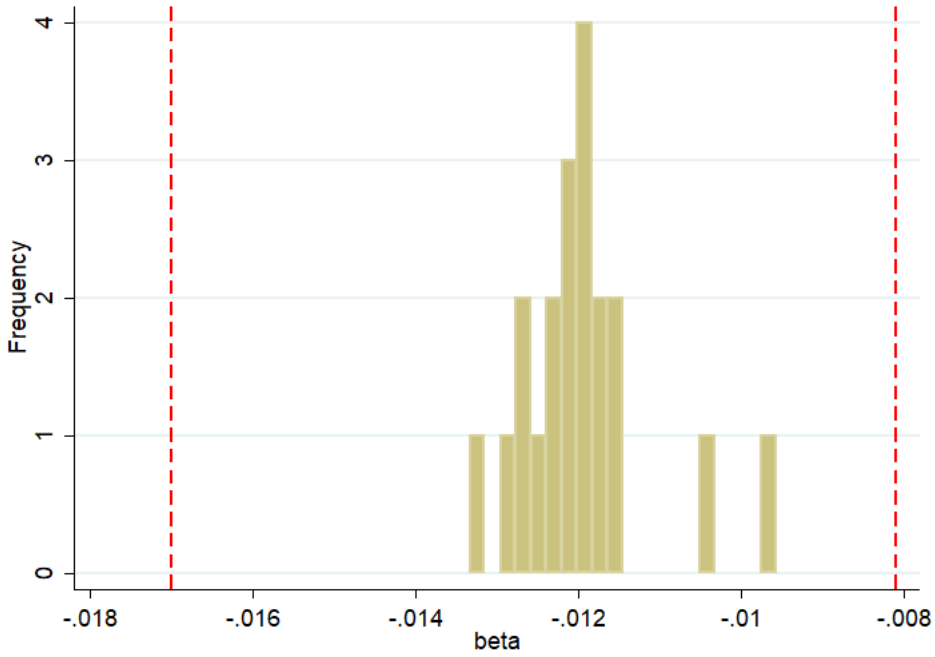
Note: Dependent variable in all regressions is an unemployment indicator. The sample includes individuals between 18 and 65 who are in the labor force. In Panel B, time fixed-effects absorb the 'Covid' indicator. For comparison, column 4 in both panels replicate the corresponding estimates using the fully saturated model. Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

Across many dimensions of heterogeneity, we also find that licensed workers experience less job loss during recessions than their unlicensed peers. For example, licensed workers who are college educated and licensed workers without college degrees both experience less job loss during recessions compared to their unlicensed peers (Online Appendix Figure A3). This result holds notwithstanding the research showing that workers without college degrees experience more downward mobility (Autor, 2014; Blair et al., 2021). In both red and blue states, we document a similar impact of licensing on protecting workers from recession-induced job loss, as shown in Figure A3.[9] The only ex-

[9]We define the political affiliation of a state based on the 2016 presidential election.

ception to the homogeneity of the treatment effects is that licensing appears to provide stronger protection from recession-induced job loss for workers in the private sector than for workers employed by the government. The job shielding effect of licensing appears to be consistent across industries. Notably, we show in Figure 5 that dropping all observations from any one of the 20 industries and re-estimating the model does not yield substantial departures from the average treatment effect that we obtain from using all industries. In fact, all 20 industry permutations fall within the 95% confidence interval of the main treatment effect using the lockdown shock.

Figure 5: Job Shielding Impact of Licensing during COVID-19 Similar Across Industries



Note: This figure plots the distribution of the 20 estimates on the shielding effect of licensing by dropping the 20 industries one at a time using lockdown shock (comparable to column 4 of Table 4). The red line marks the 95% confidence interval of the main estimate. The raw coefficients in the 20 iterations are all significant at 1% level. All coefficients center around the ATE (-0.0128) obtained in column 4 of Table 4.

4 Generalizing the Results to the Great Recession

We tested the generalizability of our findings by applying our research design to the Great Recession using monthly employment and demographic data from the CPS. In total we have 3.9 million worker-month observations in the two years before and after the Great Recession, i.e., January 2006 to December 2010. Because continuous data on self-reported licensing were sparse before 2015, we construct a state-by-occupation measure

of licensing that is contemporaneous with the Great Recession by combining data from three sources: 1) a topical module on occupational licensing from the 2008 Survey of Income and Program Participation (Gittleman et al., 2018), 2) data from the American Bar Association (ABA) on licensing statutes that have restrictions on felons (Blair and Chung, Forthcoming), and 3) data on occupations that are universally licensed (Kleiner et al., 1982; Johnson and Kleiner, 2020b).

The 2008 SIPP data are the first nationally representative household survey that contains individual license attainment. We follow the threshold rule of 50% used in the literature to define a state-occupation as licensed if more than 50% of individuals report requiring a license to work in the corresponding state-occupation cell. Defining a state-occupation measure of licensing from the SIPP data permits us to combine it with the ABA licensing data and the data on universally licensed occupations which are both reported at the state-occupation level.[10] We code a worker as licensed if the worker is working in a state where the occupation is coded as requiring a license in any of the three data sets that we have assembled. We find that 29% of the individuals in the CPS (2006-2010) sample are coded as licensed, using this definition. Because one of the three data sources, that is, 2008 SIPP, comes from a time period that follows the Great Recession, we were concerned that our estimate of the fraction of licensed workers could be subject to measurement error.[11] To test this, we compared our fraction of licensed workers with the fraction of licensed workers estimated by Kleiner and Krueger (2013) in 2008 using a Gallup survey. They find that 29% of the workers are licensed, which is similar to what we find within a few decimal points.

As was the case with the summary statistics for the window around the COVID-19 recession, the summary statistics for the Great Recession make it intriguing to consider whether occupational licensing protects licensed workers from job loss during recessions above and beyond what could be explained by selection on observable worker characteristics. In Table 6 we report the means before the Great Recession and after the Great Recession of our outcome of interest, the unemployment rate, and demographic characteristics separately for licensed and unlicensed workers. In the pre-Great Recession period, we find that licensed workers are less likely to be unemployed by 1.94 p.p. and they also appear to be selected on each of the individual characteristics. Likewise, in the post-Great Recession period we also find that licensed workers are less likely to be unemployed than unlicensed workers by 3.61 p.p. and they are also selected on seven of the nine individual characteristics.

[10] We use the 6-digit SOC code to define an occupation.

[11] However, the licensing data were only collected during its Wave 13 in 2012/2013.

When we examine the difference in the difference measure, licensed workers are on average 1.67 p.p. less likely to experience job loss during the recession than their unlicensed peers. Examining the difference in the difference for the nine demographic characteristics, we find that they are each economically small and that five of the nine are statistically indistinguishable from zero. In the four cases where the difference-in-differences for the individual characteristics are statistically significant, i.e., female, union membership, government employee and self-employed, the magnitudes of the difference-in-differences are economically small — ranging from 3.8% to 1.5% of the pre-Great Recession mean for both licensed and unlicensed workers.

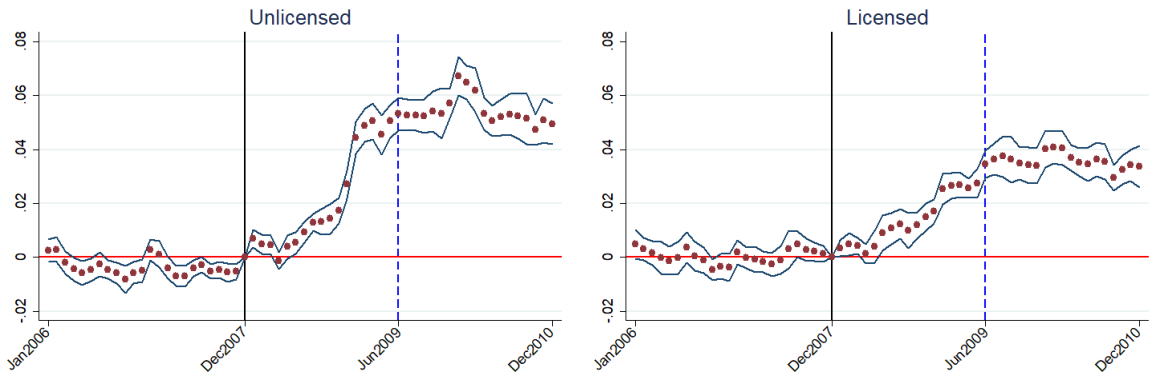
Table 6: Average Unemployment and Demographics by License Status before and after the Great Recession

	Pre-Great Recession			Post-Great Recession			
	Unlicensed	Licensed	Diff	Unlicensed	Licensed	Diff	Diff-in-Diff
Outcome							
unemployed	0.051	0.031	-0.0194***	0.092	0.056	-0.0361***	-0.0167***
			(0.00101)			(0.00162)	(0.00150)
Individual Characteristics							
female	0.432	0.538	0.106***	0.433	0.546	0.113***	0.00667***
			(0.0102)			(0.00964)	(0.00243)
age	39.511	41.247	1.737***	39.901	41.562	1.661***	-0.0752
			(0.173)			(0.207)	(0.0923)
black	0.116	0.116	-0.000289	0.117	0.116	-0.00113	-0.000839
			(0.00435)			(0.00425)	(0.00136)
hispanic	0.155	0.110	-0.0442***	0.161	0.117	-0.0444***	-0.000132
			(0.00856)			(0.00904)	(0.00192)
asian	0.046	0.045	-0.000984	0.048	0.047	-0.000916	-0.000068
			(0.00259)			(0.00216)	(0.00117)
union membership	0.240	0.256	0.0163***	0.230	0.252	0.0220***	0.00574***
			(0.00284)			(0.00257)	(0.00106)
college	0.250	0.435	0.186***	0.259	0.447	0.188***	0.00262
			(0.00765)			(0.00790)	(0.00329)
govt	0.117	0.201	0.00931***	0.118	0.206	0.0878***	0.00387**
			(0.0110)			(0.0116)	(0.00184)
self employed	0.102	0.111	0.00862***	0.098	0.103	0.00548*	-0.00383**
			(0.00289)			(0.00281)	(0.00156)
Observations	1137463	442252		1685915	663237		

Data: Monthly CPS (Jan 2018 to Dec 2022)

Note: 'Licensed' refers to individuals who work in a licensed state-occupation defined using the data described in Section 4. 'Pre-Recession' refers to the period before Dec 2007. Sample weight apples. Standard errors are clustered at the state level in testing differences.

Figure 6: Descriptive Pattern in 2008 Recession



Data: IPUMS Monthly Current Population Survey (2006 - 2010).

Note: Sample includes individuals between 18 and 65 who are in the labor force. The upper panel compares the unemployment pattern by plotting the time dummies between unlicensed and licensed workers, conditional on basic characteristics (age, race, gender, education). The lower panel shows the difference between the unlicensed and the licensed with a 95 percent confidence interval. We define 'licensed' using external data sources described in this section. Sample weights apply. Standard errors are clustered at the state level.

In Figure 6 we use an event study to illustrate the difference in the unemployment rate before and after the Great Recession for unlicensed workers and unlicensed workers – using the month before the Great Recession as a benchmark. Both licensed and unlicensed individuals experienced a gradual increase in unemployment beginning in December 2007. In the latter part of 2008, we observe a more rapid increase in unemployment for unlicensed workers than for licensed workers. This period coincides with the failure of Lehman Brothers in September 2008, which accelerated the financial crisis during the Great Recession.

In Table 7, we report the results of our analysis in which we estimate the difference in the average unemployment rate between licensed and unlicensed workers in the two years after the Great Recession compared to its value in the two years prior to the Great Recession, using the difference-in-difference regression from Equation 1 and the state-occupation-level measure of licensing. Since the license variable is defined at the state-occupation level, this limits the variation to include occupation fixed effects and the state-occupation ability proxies. In column (1) of Table 7, we report results from a model that only includes control variables for worker demographics and state fixed effects. In column (2) we enrich the model to include industry fixed effects. In column (3) we add an interaction between an indicator for whether worker i completed a four-year college degree and the '*post*' recession indicator. In column (4), we include an interaction between worker union status and the recession indicator. In column (5) we control for differences in regional time trends. In column (6), we drop observations from all universally licensed occupations.

Table 7: Licensure Shields Workers from Unemployment during the Great Recession

	(1)	(2)	(3)	(4)	(5)	(6)
license × post	-0.0165***	-0.0167***	-0.0124***	-0.0121***	-0.0122***	-0.0111***
	(0.00145)	(0.00142)	(0.00120)	(0.00115)	(0.00120)	(0.00135)
license	-0.00722***	0.000994	-0.00159	-0.00182*	-0.00173	-0.00135
	(0.00103)	(0.00114)	(0.00107)	(0.00105)	(0.00107)	(0.00145)
post	0.0419***	0.0422***	0.0481***	0.0487***	0.0142***	0.0128***
	(0.00303)	(0.00309)	(0.00367)	(0.00373)	(0.00173)	(0.00174)
Observations	3,928,867	3,928,867	3,928,867	3,928,867	3,928,867	3,496,543
R-squared	0.031	0.038	0.038	0.039	0.041	0.040
Ind FE		X	X	X	X	X
College x recession			X	X	X	X
Union x recession				X	X	X
Regional trend					X	X
Sample	All workers					No universal licenses

Data: IPUMS Monthly Current Population Survey (2006 - 2010).

Note: Dependent variable in all regressions is an unemployment indicator. The sample includes individuals between 18 and 65 who are in the labor force. 'Recession' refers to the period after the mid-point of the recession (Dec 2007). 'License' is defined using the 50% threshold at the state-occupation level pooled from SIPP Panel 2008, the universal licensed professions (Johnson and Kleiner, 2020b), and the felony license data. All regressions control for demographic characteristics (age, race and ethnicity, gender), a college indicator, a union indicator, a public sector indicator, a self-employed indicator, an indicator of whether the license is required by the job, an indicator of possessing a professional certification, state fixed effects. Sample weights apply. Standard errors are clustered at the state level.

Based on the model specification in column (1), we find that licensing shields workers from a 1.65 p.p. increase in unemployment. The result is statistically significant at the 1% level. Adding industry fixed effects increases the magnitude of the shielding effect of licensing slightly to 1.67 p.p., without altering the level of significance at the 1% level. Relative to the model with industry fixed effects, the model in which we control for ability – as measured by college degree attainment in column (2) – exhibits a statistically significant shielding effect of 1.24 p.p., which is roughly 26% smaller.[12] Had we not controlled for differences in education, our estimate of the shielding effect of occupational licensing would have been subject to a substantial amount of omitted variable bias.

Among the checks that we perform in columns (4) to (6) of Table 7, dropping the observations from the universally licensed occupations reduces our estimate of the shielding effect of licensing the most, reducing it from 1.24 p.p. to 1.11 p.p. Even then, the estimate of our coefficient of interest remains statistically significant at the 1% level. The shielding effect of licensing of 1.11 p.p. represents 31% of the gap in the post-Great Recession unemployment rate between unlicensed and licensed workers or 56% of the pre-pandemic gap in the unemployment rate. Compared to what we found with the COVID-19 recession, the shielding effect of licensing during the Great Recession is of a similar magnitude,

[12] In our main results we do not employ the three ability measures (math, English, science) since they are tabulated using the survey after 2008.

i.e., 1.11 p.p. versus 0.82 p.p., suggesting that the phenomenon we document is a general phenomenon.

4.1 Recession Intensity using Industry Bartik Shocks

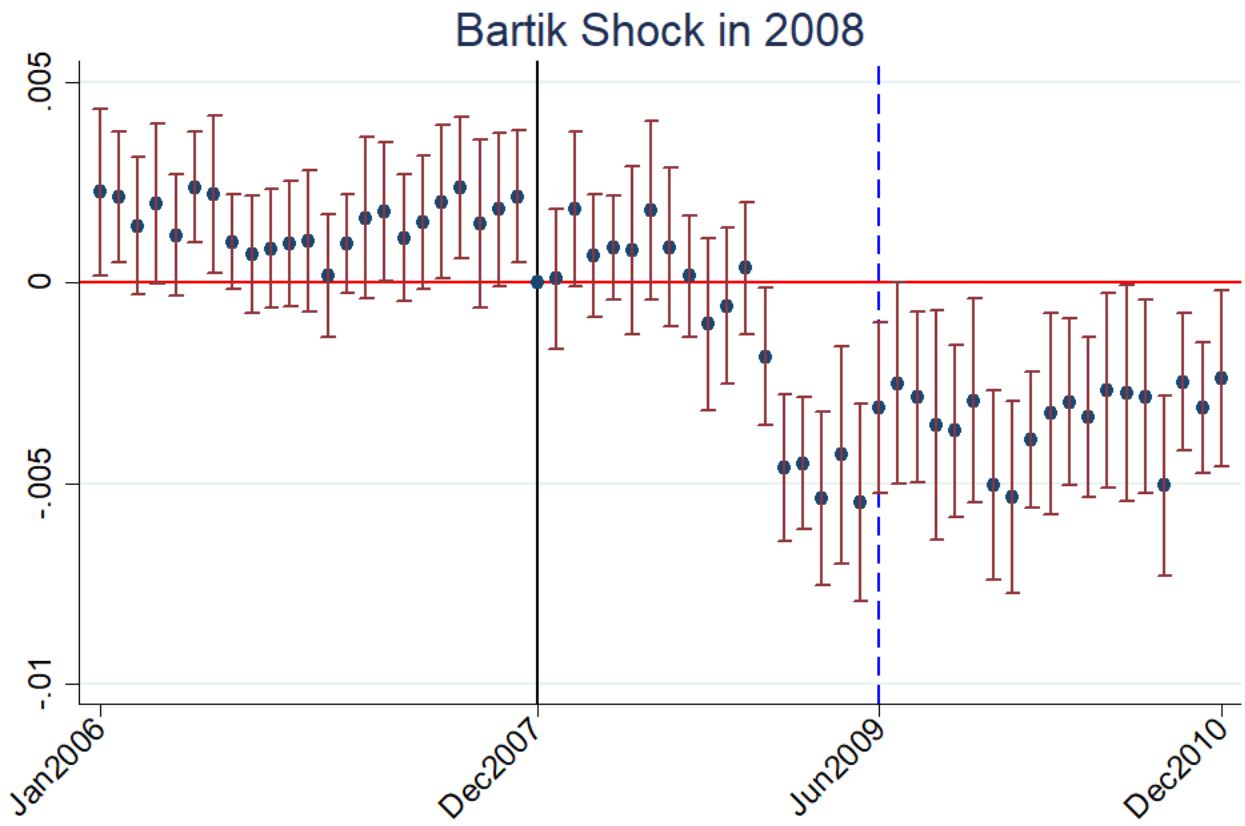
From our analysis of the COVID-19-induced recession, we found that occupational licensing shielded workers from job loss in places hardest hit by the recession. Was this also the case during the Great Recession? We follow Hershbein and Kahn (2018) in using Bartik shocks as a source of plausibly exogenous variation in exposure to negative labor demand shocks during the Great Recession. The Bartik shocks provide simulated unemployment changes in a Metropolitan Statistical Area (MSA) during the Great Recession by projecting national shocks to unemployment by industry (during the recession) onto MSAs using the MSA industry shares from 2004 and 2005 — a few years before the Great Recession. We regress an indicator for whether an individual 'i' in MSA 'c' living in state 's' at time 't' working in occupation 'p' and industry 'd' is unemployed (Y_{icstpd}) on an indicator for whether the individual workers in a licensed occupation and a triple interaction between the license indicator, a post-recession indicator and the value of the simulated employment shock to the MSA measured by '$Bartik'_c$. The exact empirical specification that we run is:

$$\begin{aligned} Y_{icstd} =& \beta_0 + \beta_1 license_{ist} + \beta_2 Bartik_c + \beta_3 Bartik_c \times post \\ &+ \beta_4 license_{ist} \times Bartik_c \times post + \Gamma X_{ist} + \theta_s + \theta_t + \theta_d + e_{icstd}, \end{aligned} \tag{4}$$

where the control variables are the same as in Equation 1. Our coefficient of interest, β_4, measures the average difference in the shielding effect of occupational licenses during the Great Recession between an MSA predicted to be in the 90th versus the 10th percentile of the recessionary unemployment shock. Negative values of β_4 imply that licensing offers stronger protection from job loss for licensed workers in MSAs hardest hit by the Great Recession.

In Figure 7 we plot event study estimates of β_4 over time relative to its value in December 2007, which marked the beginning of the Great Recession. Qualitatively, we see that prior to the Great Recession there was no difference in the relative unemployment gap between licensed and unlicensed workers as a function of how hard an MSA is predicted to be during the Great Recession. In the months after Lehman Brothers failed, we see the emergence of a gap between places that are predicted to be hit harder by the Great Recession in how insulated licensed workers are from job losses as compared to unlicensed workers.

Figure 7: Event Study of Shielding Effect - 2008 Bartik Shock



Data: IPUMS Monthly Current Population Survey (2006 - 2010).

Note: This figure plots the time dummies of the shielding effect using Bartik exposure to measure shock intensity (Hershbein and Kahn, 2018). The dependent variable in all regressions is an unemployment indicator. The sample includes individuals between 18 and 65 who are in the labor force. Sample weights apply. Standard errors are clustered at the state level.

In Table 8, we present estimates of the average value of β_3 for increasingly rich implementations of Equation 4. To begin with, the Bartik shock captures a meaningful variation in the intensity of the Great Recession. A one-unit increase in the Bartik shock predicts an increase in the unemployment rate of 1.65 p.p. to 2.27 p.p. during the Great Recession. Occupational licensing, however, dampens the increase in the unemployment rate by an average of 0.30 p.p. to 0.44 p.p. for licensed workers in MSAs in the 90th percentile of the Bartik shock distribution when compared to their peers in MSAs in the 10 percentile. As was the case with COVID-19 results, controlling for educational attainment reduces the omitted variable bias of β_4 the most (by 25%). In our most stringent specification, we estimate that the magnitude of the shielding effect of occupational licensing is larger by 0.30 p.p. (or 18%) in MSAs that are hardest hit by negative labor demand shocks during the Great Recession – mirroring the lockdown results from the COVID-19 analysis.

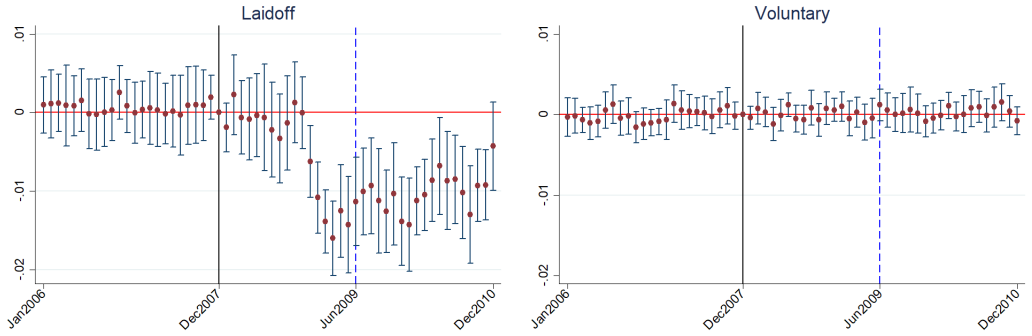
Table 8: The Shielding of Licensing in 2008 - Bartik Shock

	(1)	(2)	(3)	(4)	(5)	(6)
lic. × Bartik × post	-0.00436***	-0.00441***	-0.00327***	-0.00317***	-0.00318***	-0.00297***
	(0.000363)	(0.000355)	(0.000320)	(0.000311)	(0.000331)	(0.000386)
license (lic.)	-0.00723***	0.000635	-0.00197*	-0.00219**	-0.00217**	-0.00216
	(0.000960)	(0.00113)	(0.00109)	(0.00109)	(0.00108)	(0.00147)
Bartik × post	0.0214***	0.0222***	0.0218***	0.0215***	0.0165***	0.0177***
	(0.00498)	(0.00512)	(0.00485)	(0.00495)	(0.00347)	(0.00341)
Observations	2,673,125	2,673,125	2,673,125	2,673,125	2,673,125	2,376,333
R-squared	0.034	0.041	0.042	0.042	0.042	0.042
Ind FE		X	X	X	X	X
College × Bartik × post			X	X	X	X
Union × Bartik × post				X	X	X
Regional trend					X	X
Sample			All workers			No universal licenses

Data: IPUMS Monthly Current Population Survey (2006 - 2010).

Note: Dependent variable in all regressions is an unemployment indicator. The sample includes individuals between 18 and 65 who are in the labor force. 'Shock' refers to the Bartik measure employed by Hershbein and Kahn (2018). 'License' is defined using the 50% threshold at the state-occupation level pooled from SIPP Panel 2008, the universal licensed professions (Johnson and Kleiner, 2020b), and the felony license data. All regressions control for demographic characteristics (age, race and ethnicity, gender), a college indicator, a union indicator, a public sector indicator, a self-employed indicator, an indicator of whether the license is required by the job, an indicator of possessing a professional certification, state fixed effects. Sample weights apply. Standard errors are clustered at the state level.

Figure 8: Licensing Shields worker from layoffs during Great Recession



Data: IPUMS Monthly Current Population Survey (2006 - 2010).

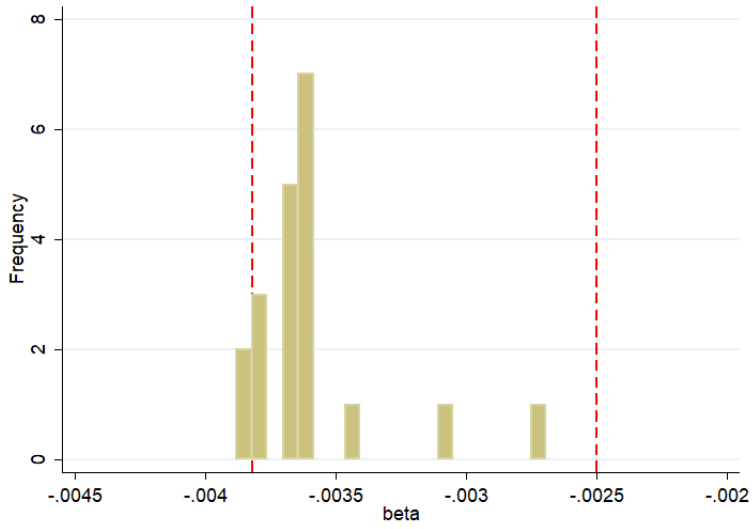
Note: This figure compares the shielding effect on laidoff (upper-left), voluntary separation (upper-right), hourly wage (bottom-left), and hours worked (bottom-right). The event study regressions use the Bartik full specification. Sapmle weights apply. Standard errors are clustered at the state level.

Consistent with the evidence that licensing shields workers from unemployment during recessions most strongly in places where labor demand shocks are largest, in the top panel of Figure 8, we find that involuntary separations from layoffs explain the pattern that we observed in the data. In contrast, there is no change in unemployment due to voluntary separations during the recession.

The shielding effect of licensing during the Great Recession appears to be consistent across industries. Notably, we show in Figure 9 that dropping all observations from any

one of the 20 industries and re-estimating the model does not yield substantial departures from the average treatment effect that we obtain from using all industries. Eighteen of the 20 estimated treatment effects fall within the 95% confidence interval that we obtain when we use all industries in the Bartik specification. The two iterations outside the confidence level in fact give a larger negative estimate than the estimate in column 5 of Table 8.[13]

Figure 9: Job Shielding of Licensing during the Great Recession Similar Across Industries



Note: This figure plots the distribution of the 20 Bartik estimates on the shielding effect of licensing by dropping the 20 industries one at a time using the regression from column 5 of Table 8. The red line marks the 95% confidence interval of the main estimate. Eighteen of the 20 estimated treatment effects fall within the 95% confidence interval that we obtain when we use all industries in the Bartik specification. Two of the iterations are significantly larger than the main estimate.

Overall, we find that occupational licensing protects licensed workers from job loss during the Great Recession, as it did during COVID-19. During both recessions, we find that occupational licensing provided the strongest protection against job loss due to layoffs and for workers in places that were hardest hit by negative labor demand shocks during the recession. Moreover, the magnitude of the job shielding impacts is persistent throughout the two-year period that we study.

5 Selection on Unobservables

In this section, we probe our results along three dimensions. First, we use the method in Altonji et al. (2005) and Oster (2019) to measure how large the selection on unobservables relative to the selection on observables would need to be to overturn our results. Second,

[13]We also reproduce the permutation exercise using the DID estimation in Figure A5 in the Appendix. Nineteen of the 20 DID estimates are within the confidence interval of the main DID estimate

we exploited the two years of pre-recession data to conduct a placebo test to baseline whether our headline findings could have been generated from spurious correlations in the data. Third, we measure whether the shielding impacts of occupational licensing persist or dissipate overtime, extending our post-period from 24 months to 51 months after the Great Recession and to 33 months after the COVID-19 recession.

We follow the generalized approach developed by Oster (2019) in computing the implied ratio (δ) of the importance of selection on unobservables relative to selection on observables. The larger the ratio, the less likely our estimate of the shielding effect of occupational licensing during recessions is driven by omitted unobservables. Using the R^2 of our saturated model as the baseline (the regression model from column 6 of Table 3 for the COVID-19 recession and the regression model from column 5 in Table 7 for the Great Recession), in Table 9 we present the values of δ under different assumptions of about the maximum explanatory power, i.e., R^2_{max}, of a regression that includes both the variables that we observe and the omitted observables.

When $R^2_{max} = 1.1 \times R^2$, we assume that the omitted unobservables play a limited role that only explains 10% more of the residual variation of unemployment in the saturated model. The implied ratio of the shielding estimate for the 2008 recession is 3.268, meaning selection on unobservables needs to be about three times more important than selection on observables to nullify the shielding estimate. The implied ratio for the COVID-19 recession is even higher at 5.404. When $R^2_{max} = 1.3 \times R^2$, which is the recommended benchmark by Oster (2019), the implied ratio for COVID-19 and the Great Recession drops to 2.045 and 1.136, respectively. Since both ratios are above 1, selection on unobservables would have to be more important than selection on observables to entirely explain away our findings — an unlikely scenario given the guidance in that $\delta > 1$ implies implausibly large selection on unobservables (Altonji et al., 2005).[14]

Table 9: Assessing Selection on Unobservables to Nullify the Shielding Estimate

$R^2_{max} =$	$1.1 \times R^2$	$1.2 \times R^2$	$1.3 \times R^2$	$1.4 \times R^2$	$1.5 \times R^2$
COVID-19 Recession (δ)	5.404	2.967	2.045	1.560	1.261
Great Recession (δ)	3.268	1.685	1.136	0.856	0.687

Note: The numbers represent the implied ratios of selection on unobservables relative to selection on observables to completely explain away the shielding effect of licensing, under different assumptions of the explanatory power of a full model (R^2_{max}) (Altonji et al., 2005; Oster, 2019). The bigger the ratio, the less likely the shielding estimate is solely driven by omitted unobservables.

[14]When we further extend to an even more stringent standard $R^2_{max} = 1.5 \times R^2$ than the suggested benchmark, the value of δ for the COVID-19 recession remains above 1. Although the ratio for the 2008 recession drops to 0.687, it is 20% higher than the implied ratio of the license wage premium obtained in Kleiner and Krueger (2013) – a seminal result in the literature.

6 Inequality between Licensed and Unlicensed Workers

We write a simple model of the indirect utility of a worker as a function of earnings and licensure status to ballpark the implications of our findings for inequality between licensed and unlicensed workers. According to the model, during a recession, an individual with earnings $\omega_0(L)$ keeps his job with probability $p(L)$, where both earnings and the probability of keeping the job are a function of whether the occupation is licensed L.[15] With probability $1 - p(L)$, the worker is unemployed during the recession and earns a fraction of his regular earnings: $(1 - \delta)$, where $0 < \delta < 1$. We assume that δ is not a function of licensing, i.e., $\frac{\partial \delta}{\partial L} = 0$.[16] Following the literature, we assume earnings are a log-linear function of licensing, i.e., $log(\omega_0(L)) = \alpha + \psi L$ such that $\frac{\partial \omega_0}{\partial L} = \omega_0 \psi$, where ψ is the licensing earnings premium which consists of the impact of licensing on wages and hours worked (Kleiner and Krueger, 2010, 2013; Gittleman et al., 2018; Kleiner and Soltas, 2023). We model the employment probability $p(L)$ as a linear function of licensing, and estimate the quantity $\frac{\partial p}{\partial L}$ from the data.

The worker has an indirect utility function $V(\omega_0; \eta)$ that exhibits constant relative risk aversion η:

$$V(\omega_0) = \frac{\omega_0^{1-\eta} - 1}{1 - \eta} \implies -\omega_0 \frac{V''(\omega_0)}{V'(\omega_0)} = \eta. \tag{5}$$

The worker's expected utility is:

$$E[U] = pV(\omega_0) + (1 - p)V(\omega_0(1 - \delta)), \tag{6}$$

where we have suppressed the L dependence of wages and the probability of employment to simplify the notation. When $\delta < 1$, to first-order approximation of the expected utility is:

$$E[U] \approx pV(\omega_0) + (1 - p)[V(\omega_0) - \delta\omega_0 V'(\omega_0)] = V(\omega_0) - \delta\omega_0(1 - p)V'(\omega_0). \tag{7}$$

The worker's expected utility is decreasing in the probability of unemployment, $1 - p$, and decreasing share of wage loss conditional on unemployment, δ.

We Taylor-expand $E[U|L = 1]$ at the point $L = 0$ to measure how much licensing changes the expected utility. We show that the difference in expected utility between a licensed and unlicensed worker, our measure of inequality, is approximately equal to the

[15] We assume that the earning is net of the licensing cost, so that the functional dependence of the earnings on licensure directly includes the cost of licensure.

[16] Since unemployment insurance is not a function of whether an individual works in a licensed occupation.

marginal utility of licensing:

$$E[U|L=1] \approx E[U|L=0] + \left.\frac{dE[U]}{dL}\right|_{L=0} \times \Delta L \implies \underbrace{E[U|L=1] - E[U|L=0]}_{\text{inequality measure}} \approx \left.\frac{dE[U]}{dL}\right|_{L=0} \tag{8}$$

Differentiating the expected utility in Equation (7) with respect to L,[17] we obtain:

$$\begin{aligned}
\left.\frac{dE[U]}{dL}\right|_{L=0} &\approx V'(\omega_0)\frac{\partial \omega_0}{\partial L} - \frac{\partial \delta}{\partial L}\omega_0(1-p)V'(\omega_0) - \delta\frac{\partial \omega_0}{\partial L}(1-p)V'(\omega_0) \\
&\quad + \delta\omega_0\frac{\partial p}{\partial L}V'(\omega_0) - \delta\omega_0(1-p)V''(\omega_0)\frac{\partial \omega_0}{\partial L} \\
&\approx \underbrace{V'(\omega_0)\frac{\partial \omega_0}{\partial L}\left[1 + (1-p)(\delta\eta - \delta)\right]}_{\text{Earnings Effect}} + \underbrace{V'(\omega_0)\frac{\partial \omega_0}{\partial L}\left(\frac{\delta}{\psi}\frac{\partial p}{\partial L}\right)}_{\text{Unemployment Effect}}
\end{aligned}$$

The difference in expected utility for a worker on account of licensing arises either because licensing increases earnings, the "earnings effect," or because licensing changes the probability of getting laid-off during a recession, the "unemployment effect."

The key parameters for quantifying the wage effect are known from the literature: $\eta = 1.19$ (Layard et al., 2008), $\delta = 0.218$ (Farber, 2011), $(1 - p(L=0)) = 0.065$ (Table 1: COVID-19), $(1 - p(L=0)) = 0.092$ (Table 6: Great Recession). Quantifying the unemployment effect relies on estimates of $\frac{\partial p}{\partial L}$, which are new to the literature and calculated in this paper, and estimates of the licensing earnings premium ψ, which we calculate in Table 10.[18] Given our finding that licensed workers are less likely to be unemployed during recessions, it could be that licensed workers trade off lower relative unemployment risk for lower relative wages. A negative compensating differential of this type would cause the license premium to fall during recessions, in accordance with theoretical results and evidence of compensating differentials in the US labor market (Rosen, 1974, 1986; Sorkin, 2018).

For the Great Recession we use $\frac{\partial p}{\partial L}\big|_{[L=0]} = 0.011$ (Table 7, column 6). For COVID-19 we use $\frac{\partial p}{\partial L}\big|_{[L=0]} = 0.010$ (Table A3, column 1). Both estimates are based on the state-by-occupation variation in licensing using the 50% threshold. We find that the licensing

[17] In practice, our state-level measure of licensing, a binary variable, is constructed from a continuous measure — the fraction of workers in the occupation who are licensed — and then discretized using a threshold rule.

[18] For completeness, we also include regressions where we decompose the licensing earnings premium into the components due to the licensing wage premium and the licensing hours premium by regressing log(wages) and log(hours) on licensing and an interaction of licensing with a recession indicator following the approach in Equation (1).

Table 10: Licensing Earnings Premium before and after recession

	COVID-19 Recession			Great Recession		
	log(income)	log(wage)	log(hours)	log(income)	log(wage)	log(hours)
license × recession	0.000527	-0.0114***	0.0121***	0.0123**	0.00409	0.00813**
	(0.00670)	(0.00410)	(0.00429)	(0.00487)	(0.00328)	(0.00314)
license	0.0461***	0.0399***	0.00614	0.0768***	0.0715***	0.00539*
	(0.00913)	(0.00829)	(0.00567)	(0.00722)	(0.00562)	(0.00290)
recession	-0.00770*	-0.00395	-0.00377	-0.0210***	0.00472*	-0.0257***
	(0.00427)	(0.00258)	(0.00367)	(0.00405)	(0.00257)	(0.00233)
Observations	350,371	350,555	350,371	448,583	448,812	448,583
R-squared	0.366	0.436	0.154	0.291	0.341	0.125

Data: IPUMS Monthly Current Population Survey.

Note: The sample includes individuals between 18 and 65 who are in the labor force. The 'license' variable in the Covid sample uses individual license attainment in CPS, while that in the 2008 sample uses the three external data mentioned in Section 4. 'Recession' indicator equals 1 for the sample months after March 2020 in columns 1 to 3. 'Recession' indicator equals 1 for the sample months after Dec 2007 in column 4-6. All regressions run with the fully saturated model in the corresponding sample analysis. Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

earnings premium before the COVID-19 recession was 4.61%.[19] In the aftermath of the COVID-19 Recession, the licensing earnings premium changes by an economically small and statistically insignificant 0.05 p.p., therefore we do not find evidence of a compensating earnings differential between licensed workers and unlicensed workers during the recession.[20] We find that the licensing earnings premium prior to the Great Recession was 7.68%.[21] In the aftermath of the Great Recession, the licensing earning premium increases by a statistically significant 1.23 p.p., therefore, giving us a value $\psi_{GR} = 8.91$. Instead of a compensating differential, we find evidence of an augmenting differential, in the spirit of Mortensen (2003), that partially offsets the 2.1 p.p. reduction in earnings due to the recession.[22]

Table 11: Decomposition of Inequality between licensed and unlicensed workers

	Wage Effect	**Unemployment Effect**
COVID-19 Recession	1.002	0.067
Great Recession	1.004	0.029

In Table 11, we report our values of the "wage effect" and the "unemployment effect" of

[19]The licensing wage premium is 3.99% and contributes more to the licensing earnings premium than the licensing hours premium which is 0.61% and statistically insignificant.

[20]The absence of an overall compensating earnings differential masks the fact that the licensing wage premium goes down by 1.14 p.p. which is nearly enough to completely offset the increase in the licensing hours premium of 1.21 p.p.

[21]It is primarily due to a licensing wage premium of 7.15%. The licensing hours premium is comparatively smaller 0.54% and contributes less to the earnings premium.

[22]The increase in licensing earnings premium following the Great Recession loads onto licensed workers experiencing a smaller decline in hours than unlicensed workers.

licensing during the two recessions in units of marginal utility $V'(\omega_0)\frac{\partial \omega_0}{\partial L}$. For COVID-19 we find that the wage effect is 1.002 and the unemployment effect is 0.067. For the Great Recession, the wage effect is 1.001 and the unemployment effect is 0.027. Overall, we find that inequality between licensed and unlicensed workers is 2.9% to 6.7% larger than previously thought during the Great Recession and the COVID-19 Recession (respectively) on account of the fact that occupational licensing shields licensed workers from job loss relative to their unlicensed peers. For comparison, Finkelstein et al. (2024) find that the unemployment induced by the Great Recession increased life expectancy by 2.3%, which is the same order of magnitude of the estimates we find here, albeit for a different outcome.

7 Conclusion

Occupational licensing affects a significant portion of the U.S. workforce and plays a central role in current policy discussions. This paper is the first to examine how occupational licensing interacts with economic recessions and its implications for inequality. We find that licensing provides licensed workers with protection from job loss during both the COVID-19 recession and the Great Recession, especially in the places hardest hit by the recession. This "shielding effect" is a robust industry-wide phenomenon. It is driven by rehiring frictions created by licensing requirements that make firms less likely to lay off licensed workers than unlicensed workers. Importantly, there is no negative earnings differential accompanying this job protection, indicating that inequality between licensed and unlicensed workers widens during recessions.

Our findings also show that the job-shielding effect of licensing persisted after the Great Recession but diminished more quickly following the COVID-19 recession. This suggests that longer, more severe recessions may cause lasting shifts in labor market dynamics, increasing inequality by amplifying the demand for credentialed workers. This is consistent with the evidence that the Great Recession led to a sustained increase in the demand for workers with bachelor's degrees, a form of credential with similar human capital and signaling characteristics as occupational licensing (Blair and Deming, 2020). Moreover, the gap in unemployment rates between licensed and unlicensed workers heading into the COVID-19 recession reflects the long-lasting impact of the Great Recession in widening unemployment inequality between licensed and unlicensed workers. Licensing, therefore, can compound inequality across successive recessions through its impact on the likelihood of unemployment.

While occupational licensing has traditionally been viewed as a barrier to entry that

exacerbates inequality during normal times, our findings demonstrate that licensing also increases inequality by serving as more of a barrier to job exit during economic recessions for licensed workers than their unlicensed colleagues. The shielding effect caused by this barrier adds a novel angle to measure economic rent caused by occupational licensing.

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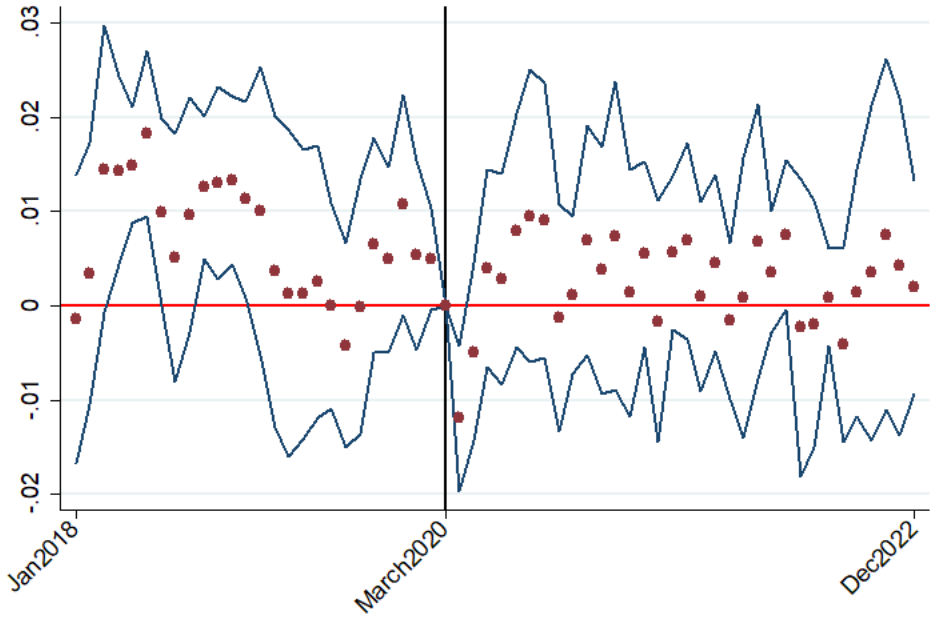
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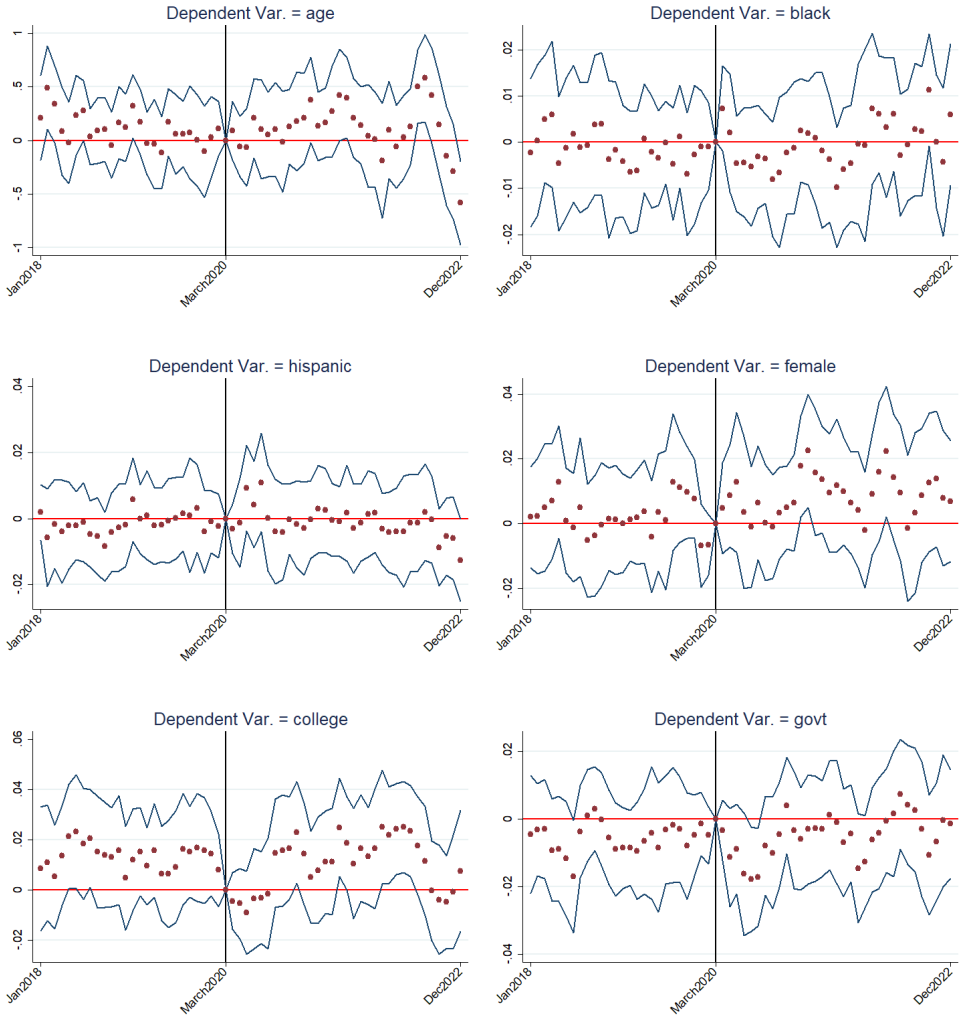
Online Appendix Figures A

Figure A1: Auxiliary Regression on License Status



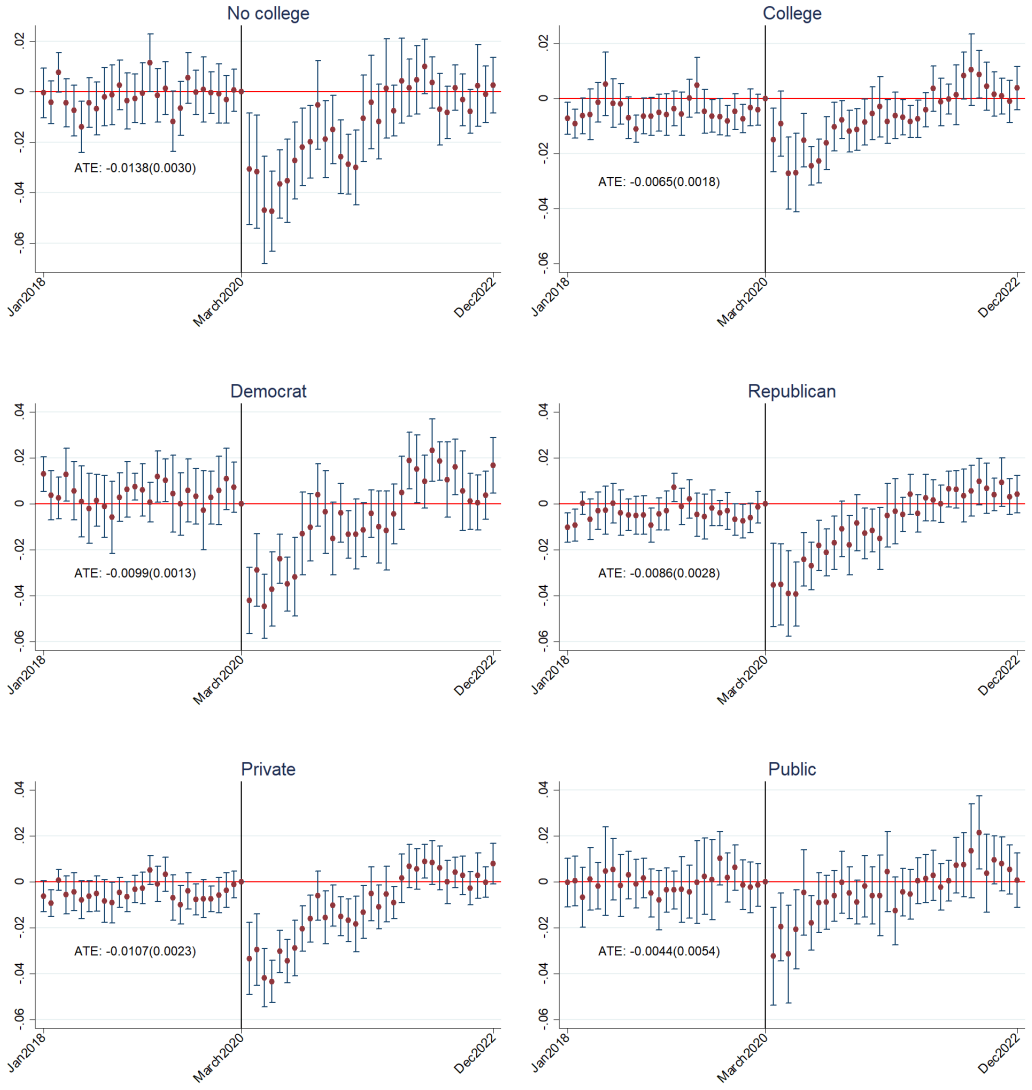
Note: This figure plots the event time dummies (with 95% confidence interval) on license status. License attainment of individuals before and after COVID-19 does not experience significant changes.

Figure A2: Auxiliary Regressions on Sample Characteristics



Note: This figure plots the event time dummies interacted with licensing (with 95% confidence interval) on the corresponding individual characteristics. The difference of characteristics between licensed and unlicensed individuals before and after COVID-19 does not experience significant changes.

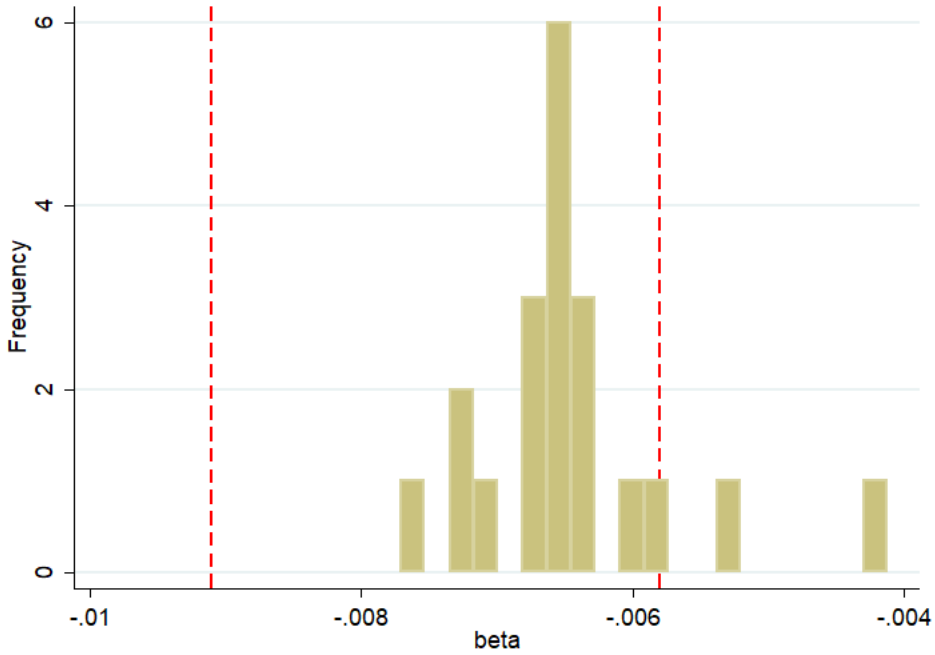
Figure A3: Heterogeneity by Education and Industry



Data: IPUMS Monthly Current Population Survey (2018 - 2022).

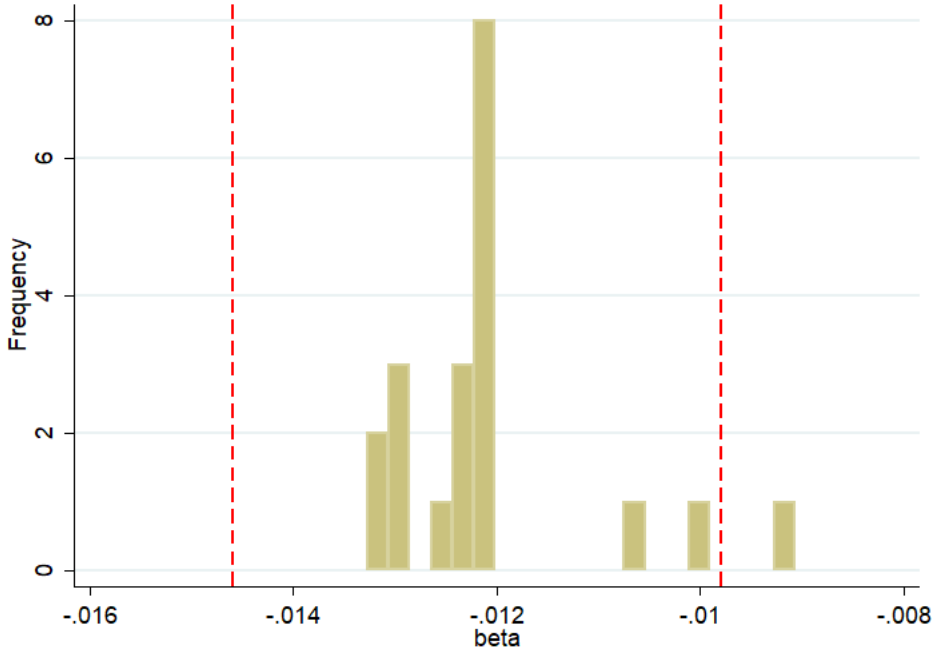
Note: Dependent variable in all regressions is an unemployment indicator. Sample includes individuals between 18 and 65 who are in the labor force. This figure includes event study plots (full specification) of the COVID-19 shock using different sub-samples. We use the lockdown triple-differences specification for college/no-college and public/private sub-sample. Since all Democrat states implemented lockdown during Covid, the triple-differences approach in Equation 3 does not have variation if we split the sample by political affiliation of a state. The plots present the event study dummies using the DID setup in this sub-analysis. The shielding pattern of licensing is homogeneous across education (upper panel) and state political status (middle panel). The lower panel shows that the shielding is more apparent for private workers.

Figure A4: Sensitivity Check: Iteration of Dropping 20 Industries (COVID-19)



Note: This figure plots the distribution of the twenty estimates on the shielding effect of licensing by dropping the 20 industries one at a time. The left shows the full model using the basic DID (comparable to column 6 of Table 3).

Figure A5: Sensitivity Check: Iteration of Dropping 20 Industries (2008 Recession)



Note: This figure plots the distribution of the twenty estimates on the shielding effect of licensing by dropping the 20 industries one at a time and running the regression in column 5 of Table 7. The red line marks the 95% confidence interval of the main estimate. The raw coefficients in the 20 iterations are all significant at 1% level. Nineteen of the 20 DID estimates are inside the confidence interval of the main estimate.

Online Appendix Tables

Table A1: Ability Predicts Licensure, Unemployment, Wages, & Educational Attainment

	(1)	(2)	(3)	(4)	(5)	(6)
Y = license						
Math	0.0447***	0.0195***				
	(0.00724)	(0.00583)				
English			0.0629***	0.0338***		
			(0.0119)	(0.0105)		
Science					0.0654***	0.0385***
					(0.00733)	(0.00656)
Constant	0.188***	0.0414***	0.190***	0.0449***	0.188***	0.0445***
	(0.00494)	(0.00433)	(0.00366)	(0.00426)	(0.00485)	(0.00436)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461
Y = unemployed						
Math	-0.0102***	-0.00493***				
	(0.000834)	(0.000612)				
English			-0.0105***	-0.00516***		
			(0.00127)	(0.000893)		
Science					-0.0109***	-0.00537***
					(0.000998)	(0.000750)
Constant	0.0486***	0.0933***	0.0482***	0.0931***	0.0486***	0.0932***
	(0.00174)	(0.00280)	(0.00154)	(0.00271)	(0.00171)	(0.00277)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461
Y = log(wage)						
Math	0.0840***	0.0547***				
	(0.00928)	(0.00655)				
English			0.0736***	0.0495***		
			(0.00788)	(0.00563)		
Science					0.0919***	0.0629***
					(0.00942)	(0.00678)
Constant	2.869***	2.581***	2.869***	2.582***	2.870***	2.583***
	(0.0142)	(0.0126)	(0.0156)	(0.0130)	(0.0145)	(0.0126)
Observations	373,982	373,982	373,982	373,982	373,982	3,019,461
Y = college						
Math	0.148***	0.126***				
	(0.00972)	(0.00766)				
English			0.131***	0.103***		
			(0.0135)	(0.0100)		
Science					0.154***	0.130***
					(0.0105)	(0.00837)
Constant	0.393***	0.312***	0.397***	0.317***	0.393***	0.314***
	(0.00740)	(0.0194)	(0.00972)	(0.0223)	(0.00765)	(0.0198)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461
Individual Characteristics		X		X		X

Source: Survey of Income and Program Participation (Panel 2008); Current Population Survey (2018-2022).

Note: This table assesses the predictive power of the three SIPP ability measures (ever taken advanced English, math, and advanced science) on license attainment, college attainment, wages, and employment. The CPS monthly sample includes individuals who are between 18-65 and in the labor force. For the wage analysis, we drop the wage outliers and missing observations. Individual controls include age, gender, race, and control for government worker and self-employment. Sample weights apply.

Table A2: Balancing Test: Predictability of Lockdown decision

	(1) 2018	(2) 2019
State percentage:		
license	0.00710	-0.0256
	(0.0303)	(0.0271)
cert	0.0860	0.0446
	(0.0835)	(0.0880)
unemployed	0.0916	0.0935
	(0.0700)	(0.0674)
black	0.00151	0.00357
	(0.00690)	(0.00687)
hispanic	0.00326	0.00297
	(0.00565)	(0.00559)
hourly wage	0.00566	0.00225
	(0.00407)	(0.00443)
self-employment	-0.0337	-0.00884
	(0.0355)	(0.0378)
F-stat	1.76	1.31
p-value for joint significance	0.1197	0.27
Number of states	51	51
R-squared	0.223	0.175

Note: Dependent variable equals 1 if a state implements statewide stay-home order in March/April 2020. The explanatory variables are the state average (with sample weight) of the corresponding characteristics in a particular pre-COVID-19 year. Standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: DID Results using Licensing Thresholds - Covid

	(1)	(2)	(3)	(4)	(5)
	0.5	0.45	0.4	0.35	0.3
license*covid	-0.00399***	-0.00361***	-0.00405***	-0.00346***	-0.00351***
	(0.00141)	(0.00131)	(0.00127)	(0.00125)	(0.000999)
license	-0.00505***	-0.00488***	-0.00521***	-0.00575***	-0.00671***
	(0.000674)	(0.000657)	(0.000604)	(0.000740)	(0.000698)
covid	0.0796***	0.0797***	0.0798***	0.0798***	0.0799***
	(0.00559)	(0.00559)	(0.00558)	(0.00559)	(0.00561)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461
R-squared	0.027	0.027	0.027	0.027	0.027

Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: Dependent variable in all regressions is an unemployment indicator. The sample includes individuals between 18 and 65 who are in the labor force. 'License' is defined using the corresponding pre-shock threshold at the state-occupation level. All regressions control for demographic characteristics (age, race and ethnicity, gender), a college indicator, a union indicator, a public sector indicator, a self-employed indicator, an indicator of whether the license is required by the job, an indicator of possessing a professional certification, industry, state, and month fixed effects, and the additional controls in the full model. Sample weights apply. Standard errors are clustered at the state level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix B: Additional Results (2008 Recession)

Table B1: Summary Statistics for Great Recession Analysis - Alternative cutoff

	Pre-Recession			Post-Recession			
	(1)			(2)			
	Unlicensed	Licensed	Diff	Unlicensed	Licensed	Diff	Diff-in-Diff
Outcome							
unemployed	0.053	0.033	-0.0203***	0.101	0.061	-0.0400***	-0.0197***
			(0.000973)			(0.00162)	(0.00143)
Individual characteristics							
female	0.432	0.539	0.107***	0.434	0.547	0.114***	0.00718***
			(0.0100)			(0.00961)	(0.00223)
age	39.566	41.255	1.689***	39.950	41.644	1.693***	0.00472
			(0.184)			(0.199)	(0.0589)
black	0.117	0.116	-0.000844	0.117	0.117	-0.000741	0.000103
			(0.00443)			(0.00415)	(0.00148)
hispanic	0.155	0.112	-0.0435***	0.163	0.117	-0.0453***	-0.00185
			(0.00872)			(0.00895)	(0.00151)
asian	0.047	0.046	-0.000840	0.048	0.047	-0.00106	-0.000218
			(0.00250)			(0.00213)	(0.00109)
union membership	0.240	0.256	0.0167***	0.228	0.251	0.0232***	0.00656***
			(0.00274)			(0.00258)	(0.000898)
college	0.251	0.438	0.186***	0.260	0.448	0.188***	0.00143
			(0.00735)			(0.00824)	(0.00308)
govt	0.117	0.202	0.0847***	0.119	0.207	0.0881***	0.00335*
			(0.0110)			(0.0118)	(0.00171)
self employed	0.102	0.110	0.00862***	0.097	0.102	0.00518*	-0.00344**
			(0.00284)			(0.00297)	(0.00148)
Observations	1514868	589399		1308510	516090		

Data: Monthly CPS (Jan 2018 to Dec 2022)

Note: 'Licensed' refers to individuals who work in a licensed state-occupation defined using the data described in Section **??**. 'Pre-Recession' refers the period before Aug 2008. Sample weight applies. Standard errors are clustered at the state level in testing differences.

Table B2: Difference-in-differences Estimates - 2008 Recession (Alternative Cutoff)

	(1)	(2)	(3)	(4)	(5)	(6)
license × recession	-0.0196***	-0.0198***	-0.0150***	-0.0146***	-0.0146***	-0.0134***
	(0.00141)	(0.00140)	(0.00125)	(0.00121)	(0.00127)	(0.00146)
license	-0.00803***	0.000187	-0.00206**	-0.00226**	-0.00220**	-0.00177
	(0.000904)	(0.00105)	(0.00102)	(0.00101)	(0.00102)	(0.00133)
recession	0.0489***	0.0492***	0.0558***	0.0566***	0.0404***	0.0402***
	(0.00304)	(0.00312)	(0.00366)	(0.00372)	(0.00190)	(0.00192)
Observations	3,928,867	3,928,867	3,928,867	3,928,867	3,928,867	3,496,543
R-squared	0.033	0.040	0.041	0.041	0.042	0.041
Ind FE		X	X	X	X	X
College x recession			X	X	X	X
Union x recession				X	X	X
Regional trend					X	X
Sample	All workers					Drop universal licenses

Note: Recession refers to the period after the beginning of the recession (Aug 2008).

Table B3: Bartik Shock - Aug 2008 as Alternative cutoff

	(1)	(2)	(3)	(4)	(5)	(6)
license*shock	-0.00523***	-0.00529***	-0.00402***	-0.00390***	-0.00390***	-0.00374***
	(0.000383)	(0.000373)	(0.000359)	(0.000351)	(0.000368)	(0.000421)
license	-0.00788***	-1.56e-05	-0.00228**	-0.00249**	-0.00248**	-0.00230
	(0.000919)	(0.00112)	(0.00110)	(0.00111)	(0.00109)	(0.00141)
shock	0.0227***	0.0235***	0.0232***	0.0228***	0.0187***	0.0198***
	(0.00508)	(0.00523)	(0.00495)	(0.00506)	(0.00373)	(0.00374)
Observations	2,673,125	2,673,125	2,673,125	2,673,125	2,673,125	2,376,333
R-squared	0.035	0.041	0.042	0.042	0.042	0.042
Ind FE		X	X	X	X	X
College x shock			X	X	X	X
Union x shock				X	X	X
Regional trend					X	X
Sample	All workers					Drop universal licenses

Data: IPUMS Monthly Current Population Survey (2006 - 2010).

Note: Dependent variable in all regressions is an unemployment indicator. Sample includes individuals between 18 and 65 who are in the labor force. 'Shock' refers to the Bartik measure employed by Hershbein and Kahn (2018). 'License' is defined using the 50% threshold at the state-occupation level pooled from SIPP Panel 2008, the universal licensed professions (Johnson and Kleiner, 2020b), and the felony license data. All regressions control for demographic characteristics (age, race and ethnicity, gender), a college indicator, a union indicator, a public sector indicator, a self-employed indicator, an indicator of whether the license is required by the job, an indicator of possessing a professional certification, state fixed effects. Sample weights apply. Standard errors are clustered at the state level.