Online Appendix for "COBOLing Together UI Benefits: How Delays in Fiscal Stabilizers Affect Aggregate Consumption" (NOT FOR PUBLICATION)

Michael A. Navarrete*
Federal Reserve Bank of Atlanta

June 26, 2026

1 Robustness Checks

1.1 Heterogeneity Analysis

Throughout this analysis, I have focused on relative consumption for all consumption categories among all consumers. However, one of the benefits of using the Affinity Solutions data is that consumption at the state level can be decomposed by type of goods purchased, by type of services purchased, or by income quartile.[1] I focus on each income quartile and the four mutually exclusive aggregated consumption types defined by Chetty et al. (2023): durable goods, nondurable goods, remote services, and in-person services. If discouraged filers are playing a role in the relative consumption decline, then I would expect durable-goods consumption to be negatively affected by the large UI benefit transfers during the pandemic recession. Parker et al. (2013) found a shift towards durable goods under the Economic Stimulus Act of 2008 where the typical single

*Email: michael.navarrete@atl.frb.org. Address: 1000 Peachtree Street NE, Atlanta, GA 30309.

[1] Due to data limitations, I cannot decompose results by goods or services within an income quartile at the state level using the Economic Tracker.

household received \$300 to \$600. Unemployment Insurance benefits between April 2020 and July 2020 were much larger because of the provision granting unemployed workers an extra \$600 per week in benefits. I also decompose consumption by income quartiles because income groups were differentially exposed to the COVID-19 shock. I expect consumption of in-person services to have decreased more in COBOL states than non-COBOL states because when households receive a negative income shock, they reduce their consumption at restaurants and on entertainment, which count as in-person services. In addition, studies such as Amburgey et al. (2020) find that the top quintile had the smallest shift in its unemployment rate during the pandemic recession. If one was not unemployed, they would have been ineligible for UI benefits and could not have suffered from delayed UI benefits nor become a discouraged filer. I therefore expect the richest income quartile, quartile 4, to experience at most a small drop in relative consumption in COBOL states relative to non-COBOL states.

I use the Affinity Solutions data to see whether durable-goods consumption was affected by having an antiquated UI system. Durable-goods consumption is defined as consumption in the following merchant category codes: (1) building materials, gardening equipment, and supplies; (2) electronics and appliances; (3) furniture and home furnishings; (4) sporting goods, hobbies, musical instruments, and bookstores; (5) telecommunications; and (6) vehicles and parts. Nondurable-goods consumption is defined as consumption in the following codes: (1) clothing and clothing accessories; (2) food and beverage stores; (3) general merchandise; (4) health and personal care stores; and (5) wholesale trade. Remote-services consumption is defined as consumption in the following codes: (1) administrative and support and waste management and remediation services; (2) education; (3) finance and insurance; (4) information; (5) professional, scientific, and technical; (6) public administration; and (7) utilities, construction, and manufacturing. In-person-services consumption is defined as consumption in the following codes: (1) accommodation and food services; (2) healthcare and social assistance; (3) arts, entertainment, and recreation; (4) transportation and warehousing; (5) rental and leasing; (6) repair and maintenance; and (7) personal and laundry services.

To formally estimate the effect of increased administrative burden by type of good or service consumed, I use a TWFE estimator. Specifically, I use a TWFE estimator similar to my preferred baseline specification to estimate heterogeneous relative consumption differences between COBOL and non-COBOL states. The only difference is that the dependent variable changes from relative consumption in all categories to relative consumption in one of these four aggregated categories. In all four specifications, I match the controls of my preferred baseline specification where I include state and day fixed effects in addition to controlling for the interaction of Republican and Post. Column 1 of Table B.2 provides suggestive evidence that the increased administrative burden and reduced UI administrative capacity from antiquated systems reduced durable-goods consumption. The coefficient on the interaction of COBOL and Post is marginally insignificant at the 10% level (significant at 10.2% level). The coefficient corresponds to a 2.4-percentage-point decline in durable-goods consumption in COBOL states relative to non-COBOL states. The patterns in durable goods consumption differ from those of aggregate consumption in that durable goods consumption declined sharply at the start of the pandemic but quickly recovered, exceeding pre-pandemic levels soon afterward. By the end of May, durable-goods consumption was above baseline values and remained elevated for the remainder of the sample period for both COBOL and non-COBOL states. This suggestive finding of a relative decline in consumption of durable goods over the entire sample period may suggest more discouraged filers in COBOL states because delays would only lower durables initially. Durable goods are large purchases that arguably are less sensitive to delays in the disbursement of UI benefits.[2]

Unlike durable goods, nondurable goods should be affected by both discouraged filers and delayed payments. In column 2 of Table B.2, I estimate the effect of the increased administrative burden in UI benefit systems and reduced UI administrative state capacity on nondurable goods consumption. The table shows a relative decline of 3.5 percentage points more in COBOL states than non-COBOL states, which is significant at the 5% level. If households are not able to perfectly smooth consumption, then they will reduce their consumption of nondurable goods prior to the receipt of their delayed UI benefits. Column 3 estimates the impact on in-person services, showing a 2.8-percentage-point relative decline, which is significant at the 10% level. Consumers typically reduce their consumption of in-person services such as dining in restaurants when they receive a negative income shock. In column 4, I estimate the impact on remote services and find no effect.

Instead of looking at the goods or services purchased, as in Table B.2, I next examine which indi-

[2]Note that delays may also partially encourage durable goods consumption because the first payment of delayed UI payments will be larger than UI payments that are not delayed. For example, if an individual is entitled to 8 weeks of UI, but their claim is delayed over 10 weeks (topcoded), then the recipient will receive all their UI benefits in one lump sum transfer. This pattern of behavior is consistent with the findings in Gelman et al. (2024).

viduals experienced the largest declines in relative consumption. Specifically, I sort the individuals into income quartiles.[3] I repeat the analysis from Table B.2 using income quartiles as the dependent variable. I report the results in Table B.3. Column 1 corresponds to consumption in the bottom quartile, column 2 corresponds to consumption in the second income quartile, and so forth. All the specifications include state and day fixed effects as well as the interaction of Republican and Post as an additional control. The results show that as the income quartiles increase, the standard errors shrink. Even though the top income quartile has the smallest standard error, I find an insignificant result, as expected. The richest income quartile was the least likely to become unemployed during the pandemic recession and thus the least likely to receive UI benefits, independent of administrative burdens and state UI administrative capacity. The strongest effects are for the second- and third-income quartiles. There are two possible reasons for not finding a strong result for the bottom quartile: (1) larger standard errors or (2) fewer discouraged filers. It could be that unemployed individuals in the bottom quartile were less susceptible to an increase in administrative burden because they were more likely to depend on the benefits to cover necessities such as rent payments and food expenses. Administrative burdens in programs like UI may be a form of targeting (Nichols and Zeckhauser, 1982) in which only the most motivated claimants overcome all the hurdles. In columns 2 and 3, I find a 3.2- and 2.7-percentage-point decline for the second and third income quartiles, respectively, both of which are significant at the 10% level.

1.2 Republican Governor Controls

In my preferred specification for my consumption analysis, I have state fixed effects, day fixed effects, and the 2016 presidential Republican vote share interacted with Post as controls. In Table B.4, instead of using the 2016 presidential Republican vote share as a control, I use the Republican governor. Unlike the 2016 Republican vote share, there are statistically significant differences in Republican governor between COBOL and non-COBOL states. Columns 2 and 3 are significant at the 5 percent level and have a marginally higher point estimate, 3.0 ppt. relative decrease, than the baseline case with the Republican vote share. Columns 4 and 5 that introduce the state characteristics interacted with post noticeably decrease the point estimates to 2.1 ppt. and 2.0 ppt.,

[3] Two states, Alaska and Hawaii, are omitted from the sample because consumption data for the bottom quartile are unavailable.

respectively. These results are significant at the 10 percent level. I prefer using Republican vote share over Republican governor given that Republican vote share is a continuous variable while Republican governor is a binary variable.

However, one could view the Republican vote share and Republican governor as picking up different sources of variation. Republican vote share could capture COVID-19 cautiousness, while the Republican governor could capture different policies implemented during the pandemic. In Table B.5 I use the Republican governor and Republican vote share as controls simultaneously. My results are robust across all specifications. The point estimates range from a 2.1 ppt decline to a 2.6 ppt. decline in specifications with controls other than fixed effects. All specifications are significant at the 10 percent level and have similar point estimates to the version without Republican governor. These new point estimates are slightly lower than the baseline, but are not statistically different than the baseline.

Figure B.2 shows the history of weekly UI initial claims since they started to be recorded in 1967 to the end of 2020, highlighting the unprecedented surge in the pandemic recession. Figure B.3 shows the average unemployment rate between COBOL and non-COBOL states. We see similar patterns prior to August 2020 when non-COBOL states recovered more quickly. This divergence starting in August 2020 is consistent with antiquated UI benefit systems hampering the effectiveness of UI as a fiscal stabilizer. In Figure B.6, I add each of the five confounders added individually to my preferred specification in my relative consumption results. All cases are significant at the 5 percent level with stable point estimates except when using the percentage of the population living in an urban area as a confounder. The specification using this confounder is still significant at the 10 percent level and corresponds with a 2.6 percentage point decline in relative consumption in COBOL states relative to non-COBOL states from March 13, 2020 to December 31, 2020.

1.3 Google Mobility Data Controls

Although COBOL and non-COBOL states experienced comparable COVID-19 case and death rates, differences in attitudes toward the pandemic may have affected consumption behavior. Figure B.5 provides evidence consistent with this concern: households in COBOL states spent relatively more time at home after the emergency declaration than households in non-COBOL states. The figure is based on state-day data from Google Mobility Reports. In my preferred specifications, I address this concern by controlling for the 2016 Republican presidential vote share interacted with Post. This control is intended to capture both differences in COVID-19 cautiousness and differences in state policy responses to the pandemic. As an additional robustness check, Table B.6 adds relative time spent in residential areas as a direct control for mobility behavior.

The estimates in Table B.6 remain negative and statistically significant at least at the 10 percent level. The point estimates range from -3.5 percentage points to -2.4 percentage points, consistent with the baseline findings. In Table B.7, I further add controls for relative time spent in workplaces and in grocery stores or pharmacies. The results remain robust: all specifications are negative and statistically significant at least at the 10 percent level, with point estimates ranging from -3.6 percentage points to -2.4 percentage points. The stability of the estimates across these specifications suggests that the baseline results are unlikely to be driven by differential mobility patterns or COVID-19 cautiousness across COBOL and non-COBOL states.

1.4 Other Pandemic Transfers as Controls

In the main text, I discuss three other government transfer programs that were implemented while UI benefits were being disbursed in 2020: the Paycheck Protection Program (PPP), the Supplemental Nutrition Assistance Program (SNAP), and the Economic Impact Payments (EIP). Two of these programs, PPP and EIP, were federal programs. I find no statistically significant differences in disbursements between COBOL and non-COBOL states for any of the three programs. Nevertheless, as an additional robustness check, I separately control for outlays from each program.

The three programs differ in timing and data frequency. PPP data are available at the daily frequency and begin on April 3, 2020. SNAP data are available at the monthly frequency and cover periods before and after 2020. For EIP, I use data from the first round of payments, which was the only round distributed during the sample period. These data report aggregate first-round EIP outlays by state. Households began receiving direct deposits from the first round of EIP in mid-April 2020.

Table B.8 controls for the initial PPP loan amount received by firms in each state on each day in 2020. Because a large share of PPP loans were ultimately forgiven, these amounts should be interpreted as transfers rather than conventional loans. Including this control has little effect on the coefficient of interest, the interaction between COBOL and Post. The point estimates range from -4.1 percentage points to -2.4 percentage points, and all are statistically significant at the 5 percent level. The coefficient on PPP outlays is not statistically significant at the 10 percent level.

Table B.9 controls for monthly SNAP outlays. Including this control attenuates the coefficient on the interaction of COBOL and Post, but the estimated effects remain negative and statistically significant. The point estimates range from -3.3 percentage points to -2.0 percentage points, and all are statistically significant at the 10 percent level. The coefficient on SNAP outlays is negative and statistically significant at least at the 5 percent level, implying that higher SNAP outlays are associated with lower credit and debit card spending.

Table B.10 controls for first-round EIP outlays. A limitation is that the EIP data contain only one value per state: total first-round EIP outlays. To incorporate this measure into the daily panel, I interact state-level EIP outlays with Post_2, an indicator equal to one beginning on April 15, 2020. Including this control attenuates the coefficient on the interaction of COBOL and Post, but the estimated effects remain negative and statistically significant. The point estimates range from -2.4 percentage points to -1.8 percentage points, and all are statistically significant at the 10 percent level. The coefficient on EIP outlays is positive and statistically significant at least at the 1 percent level, implying that higher first-round EIP outlays are associated with higher credit and debit card spending.

1.5 Penalized Synthetic Control Method

I use the penalized synthetic control method developed by Abadie and L'Hour (2021) to measure the decline in relative consumption for COBOL states relative to non-COBOL states after the emergency declaration.

This method uses covariates in the pre-intervention period and the donor pool to create a synthetic control for each treated unit. In my setting, I have 28 treated units, COBOL states, and 22 control units in the donor pool, non-COBOL states. The innovation of the penalized synthetic control method over the traditional synthetic control method is that there is a tuning parameter, λ, that puts additional weight on pairwise comparisons instead of the aggregate comparison. The higher the value of this tuning parameter, the more sparse the synthetic controls will be, and fewer non-COBOL states will be selected from the donor pool. As the tuning parameter approaches 0, the penalized synthetic control method becomes the traditional synthetic control method that minimizes the sum of pairwise discrepancies. As the tuning parameter approaches ∞, the penalized synthetic control method becomes the nearest-neighbor matching with replacement estimator.

The penalized synthetic control method is similar to the traditional synthetic control method in that they are both heavily dependent on the controls selected from the pre-intervention period. These controls affect which non-COBOL states are selected in the synthetic control in addition to the weight assigned in the synthetic control. Typically, more controls are used in a synthetic control setting than in a TWFE setting given the lack of fixed effects. I select 15 covariates to match on: (1) Republican vote share (2016), (2) income share in accommodation and food services (2019), (3) the percentage of the population living in urban areas (2010), (4) UI generosity (Jan. 2020), (5) the percentage of the population living in poverty (2019), (6) the percentage of the population with at least a bachelor's degree (2019), (7) the employment-to-population ratio (2019), (8) the log of income per capita (2019), (9) median age (2019), (10) the African American population share (2019), (11) the relative replacement rate (2020), (12) teleworkable employment (2019), (13) a Republican governor indicator (2019), (14) labor force population, and (15) real GDP (2019).

Table B.11 reports the relative consumption decline for COBOL states using the penalized synthetic control method. The last three columns report results using this method. The column labeled PSC fixed λ corresponds to a fixed value for the tuning parameter of 0.1. The other two penalized synthetic control estimator columns choose the tuning parameter in a data-driven manner. The column labeled PSC MSE λ uses a leave-one-out cross-validation procedure to select λ by minimizing the mean squared prediction error in the post-intervention period (after the emergency declaration). The column labeled PSC Bias λ uses validation over the outcomes (relative consumption) in the pre-intervention period (prior to the emergency declaration) to select the tuning parameter. The average treatment effects across these three specifications with different tuning parameters yield a relative decline in consumption for COBOL states of between 3.7 and 4.8 percentage points. The results from the penalized synthetic control method are not meaningfully different than the baseline results, which exclude the interaction of 2016 Republican vote share interacted with Post.

To conduct inference with the penalized synthetic control method, permutation tests are typically conducted. I randomly assign treatment across 28 of the 50 states 10,000 times and estimate a relative consumption decline using a tuning parameter identical to the one from the column labeled PSC MSE λ in Table B.11 (0.01) in each iteration. To be consistent with the results from Table B.11, I aggregate the 28 cohort treatment effects using population weights. Figure B.1 shows the distribution of these 10,000 simulations. The red dashed line corresponds to the average treatment effect for the 28 COBOL states with a tuning parameter of 0.01. This permutation test yields an effect that is significant at the 10% level.

1.6 Additional Delay Measures

Figure B.7 focuses on a larger set of claims that were delayed: claims that experienced at least a 5 week processing delay. It is harder to see the pattern in Figure B.7 relative to the figure depicting the share of topcoded claims, but COBOL states experience a larger share of claims that experience at least a 5 week delay. Given that this definition includes a larger set of delayed claims, it is unsurprising that the resulting shares are, by construction, higher than those in the topcoded analysis. For example the maximum value in Figure B.7 is around 40%, while the maximum value in the topcoded figure is around 25%. One should note that when analyzing claims that are at least delayed by 5 weeks that the range in delays mechanically increases relative to claims that are topcoded. Delays now range from 5 weeks to over 10 weeks. Unlike the topcoding analysis, I only exclude March 2020 from the sample given that claims made early in the pandemic that are delayed by at least 5 weeks could appear in April 2020 (unlike topcoded claims). Given this heterogeneity in lags in conjunction with COBOL states experiencing more topcoded claims, non-COBOL states peak sooner than COBOL states (June 2020 peak for non-COBOL states and August 2020 peak for COBOL states).

I perform a similar analysis in Table B.12 with the share of claims that were delayed at least 5 weeks as the dependent variable. I use the same five confounders and I find that COBOL states experienced between a 3.1 ppt. increase and a 4.4 ppt. increase in the share of claims with at least a 5 week delay relative to non-COBOL states after the emergency declaration. These results are significant at the 5 percent level across all specifications. In sum, I find that COBOL states experienced longer delays in the form of higher share of topcoded claims and higher share of claims delayed by at least 5 weeks relative to non-COBOL states after the emergency declaration.

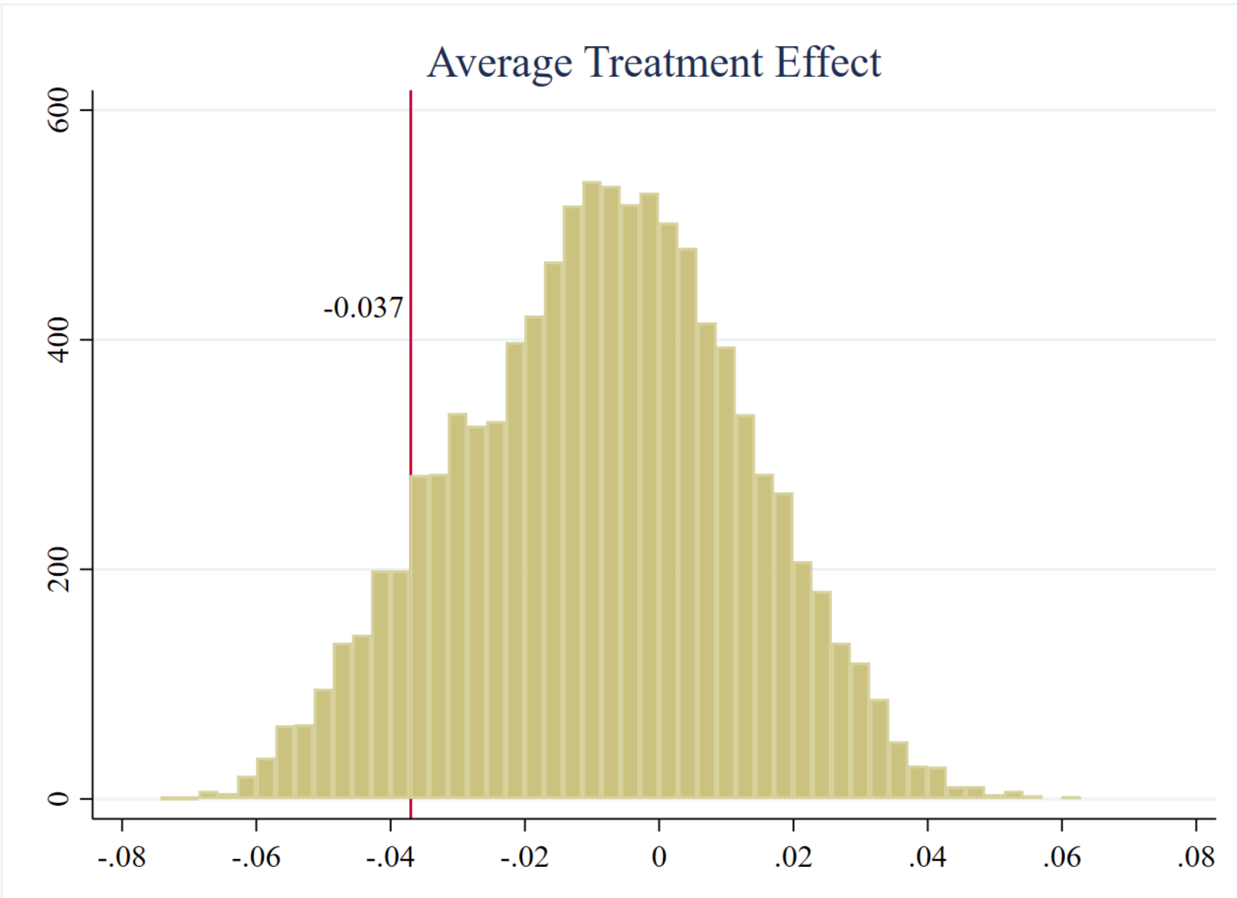
1.7 Unweighted Discouraged Filers

My baseline results are weighted to estimate the average national impact of antiquated UI benefit systems during the pandemic. However, in the discouraged-filer analysis based on the Google survey from Zipperer and Gould (2020), not all respondents have survey weights. To address the concern that respondents with survey weights may differ systematically from those without survey weights, I report unweighted estimates in Table B.13. This increases the sample size from 3,012 to 4,066.

Table B.13 shows broadly similar results, with point estimates ranging from 2.7 percentage points to 4.1 percentage points. The specification without controls is not statistically significant at the 10 percent level, while all remaining specifications are statistically significant at the 5 percent level. These findings are consistent with a higher share of discouraged filers in COBOL states relative to non-COBOL states.

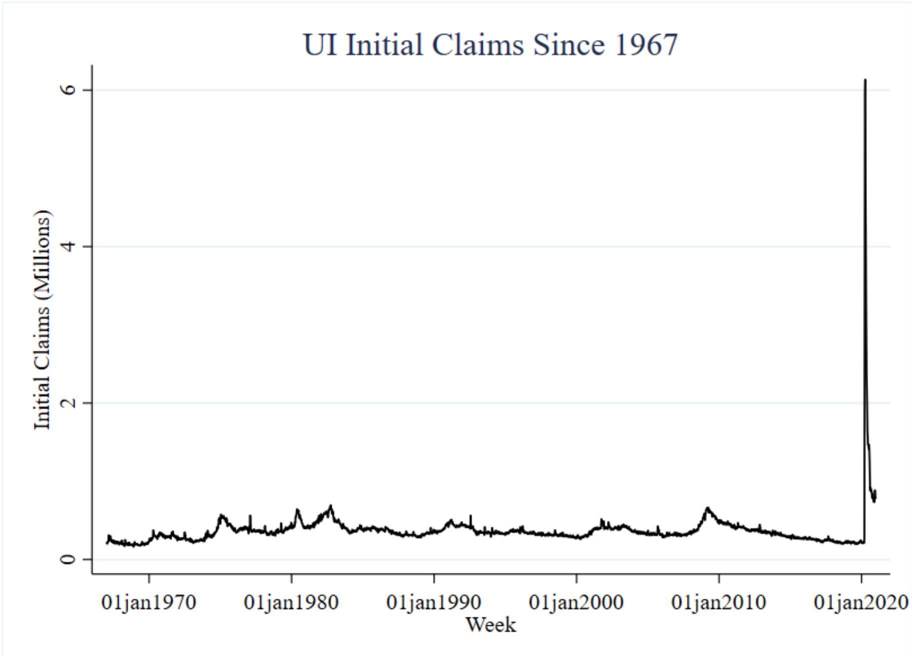
2 Additional Figures and Tables

Figure B.1: Permutation Test for Penalized Synthetic Control Method (10,000 Simulations)



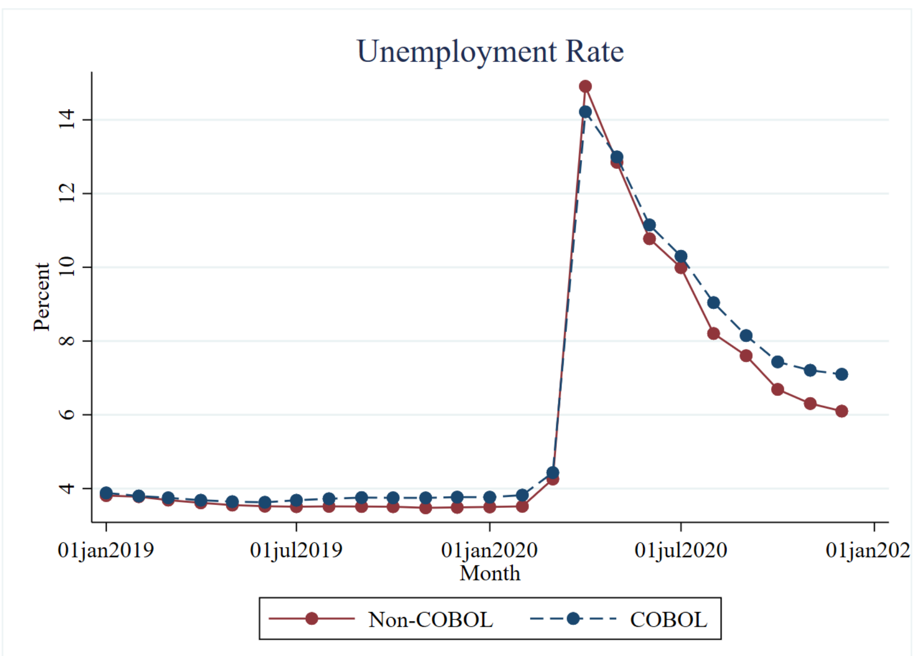
Note: The histogram shows the distribution of average treatment effects when treatment is randomly assigned across 28 of the 50 states 10,000 times using the penalized synthetic control method. The tuning parameter is identical to the one from the column labeled PSC MSE λ in Table B.11 (0.01) in each iteration. To be consistent with the results from Table B.11, I aggregate the 28 cohort treatment effects using population weights. The red dashed line corresponds to actual treatment effect with the 28 COBOL states: a 3.7-percentage-point decline. This permutation test yields an effect that is significant at the 10% level.

Figure B.2: National UI Initial Claims



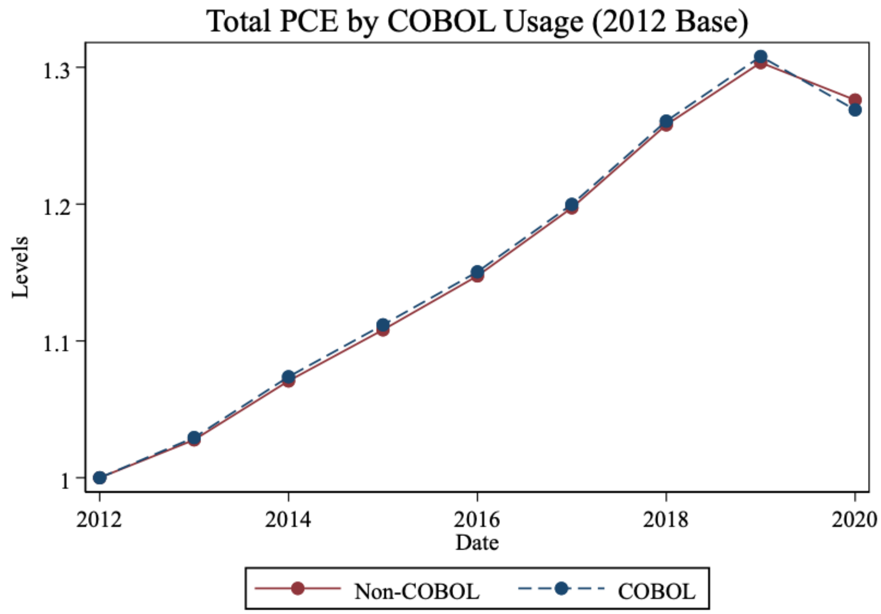
Note: This figure uses weekly initial claims data from 1967 to the end of 2020. The data used are from the Department of Labor Employment Training Administration (DOLETA). The peak in initial claims corresponds to the first week of April 2020 where there was just north of 6 million initial claims filed that week at the national level.

Figure B.3: Unemployment Rate by COBOL Usage



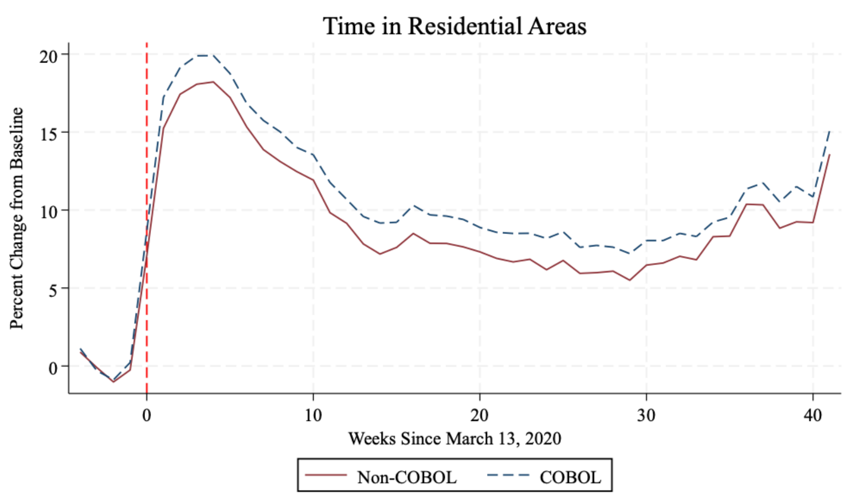
Note: This figure uses monthly seasonally adjusted state unemployment rate from the BLS. The data range from January 2019 to December 2020. The maroon line corresponds to non-COBOL states and the navy line corresponds to COBOL states. These two groups of states are aggregated using 2019 population weights.

Figure B.4: Official Aggregate Consumption Patterns



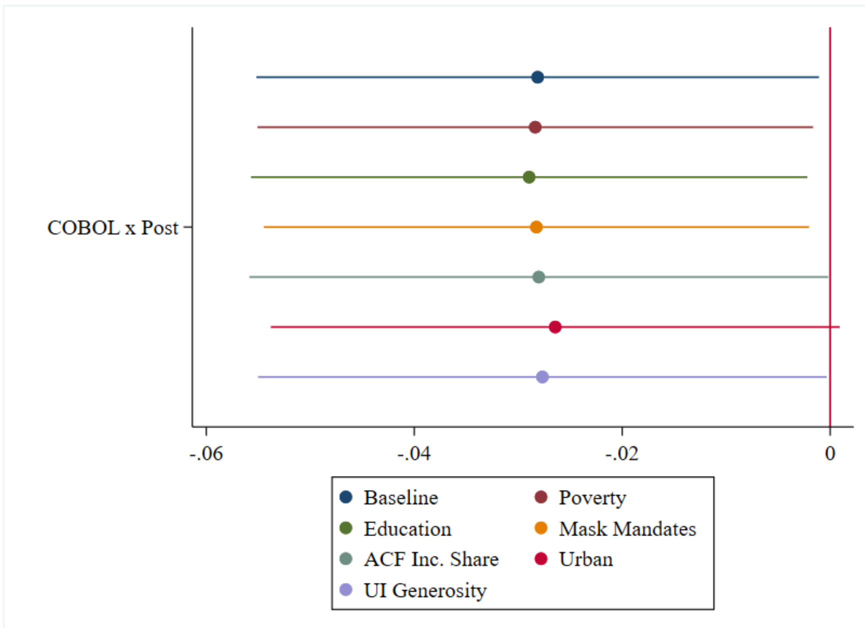
Note: This figure uses annual personal consumption expenditures (PCE) data from 2012 to the end of 2020. The data used are from the Bureau of Economic Analysis. Expenditures are aggregated by COBOL status and expenditures are normalized to 2012.

Figure B.5: Potential COVID-19 Cautiousness



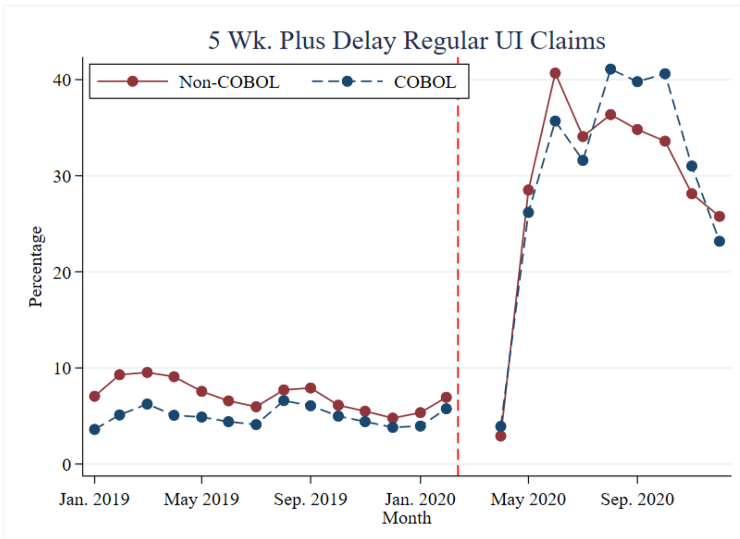
Note: This figure uses daily Google Mobility data from February 2020 to December 2020. The data is relative time spent in residential area relative to that's baseline period of time in residential areas. The baseline period corresponds to the first six weeks of 2020. I aggregate the data to the weekly frequency. Weeks a are determined relative to the week ending on March 13, 2020, which corresponds to the red vertical dashed line. The maroon line corresponds to non-COBOL states and the navy line corresponds to COBOL states. These two groups of states are aggregated using 2019 population weights.

Figure B.6: Coefficient Plot Interacting Potential Confounders Individually



Note: This figure plots the coefficient on $COBOL \times Post$ from the TWFE estimator (state fixed effects and day fixed effects). The baseline definition includes the COVID-19 controls and the interaction of COBOL state and the 2016 Republican presidential vote share. The remaining five coefficients build upon the baseline specification by adding one confounder, $Confounder_i$, and interacting it with $Post_t$. The figure plots coefficients on $COBOL \times Post$ ranging from a 2.6 percentage point decline in relative consumption to a 2.9 percentage point decline. The effect is significant at the 5 percent level in all specifications except for the one that adds percentage of the population living in an urban area (still significant at the 10 percent level). Standard errors are clustered at the state level.

Figure B.7: Percentage of Claims Delayed at Least 5 Weeks (Processing Delays)



Note: This figure is based on first-payment time-lapse data from the Department of Labor Employment and Training Administration's 9050 reports. The groups are population weighted using 2019 Census estimates. The figure depicts the percentage of intrastate regular UI claims reported as having at least a 5 week processing delay between January 2019 and December 2020 for COBOL and non-COBOL states. The vertical red dashed line corresponds to March 13, 2020. Because topcoding is a lagging indicator, I drop March 2020 from the sample.

Table B.1: List of COBOL and Non-COBOL States

COBOL States	Non-COBOL States
AK	AL
AR	FL
AZ	ID
CA	IL
CO	IN
CT	LA
DC	MA
DE	ME
GA	MI
HI	MN
IA	MO
KS	MS
KY	NC
MD	NE
MT	NH
ND	NM
NJ	NV
NY	SC
OH	TN
OK	UT
OR	WA
PA	WY
RI	
SD	
TX	
VA	
VT	
WI	
WV	

Note: The table lists states classified as COBOL and non-COBOL for the purposes of this paper. Washington, D.C. is classified as COBOL but is excluded from the empirical analysis. The table reports the same COBOL status classification shown in the map.

Table B.2: TWFE COBOL Usage by Consumption Type

	(1) Durables	(2) Nondurables	(3) In-person serv.	(4) Remote serv.
COBOL $\times$ Post	-0.024	-0.034**	-0.028*	-0.014
	[0.014]	[0.014]	[0.015]	[0.016]
Republican $\times$ Post	0.002***	0.001	0.006***	0.001
	[0.001]	[0.001]	[0.001]	[0.001]
State FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Days	335	335	335	335
States	50	50	50	50
Observations	16,750	16,750	16,750	16,750

Note: The table provides results from a two-way fixed-effects (TWFE) estimator with day and state fixed effects, where consumption is broken down by consumption type. The dependent variable is the percentage-point change in a type of credit and debit card consumption measured at a daily frequency relative to the base period, January 2020. Column 1 corresponds to durable-goods consumption, column 2 to nondurable-goods consumption, column 3 to in-person services consumption, and column 4 to remote-services consumption. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The main interaction term is the product of *COBOL* and *Post*. As an additional control in all specifications, I interact *Post* and the 2016 Republican presidential election vote share. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level. Standard errors are reported in brackets.

Standard errors: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table B.3: TWFE COBOL Usage on All Card Consumption by Income Quartiles

	(1) Rel Cons (Q1)	(2) Rel Cons (Q2)	(3) Rel Cons (Q3)	(4) Rel Cons (Q4)
COBOL × Post	-0.014	-0.032*	-0.027*	-0.011
	[0.020]	[0.019]	[0.015]	[0.010]
Republican × Post	0.004***	0.002	0.002	0.002**
	[0.001]	[0.001]	[0.001]	[0.001]
State FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Days	335	335	335	335
States	48	50	50	50
Observations	16,080	16,750	16,750	16,750

Note: The table provides results from a two-way fixed-effects (TWFE) estimator with day and state fixed effects, where consumption is broken down by income quartiles. Column 1 corresponds to the bottom quartile, column 2 to the second quartile, column 3 to the third quartile, and column 4 to the top quartile. The dependent variable is the percentage-point change in credit and debit card consumption (measured at a daily frequency) for the relevant income quartile relative to the base period. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The main interaction variable is the product of *COBOL* and *Post*. As an additional control in all specifications, I interact *Post* with the 2016 Republican presidential election vote share. Alaska and Hawaii are omitted in column 1 because their consumption data are missing. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.4: TWFE COBOL Usage on All Card Consumption (Republican Governor, Replacement)

	(1) Rel Cons	(2) Rel Cons	(3) Rel Cons	(4) Rel Cons	(5) Rel Cons
COBOL × Post	-0.041**	-0.030**	-0.030**	-0.021*	-0.020*
	[0.020]	[0.015]	[0.015]	[0.011]	[0.011]
RepGov × Post		0.037*	0.038*	0.031	0.032
		[0.021]	[0.021]	[0.020]	[0.019]
UR					0.002
					[0.002]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *RepGov* is a binary variable corresponding to whether a state had a Republican governor in 2019. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. Column 1 only includes state and day fixed effects. Column 2 adds the interaction of *Republican* and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.5: TWFE COBOL Usage on All Card Consumption (Republican Governor, Inclusion)

	(1) Rel Cons	(2) Rel Cons	(3) Rel Cons	(4) Rel Cons	(5) Rel Cons
COBOL × Post	-0.041**	-0.026*	-0.027*	-0.022**	-0.021*
	[0.020]	[0.014]	[0.014]	[0.011]	[0.011]
Republican Gov. × Post		0.006	0.007	0.018	0.019
		[0.016]	[0.016]	[0.018]	[0.017]
Republican × Post		0.003***	0.003***	0.003**	0.003***
		[0.001]	[0.001]	[0.001]	[0.001]
UR					0.002
					[0.002]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *Republican* is the Republican vote share in the 2016 presidential election. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. Column 1 only includes state and day fixed effects. Column 2 adds the interaction of *Republican* and *Post* as well as interacting a binary variable indicating whether a state had a Republican governor and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.6: TWFE COBOL Usage on All Card Consumption (Residential Time)

	(1)	(2)	(3)	(4)	(5)
	Rel Cons	Rel Cons	Rel Cons	Rel Cons	Rel Cons
COBOL × Post	-0.035*	-0.026*	-0.027**	-0.025**	-0.024**
	[0.018]	[0.013]	[0.013]	[0.011]	[0.011]
Residential	-0.004***	-0.002***	-0.001	-0.001	-0.001*
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Republican × Post		0.003***	0.003***	0.003**	0.004***
		[0.001]	[0.001]	[0.001]	[0.001]
UR					0.002
					[0.002]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *Republican* is the Republican vote share in the 2016 presidential election. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. *Residential* is relative time in residential areas from daily Google Mobility data. Column 1 only includes *Residential*, state fixed effects, and day fixed effects. Column 2 adds the interaction of *Republican* and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** p<0.01, ** p<0.05, * p<0.1

Table B.7: TWFE COBOL Usage on All Card Consumption (Google Mobility)

	(1) Rel Cons	(2) Rel Cons	(3) Rel Cons	(4) Rel Cons	(5) Rel Cons
COBOL × Post	-0.036*	-0.026*	-0.028**	-0.025**	-0.024**
	[0.018]	[0.013]	[0.013]	[0.011]	[0.011]
Residential	-0.003***	-0.002***	-0.001	-0.001	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Work	-0.000	-0.001	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Grocery	0.001*	0.001	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Republican × Post		0.003***	0.003***	0.003**	0.004***
		[0.001]	[0.001]	[0.001]	[0.001]
UR					0.003
					[0.002]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *Republican* is the Republican vote share in the 2016 presidential election. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. *Residential* is relative time in residential areas from daily Google Mobility data. *Work* is relative time in work areas from daily Google Mobility data. *Grocery* is relative time in grocery or pharmacy areas from daily Google Mobility data. Column 1 only includes *Residential*, *Work*, *Grocery*, state fixed effects, and day fixed effects. Column 2 adds the interaction of *Republican* and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** p<0.01, ** p<0.05, * p<0.1

Table B.8: TWFE COBOL Usage on All Card Consumption (PPP)

	(1) Rel Cons	(2) Rel Cons	(3) Rel Cons	(4) Rel Cons	(5) Rel Cons
COBOL × Post	-0.041**	-0.028**	-0.028**	-0.026**	-0.024**
	[0.020]	[0.013]	[0.013]	[0.011]	[0.011]
Republican × Post		0.003***	0.003***	0.003***	0.004***
		[0.001]	[0.001]	[0.001]	[0.001]
UR					0.002
					[0.002]
PPP	-0.000	-0.000	-0.000	-0.000	-0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *Republican* is the Republican vote share in the 2016 presidential election. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. PPP denotes the initial loan amount of dollars (in thousands) that a state received in the 2020 at daily frequency from the Paycheck Protection Program. PPP started on April 3, 2020. Column 1 only includes *PPP*, state fixed effects, and day fixed effects. Column 2 adds the interaction of *Republican* and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.9: TWFE COBOL Usage on All Card Consumption (SNAP)

	(1) Rel Cons	(2) Rel Cons	(3) Rel Cons	(4) Rel Cons	(5) Rel Cons
COBOL × Post	-0.033*	-0.023*	-0.024*	-0.022*	-0.020*
	[0.017]	[0.014]	[0.014]	[0.011]	[0.011]
Republican × Post		0.003***	0.003***	0.003***	0.003***
		[0.001]	[0.001]	[0.001]	[0.001]
UR					0.003**
					[0.001]
SNAP	-0.000**	-0.000**	-0.000**	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *Republican* is the Republican vote share in the 2016 presidential election. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. SNAP denotes the monthly cost (in thousands of dollars) that a state incurred in 2020 from the Supplemental Nutrition Assistance Program. Column 1 only includes *SNAP*, state fixed effects, and day fixed effects. Column 2 adds the interaction of *Republican* and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table B.10: TWFE COBOL Usage on All Card Consumption (EIP)

	(1) Rel Cons	(2) Rel Cons	(3) Rel Cons	(4) Rel Cons	(5) Rel Cons
COBOL × Post	-0.024*	-0.020*	-0.020*	-0.021*	-0.018*
	[0.013]	[0.012]	[0.012]	[0.010]	[0.010]
Republican × Post		0.002***	0.002***	0.003***	0.003***
		[0.001]	[0.001]	[0.001]	[0.001]
UR					0.003***
					[0.001]
EIP × Post_2	0.001***	0.000***	0.000***	0.000***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
State FE	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes
COVID-19 Controls	No	No	Yes	Yes	Yes
State Char. × Post	No	No	No	Yes	Yes
Days	335	335	335	335	335
States	50	50	50	50	50
Observations	16,750	16,750	16,750	16,750	16,750

Note: The table presents results from a TWFE estimator with day and state fixed effects. The dependent variable is the percentage-point change relative to the base period in credit and debit card consumption measured at the daily frequency. *Post* is a binary variable that takes the value 1 if the date is on or after March 13, 2020. *COBOL* is a binary variable that takes the value 1 if a state uses COBOL in its UI benefits system. The interaction term of interest is the product of *COBOL* and *Post*. *Republican* is the Republican vote share in the 2016 presidential election. COVID-19 controls include new COVID-19 death rates and new COVID-19 case rates. EIP denotes the amount of dollars (in thousands) that a state received in the first round of Economic Impact Payments. Post_2 is a binary variable that takes the value one after April 15, 2020. Column 1 only includes the interaction of EIP and Post_2, state fixed effects, and day fixed effects. Column 2 adds the interaction of *Republican* and *Post*. Column 3 adds the COVID-19 controls. Column 4 adds five terms of *Post* interacted with another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 5 adds the monthly unemployment rate. These estimates cover the sample period of February 1, 2020, to December 31, 2020. State populations in 2019 are applied as analytic weights. Standard errors are clustered at the state level.

Standard errors: *** p<0.01, ** p<0.05, * p<0.1

Table B.11: Penalized Synthetic Control Method, Results

	Treated	Control	PSC fixed λ	PSC MSE λ	PSC Bias λ
Sample Size	28	22	18	22	20
Republican	44.43	48.80	48.88	49	48.42
Urban	82.95	77.45	81.61	81.46	82.31
UI Generosity	12.3	9.11	7.02	7.55	7.31
ACF Incshare	3.37	3.930	4.290	4.360	4.220
Poverty	12.20	12.540	12.650	12.470	12.400
Education	33.81	31.810	31.330	31.380	31.620
EPOP	46.01	45.540	44.340	44.230	44.670
Income Per Cap.	10.96	10.87	10.89	10.9	10.89
Median Age	37.72	38.92	39.73	40.14	39.72
AA Pop. Share	0.11	0.140	0.150	0.140	0.150
Rel. Rep. Rate	1.01	1.09	1.13	1.12	1.12
Teleworkable Emp.	0.37	0.350	0.350	0.350	0.350
Republican Governor	0.46	0.780	0.750	0.900	0.800
Labor Force Pop.	8,903,412	4,695,989	6,589,242	6,579,186	6,578,733
Real GDP	1,179,523	484,750	652,204	647,904	650,749
Treatment Effect	NA	-0.041	-0.039	-0.048	-0.037
λ	NA	NA	0.100	0.001	0.010
Min. Density	NA	NA	1	1	1
Median Density	NA	NA	2	22	2
Max. Density	NA	NA	3	22	4

Note: The table presents results from the penalized synthetic control method (Abadie and L'Hour, 2021) in comparison and the traditional TWFE. The sample size corresponds to how many states are used to create synthetic control groups. In the TWFE setting, the control group is all 22 non-COBOL states. With the penalized synthetic control method, not all states from the donor pool may get selected. For both the traditional TWFE estimator and the penalized synthetic control method, the 28 treated states are the COBOL states. Fifteen covariates are used for creating synthetic controls that are measured prior to the emergency declaration. The one parameter changing across the three penalized synthetic control methods is the penalization parameter: λ. This parameter makes a trade-off between the component-wise fit (to a COBOL state) and aggregate fit (to all COBOL states). The column labeled "PSC fixed λ" corresponds to a fixed value for λ of 0.1. The other penalized synthetic control estimator columns choose lambda in a data-driven manner. One uses a leave-one-out cross-validation procedure to select λ by minimizing the mean squared prediction error in the post-intervention period (after the emergency declaration). The other method chooses λ on validation over the outcomes (relative consumption) in the pre-intervention period (prior to the emergency declaration). All five confounders as well as the 2016 Republican vote share are included in this analysis. The density refers to the number of non-COBOL states used for creating the synthetic control of the COBOL states. For example, a maximum density of 22 refers to at least one COBOL state using all 22 non-COBOL states in its synthetic control. All results use 2019 population weights.

Table B.12: TWFE Fraction of Claims Delayed at Least 5 Weeks

	(1)	(2)	(3)	(4)
	FracIntra5Wks	FracIntra5Wks	FracIntra5Wks	FracIntra5Wks
COBOL × Post	3.1**	3.3**	4.3***	4.4***
	(1.42)	(1.54)	(1.13)	(1.08)
Republican × Post		0.0	-0.3**	-0.3**
		(0.07)	(0.11)	(0.12)
UR				0.2
				(0.65)
State FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
State Char. x Post	No	No	Yes	Yes
Obs.	1150	1150	1150	1150
Depvar	4.83	4.83	4.83	4.83

Note: This table relies on first-payment time-lapse data from the Department of Labor Employment and Training Administration's 9050 reports. The dependent variable is the fraction of intrastate claims that are delayed at least 5 weeks. All specifications correspond to a TWFE estimator with state and month fixed effects. Column 1 does not include any additional controls. Column 2 includes the interaction of 2016 presidential Republican vote share and Post. Column 3 adds multiple interaction terms of post and another confounder: (1) income share in accommodation and food services (2019), (2) the percentage of the population living in urban areas (2010), (3) UI generosity (Jan. 2020), (4) the percentage of the population living in poverty (2019), and (5) the percentage of the population with at least a bachelor's degree (2019). Column 4 adds the unemployment rate. The sample starts in January 2019 and ends in December 2020, with the post-period starting in April 2020. Given the spurious nature of topcoding being a lagging indicator, I drop March 2020 from the sample. Depvar corresponds to the average value of the fraction of claims delayed at least 5 weeks from January 2019 to February 2020 across all 50 states (unweighted). The standard errors are clustered at the month level.

Standard errors: *** p<0.01, ** p<0.05, * p<0.1

Table B.13: COBOL UI Systems and Discouraged Filing (Unweighted)

	(1) Discouraged	(2) Discouraged	(3) Discouraged	(4) Discouraged	(5) Discouraged
COBOL	0.027	0.041**	0.040**	0.040**	0.037**
	[0.020]	[0.019]	[0.017]	[0.017]	[0.018]
UI Generosity		-0.004	-0.005*	-0.005*	-0.003
		[0.003]	[0.003]	[0.003]	[0.003]
Individual Char.	No	No	Yes	Yes	Yes
State Char.	No	No	No	Yes	Yes
Region FE	No	No	No	No	Yes
Obs.	4,066	4,066	4,066	4,066	4,066
Depvar	0.43	0.43	0.43	0.43	0.43

Note: This table reports individual-level regressions of an indicator for being a discouraged unemployment insurance (UI) filer on an indicator for residing in a COBOL state. The sample is restricted to respondents who lost a job and either applied successfully, tried to apply, or did not apply because the process was too difficult or because their application was rejected. The dependent variable equals one for respondents who tried to apply but could not get through, tried but had their application rejected, or did not apply because it was too difficult, and equals zero for respondents who applied successfully. COBOL is an indicator for states using COBOL-based UI systems. UI Generosity is defined as the maximum weekly benefit amount multiplied by the maximum benefit duration, divided by 1,000. Column 1 includes no additional controls. Column 2 adds UI generosity. Column 3 adds individual controls for gender and age. Column 4 adds state-level controls for 2016 Republican vote share, urban population share, educational attainment, the income share in accommodation and food services, and the poverty rate. Column 5 adds Census region fixed effects. All regressions are unweighted. Depvar reports the unweighted mean of the dependent variable in the estimation sample. The survey information comes from the Google Survey analyzed in Zipperer and Gould (2020). Standard errors, reported in brackets, are clustered at the state level.

Standard errors: *** p<0.01, ** p<0.05, * p<0.1

References

Abadie, A. and J. L'Hour (2021). A penalized synthetic control estimator for disaggregated data. *Journal of the American Statistical Association 116*(536), 1817–1834.

Amburgey, A., S. Birinci, et al. (2020). Which earnings groups have been most affected by the covid-19 crisis. *Economic Synopses*.

Chetty, R., J. N. Friedman, M. Stepner, and O. I. Team (2023, 10). The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data*. *The Quarterly Journal of Economics 139*(2), 829–889.

Gelman, M., Z. Orlando, and D. Patki (2024). The impact of government transfer payment frequency on consumption: Evidence from delayed ui. Working Paper 24-16, Federal Reserve Bank of Boston.

Nichols, A. L. and R. J. Zeckhauser (1982). Targeting transfers through restrictions on recipients. *American Economic Review 72*(2), 372–377.

Parker, J. A., N. S. Souleles, D. S. Johnson, and R. McClelland (2013, October). Consumer spending and the economic stimulus payments of 2008. *American Economic Review 103*(6), 2530–53.

Zipperer, B. and E. Gould (2020, April). Unemployment filing failures: New survey confirms that millions of jobless were unable to file an unemployment insurance claim. Working Economics Blog, Economic Policy Institute.