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ABSTRACT

Licensed workers could be shielded from unemployment during recession since occupational licensing laws are asymmetric—making unlicensed workers an illegal substitute for licensed workers but not the reverse. We test our hypothesis using a difference-in-differences event study research design that exploits cross-state variation in licensing laws to compare the unemployment rate between licensed and unlicensed workers before and after the COVID-19 recession and the Great Recession. Controlling for worker ability, we find that licensing shields workers from a recession-induced increase in the unemployment rate of 0.82 p.p. during COVID-19 and 1.11 p.p. during the Great Recession.

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1 Introduction

When the state introduces an occupational licensing requirement, it is illegal to work for pay in the occupation without a license. Since Adam Smith, economists have theorized that occupational licensing is an inefficient and perhaps illiberal labor market institution that would reduce labor supply and increase prices paid by consumers without improving service quality (Friedman and Kuznets, 1945; Friedman, 1962; Leland, 1979; Shapiro, 1986; Kleiner, 2000). The empirical evidence largely supports the theoretical predictions of economists with a few exceptions (Kleiner and Krueger, 2010, 2013; Thornton and Timmons, 2013; Pizzola and Tabarrok, 2017; Gittleman et al., 2018; Blair and Chung, 2019; Farronato et al., 2020; Anderson et al., 2020; Blair and Fisher, 2022; Deyo and Plemmons, 2022; Chung, 2022; Kleiner and Soltas, 2023; Blair and Chung, Forthcoming).[1]

While empirical analyses of occupational licensing as a stand alone labor market institution maps closely to the orthodoxy of licensing as a labor market friction, there is virtually no evidence on how occupational licensing interacts with macroeconomic shocks, despite the existence of a robust literature exploring the link between macroeconomic shocks and other significant labor market institutions (Nickell, 1997; Blanchard and Wolfers, 2000; Bertola et al., 2001; Giupponi and Landais, 2023).[2] Filling this gap in the literature is vital because licensing requirements are pervasive. In the United States and the European Union one in five workers are subjected to occupational licensing requirements (Gittleman et al., 2018; Koumenta and Pagliero, 2018). In fact, in the United States licensing requirements cover twice as many workers as labor unions or the federal minimum wage. In this paper, we provide the first causal estimates of the impact of occupational licensing on unemployment during recessions. We find that occupational licensing shields workers from unemployment during recessions, acting as a protection

[1] A notable exception to the finding that licensing does not improve quality is Anderson et al. (2020), who find midwifery licensing laws in the early 1900s reduced maternal and infant mortality.

[2] Nickell (1997), Blanchard and Wolfers (2000), and Bertola et al. (2001) focus on the unemployment insurance, collective bargaining, employment protection laws, government spending on active labor market policy, unionization, and income taxation.

from job loss, especially for workers who are hardest hit by recessions.

There are several reasons why occupational licensing may shield licensed workers from unemployment during recessions. First, licensing laws are asymmetric — prohibiting unlicensed workers from substituting for licensed workers but not the reverse. Therefore, 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 since the fraction of workers who sort into an occupation is 17%-27% lower if the occupation requires a license; consequently, firms may be reluctant to layoff licensed workers during recessions if they anticipate intense competition for rehiring them during the recovery. Third, licensed workers may be positively selected on ability because they have to pass exams, undergo training, and are screened on felony status (Gittleman et al., 2018; Blair and Chung, 2021, Forthcoming).

To test whether licensing reduces job exit during recessions, we leverage cross-state variation in licensing laws to compare the difference in unemployment between licensed and unlicensed workers in the same industry during each month in the two years before and the two years after the onset of a recession. Because the Current Population Survey (CPS) first began continuous collecting individual data on occupational licensing in 2015, the COVID-19 induced recession provides the first opportunity to do a study of the causal impact of licensing on unemployment during a recession using individual level licensing data. We test for the generalisability of our findings by applying our research design to the Great Recession using demographic data from the CPS and licensing data at the state-occupation level from a special module of the 2008 Survey of Income and Program Participation (SIPP). In total we have over 3 million individual-month observations for each recession.

Our key outcome of interest is whether an individual reports being unemployed. Our key parameter of interest is the coefficient on the interaction term between the indicator for whether an individual has license (or the occupation is licensed) and an indicator for whether the observation comes from the period that follows the onset of the recession. 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). The coefficient of interest measures how much occupational licensing differentially shields licensed workers from unemployment as compared to unlicensed workers during recession as compared to non-recession times. In the regression, we control for a pre-labor market measure of worker ability, worker demographics, time trends in unemployment by region, interactions between worker education and union status and the recession indicator, and fixed effects for industry, survey month, and state.

The key 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 pre-period 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, license status, and college attainment, and our preferred treatment effects of licensing on unemployment during 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 COVID-19. We find that 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 for the Great Recession, and states that mandated lockdowns during the onset of COVID-19. Moreover, in both recessions we find that licensing shields workers from unemployment due to layoffs, while having no shielding effect on unemployment due to voluntary quits. The pattern of results is consistent with licensing buffering licensed workers from a reduction in labor demand by firms during a recession, rather than licensed workers responding to recessions by increasing labor supply. Further supporting this interpretation of the findings, we find no evidence for relative adjustments to wages or hours worked between licensed workers and unlicensed workers — ruling out a scenario in which licensed workers and firms agree to trade-off lower unemployment for lower wages and/or fewer hours worked. Finally, 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. Instead we find that during COVID-19 the unemployment rate for unlicensed workers increases less in industries where the fraction of licensed workers is above the national average.

We conduct a series of robustness tests to complement the placebo test that we ran. 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. Estimating our model using an alternative state-occupation measure of licensing following the approach in Blair and Chung (2019) yields similar results to those obtained using the self-reported individual licensing data. Moreover, selection on unobservables would need to be implausibly large to explain our findings (Altonji et al., 2005; Oster, 2019).

The robustness of our findings convinces us that we have documented a new and important fact: occupational licensing protects workers from job loss during recessions.

The rest of the paper is organized as follows: Section II provides a review of the literature on licensing laws and unemployment. Section III describes the data and methods used in the analysis. Section IV presents the results of the analysis. Section V discusses the implications of the findings and suggests areas for future research.

2 Data and Empirical Strategy

2.1 Employment and Licensing Data

The data used in the study is drawn from the monthly Current Population Survey (CPS). The CPS is a nationally representative survey of US workers with rich labor market and demographic information, including whether an individual is employed or unemployed. Equally important for our study, 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). There were also surveys conducted by Gallop and Westat those provided a snapshot of the prevalence of occupational licensing Kleiner and Krueger (2010, 2013). One further advantage of using the CPS data is that it allows us to measure the licensure status of workers whether they are employed or unemployed. In the CPS, employed workers are asked whether 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 as compared to normal economic times.

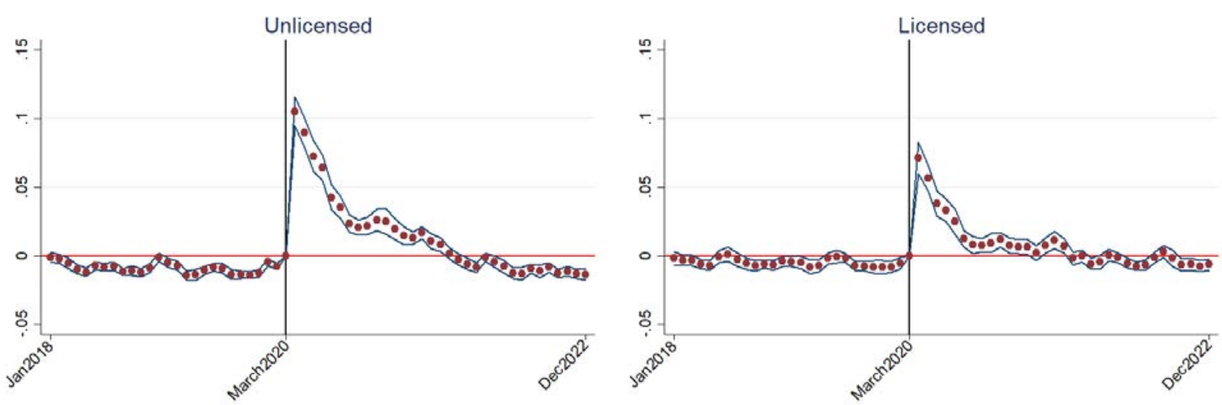
Our estimation sample consists of individuals between 18 and 65 who are in the labor force, excluding armed forces and unpaid family workers.[3] For our analysis of the

[3] We later differentiate non-government wage workers from government workers and self-employed to explore heterogeneity of our estimates.

impact of licensing on unemployment during the COVID-19 recession we use licensing and unemployment data from the CPS covering January 2018 to December 2022. For our analysis of the impact of licensing on unemployment during the Great Recession we use unemployment data from the CPS data covering January 2006 to December 2010, and the licensing data from the 2008 SIPP. The monthly nature of the CPS, and the two-year pre-period and two year post-period are useful for implementing our event study difference-in-differences research design.

Because we will use the Great Recession as a test of the external validity of our results from the COVID-19 induced recession, we focus on first describing the data for the COVID-19 portion of the study and defer describing the data for the Great Recession to Section 4. In Figure 1, we plot the unemployment rate for licensed and unlicensed workers in the two year window before and after the COVID-19 recession relative to its value in the month just before COVID-19 hits. Unemployment spikes for both licensed and unlicensed workers at the onset of the recession; however, it spikes more for unlicensed workers (12 p.p.) than for licensed workers (7 p.p).

Figure 1: Event Study for Unemployment Rate of Worker during COVID-19



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

Note: Sample includes individuals between 18 and 65 who are in the labor force. We plot the probability of unemployment for unlicensed workers and licensed workers separately, conditional on basic characteristics (age, race, gender, education), for each time period in the two-year window around the COVID-19 recession. ‘Licensed’ refers to workers who possess a government-issued occupational license required by current/previous job. Sample weights apply. Standard errors are clustered at the state level.

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). 'Pre-COVID-19' refers the period before March 2022. The three ability measures are state-occupation ability proxies pooled from the Survey of Income and Program Participation (Panel 2008). Sample weight apples. Standard errors are clustered at the state level in testing differences.

In Table 1 we report the average unemployment rate separately for licensed and unlicensed workers pre-COVID-19 and post-COVID-19. We also calculate 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. We also measure 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. In the pre-COVID-19 period, we find that licensed workers are less likely to be unemployed by 2.84 p.p.; they also appear to be selected on each of the individual characteristics. Likewise, in the post-COVID-19 period we also find that licensed workers are less likely to be unemployed than unlicensed workers by 3.79 p.p. and they are also selected on each of the individual characteristics.

When we examine the difference-in-differences measure, licensed workers are on average 0.96 p.p. less likely to experience job loss during the recession than their unlicensed peers despite both categories of workers being more likely to be unemployed during the recession. Examining the difference-in-differences for the nine individual worker characteristics, we find that they are each economically small and eight of the nine are statistically indistinguishable from zero. 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. The one characteristic that is statistically significant 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). The summary statistics in Table 1 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.

2.2 Empirical Strategy

To test the hypothesis that individuals with occupational licenses experience less job loss during recessions than their unlicensed peers, ideally one would randomize the occupational license attainment of individuals before a recession and measure whether the gap in unemployment between licensed and unlicensed workers changes during the recession.[4] There are two challenges to implementing the ideal experiment. First, it is nearly impossible to forecast the timing of a recession. Second, randomly assigning licensing raises ethical concerns given the body of work showing that workers with licenses earn a wage premium vis-a-vis their unlicensed peers (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 are unable to forecast recessions nor randomly assign occupational licenses to individuals, we make progress on the question animating this paper by leveraging a natural experiment.

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.[5] 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

[4]By construction, individuals with an occupational license would be legally permitted to work for pay in the occupation where they are licensed whereas those without could not be legally employed for pay in any occupation that requires a license.

[5]The variation in licensing laws across states functions effectively as an instrument for whether an individual in the occupation reports being licensed.

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 a steady deterioration in macroeconomic conditions.

The plausible exogeneity of the state variation in licensing laws alone may not be enough, however, for our natural experiment to yield causal estimates. We must overcome endogeneity due to ability bias. Selection into licensed occupations within 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 (Blair and Chung, 2019). Furthermore, the baseline differences in worker ability could also shape how workers experience an economic shock independently of occupational licensing. For our natural experiment to yield valid causal estimates, we therefore also require a measure of worker ability at the state-occupation level to account for non-random selection within state into licensed occupations and differential shocks to unemployment by ability during the recession.

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: 'License' refers to individuals who report having a government-issued license and is required by the job.

Table 3: 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)
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)
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)
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)
Individual Characteristics		X		X		X

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

Note: Individual controls include age, gender, race, and control for government worker and self-employed.

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 whether they have an occupational license, we can test whether licensed workers are on average more "able" than unlicensed workers. As reported in Table 2, licensed workers are more likely to have taken advanced math (7.5 p.p.), science (10.7 p.p.) and English courses (9.3 p.p.) in high school than their unlicensed peers. Second, because the SIPP contains earnings, employment, and educational attainment we can quantify the usefulness of our ability measure by exploring its correlations with educational attainment and labor market outcomes. As reported in Table 3, a one unit increase in our ability proxies 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 pre-determined, which rules out reverse causality. In our preferred empirical specification, we will include all three measures of worker ability as control variables.

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 further include an interaction term between the worker's license status and an indicator '*post*' that equals one for all observations from time periods following the onset of the recession being studied. The coefficient on the interaction between license $\times$ post is our coefficient of interest. To test whether our main effect is affected 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 the its interaction with the '*post*' recession indicator, worker demographics 'X_{ist},' and fixed effects for the worker's state of residence 'θ_s' and worker industry 'θ_d'. The exact regression that we run is:

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

The β_3 coefficient on the interaction term '$license_{ist} \times post$,' our parameter of interest, measures how the gap in unemployment between licensed and unlicensed workers changes after the recession as compared to the value of the unemployment gap prior to the recession. If this coefficient is negative we will say that occupation licensing is "shielding" licensed workers from increases in unemployment during the recession (as 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 in for us to interpret β_3 as a causal parameter. First, we need to assume that in the absence of the recession that the unemployment gap between unlicensed and licensed workers would have evolved similarly in the post period to its path in the pre-period. Second, we need to assume that the timing of the recession is orthogonal to other treatments that could have shielded licensed workers from unemployment as compared to their unlicensed peers. Third, we need that our measure of pre-labor market ability is a valid proxy for controlling for selection.

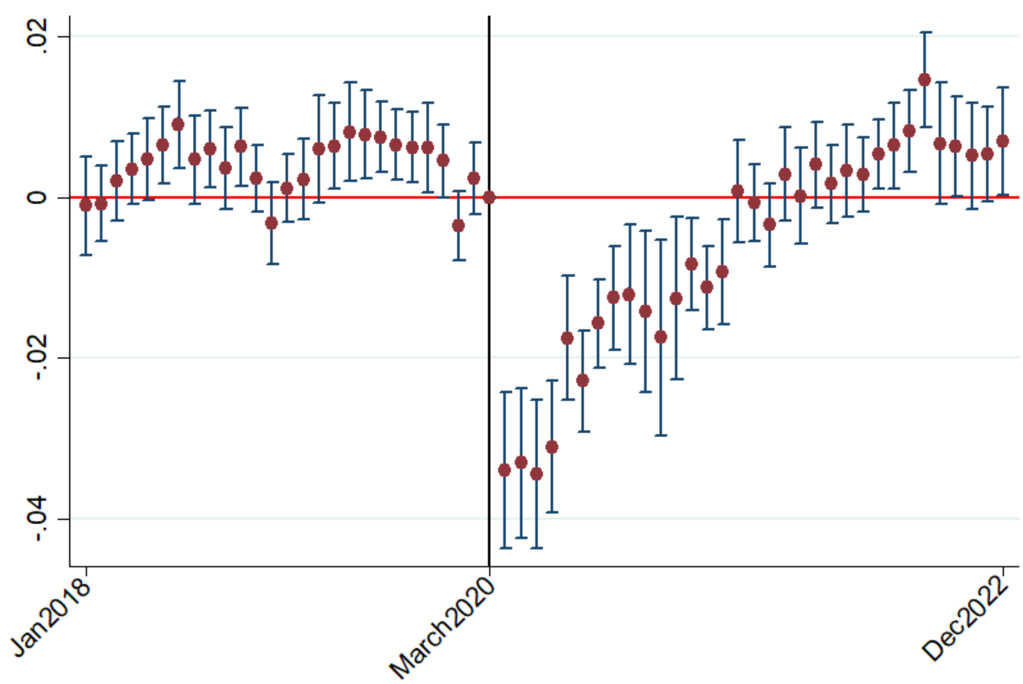
3 Results from COVID-19 Recession

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:

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

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 the event month immediately preceding the recession $\tau = -1$, i.e., March 2020 (where t^* equals April 2020).

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, conditional on basic characteristics (age, race, gender, education). 'Licensed' refers to workers who possess a government-issued occupational license required by current/previous job. Sample weights apply. Standard errors are clustered at the state level.

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 time period, relative to its value in $\tau = -1$. We call this difference the relative unemployment gap. In the period before the recession, we do not see substantial differences in the relative unemployment gap. In fact, the gap in unemployment bounces around between zero to one percentage point, will all the confidence intervals overlapping. By contrast, when the COVID-19 recession hits in March 2020, we see an immediate and statistically significant decrease in the unemployment rate of licensed workers as compared to that of unlicensed workers. Licensed workers are 4 percentage points less likely to be unemployed than their unlicensed peers. Over the next 16 months licensed workers continue to be differentially shielded from the increase in unemployment from COVID-19. Following the 16-month mark, we return to the pre-recession baseline.

In Table 4, we report the results from 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 as compared to its value in the two years prior to the recession, using the difference-in-difference regression from Equation 1. The analysis permits us to quantify the average effect of occupational licenses in shielding licensed workers from recession-induced job loss in the two year following the onset of the recession. In column (1) of Table 4 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 so that we are leveraging variation in licensing laws across states, and across occupations within industry-state pairs. The model in column (3) includes our measure of pre-labor market ability and an interaction between ability and the *post* recession indicator. By comparing this model which corresponds to the specification in Equation 1 to the models in columns (1) and (2) we can discern how much of the the shielding effect of licenses during recessions is due to differences in ability.

Based on the first specification in column (1) we find that licensing shields workers from a 0.96 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 1.01 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 exhibits a statistically significant shielding effect of 0.93 p.p., which is roughly 7% smaller. Had we not controlled for differences in ability, our estimate of the shielding effect of occupational licensing would have been subject to omitted variable bias.

To measure the shielding effect of licensing that is independent of the fact that licensed workers are on average more educated than unlicensed workers, and that workers with more education are shielded from unemployment during COVID-19 as in Beuermann et al. (2024), in column (4), we add an interaction between an indicator for whether worker i completed a four-year college degree and the '*post*' recession indicator. In column (5), we add an interaction between worker union status and the '*post*' recession indicator. Recall from the summary statistics that union status was the sole observable for which there was a statistically significant difference in the pre and post COVID-19 worker attributes. In column (6), we control for differential time trends in unemployment by region prior to the recession. In column (7) we replace the industry fixed effects with occupation fixed effects, which allows for a finer comparison of workers in the same occupation across states that differ in licensing laws. In column (8) 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.

Table 4: Licensure Shields Workers from Unemployment during COVID-19 Recession

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
license × post	-0.00957***	-0.0101***	-0.00930***	-0.00722***	-0.00682***	-0.00749***	-0.00772***	-0.00819***
	(0.00106)	(0.00105)	(0.000961)	(0.000822)	(0.000814)	(0.000815)	(0.000848)	(0.00111)
license	-0.0162***	-0.0112***	-0.0112***	-0.0124***	-0.0126***	-0.0124***	-0.0103***	-0.00802***
	(0.000624)	(0.000758)	(0.000720)	(0.000680)	(0.000674)	(0.000656)	(0.000829)	(0.000955)
post	0.0227***	0.0226***	0.0284***	0.0295***	0.0297***	0.0799***	0.0799***	0.0824***
	(0.00203)	(0.00202)	(0.00335)	(0.00338)	(0.00342)	(0.00559)	(0.00555)	(0.00573)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	2,652,796
R-squared	0.018	0.022	0.023	0.023	0.023	0.027	0.084	0.088
Ind FE		X	X	X	X	X		
Ability			X	X	X	X	X	X
College				X	X	X	X	X
Union					X	X	X	X
Regional trend						X	X	X
Occ. FE							X	X
Sample	All workers							Drop universal Licensed occs.

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. 'License' refers to individuals who possess a government-issued occupational license required by a job. *Post* refers to the post-COVID-19 period after March 2020. 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 (2020) 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.

Among the checks that we perform in column (4) to (8) of Table 4, adding interaction between education reduces our estimated coefficient of the shielding effect of licensing the most. In particular we find that the shielding effect of licensing drops from 0.93 p.p. to 0.72 p.p., or by 23% when we add the education recession interaction. The point estimate remains statistically significant at the 1% level. When we add controls for unionization, regional time trends, occupation fixed effects and drop universally licensed occupations in column (8), we estimate a shielding effect of 0.82 p.p. that is also statistically significant at the 1% level. While controlling education is important, our results suggest that doing this alone may cause one to understate the extent to which occupational licenses shield workers from job loss during recessions.

We establish the economic importance of the shielding effect of occupational licensing that we estimate by comparing our estimate of 0.82 p.p. to three benchmarks. First, when compared to the standard deviation of unemployment in the post and pre-COVID-19 time periods, we find that the shielding effect of licensing is 0.5 to 0.66 standard deviations (respectively). Second, in the absence of the shielding effect of occupational licensing, the average unemployment for licensed workers would have been 3.52% rather than 2.7% over the two years of the COVID-19 pandemic. Third, the shielding effect of licensing represents one fifth of the gap in the post-COVID-19 unemployment rate between unlicensed and licensed workers or 29% of the pre-pandemic gap in unemployment rate (see Table 1 for the gaps in unemployment rates).

3.1 Recession Intensity

We build on our analysis by exploiting spatial variation in the intensity of the COVID-19 recession to test whether occupational licensing shields licensed worker more strongly in places that were more severely hit by the recession. In particular, we compare the shielding effect of licensing during the recession in places that imposed a mandatory lockdown to states that did not. In the beginning (March and early April) of COVID-19, 42 states plus DC 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. While 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 because of the government order. For example, Alexander and Karger (2023) show that stay-at-home orders decreased individual mobility and spending. We leverage this unanticipated (one-time) policy response with the COVID-19 timing and generate state-by-time variation in the intensity of shock.

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. We estimate the following regression:

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

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 as compared to states that that did not impose a lockdown. The coefficient δ_3 is an estimate of the labor demand shock associated with lockdowns — specifically, it measures how much unemployment increased for workers in states that issued lockdowns. Positive values $\delta_3 > 0$ indicate that places with lockdowns experienced higher unemployment during the COVID-19 pandemic than places without lockdowns.

Comparing δ_4 to δ_3 provides a useful benchmark for quantifying how large the shielding effect of occupational licensing is during the recession relative to the negative labor demand shock of the lockdown.

The identification of δ_4 as a causal parameter relies on the idiosyncratic timing of COVID-19 and the emergency reaction of 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. In Figure A1 of appendix, we first test whether the proportion of people reporting a license changes around the time of the COVID-19 pandemic. There is no significant change or trend in individuals' license attainment before and after the shock. In Figure A2 of appendix, 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 the event time dummies. We do not observe significant changes in observable characteristics of licensed workers as a result of the pandemic. Both test suggest that reverse causality is unlikely to drive any results that we find. In Table 5, we test the orthogonality between state unemployment rate in 2018 and 2019 and the state lockdown decision in 2020. We also include the percent of workers in the state who: have a license or professional certification, are self-employment, the mean hourly wage, and the racial composition of the state. In both 2018 and 2019, we do not find significant predictive power of these variables on whether a state adopts a stay-home order in 2020.

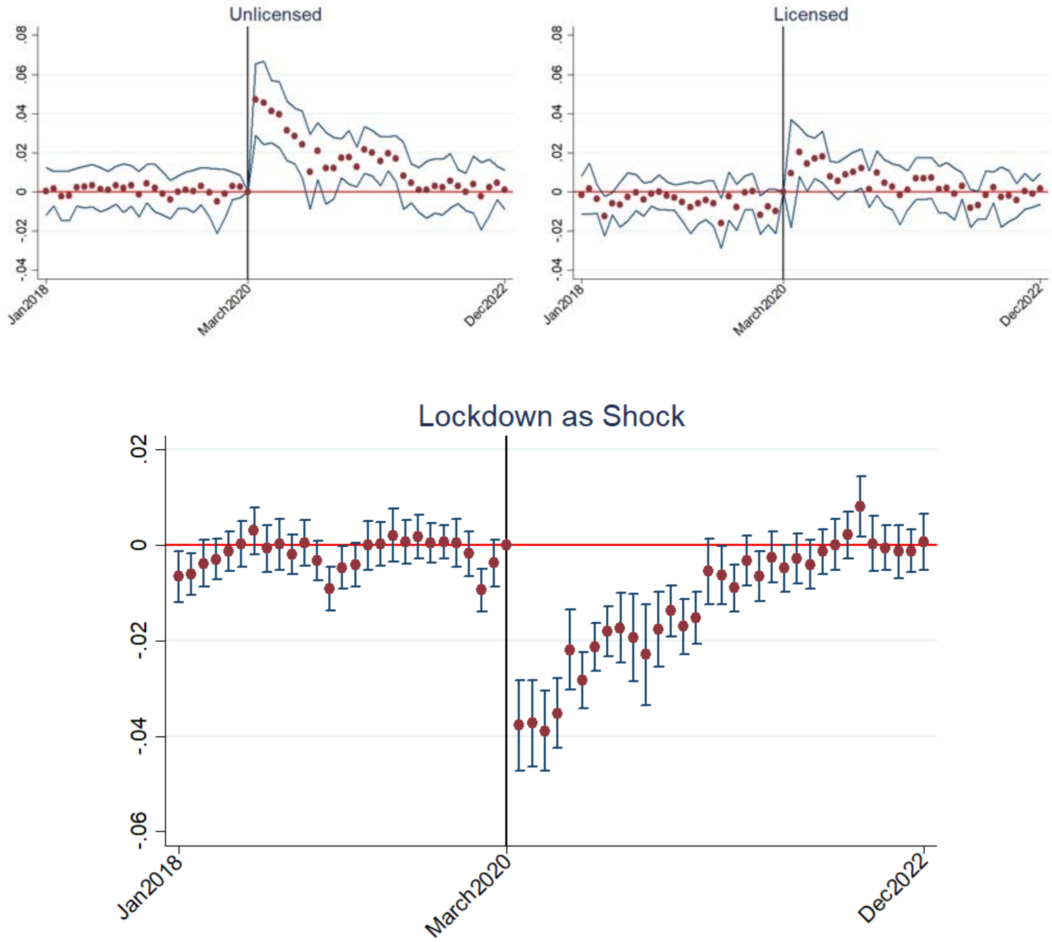
Table 5: Balancing Test: Predictability of Lockdown decision

	(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 state average (with sample weight) of the corresponding characteristics in a particular pre-COVID-19 year. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The upper panel of Figure 3 is an event study of the difference in the probability of unemployment of licensed (and unlicensed) workers between states that issued lockdowns and states that did in the two year window around the COVID-19 recession. Unlicensed workers in states that issued lockdowns experience a sharp 5 p.p. spike in unemploy-

Figure 3: Lockdown Policy to Proxy for Recession Intensity



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

Note: The first panel compares the unemployment pattern by plotting the time dummies between unlicensed and licensed workers, conditional on basic characteristics (age, race, gender, education). The second panel shows the difference between the unlicensed and the licensed with a 95 percent confidence interval. 'Licensed' refers to workers who possess a government-issued occupational license required by current/previous job. Sample weights apply. Standard errors are clustered at the state level.

ment when compared to their peers in states without lockdowns. Licensed workers in states with lockdowns by contrast experience a less pronounced 2 p.p. increase in relative unemployment. In the lower panel of Figure 3, we present the results of an event study in which we plot the coefficient on the triple interaction between license × lockdown × post over time. We find that in states with lockdowns, which are the states that experience the largest increase in unemployment during the recession, that licensed workers are shielded from a 3 p.p. increase in unemployment at the onset of the COVID-19 recession and that this shielding eventually fades out after 15 months.

Table 6: Job Shielding Effect of Licensing strongest in states imposing Lockdowns

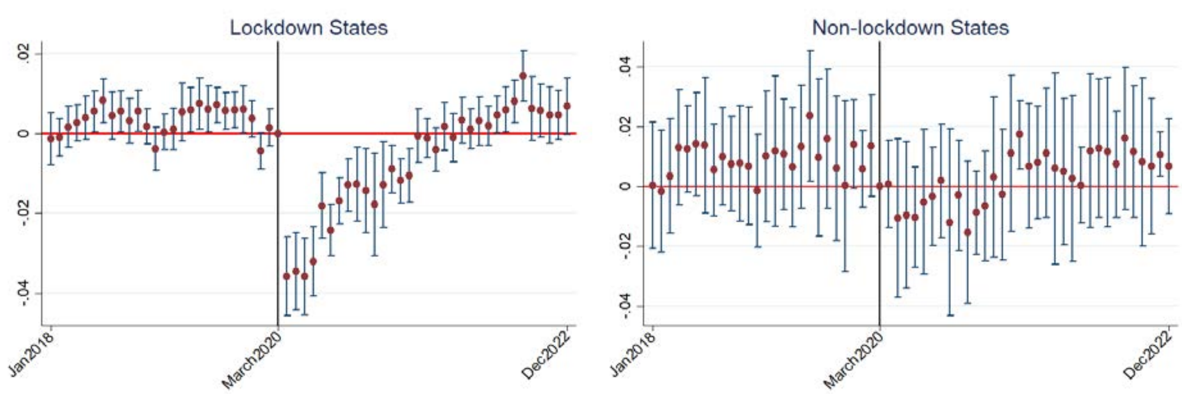
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
license × lockdown × post	-0.0111***	-0.0104***	-0.00910***	-0.00947***	-0.00947***	-0.00943***	-0.00892***	-0.00783***
	(0.00256)	(0.00235)	(0.00224)	(0.00221)	(0.00221)	(0.00221)	(0.00225)	(0.00214)
license × post	0.000328	-0.000829	-0.00116	0.00162	0.00162	0.00170	0.000966	-0.000880
	(0.00243)	(0.00220)	(0.00213)	(0.00209)	(0.00209)	(0.00210)	(0.00215)	(0.00209)
license	-0.0163***	-0.0113***	-0.0113***	-0.0126***	-0.0126***	-0.0127***	-0.0106***	-0.00807***
	(0.000629)	(0.000764)	(0.000727)	(0.000691)	(0.000691)	(0.000673)	(0.000854)	(0.000972)
lockdown × post	0.0152***	0.0151***	0.0221***	0.0201***	0.0201***	0.0195***	0.0187***	0.0194***
	(0.00281)	(0.00279)	(0.00386)	(0.00367)	(0.00367)	(0.00345)	(0.00352)	(0.00357)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461	2,652,796
R-squared	0.028	0.032	0.032	0.032	0.032	0.032	0.089	0.092
Ind FE		X	X	X	X	X		
Ability			X	X	X	X	X	X
College				X	X	X	X	X
Union					X	X	X	X
Regional trend						X	X	X
Occ FE							X	X
Sample	All workers							Drop universal licensed occs.

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. 'License' refers to individuals who possess a government-issued occupational license required by a job. 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 and month fixed effects. Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

In Table 6, we report the results that we obtain from estimating Equation 3 with varying levels of control variables, following the structure of Table 4. Our coefficient of interest comes from the interaction license $\times$ lockdown $\times$ post, which measures the extent to which occupational licenses differentially shielded workers from job loss in states that implemented lockdowns at the onset of COVID-19. States that imposed lockdowns experienced an unemployment rate that was 1.5 to 2 p.p greater (see the coefficient on lockdown $\times$ post). Indeed, the lockdown pinpoints variation in the intensity of the recession. Across the eight specifications in Table 6 we find that occupational licensing mutes between 0.78 to 1.1 p.p. of the increase in unemployment due to the lockdown. Although we know that unemployment also increased in the states that did not impose a lockdown, we do not find a shielding effect of licensing from recession-induced job loss in states without a lockdown. The coefficient on the interaction license $\times$ post is not only statistically insignificant across all specifications, it is an order of magnitude smaller than coefficient on the triple interaction license $\times$ lockdown $\times$ post.

Figure 4: Shielding Effect in Lockdown vs Non-lockdown States



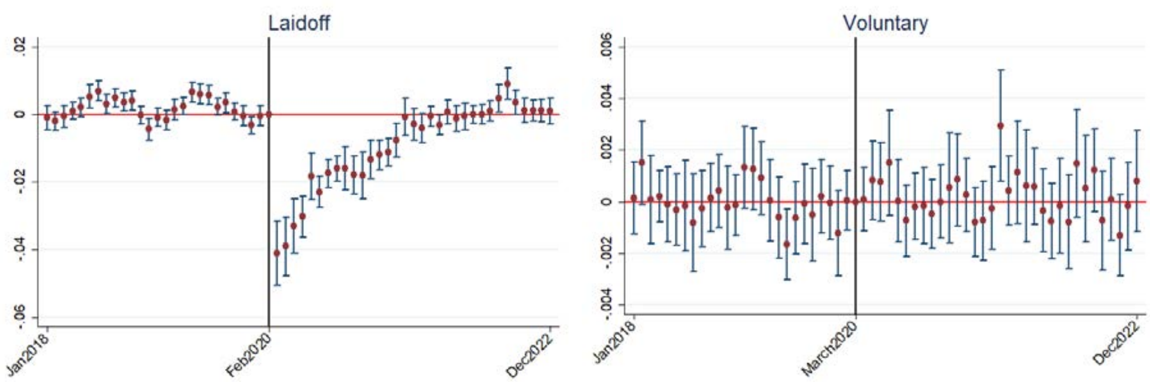
Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: This figure compares the time dummies of the shielding effect of licensing in lockdown states (left) and non-lockdown states (right) with a 95% confidence interval. Sample weights apply. Standard errors are clustered at the state level.

The event study in Figure 4 in which we split our sample into states with lockdowns and non-lockdown states and estimate the difference in unemployment between licensed and unlicensed workers following the approach in Equation 2 confirms the findings from our triple difference regression model. This pattern of results is consistent with the hypothesis that licensing shields workers from job loss due to negative labor demand shocks but not against common labor supply shocks.

We now directly test the hypothesis that licensing shields against recession-induced job loss due to negative labor demand shocks but not labor supply shocks. In the data we observe whether an individual is unemployed due to a layoff, which we consider to be more closely related to a negative labor demand shock, or a voluntary quit, which we consider to be a more closely related to a labor supply decision. In Figure 5 we estimate our event study of changes in the relative unemployment gap separately by layoffs and voluntary quits, using the triple difference approach. 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 5: Licensing Reduces Job Loss due to Layoffs in COVID-19



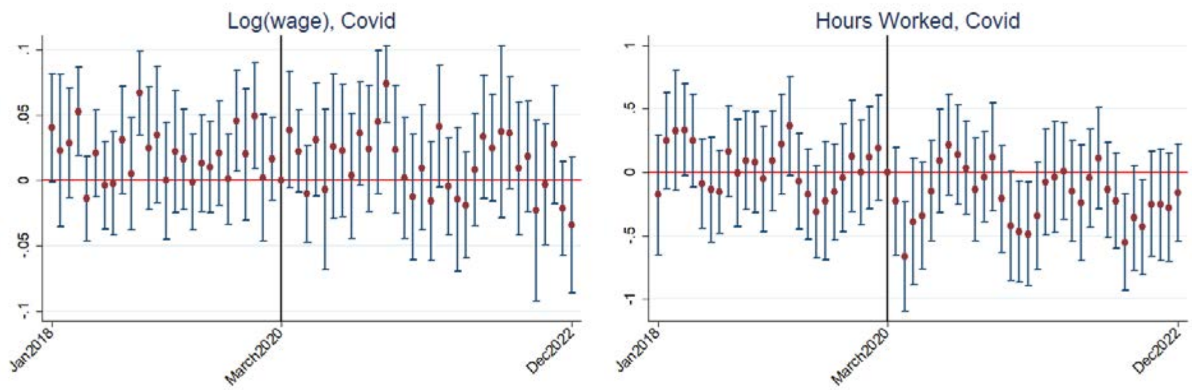
Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: This figure compares the time dummies of the shielding effect of licensing on laidoff (left) and voluntary separation (right) with a 95% confidence interval. Sample weights apply. Standard errors are clustered at the state level.

We further test whether the protection that licensed workers experience from job loss due to the recession involves trading off lower wages or fewer hours worked. Relative to their unlicensed peers, licensed workers earn a wage premium; therefore it is plausible that firms and workers could negotiate job protection for lower wages or fewer hours worked. In Figure 6, we show results for the event study of log wages and hours worked.

We do not find evidence that the licensing wage premium is reduced during the recession, neither do we find a reduction in relative hours worked between licensed and unlicensed workers among those who remain employed.

Figure 6: Other Outcomes - Wages and Hours Worked



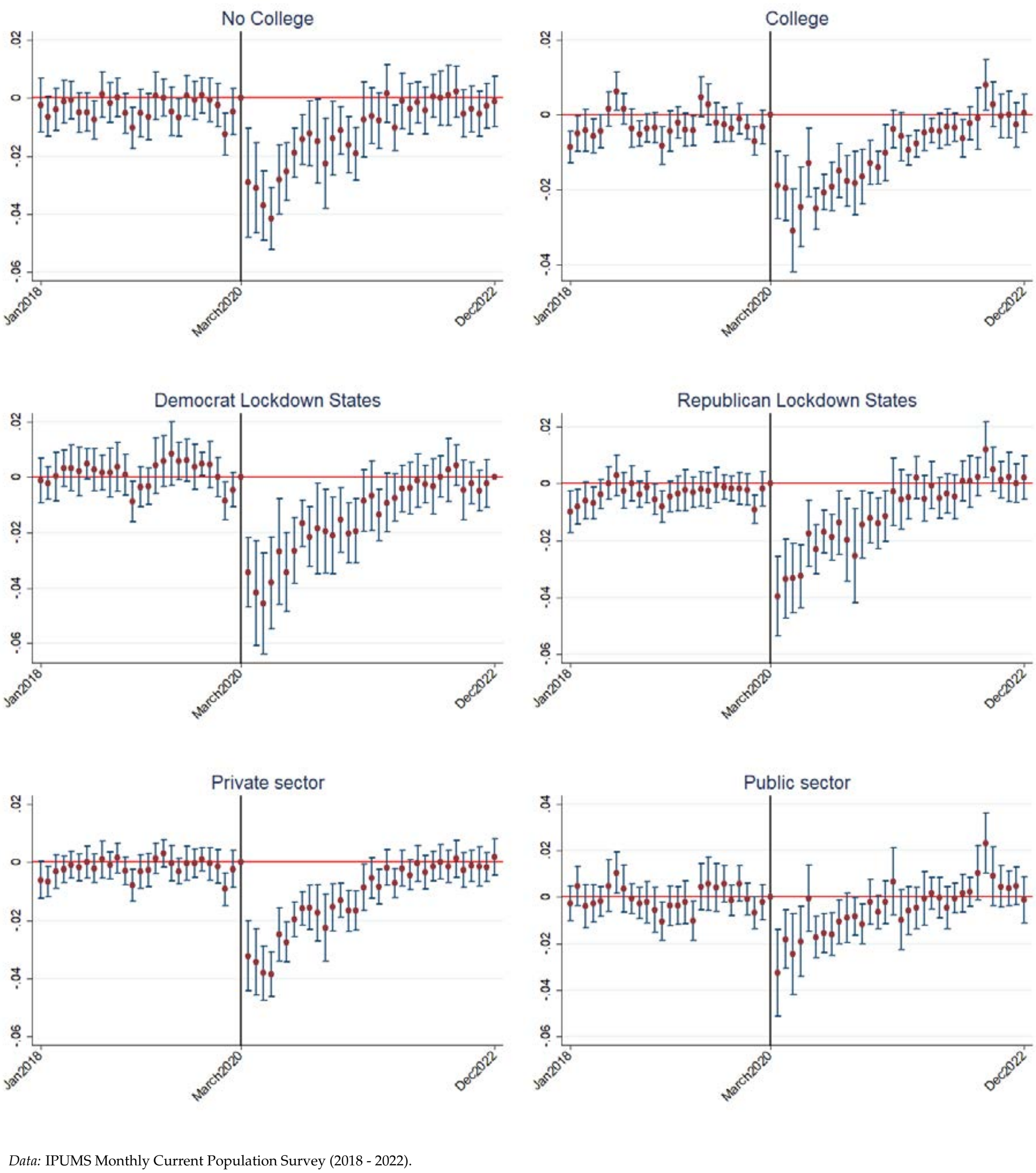
Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: This figure plots the time dummies of the shielding estimate on log hourly wages (left) and hours worked (right) with a 95% confidence interval. Sample weights apply. Standard errors are clustered at the state level.

Across many dimensions of heterogeneity, we 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 when compared to their unlicensed peers, as shown in Figure 7. 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 states and blue states, we document similar impact of licensing on protecting workers from recession-induced job loss, as shown in Figure 7.[6] The one exception 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.

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

Figure 7: Heterogeneity by Education and Industry

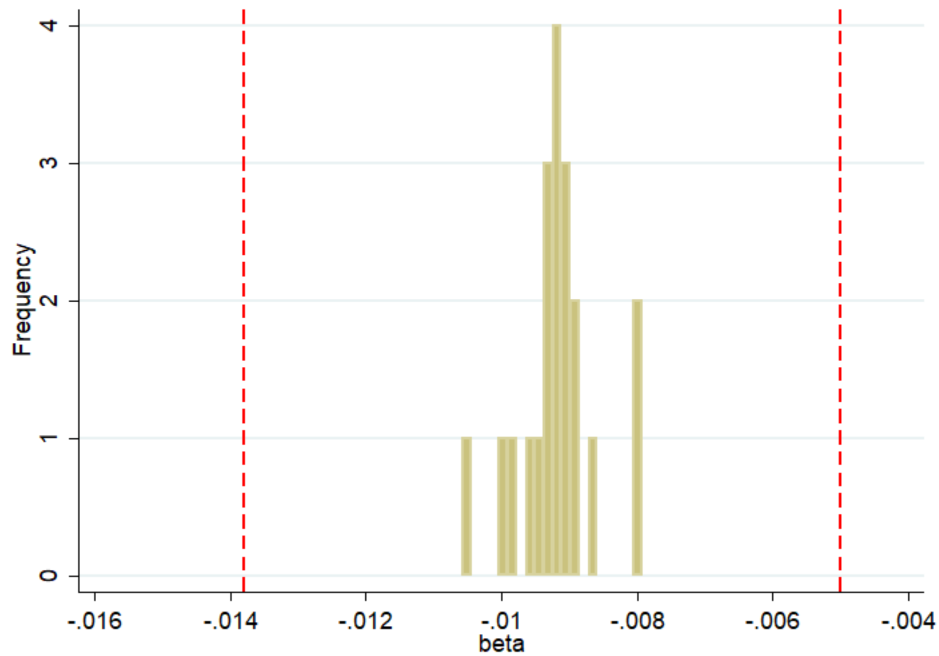


Data: IPUMS Monthly Current Population Survey (2018 - 2022).

Note: This figure includes event study plots of the COVID-19-lockdown shock using different sub-samples. 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.

The job shielding effect of licensing appears to be consistent across industries. Notably, we show in Figure B1 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 of the 20 industry permutations fall within the 95% confidence interval of the main treatment effect using the lockdown shock.

Figure 8: Job Shielding Impact of Licensing during COVID-19 Similar Across Industries



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 using lockdown shock (comparable to column 6 of Table 6). 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. Two of the DID estimates smaller than the main DID estimate, while none of the iterations are significantly different from the lockdown estimate.

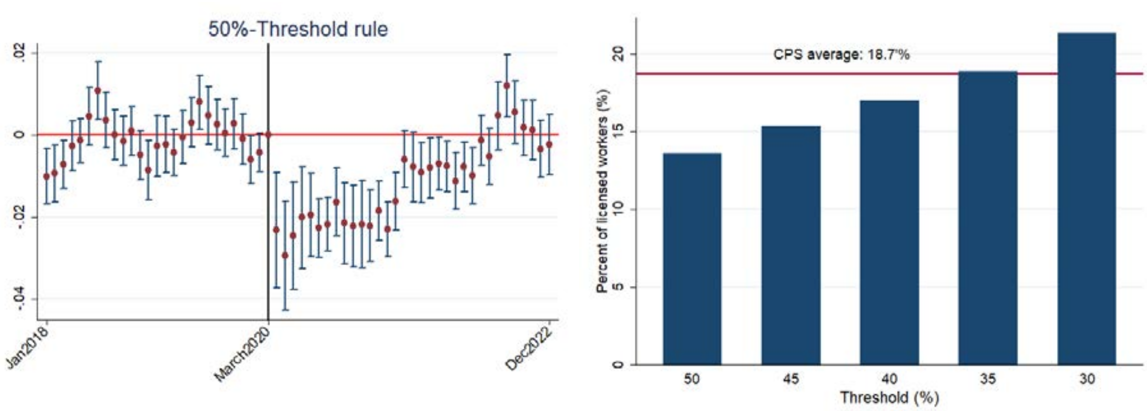
3.2 Alternative Measures of Licensing

The license attainment variable we employ is self-reported in the CPS that may be susceptible to measurement error (Kleiner and Vorotnikov, 2017). In this subsection, we adopt a threshold rule as an alternative way to define license requirements at the occupation-by-state 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 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.

On the left panel of Figure 9, we plot an event study graph of the relative unemployment gap between licensed workers and unlicensed workers the 50%-threshold, which is a common standard in the literature. Qualitatively the picture looks similar to what we found when we use the individual self-reported licensing variables in Figure 2. Prior to the onset of COVID-19, the relative unemployment gap between licensed and unlicensed workers bounces around zero before dropping immediately in the aftermath of COVID-19. In the right panel of Figure 9, we plot the fraction of licensed workers that we obtain by assigning an individual's license status using the outcome of a threshold rule for state-occupation licensing and compare it to the average licensing rate from the individual self-reports in the CPS which is 18.7%. Our comparison suggests that 50%-rule might underestimate the license attainments, while the 30%-rule might overstate it.

Figure 9: Sensitivity Check: 50%-Threshold Rule to Define Licensure



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

Note: The left panel compares the tabulated average of licensed workers using the corresponding threshold with the raw sample average (18.7%). Using the 50% gives the closest mean. The right panel plots the event study graph of the shielding effect using the 35%-threshold.

Table 7: Results Consistent across Licensing Thresholds

	(1) 0.5	(2) 0.45	(3) 0.4	(4) 0.35	(5) 0.3
license*lockdown	-0.0102***	-0.00961***	-0.00975***	-0.00792***	-0.00793***
	(0.00234)	(0.00214)	(0.00186)	(0.00205)	(0.00191)
license*post	0.00372	0.00368*	0.00352**	0.00266	0.00265
	(0.00230)	(0.00202)	(0.00171)	(0.00201)	(0.00181)
license	-0.00402***	-0.00395***	-0.00435***	-0.00504***	-0.00604***
	(0.000672)	(0.000662)	(0.000623)	(0.000733)	(0.000684)
lockdown	0.0203***	0.0204***	0.0206***	0.0205***	0.0207***
	(0.00345)	(0.00345)	(0.00344)	(0.00350)	(0.00357)
Observations	3,019,461	3,019,461	3,019,461	3,019,461	3,019,461
R-squared	0.031	0.031	0.031	0.031	0.031

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. '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 (column 6 of Table **??**). Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

In Table 7, we present results that probe the sensitivity of our core finding to the choice of the licensing threshold. For licensing thresholds that vary from 50% to 30% in increments of 5 p.p, we estimate the specification from column 6 in Table 6, where we replace the individual license attainment with an indicator for whether an individual in a given state-occupation is licensed as determined by the threshold rule. The regression specification includes controls for education, ability, and union status as well as their interactions with the 'post' variable to allow for the differential impacts of these variables before and after the recession. In the models we use industry fixed effects to guard against the potential that the occupation fixed effect would be collinear with the state-occupation definition. We find that licensing shielded workers from increases in unemployment but only in states that experienced a negative labor demand shock as measured by the introduction of a lockdown. The shielding effect that we estimate ranges from 0.79 p.p. using the least stringent licensing threshold of 30% to 1.02 p.p. using the most stringent threshold of 50%. For comparison when we used the individual licensing attainment, we measured a shielding effect of 0.94 p.p. (column 6 in Table 6). Measurement error from using the individual licensing self-reports leads to an underestimate of the treatment effect by roughly 6%.

4 Results Generalizable to the Great Recession

Is our finding that occupational licensing protects workers from job loss during a recession a general result? Or is it a finding that is unique to the COVID-19 induced 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 was sparse before 2015, we construct a state-by-occupationa 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 (A.B.A.) on licensing statutes that have restrictions on felons (Blair and Chung, Forthcoming) and 3) data on occupations that are universally licensed (Johnson and Kleiner, 2020).

The 2008 SIPP data is the earliest nationally representative household survey that contains individual license attainment. The licensing data was collected during its Wave 13 in 2012/2013. 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 licening from the SIPP data permits us to combine it with the A.B.A. licensing data and the data on universally licensed occupations which are both reported at the state-occupation level. We code a worker as licensed if the worker is working in an 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 individuals in the CPS (2006-2010) sample are coded as licensed, using this definition. Because these three data sources come from a time period that follows the Great Recession, we were worried that our estimate of the fraction of licensed workers could be subjected to measurement error. To test this, we compared our fraction of licensed workers to the fraction of licensed workers estimated by Kleiner and Krueger (2013) in 2008 using a Gallup survey. They find that 29% of workers are licensed, which is similar to what we find within a few decimal points.

In Table 8 we report pre-Great Recession and post-Great Recession means of our outcome of interest, the unemployment rate separately for licensed and unlicensed workers. We also calculate 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-Great Recession and post-Great Recession means for the characteristics of workers, e.g., sex, age, race, college, separately for licensed workers and unlicensed workers. We also measure 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. 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.

Table 8: Average Unemployment and Demographics by License Status before and after the Great Recession

	Pre-Recession			Post-Recession			
	(1)			(2)			
	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)

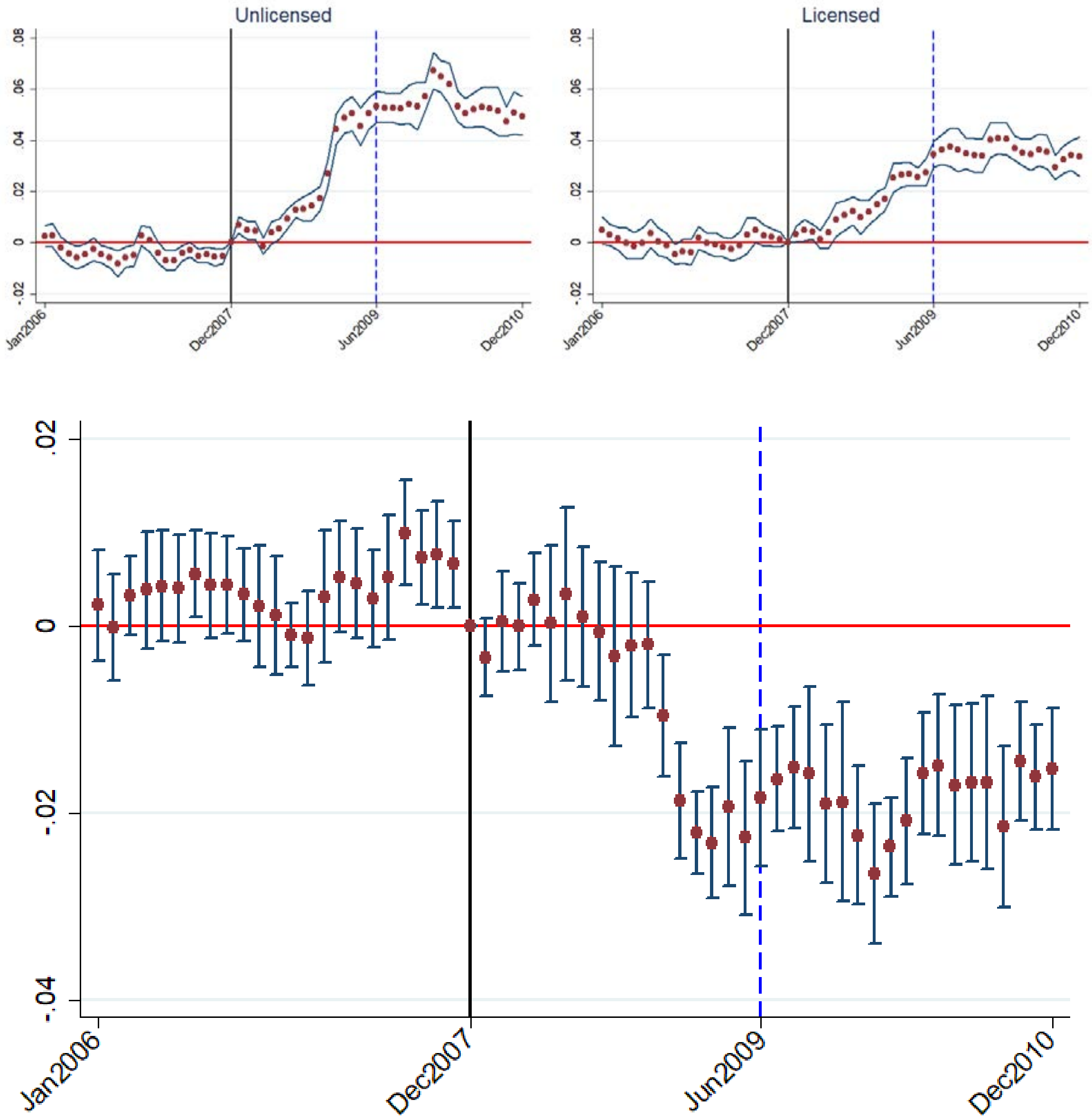
Note: 'Licensed' refers to individuals who work in a licensed state-occupation defined using the data described in Section **??**. 'Pre-Recession' refers the period before Dec 2007. Sample weight apples. Standard errors are clustered at the state level in testing differences.

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 despite both categories of workers being more likely to be unemployed during the recession. Examining the difference in the difference for the nine individual characteristics, we find that they are each economically small and 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 is economically small — ranging from 3.8% to 1.5% of the pre-Great Recession mean for both licensed and unlicensed workers. 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 Figure 10 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 rise in unemployment starting Dec 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 Lehmann Brothers in September 2008, which accelerated the financial crisis during the Great Recession. The event study in the lower panel of Figure 10 quantifyies the difference in the unemployment rate between licensed and unlicensed workers before and after the Great Recession illustrates these dynamics.

In Table 9, we report the results from 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 as compared to its value in the two years prior to the Great

Figure 10: 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 Section **??**. Sample weights apply. Standard errors are clustered at the state level.

recession, using the difference-in-difference regression from Equation 1 and the state-occupation level measure of licensing. The analysis permits us to quantify the average effect of occupational licenses in shielding licensed workers from recession-induced job loss in the two years following the onset of the recession.

Table 9: 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. 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, 2020), 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.

In column (1) of Table 9, 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.

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.[7] Had we not controlled

[7] We do not employ the three ability measures (math, eng, science) since they are tabulated using the

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 column (4) to (6) of Table 9, 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 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, i.e. 1.11 p.p. versus 0.82 p.p.

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 prior to 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

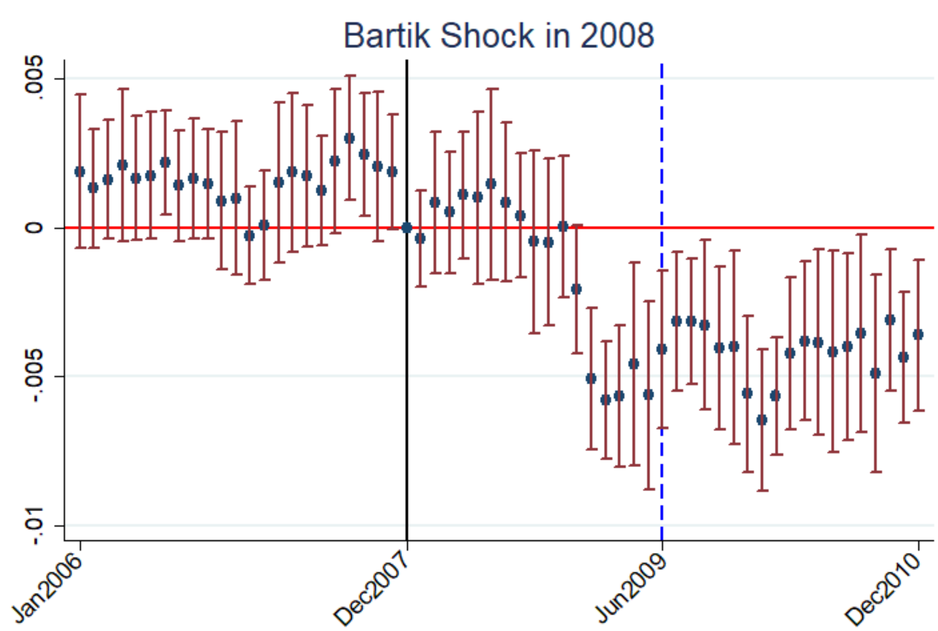
survey after 2008.

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_3, comes from the triple interaction. It measures the average difference in the shielding effect of occupational licenses during the Great Recession between an MSA that is predicted to be in the 90th versus the 10th percentile of the recessionary unemployment shock. Negative values of β_3 imply that licensing offers stronger protection from job loss for licensed workers in MSAs that are harder hit by the Great Recession.

Figure 11: 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). Sample weights apply. Standard errors are clustered at the state level.

In Figure 11 we plot event study estimates of β_3 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 is 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 Lehmann Brother's fails we see the emergence of 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.

Table 10: The Shielding of Licensing in 2008 - Bartik Shock

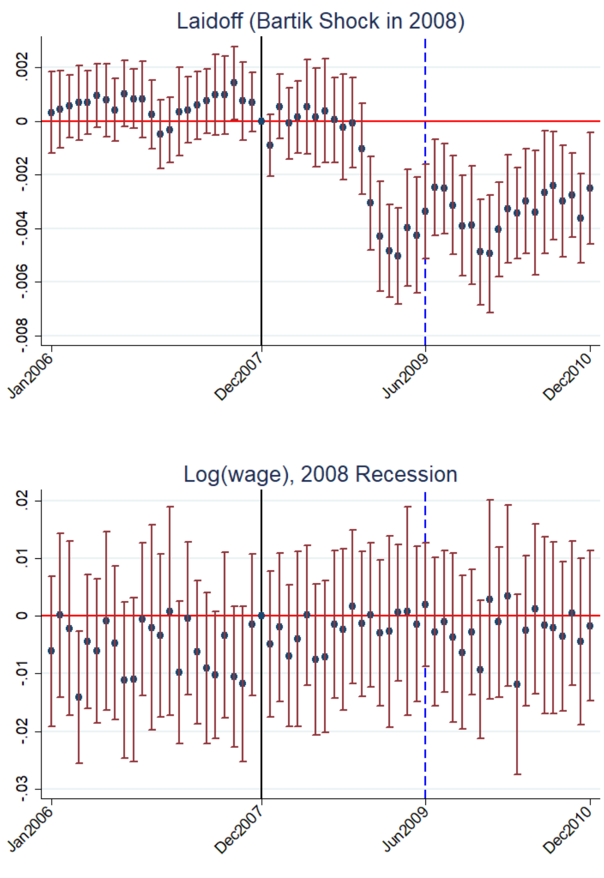
	(1)	(2)	(3)	(4)	(5)	(6)
lic. × Bartik × post	-0.00436***	-0.00441***	-0.00327***	-0.00317***	-0.00318***	-0.00297***
	(0.000363)	(0.000355)	(0.000320)	(0.000311)	(0.000331)	(0.000386)
license (lic.)	-0.00723***	0.000635	-0.00197*	-0.00219**	-0.00217**	-0.00216
	(0.000960)	(0.00113)	(0.00109)	(0.00109)	(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 x shock			X	X	X	X
Union x shock				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. 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, 2020), 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.

In Table 10, we present estimates of the average value of β_3 for increasingly rich implementations of Equation 4. To begin, the Bartik shock captures 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 omitted variable bias of β_3 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.

Figure 12: Licensing Shields worker from layoffs during Great Recession



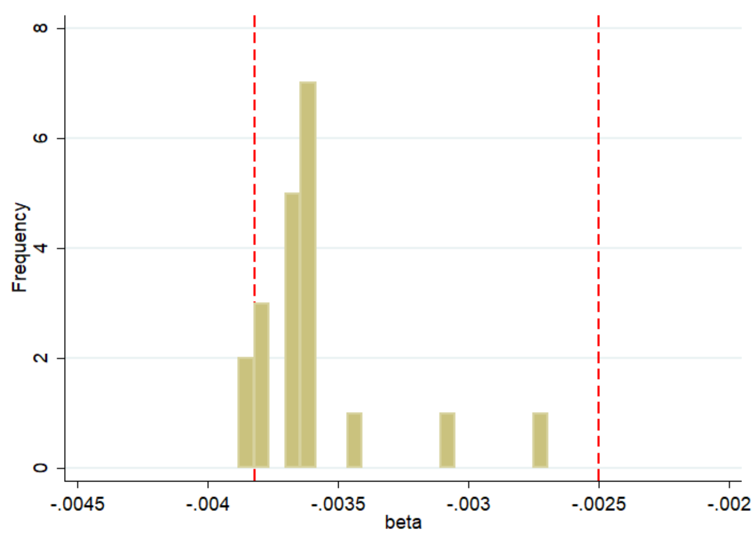
Data: IPUMS Monthly Current Population Survey (2006 - 2010).

Note: This figure compares the shielding effect on laidoff (left) and voluntary separation (right).

Consistent with the evidence that licensing shields workers from unemployment during recessions most in places where labor demand shocks are largest, in the top panel of Figure 12, we find that involuntary separations from lay-offs explain the pattern that we observed in the data. By contrast, there is no change in unemployment due to voluntary separations during to recession. Moreover we do not find evidence that wages or hours worked adjust to compensate for the reduction in unemployment exposure, as shown in the lower panel of Figure 12. Therefore, as with the COVID-19 recession, we find that the licenses shield licensed workers from unemployment without requiring them to trade-off wages or hours worked.

The shielding effect of licensing during the Great Recession appears to be consistent across industries. Notably, we show in Figure 13 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 to estimate our treatment effect. corresponding main treatment effect.

Figure 13: Job Shielding of Licensing during the Great Recession Similar Across Industries



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 using the regression from column 5 of Table 10. The red line marks the 95% confidence interval of 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 similar over the 2-year period that we study.

5 Selection on Unobservables and Placebo Tests

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 selection on unobservables relative to selection on observables would need to be in order to overturn our results. Second, we exploit 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 4 for the COVID-19 recession and the regression model from column 5 in Table 9 for the Great Recession), in Table 11 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 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 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 larger 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). 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 2008 recession drops to 0.687, it is still 20% higher than the implied ratio of license wage premium obtained in Kleiner and Krueger (2013).

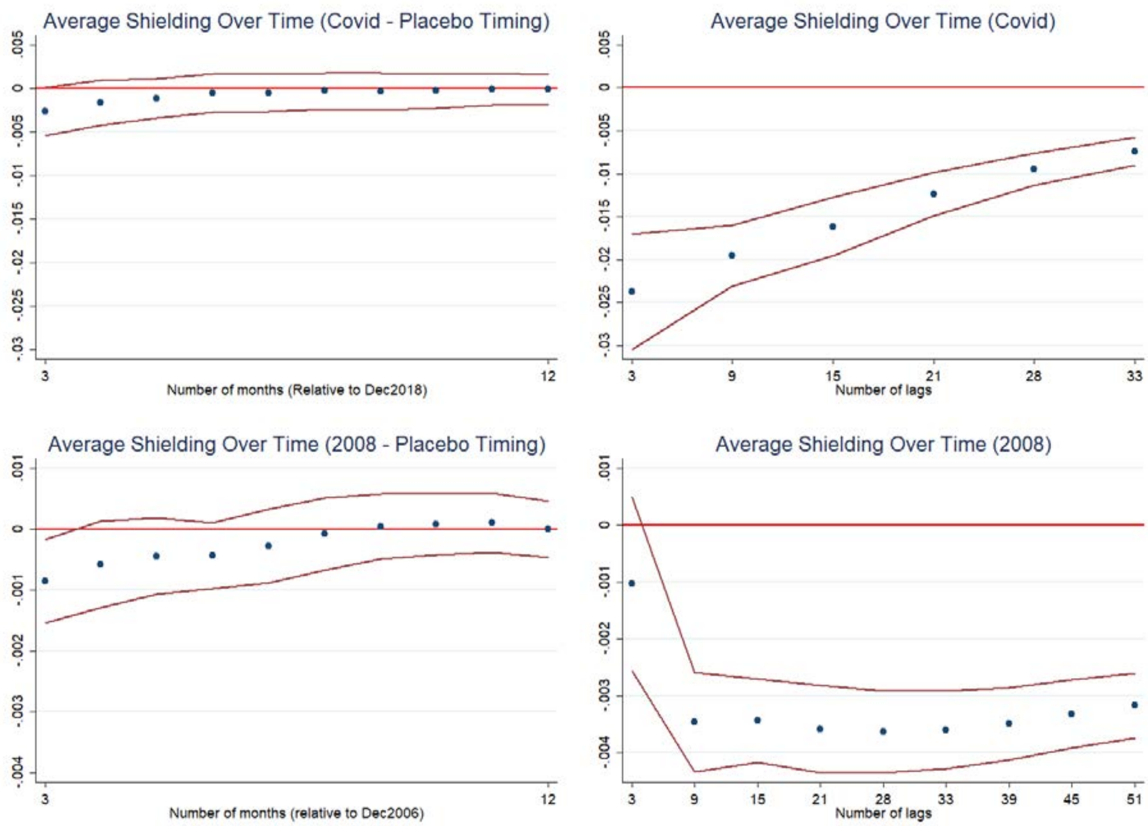
Table 11: Assessing Selection on Unobservables to Nullify the Shielding Estimate

$R^2_{max} =$	1.1×R^2	1.2×R^2	1.3×R^2	1.4×R^2	1.5×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.

We complement our selection on unobservables test with a set of placebo tests. For the placebo tests we split the 2 year pre-recession period in half and estimate the shielding effect of licensing assuming that the fictitious recession occurs in the second half of the actual pre-recession period. For our placebo analysis, we focus on estimating the triple difference models in which we exploit the intensity of the recessions using the lockdown variation from COVID-19 (Equation 3) and the Bartik variation from the Great Recession (Equation 4). In Figure 14 we report estimate of the average shielding effect of licensing from the placebo recessions averaged over months post-recession in increments of one month starting with 3 months post-recession going up to 12 months post-recession. For comparison purposes, we also report estimates of the average shielding effect of licensing using the actual recessions starting with 3 months post-recession going out as far post-recession as we possibly can, i.e., 51 months for the Great Recession and 33 months for the COVID-19 recession.

Figure 14: Placebo Effects (Left) and Persistence Effects (Right)



Note: The upper panel of the figure tracks the average shielding effect of licenses for workers with licenses in states that imposed lockdowns for COVID-19 for the placebo recession date (left) and the actual date of the COVID-19 Recession (right). The lower panel of the figure tracks the average shielding effect of the 2008 Bartik shock using the placebo recessions (left) and the actual date of the Great Recession (right).

When we use the placebo recession date we find very small and statistically insignificant treatment effects for both the COVID-19 recession and the Great Recession for the entire time from 3 months to 12 months post the fictitious recession. By contrast, when we use the factual recession dates we find comparatively larger and statistically significant estimates of the job shielding effect of licensing that started immediately for the COVID-19 recession and at the 9 month mark for the Great Recession. Comparing the persistence of the job shielding effects of licensing from the factual recessions dates, we find that the effect fades out over time for the COVID-19 recession but is persistent for up to 51 months following the Great Recession. The difference in the persistence of the shielding effect of licensing across the two recession mirrors the short-lived nature of the COVID-19 recession when compared to the relatively protracted nature of the Great Recession.

6 Spillovers from Licensed to Unlicensed workers

Does the job protection afforded to licensed workers result in corresponding job loss for unlicensed workers? To measure spillovers we construct state-industry unemployment rates in each month separately for all workers, licensed workers and unlicensed workers. If we find that the state-industry unemployment rate for unlicensed workers increases more during the recession for unlicensed workers in state-industry pairs with higher levels of pre-recession licensed workers, this would be indirect evidence that the job protection afforded to licensed workers during a recession comes at the expense of job losses for unlicensed workers. Formally, for both the COVID-19 induced recession and the Great Recession and COVID-19, we run the following state-industry level difference-in-differences regression:

$$\begin{aligned} U_{sd,m} = &\beta_0 + \beta_1 LicenseExposure_{sd} + \beta_2 post \\ &+ \beta_3 LicenseExposure_{sd} \times post + X_{sd,m}\Gamma + \theta_d + \theta_s + e_{sd,m}, \end{aligned} \tag{5}$$

where the outcome $U_{sd,m}$ is the unemployment rate of a state-industry sd in month m, 'post' is an indicator variable equal to one for all months after the onset of the recession, and the variable "LicenseExposure" is a standardized measure of the percent of licensed workers in that state-industry tabulated using the CPS in 2006 for the Great Recession and using the CPS data from 2018 for COVID-19. The control variables $X_{n,m}$ are the tabulated time-varying state-industry averages of worker characteristics. Sample weight applies to all tabulated variables and standard errors are clustered at the state level. Our coefficient of interest, β_3, measures the difference during the recession as compared to before the recession in how much the industry-state unemployment rate changes for a one standard deviation increase in state-industry exposure to occupational licensing.

Table 12: State-Industry License Exposure and Aggregate Effect

	(1)	(2)	(3)
COVID-19			
LicenseExposure*COVID-19	-0.00168	-0.00146	-0.00410***
	(0.00115)	(0.00119)	(0.00137)
LicenseExposure	0.00571***	0.00672***	0.00346*
	(0.00198)	(0.00210)	(0.00196)
COVID-19	0.0182***	0.0186***	0.0173***
	(0.00162)	(0.00169)	(0.00223)
Pre-COVID-19 Mean State-industry Unemployment	0.0371	0.0404	0.0185
Observations	58,631	58,411	48,560
R-squared	0.122	0.112	0.037
Great Recession			
LicenseExposure*Recession	-0.00332***	-0.00244**	-0.00179
	(0.000912)	(0.00111)	(0.00140)
LicenseExposure	0.00355**	0.00300*	0.00249
	(0.00169)	(0.00154)	(0.00207)
Recession	0.0313***	0.0329***	0.0251***
	(0.00194)	(0.00210)	(0.00188)
Pre-Recession Mean State-industry Unemployment	0.0427	0.0449	0.0352
Observations	58,983	58,568	53,585
R-squared	0.187	0.170	0.074
Worker Sample	All	Unlicensed	Licensed

Data: IPUMS Monthly Current Population Survey.

Note: Dependent variable in all regressions is the unemployment rate of the corresponding group of workers. Sample includes individuals between 18 and 65 who are in the labor force. 'LicenseExposure' is the tabulated percent of licensed workers in a state-industry using CPS in 2006 for Great Recession and 2018 for COVID-19, respectively. 'COVID-19' equals 1 for the sample months after March 2020. 'Recession equals 1 for the sample months after Dec 2007. All regressions control for average characteristics in Table 1, the average ability measures, state, and industry fixed effects. Sample weights apply. Standard errors are clustered at the state level. *** p<0.01, ** p<0.05, * p<0.1.

If job protection for licensed workers comes at the expense of higher job loss for unlicensed workers then we would expect to see $\beta_3 > 0$ for the model where our outcome is the state-industry unemployment rate for unlicensed workers. If instead $\beta < 0$ for the model where our outcome is the state-industry unemployment rate for unlicensed workers, then the job protection experienced by licensed workers is not a zero-sum game. In Table 12 for both COVID-19 and the Great Recession we report estimates of β_3 when our outcome is the state-industry unemployment rate for: of all workers (column 1), unlicensed workers (column 2), and licensed workers (column 3). Focusing on the results for unlicensed workers in column 2, we find that β_3 is negative in both COVID-19 and the Great recession, which suggests that we do not find evidence that the job protection of licensed workers comes at the expense of unlicensed workers.

7 Conclusion

Governments devote a lot of time and resources to muting the effects of job loss during recession. In this paper, we show that occupational licensing shields licensed workers from job loss during recessions. We first establish the core fact pattern using data from the COVID-19 recession and then show that our findings generalize to the Great Recession. In particular, licensing shields workers from job loss in the places where the labor demand shock from the recession is most severe. This results in licensed workers being less likely to be laid-off than their unlicensed peers even thought there is no change in the relative likelihood that a licensed worker becomes unemployed due to a voluntary quit. Moreover, we find that the job shielding effects of licensing are not driven by a single industry but rather is a robust general phenomenon.

An interesting distinction between the two recessions is that we see a persistent impact of licensing on shielding workers from unemployment from the Great recession that lasted several years after the great recession, whereas the job shielding effect of licensing fades out over time with the COVID-19 recession. This result suggests that longer recessions may result in the labor market moving to a different equilibrium in which licensed workers face lower levels of unemployment even long after the recession is done, providing further support to the thesis in Blair and Deming (2020) that the Great Recession caused a structural increase in the demand for education credentials.

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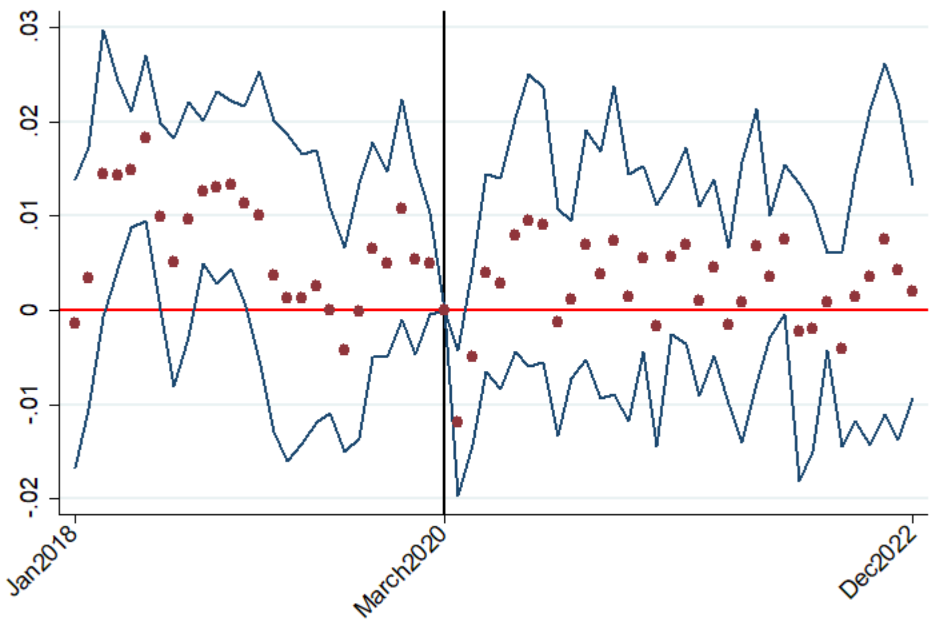
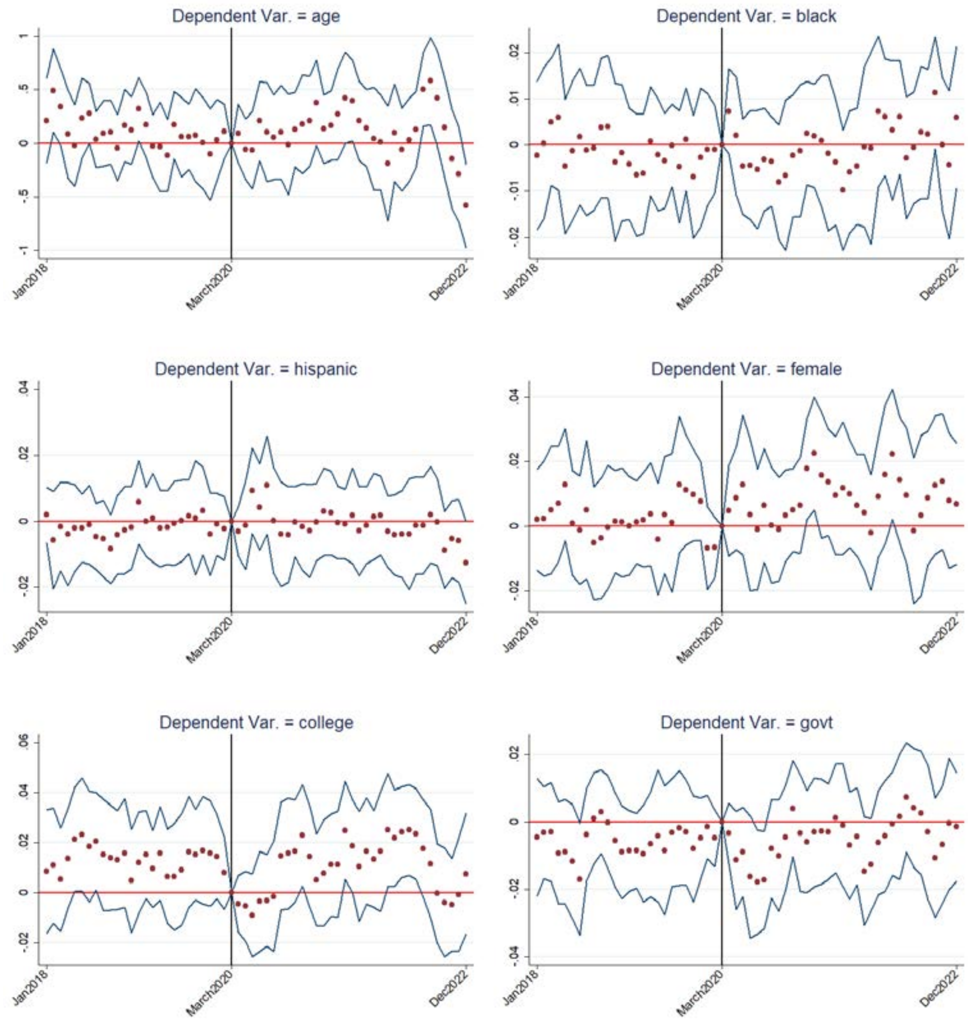
Appendix A: Additional Results (COVID-19 Recession)

Figure A1: Auxiliary Regression on License Status



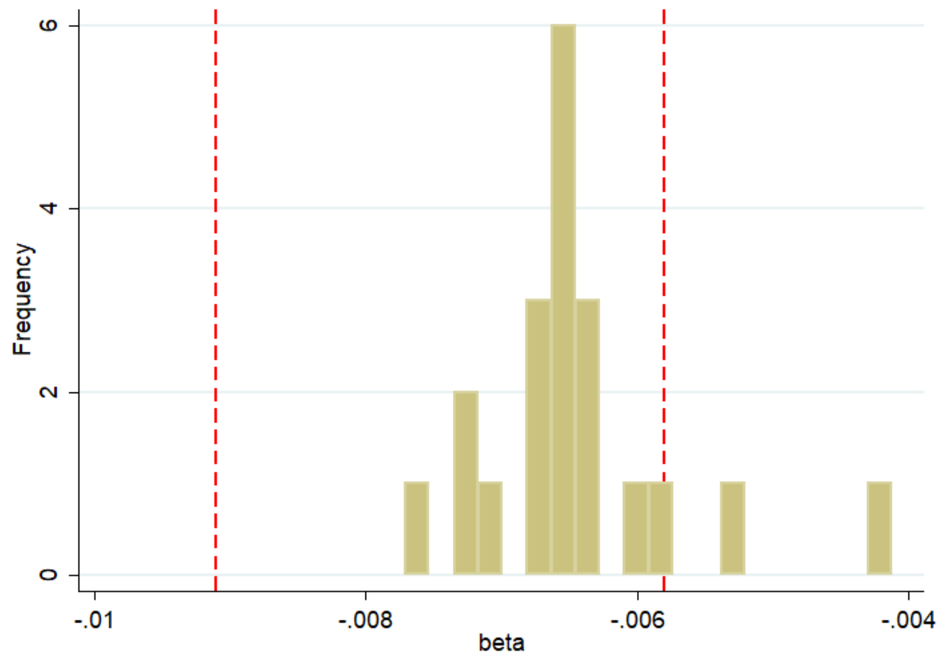
Note: This figure plots the event time dummies (with 95% confidence interval) on license status. License attainment of individuals before and after COVID-19 does not experience significant changes.

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 B1: 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 4).

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)
Constant	0.117***	0.108***	0.105***	0.105***	-0.202***	-0.210***
	(0.00272)	(0.00237)	(0.00252)	(0.00253)	(0.0241)	(0.0274)
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).

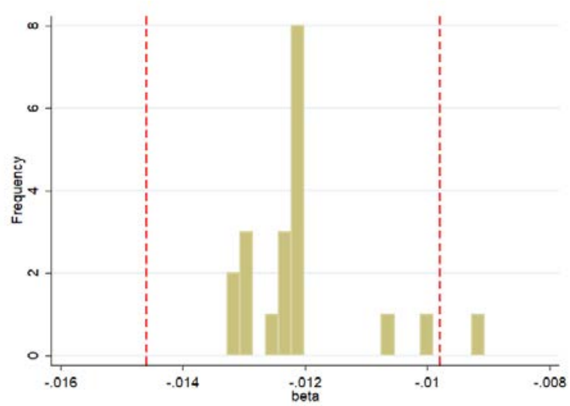
Table B3: Bartik Shock - Aug 2008 as Alternative cutoff

	(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, 2020), 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 B2: 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 10. 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. Eighteen of the 20 Bartik estimates are inside the confidence interval of the main estimate.

Appendix C: Aggregate State-Industry Analysis