Unemployment Benefits Expansion and Business Formation*

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Abstract

New business formation surged after the pandemic recession, but its causes are not well understood. In this paper, we provide evidence that unemployment insurance (UI) expansion contributed to the rise in business creation. The expansion of UI benefits under the CARES Act, coupled with the relaxation of work search requirements under FFCRA, provided unemployed potential entrepreneurs with the funds and time needed to develop business ideas. To identify the causal effect of UI benefits expansion on business formation, we exploit the fact that the variation across states in the increase in UI payments per unemployed was partly due to some states' reliance on an outdated technology, COBOL, to process UI claims. Using an instrumented difference-in-difference design, we estimate that a one percent increase in UI benefits per unemployed led to a 0.24 percent increase in new business applications. This estimate implies that more than half of the observed rise in business formation in 2020 can be attributed to the UI expansion. Our findings highlight the potential role of UI policy in contributing to economic recoveries by fostering entrepreneurship.

JEL Codes: H31, H32, L26, J65, J68
Keywords: Business Application, Entrepreneurship, Unemployment InsuranceYeah,

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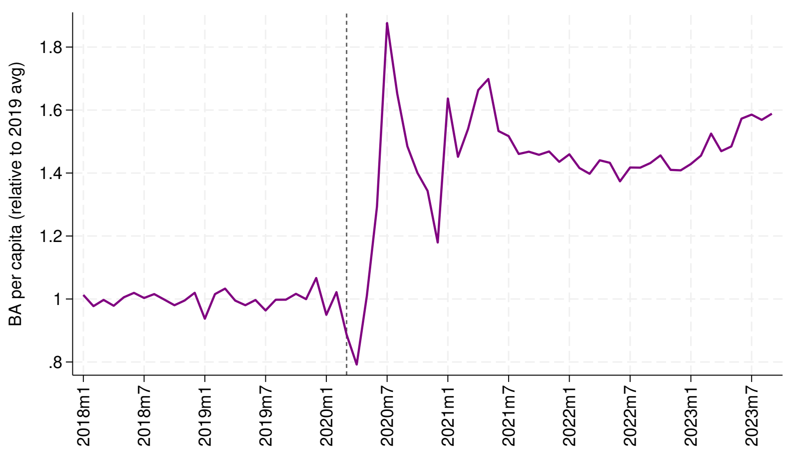
1 Introduction

Business startups play a critical role in job creation, innovation, and productivity growth in the United States. As such, the secular decline in the firm entry rate over the past several decades has received widespread attention.[1] Unexpectedly, the slowdown in startup activity has reversed substantially since the onset of the COVID-19 recession. Figure 1 shows that the number of new business applications surged starting in April 2020, and has remained elevated since. While this phenomenon has received much attention given its unprecedented scale and its potential implications for economic growth, its causes are not well understood.[2]

FIGURE 1: BUSINESS FORMATION PER CAPITA



Notes: Seasonally-adjusted monthly business applications per 1,000 people relative to its 2019 average (0.89 business applications per 1,000 people). Business application data is obtained from the U.S. Census Bureau's Business Formation Statistics.

In this paper, we use the U.S. Census Bureau's Business Formation Statistics (BFS) data on applications for Employer Identification Numbers (EINs), coupled with Bureau of Labor Statistics (BLS) data on unemployment insurance (UI), to provide evidence that the UI expansion implemented at the onset of the pandemic had a large and positive impact on business formation. The CARES Act, enacted in March 2020, contained several provisions that increased UI generosity and the Families First Coronavirus Response Act (FFCRA) relaxed work search requirements. We hypothesize that, when

[1] For example, see Decker, Haltiwanger, Jarmin, and Miranda (2014), Alon, Berger, Dent, and Pugsley (2018), Pugsley and Şahin (2019), Hopenhayn, Neira, and Singhania (2022), and Akcigit and Ates (2023).

[2] See Decker and Haltiwanger (2023) for an in-depth and extensive documentation of this phenomenon.

taken together, these provisions incentivized some unemployed individuals to pursue their entrepreneurial ideas.

There are three key aspects of the UI expansion under the CARES Act and FFCRA that are relevant for this paper. First, the CARES Act increased the UI benefit amount by an additional $600 per week until the end of July 2020, and extended the benefit duration by an additional 13 weeks. These provisions enabled unemployed individuals to accumulate excess savings.[3] It is well documented in the entrepreneurship literature that in the presence of financial constraints, an increase in savings facilitates business entry (Evans and Jovanovic, 1989; Buera, 2009). Second, the work search requirement (i.e. that UI recipients provide proof of active job search) was waived in virtually all states in 2020 and in much of 2021 by the FFCRA. The relaxation of these requirements allowed unemployed individuals to allocate more of their time to develop their business projects, while still receiving UI benefits.[4] Lastly, the UI expansion had significant stimulative effects on aggregate demand (Ganong, Greig, Noel, Sullivan, and Vavra, 2022; Navarrete, 2023), which raised expected profits for potential business entrants.

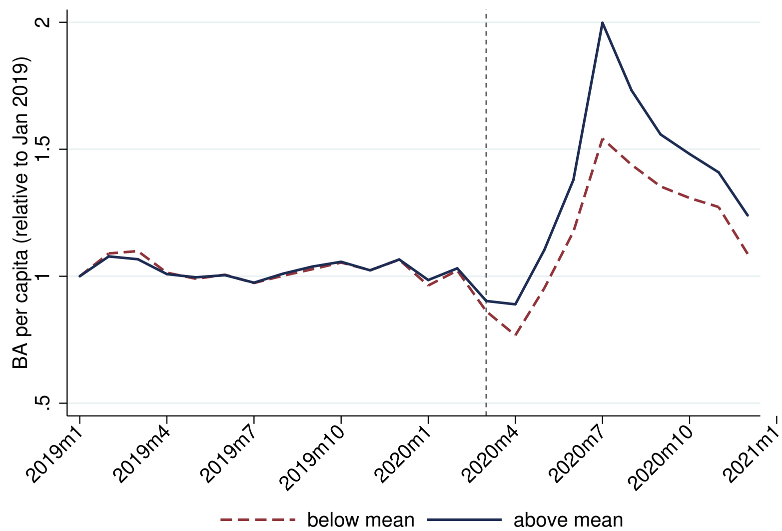
In order to estimate the effect of UI expansion on business formation, we take advantage of the fact that the increase in UI generosity varied across states. States with above average growth in UI payments per unemployed between March-July 2019 and March-July 2020, experienced, on average, a 153 percent increase, while those with below average growth experienced a 87 percent increase. Consistent with our hypothesis, Figure 2 shows that states with above-average growth in UI payment per unemployed experienced a more pronounced surge in business formation.

However, cross-state variation in the increase in UI payments per unemployed can arise for several reasons, including differences in the composition of unemployed individuals, that correlate with factors that also influence changes in business formation. To overcome this endogeneity, we exploit the fact that some states relied on an outdated programming language, COBOL, to process UI claims in 2020. UI benefit systems still using COBOL suffered severe delays in processing claims, which led to delays in the disbursement of benefits. Additionally, COBOL states may have had more discouraged filers due to the higher administrative burdens faced by potential claimants (Navarrete, 2023).

[3] See Ganong, Noel, and Vavra (2020), Ganong, Greig, Noel, Sullivan, and Vavra (2022), and Aladangady, Cho, Feiveson, and Pinto (2022) on the effect of the UI expansion on excess savings.

[4] It is important to note that the increase in the UI benefit amount did not necessarily raise the opportunity cost of entering entrepreneurship for unemployed workers, because they could still receive partial UI benefits particularly when the work search requirements were suspended. More details are provided in Section 2.3.

Figure 2: Business Formation per capita: by growth in UI generosity



Notes: This figure depicts seasonally-adjusted business applications (BA) per 1,000 population averaged across states (relative to the January 2019 value) for states with below (above) mean growth (measured as the log difference) in UI per unemployed between March-July 2019 and March-July 2020. Unemployment payments are calculated as the sum of regular UI, extended UI, and PEUC (only active in 2020). Business application data is obtained from the monthly Business Formation Statistics of the U.S. Census Bureau. Total (annual) state population is obtained from IPUMS National Historical GIS (NHGIS).

Our identifying assumption is that reliance on COBOL for processing UI claims affects business formation, only by lowering UI payments per unemployed. We document supporting evidence that COBOL is a valid instrument for differences in the increase in UI generosity. First, we show that COBOL states experienced more severe UI processing delays and smaller increases in UI payments per unemployed than non-COBOL states. Second, we document that COBOL states and non-COBOL states are statistically indistinguishable along many dimensions that are potentially related to business formation. We also show that COBOL and non-COBOL states experienced very similar pandemic-related restrictions, such as stay-at-home requirements and school closings.

Empirically, we first identify the reduced-form effect of COBOL on business formation using a two-way fixed effects (TWFE) model and we find that having a COBOL-based UI system caused a lower growth in business formation in 2020 relative to 2019. We then identify the effect of the increase in UI payment per unemployed on business formation using an instrumented difference-in-differences design. We find that states with higher growth in UI generosity, instrumented for by COBOL status, experienced a significantly higher pace of business formation during 2020. In our baseline specification, we estimate that a 1 percent increase in UI payment per unemployed raised business applications per capita by 0.24 percent. Given that the aggregate UI payment per unemployed individual has increased by 130 log points in 2020, a back-of-the-envelope calculation implies that the UI expansion resulted in a 31 percent increase in business applications per capita, which is about 60 percent of the rise in aggregate business formation in 2020.[5]

Our baseline specification is potentially subject to a weak instrument problem because the instrumental variable—COBOL—is a binary indicator while the endogenous regressor—the increase in UI payment per unemployed—is a continuous one. We conduct two tests to verify whether our baseline results are robust to this issue. First, we transform our endogenous regressor into a binary variable that indicates whether the increase in UI payment per unemployed in a state is above the cross-state average. Second, we consider an additional instrument: the share of UI claims processed in-person in local UI offices prior to COVID. The additional instrument exploits the fact that states with a higher share of UI claims processed in-person prior to COVID-19 had more capacity to process claims in-person during the pandemic when the online UI systems of virtually all states were under severe pressure. We find that our results are robust to both tests and that the F-statistics are noticeably higher.

A natural question is whether UI benefits expansion affects not just the quantity, but also the *quality* of business formation. Because low-skilled workers were more likely to become unemployed during the COVID-19 recession, we investigate whether higher UI generosity is associated with lower quality business applications. Specifically, we consider signals about the quality of new businesses available in the BFS data, such as incorporation status, hiring plans, and high likelihood of job creation (estimated by the Census Bureau). We find little evidence that higher UI generosity caused a deterioration in the quality of new business ideas.

Taken together, our analysis points to the expansion of UI benefits as an important driver behind the surge in busienss formation after the pandemic recession. Our results highlight the potential role of UI policy in enhancing the pace of recovery from recessions by fostering entrepreneurship.

Related Literature This paper lies at the intersection of two strands of literature: the literature on the impact of unemployment benefits on labor market outcomes and the literature on the cyclicality of business formation.

Recently, the literature studying the labor market impact of unemployment insur-

[5]Business applications per capita has increased, on average, by 50 percent in 2020.

ance has begun to explore the impact of UI on self-employment and entrepreneurship.[6] Several papers in the literature study labor market reforms enacted across Europe. Camarero Garcia and Murmann (2020) study a reform in Germany that shortened the potential benefit duration (PBD), and find that longer PBD is associated with an increase in necessity self-employment and lower post-entry growth. Focusing on a reform in Spain that reduced the replacement rate of long term UI, Camarero Garcia and Hansch (2021) find that the cut in UI reduces the probability, but not quality, of self-employment. Hombert, Schoar, Sraer, and Thesmar (2020) show that firm entry rose significantly after France extended UI to unemployed individuals that start a business and that the quality of those new firms did not deteriorate relative to those that entered before the reform. Meanwhile, Gaillard and Kankanamge (2023) focus on the U.S. context, where self-employment is generally not covered by UI, and finds that higher UI generosity lowers the probability of unemployed individuals entering self-employment. Through the lens of a structural model, calibrated to the U.S. economy, Gaillard and Kankanamge (2023) show that a UI system that covers self-employed individuals fosters business creation. In this paper, we build on this literature by establishing empirical evidence using a U.S. episode in which much of the increase in UI generosity was in the form of larger benefit amounts rather than extended benefit duration, accompanied by relaxation in work search requirements.

There is a growing interest in better understanding drivers of nascent entrepreneurship during normal times and economic downturns.[7] Using the U.S. Census Bureau's Business Formation Statistics (BFS), Dinlersoz, Dunne, Haltiwanger, and Penciakova (2021) compare the evolution of business formation during and after the Great Recession versus COVID-19. Fazio, Guzman, Liu, and Stern (2021) use data from the Startup Cartography Project to explore the local correlates of state business registrations during the COVID-19 pandemic. Decker and Haltiwanger (2023) use Business Formation Statistics (BFS) and the Bureau of Labor Statistics' (BLS) Business Employment Dynamics (BED) to show that the rise in business formation is observed consistently across various

[6]Traditionally, the literature on the impact of unemployment benefits on labor market outcomes focuses on re-entry into paid employment. See, for example, Atkinson and Micklewright (1991), Boone, Dube, Goodman, and Kaplan (2021), Card, Johnston, Leung, Mas, and Pei (2015), Chodorow-Reich, Coglianese, and Karabarbounis (2019), Farber, Rothstein, and Valletta (2015), Katz and Meyer (1990), Lalive, Ours, and Zweimuller (2006), Meyer (1990), Nekoei and Weber (2017), Schmieder, von Wachter, and Bender (2012).

[7]For example, see Andrews, Fazio, Guzman, Liu, and Stern (2022), Bayard, Dinlersoz, Dunne, Haltiwanger, Miranda, and Stevens (2018), Dinlersoz, Dunne, Haltiwanger, and Penciakova (2023), and Guzman and Stern (2020).

measures of new business entry, and their cross-industry and cross-regional patterns are consistent with pandemic-induced structural shift toward remote work and online shopping. While these papers discuss the surge in business formation during COVID-19, they do not establish causal evidence for its underlying drivers. This paper advances the literature by identifying UI generosity as a contributor to the rise in business formation during the 2020 phase of COVID-19.

2 Background and Hypothesis

In response to the rapid deterioration of the labor market, the FFCRA was enacted on March 18, 2020 and the CARES Act was signed into law on March 27, 2020. In this section, we describe provisions of these Acts that affected unemployment insurance and the channels through which they may have incentivized entrepreneurial activity.

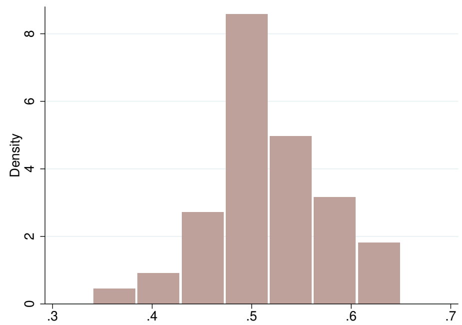
2.1 Increase in UI Generosity

Two provisions of the CARES Act increased UI generosity. First, the Act established the Federal Pandemic Unemployment Compensation (FPUC) program, which added an extra $600 in weekly federal benefits through the end of July 2020.[8] This increase in UI benefits was substantial. To illustrate, Figure 3a shows that the median replacement rate of UI benefits for each state before the pandemic varied between 34 percent and 65 percent. With the FPUC, the median replacement rate ranged from 115 percent to 166 percent as shown in Figure 3b. Consistent with the large increases, Ganong, Noel, and Vavra (2020) estimate that 76% of unemployed individuals received more than 100% of their pre-unemployment income as UI benefits due to the FPUC program. Duration of UI benefits was also extended through the Pandemic Emergency Unemployment Compensation (PEUC) program, which provided an additional 13 weeks of UI compensation.

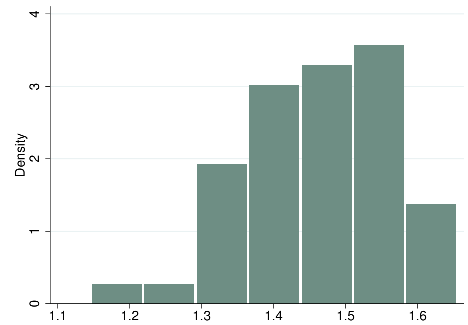
The large increase in UI generosity enabled unemployed individuals to increase not only their consumption, but also their savings. For example, Ganong, Greig, Noel, Sullivan, and Vavra (2022) use bank account data to show that while unemployed individuals who received UI benefits increased their spending, they also increased their savings relative to their employed counterparts. These increases in both spending and savings were possible due to replacement rates of over 100 percent for the majority of claimants. Consistent with this micro-level evidence, Aladangady, Cho, Feiveson, and Pinto (2022)

[8]Upon expiration, the FPUC was immediately followed by the Lost Wage Assistance (LWA) program, which provided $300 extra weekly benefits until September 5, 2020.

Figure 3: Distribution of State-Level Median Replacement Rates



(a) Replacement Rate without FPUC



(b) Replacement Rate with FPUC

Notes: These figures depict the distribution of state-level median replacement rates before the passage of the CARES Act (without FPUC) and after (with FPUC). Replacement rates are calculated using the methodology of Ganong, Noel, and Vavra (2020) using 2020 ASEC data on earnings.

estimate that UI contributed $836 billion in aggregate excess savings through the middle of 2022. Similarly, Cox, Ganong, Noel, Vavra, Wong, Farrell, Greig, and Deadman (2020) find that while the massive increase in unemployment was especially concentrated in low-income households, these households contributed disproportionately to the aggregate increase in liquid bank account balances, relative to their pre-pandemic shares.

We hypothesize that the large increase in UI generosity contributed to the rise in business formation through at least two channels. First, it enabled unemployed individuals with potential business ideas to accumulate savings to fund their startups. Indeed, a wide body of research indicates that an increase in savings leads to a higher propensity to enter entrepreneurship, as startup businesses often face financial constraints.[9] The rise in business formation during this period is most pronounced in industries with relatively low fixed costs, such as Nonstore Retailers (NAICS 454) and Professional, Scientific, & Technical Services (NAICS 541), making savings from UI expansion adequate for startup capital.[10] Second, the increase in UI had a significant stimulative effect on consumer spending (Ganong, Greig, Noel, Sullivan, and Vavra, 2022; Navarrete, 2023), raising expected profits of businesses and thus incentivizing new business entry.

[9] For example, see Evans and Jovanovic (1989), Buera (2009), Kerr and Nanda (2011), Corradin and Popov (2015), and Schmalz, Sraer, and Thesmar (2017) among many others.

[10] Table A.6 shows the top 10 industries with the largest increases in business formation in 2020.

2.2 Suspension of Work Search Requirements

Work search requirements were also effectively suspended, which amplified the impact of UI expansion on business formation. U.S. federal law mandates that unemployed individuals must be "actively seeking work" to remain eligible for UI benefits. While specific requirements vary across states, typically individuals are required to provide evidence of having contacted at least two employers each week to inquire about job openings, and they must be willing to accept suitable work if it is offered. The FFCRA allowed states the flexibility to modify or waive work search requirements. As a result, virtually all states chose to suspend these requirements until at least mid-2021, allowing unemployed individuals to continue receiving UI benefits while laying the groundwork for their startup business.

2.3 Partial UI Benefits

Even though work search requirements were suspended, an increase in the UI benefit amount could have raised the opportunity cost of starting a business if individuals were required to relinquish their UI benefits entirely upon generating business income. That was not the case, however, as self-employed individuals could continue receiving partial UI benefits. State governments require unemployed workers to report any income earned, including from their businesses or self-employment activities. While specific provisions vary by jurisdiction, workers are allowed to earn a certain amount of money while still receiving their full UI Weekly Benefit Amount (WBA). This is known as "disregarded earnings." State governments subtract the disregarded earnings from weekly income, and then subtract this adjusted earnings from the worker's WBA to calculate their partial benefit amount.[11]

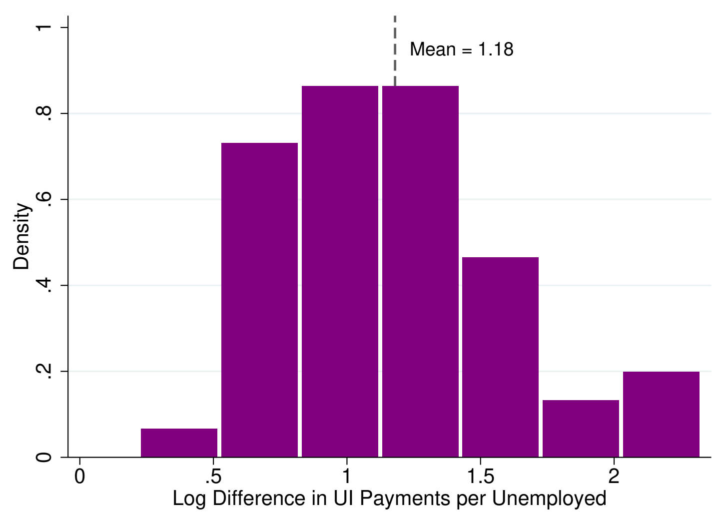
For example, consider an individual in California whose WBA is $1,000 and who raised $100 as business income in a given week. Then, under the provisions in California (either $25 or 25% of income, whichever greater), disregarded earnings for this person in this week is $25. Therefore, the partial weekly benefit amount is $1,000 - ($100-$25) = $925, and this person's gross income for the week is $925 + $100 = $1,025. Note that a decrease in the WBA does not lower this person's gross income.

[11] For a full list of these provisions across states, see Comparison of State Unemployment Insurance Laws issued by the Department of Labor.

3 Identification Strategy

The expansion of UI benefits during the COVID-19 pandemic led to a significant increase in UI payments per unemployed in 2020. To identify its effect on business formation, we leverage the fact that there is substantial variation in the growth of UI payments per unemployed across states. To illustrate, Figure 4 displays the cross-state distribution of the log difference in UI payments per unemployed between March-July 2020 relative to the same period in 2019. This growth varied widely, ranging from just 22 percent in New Jersey to 233 percent in Mississippi, with the mean growth being 118 percent.

Figure 4: Cross-State Changes in UI Payments per Unemployed

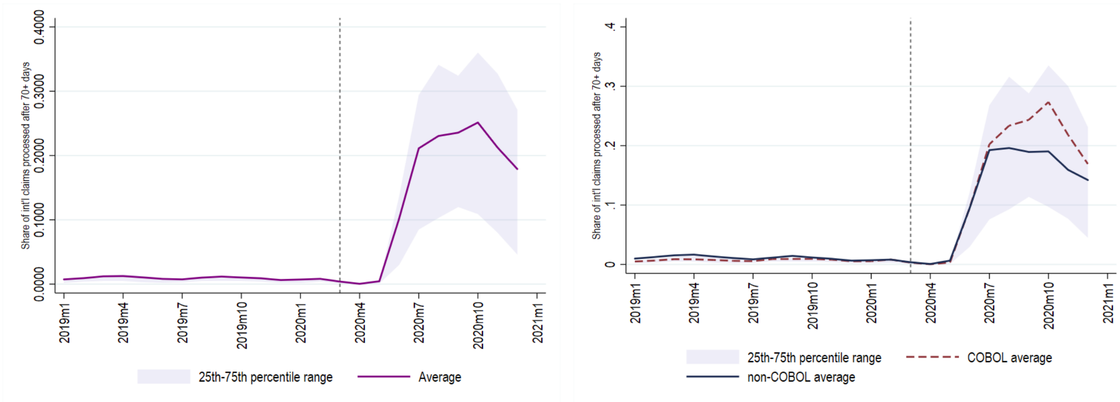


Notes: This figure depicts the cross-state distribution of the growth (measured as the log difference) in unemployment payments per unemployed between March-December 2019 and March-December 2020. The dashed grey line reports the median growth. Unemployment Payment data are obtained from the U.S. DoL's ETA 5159 Report and are measured as the sum of the regular program, extended benefits (EB) and PEUC, where payments are defined as *All Weeks Compensated (amount)*. State unemployment data are obtained from the LAUS, published by the BLS.

One factor that contributed to the cross-state variation in the growth of UI payments per unemployed is difficulties and delays in processing unemployment claims. During this period, states struggled, to varying degrees, to manage the simultaneous surge in UI claims and changes to benefits amounts and eligibility criteria. As a result, the timeliness of UI processing significantly declined. Figure 5a illustrates that, on average, the share of first UI payments delayed by 70 days or more increased from close to zero percent in March 2020 to 25 percent by October 2020.[12]

[12]Note that the values for October 2020 are associated with claims filed in August 2020 or earlier.

Figure 5: Share of First UI Payments Made After 70+ Days



(a) Average

(b) COBOL vs. non-COBOL

Notes: These figures depict the cross-state average (solid line) and 25th-75th percentile range of (a) the share of initial claims processed after 70+ days at the national level and (b) the share of initial claims processed after 70+ days in COBOL and non-COBOL states. Data are obtained from the "Benefits: Timeliness and Quality Reports" released by the BLS.

Because of endogeneity concerns associated with UI payments per unemployed, we use whether a state's UI benefits system operated on an antiquated programming language, COBOL, as a source of plausibly exogenous cross-state variation in the increase in UI generosity due to difficulties and delays in processing UI claims.[13] First introduced in 1959, COBOL was once the standard programming language for all UI systems. By 2020, nearly half of states (22) had modernized their UI systems and phased out COBOL. In the remaining 28 states that continued using COBOL, UI systems became particularly overwhelmed at the start of the COVID-19 pandemic.[14] As illustrated in Figure 5b, the share of first UI payments delayed by 70 or more days was close to zero percent in both COBOL and non-COBOL states prior to COVID-19, but by October 2020 the two groups of states diverged significantly, with the share hovering around 19 percent for non-COBOL states and 27 percent for COBOL states.

Several factors contributed to the overloading of COBOL-based UI systems. First, although COBOL is capable of performing the same tasks as more modern programming languages, adapting COBOL systems to accommodate changes in eligibility and benefits

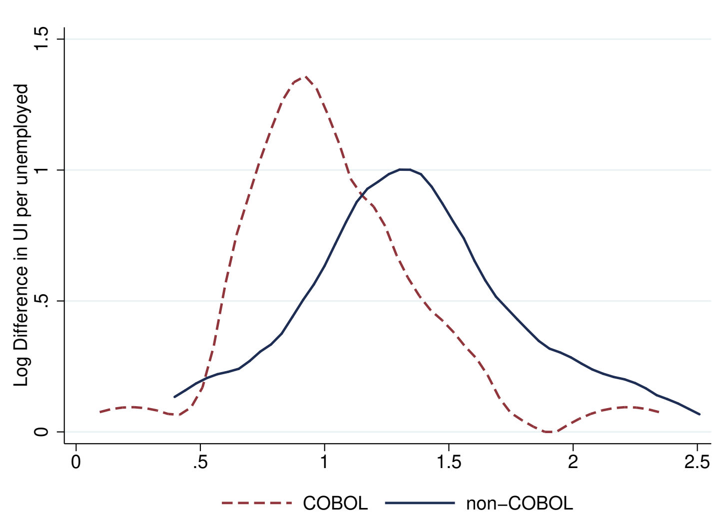
[13]In doing so, our work is complementary to Navarrete (2023), who shows that COBOL states experienced a decline in consumption in March-December 2020 relative to non-COBOL states, due to longer delays in UI benefit disbursement, more discouraged filers, and a lower UI multiplier arising from the use of COBOL to process UI claims.

[14]Figure A.1 shows the map of states by COBOL usage status.

amounts is more challenging. Second, implementing the necessary changes required some states to hire additional COBOL programmers, which was difficult because many COBOL programmers had retired. Third, and more generally relevant for any antiquated UI system, states using COBOL also had less user-friendly platforms through which unemployed individuals could file UI claims.[15] As shown in Navarrete (2023), these factors contributed to COBOL states facing relatively more severe UI processing and benefits disbursement delays and more discouraged filers. As an anecdotal example, the situation was so dire in New Jersey (a COBOL state) that in April 2020, Governor Phil Murphy pleaded for assistance from any programmers who knew the language.[16]

The frictions faced by states relying on COBOL to process UI claims contributed to lower growth in UI generosity. The average growth in UI per unemployed was significantly lower in COBOL states (104 percent) than non-COBOL states (135 percent). Moreover, as shown in Figure 6, the distribution of growth in UI payments per unemployed of COBOL states is largely to the left of the distribution for non-COBOL states.

FIGURE 6: CHANGE IN UI PER UNEMPLOYED: COBOL VS. NON-COBOL



Notes: This figure depicts the cross-state distribution of the growth (measured as the log difference) in unemployment payments per unemployed between March-December 2019 and March-December 2020, separately for COBOL and non-COBOL states. Unemployment Payment data are obtained from the U.S. Department of Labor's ETA 5159 Report and are measured as the sum of the regular program, extended benefits (EB) and PEUC, where payments are defined as *All Week Compensated (amount)*. State unemployment data are obtained from the Local Area Unemployment Statistics published by the U.S. Bureau of Labor Statistics.

[15] See Navarrete (2023) for a thorough discussion of the challenges faced by COBOL states.

[16] See Feldman, B. (2020, April 6). NJ Governor Requests Expertise of 6 People Who Still Know COBOL. *New York Magazine*. https://nymag.com/intelligencer/2020/04/what-is-cobol-what-does-it-have-to-do-with-the-coronavirus.html

While the evidence shown thus far confirms that COBOL is associated with our endogenous variable of interest, growth in UI payments per unemployed, a remaining concern is whether COBOL is also independently associated with business formation. Even though states have direct control over COBOL-usage, modernizing away from COBOL is a slow and expensive process. The decision to modernize could systematically differ between states, which would be a concern if these systematic differences were also correlated with factors associated with the rise in business formation during the pandemic.

To address this concern, we compare COBOL and non-COBOL states along several dimensions, including demographics, household characteristics, political environment, and labor market. Table 1 displays the results from regressing various state-level demographic, household, and political characteristics on a COBOL indicator. We find that COBOL and non-COBOL states are statistically indistinguishable along a variety of dimensions. Two exceptions are whether the state's governor is a Republican (measured in 2020) and the home ownership rate. Differences in the party affiliation of the state governor could potentially matter because people's political leanings were correlated with the degrees of voluntary and involuntary social distancing, which in turn may have affected economic activity and the pace of business formation. Differences in home ownership rates may also matter because of the documented importance of housing as collateral for young and small businesses (Kerr, Kerr, and Nanda, 2022; Lastrapes, Schmutte, and Watson, 2022; Davis and Haltiwanger, forthcoming).

Motivated by the fact that there is strong regional clustering in people's political leanings and home ownership rates, we control for Census division fixed effects in Table A.1, and and find that the differences in state governor's party affiliation and home ownership rates become statistically insignificant.[17] Moreover, all other demographic, household, and political differences also remain insignificant. As an additional test, in Table A.2 we use the Oxford Covid-19 Government Response Tracker (Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Cameron-Blake, Hallas, Majumdar, et al., 2021) to directly compare the pandemic-related restrictions imposed by state governments across COBOL and non-COBOL states, and find no significant differences.

Because there were strong systematic differences in the adverse impact from the COVID-19 pandemic across different industries and occupations (Adams-Prassl, Boneva, Golin, and Rauh, 2020), in Table A.3 and Table A.4 we compare firm and labor market characteristics of COBOL and non-COBOL states. We find no statistically significant differences in employment shares by firm age, firm size, sectors, or occupations. The

[17]Controlling for Census division fixed effects also controls for any region-specific factors that could affect business formation.

balance along these dimensions implies that COBOL and non-COBOL states were hit similarly by the pandemic recession. Collectively, these results support the plausible exogeneity of the COBOL indicator.

4 Main Results

We first document the reduced form relationship between COBOL usage and business formation in the aftermath of the emergency declaration in March 2020. We then use an instrumented difference-in-differences approach to evaluate whether increased UI generosity led to higher business formation.

4.1 Reduced Form Effects

In our reduced form analysis, we estimate the effect of COBOL-usage on business formation with a monthly two-way fixed effects (TWFE) event study:

$$ln(BApc)_{s,t} = \sum_{\tau=-T_0}^{T_1} \beta_\tau (COBOL_s \times I_\tau) + \delta_s + \lambda_t + \epsilon_{s,t} \tag{1}$$

where t denotes the number of months since March 2020. $ln(BApc)_{s,t}$ is the log of BFS business applications (BA) per capita (pc) in state s in month t. $COBOL_s$ indicates whether state s uses COBOL, and I_τ indicates whether the corresponding month is month τ. δ_s and λ_t are the state and time fixed effects, respectively. $\epsilon_{s,t}$ is the error term. This TWFE event study design allows us to track the monthly evolution of business formation in COBOL states relative to non-COBOL states.

Figure 7a shows evidence of parallel pre-trends and that COBOL states experienced a slower pace of business formation following the pandemic recession. The figure presents the estimated β_τ with 95 percent confidence intervals from the TWFE model. First, we see parallel pre-trends in business formation between COBOL and non-COBOL states in 2019, lending support to the assumption required for a difference-in-differences design. Second, from March 2020 to December 2020, COBOL states experienced slower growth in per capita business applications compared to non-COBOL states. Notably, we observe a V-shaped trend: the difference in business formation between the two groups of states gradually widens from March 2020 to June 2020. In July 2020, coinciding with the expiration of the FPUC, the gap reaches its peak at 15 percent, and subsequently, from August to November 2020, this difference progressively narrows.

Table 1: Balance of Characteristics

	Coefficient on COBOL indicator			
Dependent Variable	**Est.**	**Std Err.**	**P-Value**	**Mean of Dep Var.**
Demographics				
Log population	-0.096	(0.295)	0.75	15.21
Median age	-0.123	(0.706)	0.86	38.34
High school or lower	-0.001	(0.013)	0.91	0.41
Some college	-0.013	(0.009)	0.15	0.30
Bachelor's degree or higher	0.015	(0.014)	0.30	0.28
% White	-0.023	(0.036)	0.54	0.77
% Black	-0.024	(0.027)	0.37	0.10
% Hispanic	0.007	(0.028)	0.82	0.11
% Foreign born	0.023	(0.022)	0.30	0.12
Labor and Income				
Income per capita ($1,000)	2.812	(2.213)	0.21	53.45
% Below poverty	-0.009	(0.008)	0.29	0.13
Employment to population	0.010	(0.012)	0.40	0.60
Labor force participation rate	0.009	(0.011)	0.41	0.64
Self employment rate	0.002	(0.004)	0.64	0.07
Unemployment risk exposure	-0.002	(0.009)	0.82	0.08
Residential				
% Urban population	0.015	(0.042)	0.73	73.4
Homeownership rate	-0.029**	(0.011)	0.01	0.62
% Households w/ mortgage	-0.015	(0.012)	0.19	0.38
Median home value ($1,000)	454.56	(394.332)	0.26	617.96
Political Environment				
Republican governor	-0.283**	(0.132)	0.04	0.66
Republican vote share (2016)	-0.025	(0.029)	0.40	0.49
Union membership rate (2018)	0.019	(0.014)	0.21	0.10

Notes: This table reports results from regressions where each one of the state-level characteristics in Column (1) are dependent variables and the COBOL indicator is the independent variable. Variables under Demographics, Labor and Income, and Residential categories, except for income per capita and unemployment risk exposure, are obtained from the 2019 American Community Survey. We obtain income per capita in 2019 for each state from the Bureau of Economic Analysis. We calculate unemployment risk exposure using characteristics of those who became unemployed during April-July 2020 and local demographic characteristics in 2019. Percent urban is measured as of 2010 and is obtained from the U.S. Census Bureau, republican governor share is measured as of 2018 and is obtained from the National Conference for State Legislatures, union membership is measured as of 2018 and is obtained from the Bureau of Labor Statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels.

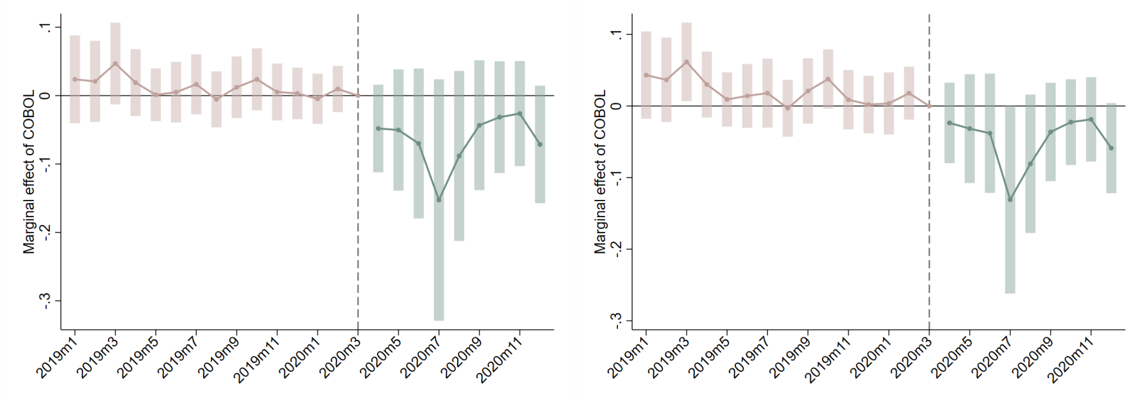
The V-shaped pattern of the estimated effects is consistent with the our hypothesis in several ways. First, as shown in Figure 5b, the difference in the share of initial claims delayed by 70 days or more between COBOL and non-COBOL states gradually widens until October 2020, indicating that the difference in the proportion of eligible unemployed workers who did not receive their UI payment increases over this period. In turn, the adverse impact on business formation is likely to increase over this period as well. Second, we claim that a channel through which the UI expansion affects business formation is the increase in savings. Given that UI payments occur on a weekly or biweekly basis, it is likely to take some time for the unemployed workers to accumulate enough savings for their business projects, and hence, the impact on business formation is also likely to increase gradually.

Given the documented differences in Table 1 between COBOL and non-COBOL states in the party affiliation of the governors and home ownership rates, there could be concerns that these omitted variables have differential, time-varying effects on business formation in the two groups of states in 2020. To address this concern, we augment our TWFEs model with Census division by year fixed effects.[18]

Figure 7b confirms parallel pre-trends, the slower pace of business formation in COBOL states, and the V-shaped pattern of the estimated effects. Further, in Figure A.2, we adopt a doubly robust estimator developed by Callaway and Sant'Anna (2021) which allows us to directly control for time varying effects of ex-ante observables in an event study setting. Specifically, we control for both party affiliation of governor and homeownership rate. Similar to Figure 7a and Figure 7b, we find parallel pre trends as well as the V-shaped pattern with the trough in July 2020.

[18]Recall that after controlling for Census division fixed effects, the differences between COBOL and non-COBOL states in the party affiliation of the governor and home ownership rates become insignificant.

Figure 7: Marginal Effect of COBOL: TWFE



(a) TWFE (b) TWFE with Division × Month FE

Notes: These figures depict the marginal effect of COBOL on log(business applications per capita). Figure (a) shows the two-way fixed effects results where month and state fixed effects are included. Figure (b) shows the two-way fixed effects where state fixed effects and month by division fixed effects. Standard errors are clustered at the state level in both figures.

4.2 Instrumented Difference-in Difference

Next, we estimate the effect of growth in UI generosity on business formation using an instrumented difference-in-differences (DiD-IV) design. We estimate the DiD-IV regression with the second stage given by equation (2) and the first stage by equation (3):

$$ln(BApc)_{s,t} = \beta_0 + \beta_1\ \widehat{\Delta(UI/unemp)_s} \times POST_t + \delta_s + \lambda_t + \varepsilon_{s,t} \tag{2}$$

$$\Delta(UI/unemp)_s \times POST_t = \alpha_0 + \gamma_1 COBOL_s \times POST_t + \psi_s + \phi_t + \epsilon_{s,t} \tag{3}$$

where $\Delta(UI/unemp)$ denotes the growth (measured as the log difference) of regular UI payments, extended benefits payments, and PEUC payments over number of unemployed between March-July 2019 and March-July 2020 in state s. $ln(BApc)_{s,t}$ is the log of business applications per capita in state s in month t. $POST_t$ is a binary variable that takes the value 1 starting in March 2020. $COBOL_s$ indicates whether a state uses COBOL to process UI claims. We also include state fixed effects, δ_s, and month fixed effects, λ_t. The estimated values of β_1 are shown in Table 2.

The first column of Table 2 shows the result of a naive OLS version of Equation (2). We find that a 1 percent increase in UI payments per unemployed is associated with a 0.16 percent increase in business applications. The second column shows the result from

Table 2: Effect of COBOL on log(BA per capita): DiD-IV

	(1)	(2)	(3)	(4)
	OLS	IV	OLS	IV
$\Delta(UI/unemp)_s \times POST_t$	0.161^{***}	0.224^{**}	0.111^{**}	0.237^{**}
	(0.045)	(0.112)	(0.044)	(0.100)
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
Division x Month FE	No	No	Yes	Yes
F-stat		7.10		7.53
Obs.	1200	1200	1200	1200
R-sq	0.94		0.97	

Notes: Unit of analysis is state by month between January 2019 and December 2020, with the post period beginning in March 2020. $\Delta(UI/unemp)$ denotes the growth (measured as the log difference) of regular UI payments, EB payments, and PEUC payments over number of unemployed between March-July 2019 and March-July 2020 in state s. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. levels. Standard errors are clustered at the state level. R^2 values suppressed as they have no statistical implications in the context of IV-2SLS regressions.

the DiD-IV regression, which indicates that a 1 percent increase in UI payments per unemployed leads to a 0.22 percent increase in business applications. Columns (3) and (4) show results from the models that include Census division by month fixed effects. While this specification addresses the potential concern regarding the differences in state governors' party affiliation and home ownership rates, the estimated β_1 in Column (4) is quantitatively similar to the estimated β_1 in Column (2), suggesting that the potential bias is likely small. Column (4)—our most preferred specification—indicates that a 1 percent increase in UI payment per unemployed resulted in a 0.24 percent rise in business formation per capita. Comparing the IV estimates to the OLS estimates suggests that the latter are downward biased. This bias could be driven by areas receiving higher UI payments per unemployed also being areas experiencing more negative economic shocks. In turn, these more negative economic shocks could create an environment in which it is more difficult to start a business.

5 Robustness Checks

5.1 Alternative Specification

One limitation of the DiD-IV results documented in Table 2 is the relatively low first-stage F-statistic. This is partly driven by the fact that our instrumental variable ($COBOL$) is a binary indicator, while the endogenous variable ($\Delta(UI/unemp)$) is continuous. In order to address this potential weak instrument concern, we construct a binary endogenous regressor, $\mathbb{1}\{\Delta(UI/unemp)\}$, which indicates whether the state's $\Delta(UI/unemp)$ is above the cross-state average.[19] Table 3 shows the results from using this binary endogenous variable. As expected, we obtain higher first-state F-statistics than in Table 2. The result in Column (2) indicates that states that had a higher-than-average increase in UI payment per unemployed experienced a 16% higher pace of business formation.

Table 3: DiD-IV with Binary Endogenous Variable

	(1) OLS	(2) IV	(3) OLS	(4) IV
$\mathbb{1}\{\Delta(UI/unemp)\} \times POST$	0.119^{***}	0.148^{**}	0.083^{***}	0.163^{**}
	(0.036)	(0.076)	(0.029)	(0.070)
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	No	No
Division x Month FE	No	No	Yes	Yes
F-stat		13.34		8.73
Obs.	1200	1200	1200	1200
R-sq	0.94		0.97	

Notes: Unit of analysis is state by month between January 2019 and December 2020, with the post period beginning in March 2020. $\Delta(UI/unemp)$ denotes the growth (measured as the log difference) of regular UI payments, EB payments, and PEUC payments over number of unemployed between March-July 2019 and March-July 2020 in state s. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. levels. Standard errors are clustered at the state level. R^2 values suppressed as they have no statistical implications in the context of IV-2SLS regressions.

5.2 Additional Instrumental Variable

As another robustness test, we consider an additional instrumental variable—the share of UI claims processed in-person in local UI offices prior to COVID. The motivation for the introduction of the new IV is that the online UI systems were under severe pressure in virtually all states, and the states that had higher shares of in-person processing prior to COVID may have been better prepared to process claims in-person during the pandemic. To validate this new instrumental variable, we conduct a test for balance of characteristics controlling for the Census division fixed effects. As shown in Table A.5, the share of UI claims processed in-person prior to COVID has no statistically significant relationship

[19] There are 23 states with above-mean values of $\Delta(UI/unemp)$ and 27 with below-mean values. Results are similar if we define the indicator based on the median.

with state-level characteristics.[20]

Table 4: DiD-IV with An Additional IV

	(1)	(2)
$\Delta(UI/unemp)_s \times POST_t$	0.266***	0.272***
	(0.066)	(0.066)
State FE	Yes	Yes
Month FE	Yes	No
Division x Month FE	No	Yes
IV	COBOL + % In-person	COBOL + % In-person
F-stat	30.46	12.10
Hansen J test p-val	0.46	0.48
Obs.	1200	1200

Notes: Unit of analysis is state by month between January 2019 and December 2020, with the post period beginning in March 2020. $\Delta(UI/unemp)$ denotes the growth (measured as the log difference) of regular UI payments, EB payments, and PEUC payments over number of unemployed between March-July 2019 and March-July 2020 in state s. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. levels. Standard errors are clustered at the state level. R^2 values suppressed as they have no statistical implications in the context of IV-2SLS regressions.

Table 4 shows the results from including the additional IV. Under this specification, we find that the point estimates are slightly higher and the F-statistics are noticeably higher compared to Table 2, further lending support to our findings. For example, Column (2) indicates that a 1 percent increase in UI payment per unemployed leads to a 0.31 percent increase in per capita business formation and the F-statistic is 12.1.

6 Other Related Outcomes

6.1 Initial Quality of New Businesses

Thus far, we have shown that the expansion of UI benefits fostered business formation in 2020, but have remained silent on whether it also affected the quality of new business ideas. Because low-skilled workers were more likely to become unemployed during the pandemic recession, we investigate whether the UI expansion disproportionately generated low quality startups. We use data from the BFS on the number of business applications that (i) are incorporated, (ii) submitted actual hiring plans, and (iii) have high likelihood of becoming actual employer startups, as estimated by the Census Bureau, to

[20]When we do not control for the division fixed effects, only the coefficient for % Black variable is positive and significant, while coefficients for all the other variables are insignificant.

proxy for the quality of business ideas. Specifically,we calculate the share of business applications with these characteristics, and use that as the outcome variable to estimate equations 2 and 3, while controlling for state and division by month fixed effects.

TABLE 5: INITIAL QUALITY OF NEW BUSINESSES

	(1) % CBA	(2) % WBA	(3) % HBA
$\Delta(UI/unemp)_s \times POST_t$	-0.023*	-0.009	-0.028**
	(0.014)	(0.007)	(0.013)
State FE	Yes	Yes	Yes
Division x Month FE	Yes	Yes	Yes
F-stat	7.53	7.53	7.53
Obs.	1200	1200	1200

Notes: Unit of analysis is state by month between January 2019 and December 2020, with the post period beginning in March 2020. $\Delta(UI/unemp)$ denotes the growth (measured as the log difference) of regular UI payments, EB payments, and PEUC payments over number of unemployed between March-July 2019 and March-July 2020 in state s. ***, **, and * indicate sig. at the 1%, 5%, and 10% sig. levels. Standard errors are clustered at the state level. R^2 values suppressed as they have no statistical meaning in the context of IV-2SLS regressions.

In Table 5, we document a a quantitatively small deterioration in the quality of business ideas. We estimate that a 1 percent increase in UI payment per unemployed results in a 0.023 percentage point decline in the share of incorporated business applications (column 1) and a 0.028 percentage point decline in the share of applications with high propensity to become employers (column 3). We do not find any evidence of a deterioration in the share of applications with planned wages (column 2).

7 Conclusion

A number of studies have documented and discussed the surge in business formation during the COVID-19 pandemic (Dinlersoz, Dunne, Haltiwanger, and Penciakova, 2021; Fazio, Guzman, Liu, and Stern, 2021; Decker and Haltiwanger, 2023). In this paper, we establish a causal link between growth in UI generosity during the 2020-phase of COVID-19 and the rise in business applications. Using an instrumented difference-in-differences design, we find that a 1 percent increase in UI payment per unemployed resulted in 0.24 percent higher business formation per capita.

As already documented by Ganong, Greig, Noel, Sullivan, and Vavra (2022) and Navarrete (2023), unemployment insurance played an important role in the sharp economic recovery from the pandemic recession by spurring consumption. In this paper, we document a new channel through which unemployment insurance further helped stabilize local labor markets. Unlike its more immediate effect on consumption, the impact of UI expansion on local labor markets through business formation may take some time to fully materialize. This is due to the fact that it takes several quarters for new businesses to hire employees and grow large enough to have a quantitatively meaningful impact on the labor market.[21]

It is important to note that the UI expansion in this study was implemented in a period when pandemic-induced structural transformation, such as increases in remote work and online shopping, potentially created new business opportunities (Decker and Haltiwanger, 2023). Therefore, it is possible that the effects of UI expansion are amplified during this period, and caution is needed in extrapolating our results to other settings. However, to the best of our knowledge, this study is the first to document that UI expansion fosters business formation, and it opens the door for more discussion on the potential role of UI policy in promoting entrepreneurship during economic recoveries.

[21]See Bayard, Dinlersoz, Dunne, Haltiwanger, Miranda, and Stevens (2018) and Dinlersoz, Dunne, Haltiwanger, and Penciakova (2023) for documentation of the lag between the filing of business applications and their transition to employer businesses.

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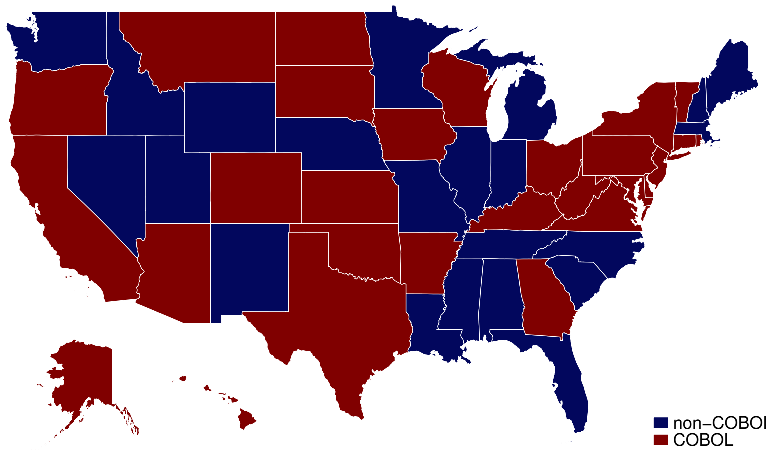
A Appendix

Figure A.1: COBOL vs. non-COBOL States



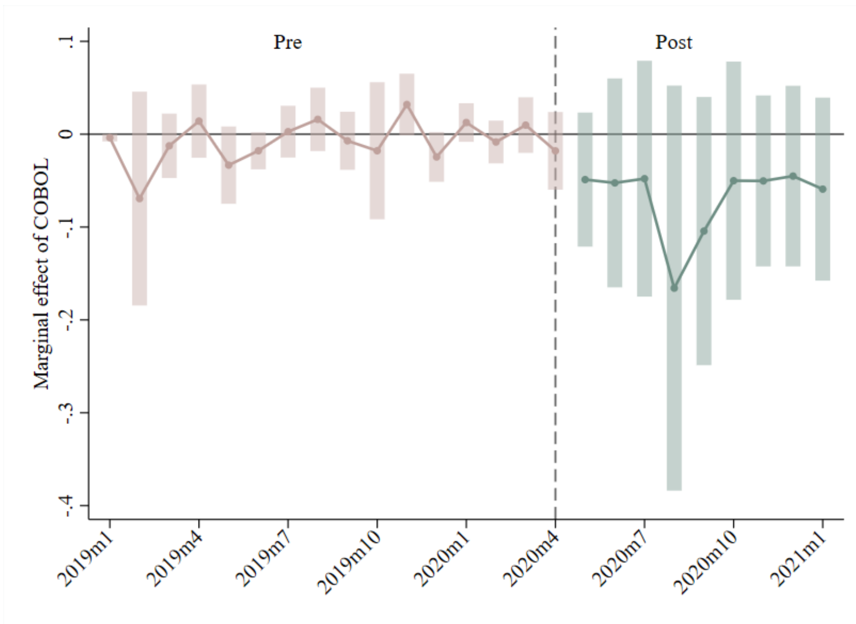
Notes: The map depicts which states use (versus not using) COBOL in their UI benefit systems in June 2020. The data on COBOL usage are collected by Navarrete (2023) primarily from emails, news articles, and information from the UI Information Technology Support Center.

Table A.1: Balance of Characteristics w/ Division Fixed Effects

	Coefficient on COBOL Indicator			
Dependent Variable	**Est.**	**Std Err.**	**P-Value**	**Mean of Dep Var.**
Demographics				
Log population	-0.339	(0.280)	(0.23)	15.21
Median age	-0.163	(0.587)	(0.78)	38.34
High school or lower	0.001	(0.011)	(0.93)	0.41
Some college	-0.006	(0.007)	(0.33)	0.30
Bachelor's degree or higher	0.005	(0.012)	(0.65)	0.28
% White	-0.003	(0.028)	(0.92)	0.77
% Black	0.014	(0.034)	(0.68)	0.10
% Hispanic	-0.032	(0.019)	(0.10)	0.11
% Foreign born	-0.005	(0.021)	(0.82)	0.12
Labor and Income				
Income per capita ($1,000)	0.561	(1.927)	(0.77)	53.45
% Below poverty	-0.005	(0.007)	(0.43)	0.13
Employment to population	0.009	(0.010)	(0.36)	0.60
Labor force participation rate	0.008	(0.009)	(0.42)	0.64
Self employment rate	0.003	(0.004)	(0.47)	0.07
Unemployment risk exposure	-0.007	(0.009)	(0.43)	0.08
Residential				
% Urban population	-0.019	(0.043)	(0.67)	73.4
Homeownership rate	-0.018	(0.012)	(0.13)	0.62
% Households w/ mortgage	-0.010	(0.011)	(0.38)	0.41
Median home value ($1,000)	45.012	(388.741)	(0.91)	617.96
Political Environment				
Republican governor	-0.101	(0.122)	(0.41)	0.66
Republican vote share (2016)	-0.003	(0.024)	(0.90)	0.10
Union membership rate (2018)	0.006	(0.010)	(0.55)	0.49

Notes: This table reports results from regressions where each one of the state-level characteristics in Column (1) are dependent variables and the COBOL indicator is the independent variable. Variables under Demographics, Labor and Income, and Residential categories, except for income per capita and unemployment risk exposure, are obtained from the 2019 American Community Survey. We obtain income per capita in 2019 for each state from the Bureau of Economic Analysis. We calculate unemployment risk exposure using characteristics of those who became unemployed during April-July 2020 and local demographic characteristics in 2019. Percent urban is measured as of 2010 and is obtained from the U.S. Census Bureau, republican governor share is measured as of 2018 and is obtained from the National Conference for State Legislatures, union membership is measured as of 2018 and is obtained from the Bureau of Labor Statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels.

Figure A.2: Marginal Effect of COBOL: CSDiD



Notes: This figure depicts the marginal effect of COBOL on log(business applications per capita) using the Callaway and Sant'Anna (2021) estimator with republican governor and homeownership rate as controls.

Table A.2: Pandemic Related Restriction

	Coefficient on COBOL indicator			
Dependent Variable	**Est.**	**Std Err.**	**P-Value**	**Mean of Dep Var.**
Stay at home reqs.	0.028	(0.058)	(0.625)	0.210
School closings	0.043	(0.032)	(0.181)	0.934
Workplace closings	0.051	(0.087)	(0.558)	0.577
Cancellation of public events	-0.043	(0.082)	(0.597)	0.539
Restrictions on gatherings	-0.027	(0.073)	(0.717)	0.858
Public transport closures	-0.058	(0.068)	(0.395)	0.088

Notes: This table reports results from regressions where pandemic related policies in Column (1) are the dependent variables and the COBOL indicator is the independent variable. The source of all pandemic related policy variables is the Oxford COVID-19 Government Response Tracker (OxCGRT). For each state, OxCGRT tracks, at a daily frequency, whether for each policy category (stay at home requirements, school closings, etc.) there are no measures (0), recommended restrictions (1), or required restrictions of varying degrees of stringency (2, 3, and 4). We take the raw data for each policy category and create a dummy variable, which takes the value of 0 when the raw value is {0,1} and takes the value of 1 when the raw value is {2,3,4}. We then calculate, for each policy category the cross-day average (between March 13 and December 31, 2020) at the state level. The resulting pandemic related policy variables are then regressed on the COBOL indicator. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels.

Table A.3: Balance of Characteristics: Employment Share By Firm Age, Firm Size, and Sector

	Coefficient on COBOL indicator			
Dependent Variable	**Est.**	**Std Err.**	**P-Value**	**Mean of Dep Var.**
Firm Age				
0	-0.001	(0.001)	(0.46)	0.02
1-5	0.000	(0.004)	(0.93)	0.08
6-10	-0.004	(0.003)	(0.21)	0.07
11+	0.006	(0.008)	(0.50)	0.83
Firm Size				
1-19	0.003	(0.010)	(0.72)	0.18
20-499	0.009	(0.007)	(0.24)	0.31
500+	-0.012	(0.016)	(0.43)	0.51
Sector				
Agriculture, Forestry, Fishing and Hunting	-0.001	(0.001)	(0.29)	0.00
Mining, Quarrying, and Oil and Gas Extraction	0.001	(0.005)	(0.85)	0.01
Utilities	0.000	(0.001)	(0.52)	0.01
Construction	-0.003	(0.003)	(0.33)	0.06
Manufacturing	-0.010	(0.012)	(0.41)	0.10
Wholesale Trade	0.001	(0.002)	(0.64)	0.05
Retail Trade	-0.002	(0.004)	(0.52)	0.13
Transportation and Warehousing	0.002	(0.003)	(0.44)	0.04
Information	0.001	(0.002)	(0.53)	0.02
Finance and Insurance	0.005	(0.004)	(0.20)	0.05
Real Estate and Rental and Leasing	0.000	(0.001)	(0.95)	0.02
Professional, Scientific, and Technical Services	0.004	(0.006)	(0.49)	0.06
Management of Companies and Enterprises	0.001	(0.003)	(0.79)	0.02
Administrative and Support and Waste Management and Remediation	-0.005	(0.007)	(0.48)	0.08
Educational Services	0.001	(0.004)	(0.74)	0.03
Health Care and Social Assistance	0.009	(0.007)	(0.23)	0.17
Arts, Entertainment, and Recreation	0.001	(0.001)	(0.68)	0.02
Accommodation and Food Services	-0.006	(0.008)	(0.45)	0.12
Other Services (except Public Admin.)	0.001	(0.001)	(0.60)	0.04

Notes: This table reports results from regressions where each one of the state-level variables in Column (1) are dependent variables and the COBOL indicator is the independent variable. Employment share at each firm age, size, and sector category is 2019 values obtained from the Business Dynamics Statistics of the Census Bureau.

Table A.4: Balance of Characteristics: Employment Share By Occupation

	Coefficient on COBOL indicator			
Dependent Variable	**Est.**	**Std Err.**	**P-Value**	**Mean of Dep Var.**
Management	0.004	(0.003)	(0.28)	0.10
Business and Financial Operations	0.003	(0.002)	(0.20)	0.05
Computer and Mathematical	0.001	(0.003)	(0.70)	0.03
Architecture and Engineering	-0.001	(0.001)	(0.64)	0.02
Life, Physical, and Social Science	0.001	(0.001)	(0.51)	0.01
Community and Social Service	0.001	(0.001)	(0.12)	0.02
Legal	0.001	(0.001)	(0.26)	0.01
Educational Instruction and Library	0.001	(0.002)	(0.60)	0.06
Arts, Design, Entertainment, Sports, and Media	0.001	(0.001)	(0.42)	0.02
Healthcare Practitioners and Technical	0.001	(0.002)	(0.78)	0.06
Healthcare Support	0.001	(0.001)	(0.43)	0.03
Protective Service	0.001	(0.001)	(0.36)	0.02
Food Preparation and Serving Related	-0.004	(0.002)	(0.12)	0.06
Building and Grounds Cleaning and Maintenance	0.000	(0.002)	(0.93)	0.04
Personal Care and Service	0.000	(0.001)	(0.87)	0.03
Sales and Related	-0.002	(0.002)	(0.41)	0.10
Office and Administrative Support	0.000	(0.002)	(0.90)	0.11
Farming, Fishing, and Forestry	0.000	(0.002)	(0.82)	0.01
Construction and Extraction	-0.002	(0.003)	(0.50)	0.05
Installation, Maintenance, and Repair	-0.001	(0.001)	(0.48)	0.03
Production	-0.008	(0.006)	(0.16)	0.06
Transportation	-0.001	(0.003)	(0.71)	0.08
Material Moving	0.002	(0.001)	(0.21)	0.00

Notes: This table reports results from regressions where each one of the state-level variables in Column (1) are dependent variables and the COBOL indicator is the independent variable. Employment shares at each occupation category is obtained from the 2019 American Community Survey.

Table A.5: Balance of Characteristics For Share of In-person UI Claims Processing in 2019

	Coefficient on % In-person			
Dependent Variable	**Est.**	**Std Err.**	**P-Value**	**Mean of Dep Var.**
Demographics				
Log population	0.788	(1.938)	(0.69)	15.21
Median age	-5.455	(3.912)	(0.17)	38.34
High school or lower	0.045	(0.076)	(0.55)	0.41
Some college	-0.006	(0.045)	(0.89)	0.30
Bachelor's degree or higher	-0.039	(0.082)	(0.64)	0.28
% White	0.004	(0.194)	(0.98)	0.77
% Black	-0.230	(0.228)	(0.32)	0.10
% Hispanic	0.200	(0.130)	(0.13)	0.11
% Foreign born	0.013	(0.143)	(0.93)	0.12
Labor and Income				
Income per capita ($1,000)	-10.831	(13.045)	(0.41)	53.45
% Below poverty	0.056	(0.046)	(0.24)	0.13
Employment to population	-0.039	(0.067)	(0.56)	0.60
Labor force participation rate	-0.030	(0.064)	(0.64)	0.64
Self employment rate	-0.009	(0.026)	(0.74)	0.07
Unemployment risk exposure	0.004	(0.060)	(0.95)	0.08
Residential				
% Urban population	0.064	(0.294)	(0.83)	73.4
Homeownership rate	-0.072	(0.081)	(0.38)	0.62
% Houesholds w/ mortgage	-0.026	(0.076)	(0.74)	0.38
Median home value ($1,000)	-15.975	(2651.931)	(1.00)	617.96
Political Environment				
Republican governor	0.865	(0.827)	(0.30)	0.66
Republican vote share (2016)	0.010	(0.164)	(0.95)	0.10
Union membership rate (2018)	-0.024	(0.070)	(0.74)	0.49

Notes: This table reports results from regressions where each one of the state-level characteristics in Column (1) are dependent variables and the COBOL indicator is the independent variable. Variables under Demographics, Labor and Income, and Residential categories, except for income per capita and unemployment risk exposure, are obtained from the 2019 American Community Survey. We obtain income per capita in 2019 for each state from the Bureau of Economic Analysis. We calculate unemployment risk exposure using characteristics of those who became unemployed during April-July 2020 and local demographic characteristics in 2019. Percent urban is measured as of 2010 and is obtained from the U.S. Census Bureau, republican governor share is measured as of 2018 and is obtained from the National Conference for State Legislatures, union membership is measured as of 2018 and is obtained from the Bureau of Labor Statistics. ***, **, and * indicate significance at the 1%, 5%, and 10% significance levels.

Table A.6: Top 10 Industries With Largest Growth in Business Applications

NAICS-3	NAICS Description	Percentage Growth
454	Nonstore Retailers	80.07
519	Other Information Services	50.48
812	Personal and Laundry Services	49.10
448	Clothing and Clothing Accessories Stores	49.06
492	Couriers and Messengers	48.36
339	Miscellaneous Manufacturing	45.81
425	Wholesale Electronic Markets and Agents and Brokers	42.30
315	Apparel Manufacturing	41.25
493	Warehousing and Storage	40.81
484	Truck Transportation	36.96

Notes: This table reports the top 10 NAICS-3 industries by growth in business applications from 2019 to 2020. NAICS-3 codes that specify no further detail are excluded. Weekly industry level data are obtained from the U.S. Census Bureau's Business Formation Statistics.