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ABSTRACT

In this paper, we examine the reasons why unemployment insurance (UI) claims have declined so dramatically over the past three decades. The fall in the UI claims rate is concerning because it suggests a reduced countercyclical effectiveness of the UI program. Additionally, weekly initial UI claims are regarded as an important leading indicator of aggregate economic activity, so their meaning has changed. We use a Oaxaca (1973) decomposition approach to identify the main factors for the decline in claims. The procedure suggests what the level of claims would have been later in the period, had values of variables or parameters of the system been at levels observed earlier in the period. Our analysis of state-year data over the past three decades suggests that the decline in UI claims stems from changes in the industrial and occupational mix of employment interacting with changes in UI program features set by individual states. Employment declines in manufacturing and increases in the health-care and education workforce, along with lower potential UI duration and lower wage replacement rates, contribute to the decline in claims. This decline could be offset by federal rules for states to improve benefit access, replacement rates, and durations. Such changes could improve the relevance of UI to the labor market and help restore UI as meaningful social insurance against job loss and as an automatic stabilizer of the macroeconomy.

JEL Classification Codes: J65, J68, H76

Key Words: unemployment insurance (UI), applications for benefits, first claims, wage replacement rate, potential duration of benefits, industrial mix of employment, occupational mix of employment

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Every Thursday morning, the U.S. Department of Labor reports the number of new unemployment insurance (UI) claims filed the previous week. Initial UI claims are an important leading indicator of the labor market and the aggregate economy.[1] However, the signal sent by UI claims about macro trends has changed significantly over the past 30 years. For any given level of unemployment, UI claims are much lower now than they were at the end of the twentieth century. Using an approach inspired by the Oaxaca (1973) decomposition, we investigate possible factors explaining why UI application rates were much higher before the dot-com recession (2001) than after the financial crisis of 2007–2009.[2]

BACKGROUND

In the year 2000, with unemployment at 3.9 percent and the labor force having 142.6 million workers, weekly unemployment insurance (UI) claims averaged 299,752. Before the pandemic in 2019, with unemployment at 3.7 percent and the labor force having 163.5 million workers, weekly UI claims averaged 216,249. In the same period, the labor force participation rate declined from 67.1 percent to 63.1 percent, but that alone cannot explain the 28 percent drop in weekly claims in a labor force that increased by 15 percent while unemployment was only slightly lower.[3]

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[1] In the Conference Board index of leading economic indicators, new UI claims account for 3 percent of the index. However, that low fraction belies the policy relevance of the weekly count. Initial claims are provided to the chair of the Federal Reserve and the macroeconomist at the Council of Economic Advisors 24 hours before their public release. In 1995, during the budget impasse that resulted in a shutdown of the federal government, Federal Reserve chair Alan Greenspan requested that Cindy Ambler be designated an essential employee of the Labor Department. Cindy was the person who reported weekly UI initial claims to Greenspan at 8:30 a.m. every Wednesday before their Thursday morning release (Reich 1997, p. 286).

[2] The National Bureau of Economic Research (NBER) business-cycle dating committee set the start of the financial crisis recession in December 2007 and the end in June 2009 (https://www.nber.org/research/business-cycle-dating).

[3] Data cited in this paragraph are drawn from weekly UI claims reports by the Labor Department (USDOL 2023) and labor force statistics from the Current Population Survey (BLS 2023). Claims data are annual averages of

To illustrate the decline in UI claims over time, we graph the yearly average values of weekly initial UI claims for 1990–2019, plotted along with the average annual number of unemployed (Figure 1). While the absolute numbers differ greatly, the two curves move together tightly on different scales until the financial crisis, when average weekly UI claims fall to a noticeably lower level. We confine our analysis of UI claims to the prepandemic years because of the major disruption in UI trends caused by the dramatic rise in layoffs and introduction of UI pandemic programs in 2020. In the months since COVID-19 became endemic in the U.S. population, the level of weekly UI claims has declined until it is now below the 2019 level. In February 2023, despite the Federal Reserve steadily increasing the target interbank lending rate,

Figure 1 Regular UI Weekly Initial Claims and the Level of Unemployment for the 50 States plus the District of Columbia, 1990–2019

SOURCE: Initial claims from U.S. Department of Labor, Employment and Training Administration, downloaded from https://oui.doleta.gov/unemploy/claimssum.asp; and unemployed data from U.S. Department of Labor, Bureau of Labor Statistics, Local Area Unemployment Statistics, downloaded from https://www.bls.gov/lau/data.htm.

weekly counts, which are the same for seasonally adjusted or unadjusted series. Puerto Rico and the Virgin Islands are excluded from these computations since they are not included in the CPS geographic coverage for this series. See Table B.1 in Appendix B for details of this example. UI claims based on monthly data are from https://oui.doleta.gov/unemploy/claimssum.asp, and BLS data are from https://www.bls.gov/cps/definitions.htm#geo.

the seasonally adjusted four-week moving average of weekly UI claims was below 200,000 per week.

RELATED LITERATURE

Previous research on the decline in UI applications has focused on four possible causes: 1) additional state eligibility requirements, 2) individual choice that can result in not claiming or delayed application for benefits, 3) administrative hassles in the application process, and 4) the role of experience rating in UI taxation on employer behavior affecting claims.

Economists often measure the use of government transfer programs in terms of the benefit take-up rate—that is, the proportion of persons who are eligible for program benefits that actually receive them. Changes in state UI legislation or administrative practices could reduce the share of unemployed who are eligible for benefits. Such restrictions can reduce the probability of UI eligibility for an unemployed person, who might then decide not to apply for UI benefits. Another measure of UI use is the recipiency rate, or the share of unemployed persons receiving benefits.

Concern about the declining rate of UI recipiency dates to the early 1980s. Gary Burtless (1983), writing in the *Brookings Papers on Economic Activity*, asserted that states responded to high UI claims and financing burdens in the 1980–1982 double-dip recession by adopting stricter eligibility rules and administrative enforcement practices. Stricter eligibility requirements, such as higher prior earnings and fewer good-cause reasons for quits, mean fewer potential beneficiaries at any level of unemployment.

The next important study of UI receipt was done by Rebecca Blank and David Card (1991), writing in the *Quarterly Journal of Economics*. After many states instituted tighter

eligibility rules in the 1980s, Blank and Card found that the majority of further reductions in UI take-up were due to individual choices not to apply. They attributed lesser importance to shifts in unemployment toward low take-up states and declines in unionization. Overall, they estimated that only about two-thirds of UI-eligible unemployed workers actually received weekly benefits.

Also writing in the *Quarterly Journal of Economics*, Patricia Anderson and Bruce Meyer (1997) found that eliminating the tax-exempt status of benefits explained part of additional declines in UI receipt. UI became taxable above modest income thresholds in 1979; the income exclusion thresholds were lowered in 1982 and then completely eliminated in 1987 when UI became fully taxable like all other labor earnings. Anderson and Meyer used data from the Continuous Wage and Benefit History project, which contained earnings and UI claims data. They found that UI take-up rates declined as net income replacement ratios fell. However, they did not examine how individual characteristics affected the duration of UI spells or the decision to apply for UI.

To more deeply investigate the reasons unemployed people might not apply for UI, the U.S. Census Bureau included occasional supplements to the monthly Current Population Survey in 1976, 1989, 1993, and 2005. The 2005 CPS included UI supplements in January, May, July, and November. Results from the supplements were summarized by Wayne Vroman (2009) in the *Monthly Labor Review*. Vroman reports that relative to the date of job loss, UI application rates are low in the first 4 weeks. Claims peak in weeks 5 to 20, then are lower beyond 20 weeks after separation. He reported that UI application rates were similar for both genders over most of the time range but higher for women at times long after job separation. Vroman reports that many workers delay filing for UI because they expect to find jobs quickly or because they have already found a job that will start soon. This results in low rates of filing in the first four weeks of unemployment, with much greater rates of filing starting in the fifth week of unemployment.

In an article in the *Monthly Labor Review*, Stephen Wandner and Andrew Stettner (2000) examined results from the 1989 and 1993 UI supplements to the CPS. They reported that the most important reason jobless workers did not apply for UI was that they did not expect to be eligible. The main reasons they had for doubting their eligibility were beliefs about disqualifying circumstances around a job separation, such as a quit or discharge, or insufficient recent earnings or hours worked. "Only nonfiling can decrease the take-up rate, because nonfiling is the only reason eligible workers do not receive benefits," they wrote (Wandner and Stettner 2000, p. 23). Wandner and Stettner also reported percentage point reductions in UI recipiency due to the perceived hassle of applications (3 points), the stigma of charity (3 points), and lack of knowledge that UI was available (3 points). A bigger factor was that 14 percent of the unemployed surveyed in 1989 and 1990 did not apply because they expected to have a job soon.

In a paper presented at the 2019 Annual Meeting of the Allied Social Sciences Association, Stephane Auray, David Fuller, and Nicolas Lepage-Saucier (2018) posit that workers with shorter expected unemployment durations are less likely to apply for UI benefits, or at least are more likely to apply later. Their work, based on newer data with a structure different from that of Blank and Card (1991), estimates UI take-up to be in the range of 0.4 to 0.6.

Ebenstein and Stange (2010) investigate whether administrative hassles in UI application procedures affect the take-up rate. They find that neither the introduction of UI telephone claims taking nor online claims taking increased the take-up rate. That is, increasing the convenience of UI applications, by applicants not having to go in person to UI local offices, does not result in increased take-up. Indeed, they find evidence that the new application methods have added barriers to UI application for some unemployed workers who have limited computer skills or are older, have disabilities, or speak English as a second language.

Adjusting for macroeconomic conditions, DeAntonio (2018) asserts that UI claims in 2018 were much lower than in the 1960s or 1990s. He identifies the main causes as being low layoff levels, increased UI eligibility requirements, declines in benefit generosity, and, finally, low take-up among otherwise eligible unemployed workers. Summarizing descriptive statistics, he points to reductions in potential duration post 2011 as a main driver of lower UI claims.

Lachowska, Sorkin, and Woodbury (2022) assess the effects of employers on UI take-up. Using state program micro administrative data, they find evidence that experience rating of UI taxes induces employers to appeal UI claims. Using an event study, they also find that appeals and claims are negatively correlated. That is, claims are lower for employers that frequently appeal. Additionally, they find evidence that low-wage workers are less likely to claim and more likely to have their claims appealed than median-wage workers. On the other hand, they label high-claim and low-appeal employers as more desirable, since they also tend to pay higher wages and have lower separation rates. Such employers are also more likely to be unionized, consistent with the idea that unions facilitate access to UI. These factors help explain a major cause of low UI take-up: that eligible workers often do not claim benefits.

METHODOLOGY

To identify the main reasons weekly UI claims are lower now than 30 years ago, we start with the methodology Oaxaca (1973) used to look at male-female wage differentials. To measure the influence of different characteristics on the gender wage gap, Oaxaca asked the question, "What would female wages be, if females had the same characteristics as males?" He called this the "endowment effect," because he was imputing characteristics males are endowed with onto females. The difference in wages between the two groups resulting from differences in the way

predictors affect wages (the parameters of the relationship), given the values of characteristics, is what Oaxaca could not explain and called discrimination.

Applying the Oaxaca decomposition to our task we ask, what would weekly UI claims be now if the values of predictor variables were the same as those that existed between 1990 and 2001? This would be the Oaxaca endowment effect. The unexplained part of the Oaxaca decomposition would be the change in claims due to differences in the influence of predictor variables on the outcome—that is, changes in the parameter values of a regression model of UI claims.

Applying the Oaxaca method to our context, we start with two time periods, for which t_0 is the earlier period and t_1 the later period.[4] Relative to the change in claiming activity, these could be referred to as the *preperiod* and *postperiod*. We are interested in estimating models for our outcome Y over the earlier and later periods of the general linear form in Equation (1):

(1) $Y_j = X_j\beta_j + \epsilon_j$, $E(\epsilon_j) = 0, j \in \{0, 1\}$,

where X is a matrix of observable predictors of Y. Denoting B as the ordinary least squares (OLS) parameter estimates of β, the mean outcomes $\bar{Y}$ for the two periods can be computed as

(2) $\bar{Y}_j = \bar{X}_j B_j$, $j \in \{0, 1\}$.

The difference in mean outcomes between the two periods is

(3) $\bar{Y}_1 - \bar{Y}_0 = \bar{X}_1 B_1 - \bar{X}_0 B_0$.

Following Oaxaca (1973), the difference in mean outcomes can be decomposed into

(4) $(\bar{X}_1 - \bar{X}_0)B_0 + \bar{X}_0(B_1 - B_0)$.

The first term in Equation (4) is the change in the outcome due to changes in endowments—that is, changes in the values of the predictor variables, assuming the way variables affect

[4] The decomposition of differences in a model outcome between time periods due to changes in predictors and parameters was first proposed by Kitagawa (1955).

outcomes in the earlier period is held constant (B_0). The second term is what Oaxaca called the unexplained part, or what others have called the coefficient effect—that is, the mean value of predictor variables in the base period multiplied by the changes in parameters between the periods.

Winsborough and Dickinson (1971) proposed a three-term decomposition, which in our context would be written as

$$(5)\ (\bar{X}_1 - \bar{X}_0)B_0 + \bar{X}_0(B_1 - B_0) + (\bar{X}_1 - \bar{X}_0)(B_1 - B_0)\ ,$$

where, left to right, the three additive terms are called 1) the endowment effect, 2) the coefficient effect, and 3) the interaction. Oaxaca and Ransom (1999) argue that the coefficient effect is underidentified, and the same could be argued for the interaction. In this paper, we examine the importance of each of these components on our outcome of interest, UI claims. We also dive deeper to assess the influence of individual variables in X and individual parameter estimates in B.

EMPIRICAL ANALYSIS

A Model of UI Claims

Predictor variables in the matrix X of Equations (1) to (5) can be grouped into categories and are listed in Table 1, along with OLS parameter estimates over the full period 1990–2019. The categories (and variables in each category) are as follows:

- UI eligibility (monetary eligibility as a share of new initial claims in the prior year, benefit denials due to separation reasons as a share of determinations in the prior year)
- UI benefit generosity (UI wage replacement rate, potential duration of UI benefits in the benefit year)
- Extended benefits availability (EUC/TEUC first payments as a share of unemployed)

- Economic conditions (average monthly unemployed in logs, part-time share of all employed persons (ages 16+), state GDP per capita yearly percentage change)
- New and re-entrants to the labor force (new entrants' share of unemployed, re-entrants' share of unemployed)
- Labor force characteristics (gender (2), race (4), ethnicity (2), age (5))
- Industry and occupation distributions in the labor force (NAICS categories (20) and SOC categories (10))
- State indicator variables (50 states plus DC)

The model does not include time indicators because we are interested in variations within and across states due to changes in UI policies and labor markets that have evolved over time—that is, changes in labor force and employment shares by demographics, industry, and occupation. Including time-indicator variables would remove much of the change over time because of these other variables.

By our methodology, the model intercept estimate is the mean of the dependent variable. We forced this result by differencing continuous variables from their sample means and forcing into the model all subcategories of indicators for each set of categorical variables. Singularity in estimation is avoided by restricting the share of each subcategory times the variable to sum to zero. This restricts the weighted sum of parameter estimates for a group of indicator variables to be zero. Such restrictions (number) are imposed for gender (2), race (4), ethnicity (2), age (5), industry (2), and occupation (10).[5] Parameter estimates on categorical variables are interpreted relative to the dependent variable mean.

Parameters of the model estimated over the full period suggest negative correlation with UI eligibility variables—the monetary eligibility and benefit denial rates (Table 1). The negative

[5] The four racial groups are 1) American Indian/Alaskan Native; 2) Asian, Native Hawaiian/Pacific Islander; 3) Black; and 4) White. The two ethnic groups are Hispanic and Not Hispanic. The five age groups are 1) 24 or less, 2) 25–34, 3) 35–54, 4) 55–64, and 5) 65+. Twenty industry groups are based on North American Industry Classification System (NAICS) two-digit codes. Ten occupation groups are based on Standard Occupational Classification (SOC) one-digit codes.

Table 1 Model of the Log of Average Monthly Regular UI Initial Claims for the 50 States plus the District of Columbia for 1990–2019, *N* = 1,502

Variable description	Variable mean	Parameter estimate	Standard error	*t*-statistic
Intercept (dependent variable mean)	9.704	9.704	0.004	2743.50
UI eligibility				
Monetary eligibility rate, *T*–1	0.881	–0.390	0.087	–4.47
Denial rate (separation), share of determinations, *T*–1	0.404	–0.422	0.045	–9.28
UI benefit generosity				
Wage replacement rate	0.361	1.396	0.184	7.60
Potential UI duration	23.356	0.014	0.003	4.90
Extended benefits/compensation availability				
EUC/TEUC first payments' share of unemployed	0.139	0.016	0.027	0.60
Economic conditions				
Log, average monthly unemployed	170,094	0.524	0.028	18.63
Share of employed persons (16+) working part-time	0.193	–0.044	0.467	–0.10
GDP per capita, % change	0.015	–1.592	0.175	–9.09
New and re-entrants to the labor force				
New entrants' share of unemployed	0.080	–1.051	0.191	–5.50
Re-entrants' share of unemployed	0.305	–0.514	0.111	–4.64
Characteristics of the labor force				
Male	0.533	–1.420	0.301	–4.72
Female	0.467	1.617	0.343	4.72
American Indian/Alaskan Native	0.014	–1.133	0.595	–1.90
Asian, Native Hawaiian/Pacific Islander	0.042	1.547	0.474	3.26
Black, African American	0.100	–0.587	0.360	–1.63
White	0.844	0.012	0.045	0.27
Hispanic	0.086	0.051	0.238	0.21
Not Hispanic	0.914	–0.005	0.022	–0.21
Age 24 or less	0.153	–0.834	0.353	–2.36
Age 25–34	0.229	–0.618	0.217	–2.85
Age 35–54	0.448	0.827	0.121	6.85
Age 55–64	0.129	–0.095	0.359	–0.26
Age 65+	0.041	–2.151	0.786	–2.74

NOTE: See Appendix B, Table B2, for the complete model, and refer to Appendix A for data sources.
SOURCE: Tabulated results are based on state-year data described in Appendix A

sign on monetary eligibility is unexpected but probably reflects the timing in the business cycle when people with different earnings profiles get laid off in a downturn, as well as the fact that our annual data are very low frequency. UI claimants with higher average earnings are laid off toward the start of a business slowdown, and annual values of variables might not capture all the labor market dynamics at play in the UI claims process. The negative coefficient on denial rates

in the prior year suggests that claimants might be reluctant to apply because of an expectation that their claim might be denied.

Positive and significant coefficients on benefit generosity variables are noteworthy, as the state average wage-replacement rate and the potential duration of benefit receipt are both lower on average later in our data period. The decline in replacement rates over our analysis period probably results from stagnant weekly benefit amount (WBA) maximums in several states.[6] We examine both patterns in detail below.

First payments for extended UI benefits as a share of all unemployed did not significantly affect UI claims in our model. Our low frequency of state-year data might not be sufficient to capture changes due to availability of extended benefits in our estimation period (1991–1994, 2002–2003, 2008–2013).[7]

The economic-conditions variables suggest that UI claims increase with unemployment but decline with per capita increases in state gross domestic product (GDP) or aggregate income. In the postperiod, unemployment was lower, while per capita GDP rose in most states.

Parameter estimates on demographic shares of the state labor force suggest that gender and age are important factors in explaining UI claims. Not surprisingly, the largest race category (White, at 84.4 percent) has little influence on the aggregate UI application rate, because the White share of the labor force did not change much over the estimation period. The coefficients on Black and Native American are negative, but the coefficients are positive on the Asian American/Pacific Islanders (AAPI) group. A positive effect is estimated for Hispanics. The

[6] Thirty-five states index their maximum WBA to average weekly wages in UI-covered employment, but nine of these states have overridden maximum WBA increases because of insufficient reserve levels (USDOL 2022). That means only half of state UI programs (26 of 52) regularly increased their maximum WBA in a period when average weekly wages steadily rose.

[7] https://oui.doleta.gov/unemploy/pdf/spec_ext_ben.pdf

prime age group (35–54) has the only positive effect on UI applications relative to the mean. The age group having the biggest effect of reducing UI applications is the age group share of (65+), which rose over the estimation period.

Oaxaca-Kitagawa Decomposition

Setting the preperiod to 1990–2001 and the postperiod to 2002–2019, a Oaxaca decomposition on models of the general form given in Table 1 produces the results in Table 2. These results indicate that the average UI application rate among unemployed persons declined by 5.0 percentage points from the pre- to the postperiod, but that changes in neither the endowments (*X*) nor the coefficients (*B*) were significant independent causes of the decline in UI claims (*Y*) from the pre- to the postperiod. The significant effect in the decomposition is the interaction component.

Table 2 Oaxaca Summary Output for Model of the Log of Initial Claims

Component	Coefficient	Standard error	z	P>|z|
Mean for 2002–2019	9.684	0.038	253.39	0.000
Mean for 1990–2001	9.734	0.045	216.00	0.000
Difference	–0.050	0.059	–0.85	0.397
Endowments	0.115	0.085	1.35	0.177
Coefficients	–0.012	0.042	–0.28	0.783
Interaction	–0.153	0.074	–2.06	0.040

NOTE: See Appendix B, Table B3 for the complete Oaxaca output.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

Separate from statistical significance, the magnitudes of results suggest that changes in the values of the predictors (*X*) had a large positive correlation with claims. This would conform with expectations if the values of most predictors declined between the two periods—the positive correlation driving claims down. The decomposition also suggests little change between the two periods in the way variables independently affect (*B*) the outcome. The large negative effect of the interaction on UI claims in the postperiod raises questions requiring further investigation.

Simulating Decompositions

Our manual simulations start by splitting the data interval and estimating Equation (1) separately on time periods 1990–2001 and 2002–2019. Those intervals were set based on visual inspection of aggregate average UI application rates over time. While the biggest drop in claims happened after the financial crisis, the two time periods roughly balance the limited number of state-year observations available.[8] The two estimated models are then evaluated, year by year, on both the pre- and postperiod data. In Table 3 we report actual annual average monthly UI claims on the left and predicted claims based on the pre- and post- models, along with the annual differences from the actuals when evaluating the estimated models (see Appendix Tables B3 and B4 for model parameter estimates).

The predicted value for 2019 at the bottom of the third column computes what the number of claims would be in 2019 if the parameter structure of the 1990–2001 relationship ($B0$) remained. The computation suggests that the number of claims would have averaged 311,643 in 2019 instead of the actual 222,409, or 89,234 fewer. On the other hand, had the relationship parameter over the later period 2002—2019, ($B1$), been in effect in 1990, the computation in the top row in the fifth column suggests that UI claims would have been 339,950, or 50,669 lower than they averaged per week in 1990. This simple exercise suggests that changes in both X and B affected the level of claims.

[8] We tested dropping a middle interval of years to focus on an earlier pre-range and a post–financial crisis range, but reliability of parameter estimates declined as standard errors increased. Estimates were not qualitatively different from the final time-period split we adopted.

Table 3 Model of Initial Claims Estimated on 1990–2001 and 2002–2019 Intervals and Solved on Both Time Periods

Year	Actual weekly claims (*1)	Estimated 1990–2001 (B_0) (n = 603)		Estimated 2002–2019 (B_1) (n = 899)	
		Predicted	Difference	Predicted	Difference
	Computation (B_0X_0)			Computation (B_1X_0)	
1990	390,619	391,054	434	339,950	–50,669
1991	449,758	433,459	–16,299	406,831	–42,927
1992	410,796	396,535	–14,261	418,483	7,686
1993	341,187	372,163	30,976	411,258	70,071
1994	340,759	358,191	17,432	347,647	6,888
1995	358,291	352,564	–5,727	341,267	–17,025
1996	357,350	343,297	–14,053	339,757	–17,593
1997	323,826	320,923	–2,904	313,633	–10,194
1998	321,392	309,373	–12,019	298,432	–22,960
1999	293,303	299,909	6,606	289,419	–3,883
2000	296,601	303,768	7,168	279,904	–16,697
2001	399,328	388,696	–10,632	341,740	–57,588
	Computation (B_0X_1)			Computation (B_1X_1)	
2002	402,560	370,985	–31,575	417,350	14,791
2003	400,063	373,219	–26,844	414,956	14,893
2004	342,201	401,097	58,896	353,210	11,009
2005	324,327	382,129	57,802	331,061	6,734
2006	307,924	371,498	63,574	314,964	7,040
2007	320,985	383,003	62,018	314,832	–6,153
2008	427,389	422,366	–5,023	387,749	–39,639
2009	573,836	564,581	–9,255	561,695	–12,140
2010	457,610	514,472	56,862	492,247	34,637
2011	409,434	496,423	86,989	429,829	20,395
2012	377,267	469,125	91,858	373,938	–3,329
2013	350,442	460,695	110,253	358,185	7,743
2014	312,126	424,002	111,877	299,280	–12,846
2015	281,638	379,895	98,257	263,306	–18,332
2016	265,214	369,806	104,592	256,369	–8,845
2017	245,372	342,854	97,483	238,062	–7,310
2018	224,869	316,084	91,216	219,142	–5,726
2019	222,409	311,643	89,234	213,100	–9,309

NOTE: (*1) The dependent variable is based on state-year data for average monthly UI initial claims, and the average weekly claims presented here were imputed from the regression sample, which also dropped a few state-year observations because of missing QCEW data. Therefore, the actual values presented here differ slightly from the published weekly initial claims figures. See Appendix B, Tables B4 and B5, for the complete models and tests of the difference in parameter estimates between them.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

Components of the Decompositions

The previous simulation considered holding all parameters or all variable means constant in the preperiod when evaluating the postperiod. To get at the main factors driving the decline in UI claims over the period, we next investigate the components of changes in X and B. Table 4 presents a summary of simulations to isolate the effects of changes in categories of variables and

parameters in our model of UI outcomes. The left three columns in Table 4 summarize the effects of restricting parameters to the preperiod values, while the right three columns show the results of restricting variable values to the means of the preperiod. The methodology for the left three columns (preperiod parameters) is as follows: estimate the model using the postperiod (2002–2019) data, then, using UI generosity as an example, take the parameters for the wage replacement rate and potential duration variables from the model estimated over the preperiod (1990–2001) and insert those parameters into a model previously estimated over 2002–2019 and solve for predicted UI claims for the years 2002–2019. The methodology for the right three columns (preperiod mean variable values) is this: estimate the full model using the 2002–2019 data, then insert each state's mean wage replacement rate and potential duration from 1990 to 2001 and solve. Table 4 presents the results for 2019, applying this general methodology for each category separately.[9]

Table 4 Predicted Weekly Initial Claims for 2019 from a Model Estimated Using Data from 2002 to 2019, Then Incrementally Simulated Using Parameters or Variable Means from Various Categories from the Model Estimated on or Data from 1990 to 2001

	Insert category parameters from 1990–2001 model			Insert category means from 1990–2001		
Simulation category	Predicted value	Change from baseline	Percent change	Predicted value	Change from baseline	Percent change
	Baseline 2019 prediction = 213,100 (B_1X_1)					
UI eligibility	227,055	13,955	6.5	220,738	7,639	3.6
UI generosity	273,509	60,410	28.3	233,068	19,968	9.4
Part-time employment	166,240	–46,860	–22.0	215,285	2,185	1.0
New or reentrants to LF	196,321	–16,779	–7.9	213,209	109	0.1
Industry and occupation	261,182	48,082	22.6	196,321	–16,779	–7.9
LF characteristics	267,960	54,860	25.7	219,659	6,559	3.1
Total from simulations		113,668	53.3		19,682	9.2

NOTE: See Appendix B, Tables B6 through B19, for complete output from the simulations.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

[9] The results summarized in Table 4 are based on models and computations presented in Appendix Tables B6 to B19.

The predicted 2019 average weekly UI claims number is listed in the top row of Table 4 as a reference baseline for the predicted average weekly claims levels in the other rows of Table 4. The baseline 2019 predicted value of average weekly UI claims, 213,100, is drawn from the bottom row of Table 3, based on predictor variable means and model parameters for the later period. Results in the left three columns of Table 4 suggest that fixing model parameters at their 1990–2001 values would increase predicted UI claims in 2019 for the categories of UI eligibility, UI generosity, industry and occupation, and labor force characteristics. The effect of the negative parameter on the share working part-time can be discounted because the parameter on that factor is statistically insignificant in Table 1. The negative effects of inserting parameters on new and reentrants to the workforce form a small share of the overall change from the baseline in predicted 2019 claims. The right three columns in Table 4 suggest that holding category variables at their preperiod means has relatively little total effect on outcomes compared to the preperiod parameter values.

The biggest effects on UI claims in the later period appear to result from changes in the parameters on benefit generosity, industry and occupation, and labor force demographic characteristics. First, we look at changes in industry and occupation shares of employment in Table 5; then, we trace demographic shares of employment in Table 6. We examine the effects of changes in benefit-generosity parameters and variable values more deeply below.

Tables 5 and 6 report on tests for differences in variable means and parameter estimates across the two time periods. Significance tests of parameter values estimated over the separate periods are reported too. The largest significant changes in industry shares of employment are a big decrease in manufacturing and increases in health care and professional services. Parameter estimates on manufacturing and health care both changed to increase the importance of those

Table 5 Characteristic Differences between the Two Analysis Time Periods for Industry and Occupation Shares of the Employed

Industry	Industry means			Industry parameter estimates		
	1990–01	2002–19	Diff	1990–01	2002–19	Diff
Agriculture, forestry, fishing	0.009	0.008	–0.001*	10.238*	–21.942***	–32.181***
Mining	0.008	0.008	0.000	–6.080**	4.474***	10.554***
Utilities	0.006	0.005	–0.002***	17.928**	–23.060	–40.988**
Construction	0.049	0.051	0.002**	3.745**	4.281***	0.536
Manufacturing	0.141	0.095	–0.046***	–2.198***	2.809***	5.007***
Wholesale trade	0.043	0.040	–0.003***	5.028	7.914*	2.886
Retail trade	0.124	0.116	–0.008***	0.080	–2.750	–2.830
Transportation, warehousing	0.031	0.032	0.001*	3.810	–2.126	–5.936
Information	0.023	0.019	–0.004***	0.411	–3.701	–4.112
Finance and insurance	0.042	0.041	–0.001	1.713	–4.734	–6.447
Real estate, rental, leasing	0.014	0.014	–0.000*	–10.735	–7.301	3.434
Professional, scientific, technical	0.043	0.053	0.010***	0.391	1.107	0.716
Company/enterprise management	0.012	0.013	0.001**	–2.542	–3.224	–0.681
Admin, support and waste mgmt	0.047	0.056	0.009***	–2.021	–2.952**	–0.931
Educational services	0.012	0.017	0.005***	16.302***	0.813	–15.489**
Health	0.096	0.123	0.026***	–5.065***	1.089	6.155***
Art, entertainment, recreation	0.014	0.015	0.001***	1.894	8.266	6.371
Accommodation, food services	0.084	0.092	0.008***	–2.847	–5.500	–2.653
Other services (ex., publ admin)	0.031	0.032	0.000	–8.460**	–3.966**	4.494
Public admin, Fed government	0.028	0.028	–0.001	3.095	–5.281***	–8.376***
State government	0.043	0.041	–0.002***	3.200	7.459***	4.259
Local government	0.098	0.102	0.004***	3.641**	5.500	1.860
Occupation	**Occupation means**			**Occupation parameter estimates**		
	1990–01	2002–19	Diff	1990–01	2002–19	Diff
Management, business, financial	0.151	0.156	0.005***	0.471	0.232	–0.238
Computers, engineering, science	0.049	0.054	0.005***	1.015	–1.585*	–2.601*
Education, legal, comm service	0.092	0.108	0.016***	–0.407	0.944	1.351
Healthcare practitioners, tech	0.042	0.054	0.012***	1.194	–2.413**	–3.608**
Service occupations	0.144	0.169	0.025***	–0.275	–0.832*	–0.557
Sales and office occupations	0.255	0.233	-	–0.230	0.570	0.800
Farming, fishing, forestry	0.011	0.009	–0.002***	–1.317	2.174	3.490
Construction and extraction	0.057	0.058	0.001	–1.312	0.966	2.278*
Installation, maintenance, repair	0.038	0.036	–0.003***	1.818	0.113	–1.705
Production, transport, material	0.161	0.123	–0.038***	–0.101	0.065	0.166

NOTE: See Appendix B, Tables B4 and B5, for complete model parameter estimates, standard errors, and difference tests.
Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

groups on UI claims, so that the decline in manufacturing employment reinforces the decline in UI claims, while health-care growth somewhat offsets the decline.

By occupation, the biggest declines in employment shares were in transport and sales, while growth occurred in services, education, and health care. The only significant change in

Table 6 Difference in Labor Force Characteristics between the Two Analysis Time Periods

Labor force characteristic	Characteristic means			Parameter estimates		
	1990–01	2002–19	Diff	1990–01	2002–19	Diff
Male	0.536	0.530	–0.006***	–0.142	–1.570***	–1.429**
Female	0.464	0.470	0.006***	0.164	1.771***	1.607**
American Indian/Alaskan Native	0.013	0.015	0.002*	0.016	–1.489**	–1.506
Asian, Native Hawaiian/Pac Islander	0.032	0.048	0.017***	0.093	2.720***	2.627***
Black, African American	0.094	0.105	0.010**	–0.346	–0.784	–0.438
White	0.861	0.833	–0.029***	0.034	–0.033	–0.068
Hispanic	0.067	0.098	0.031***	0.703**	–1.266***	–1.969***
Not Hispanic	0.933	0.902	–0.031***	–0.051**	0.138***	0.188***
Age 24 or less	0.166	0.145	–0.022***	–0.012	–1.612***	–1.599**
Age 25–34	0.247	0.217	–0.030***	–0.205	–0.382	–0.177
Age 35–54	0.462	0.439	–0.023***	0.009	1.039***	1.030***
Age 55–64	0.095	0.151	0.056***	0.176	–0.545	–0.721
Age 65+	0.030	0.049	0.019***	1.050	–1.174	–2.224

NOTE: See Appendix B, Tables B4 and B5, for complete model parameter estimates, standard errors, and difference tests.
Significance: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

parameters among these occupation groups was for health care, which changed to a significantly negative coefficient. This result, paired with an increase in the employment share of health-care workers, yields a bigger group of workers with a lower propensity to apply for benefits.

Among demographic characteristics, the biggest increases in labor force proportions between the periods were for Asians, Blacks, Hispanics, and workers aged 55 plus. Among these four groups, parameter estimates declined between the periods for all except the Asian group. The female share increased slightly between the two periods, as did the parameter estimate on females, which became more positive and significant.

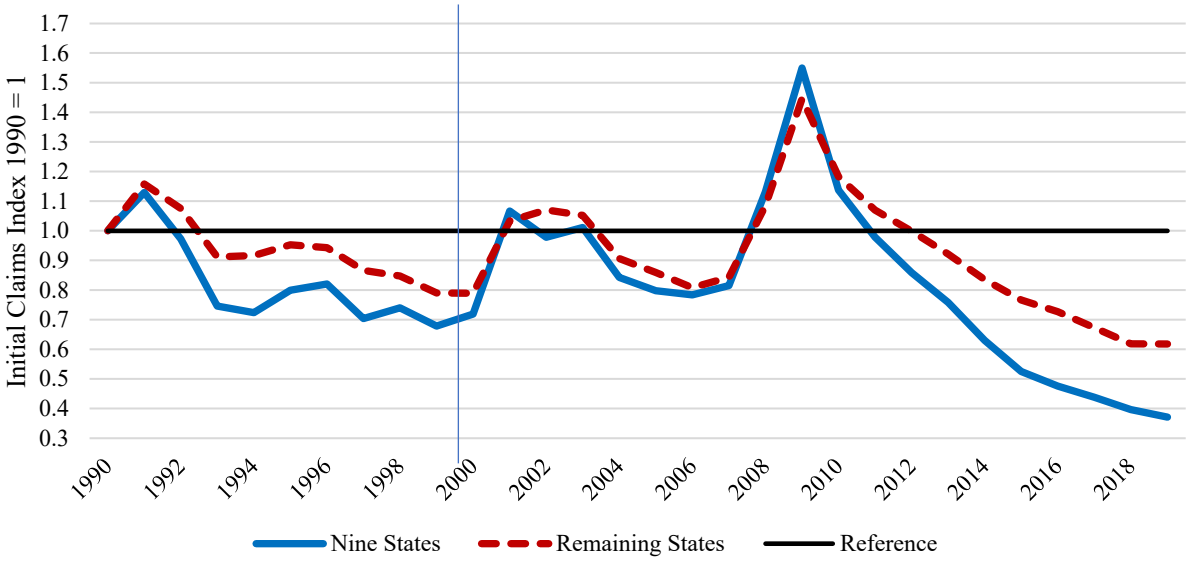
The conflicting patterns of changes in variables and parameter estimates between the two patterns may explain why the interaction term in the Oaxaca decomposition analysis accounts for most of the change in UI claims. The labor force changed, and the way labor force factors affect claims changed too. The net effect has been a decline in claims despite overall labor force growth.

Effect of Shorter Potential Duration in Some States

DeAntonio (2018) pointed to declines in benefit access and generosity as important factors contributing to the decline in weekly UI claims. Immediately following the financial crisis, nine states cut potential duration of UI in the benefit year from the common 26 weeks to shorter potential durations.[10]

To illustrate the difference in UI claims between the nine states that cut potential duration in 2011 or 2012 and those that did not, Figure 2 plots two indices of UI claims. With 1990 as the base level of claims, Figure 2 plots indices of UI claims for the nine states cutting potential

Figure 2 Regular UI Claims Indexed to 1990 for the Nine States That Reduced UI Benefits after the Financial Crisis, Compared to All Other States plus D.C., 1990–2001



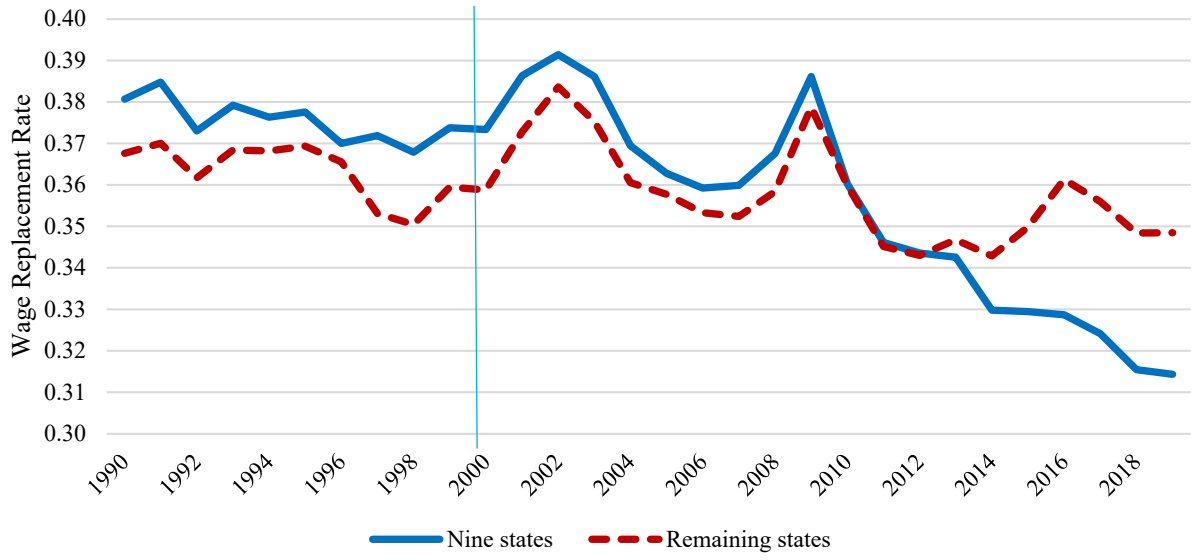
SOURCE: Graphs based on initial claims data from U.S. Department of Labor, Employment and Training Administration, downloaded from https://oui.doleta.gov/unemploy/claimssum.asp; and on unemployment data from U.S. Department of Labor, Bureau of Labor Statistics, Local Area Unemployment Statistics, downloaded from https://www.bls.gov/lau/data.htm.

[10] Ten states cut potential durations in 2011 and 2012, but Illinois quickly returned the maximum to 26 weeks. The nine states cutting potential UI durations and their 2019 average potential durations in parentheses were Arkansas (17), Florida (12), Georgia (14), Idaho (16), Kansas (15), Michigan (20), Missouri (20), North Carolina (12), and South Carolina (20). See Appendix C for more details on how states reduced potential duration. In the financial crisis, 36 states exhausted benefit reserves and borrowed to continue paying UI benefits (O'Leary and Kline 2016). Federal extended UI benefits were very generous during the financial crisis and were available to beneficiaries in states complying with a nonreduction rule that prohibited reductions in benefit formulas. However, the nonreduction rule did not prohibit reductions in potential duration of benefits.

duration and the remaining states which did not. While all states had declining UI claims rates after 2011, the solid line for states cutting potential duration dropped much more sharply.

The other important parameter among the benefit-generosity variables is on the wage replacement rate. The parameter estimate on the wage replacement rate in Table 1 (parameters of the UI claims model estimated on the full time period) is very large and positive. Figure 3 shows that the average replacement rate declined across all states since 1990, and that the decline in wage replacement has been particularly large among the nine states that cut potential durations immediately after the financial crisis. Declines in the average wage replacement rate appear to have been an important factor in driving down application rates among the unemployed.

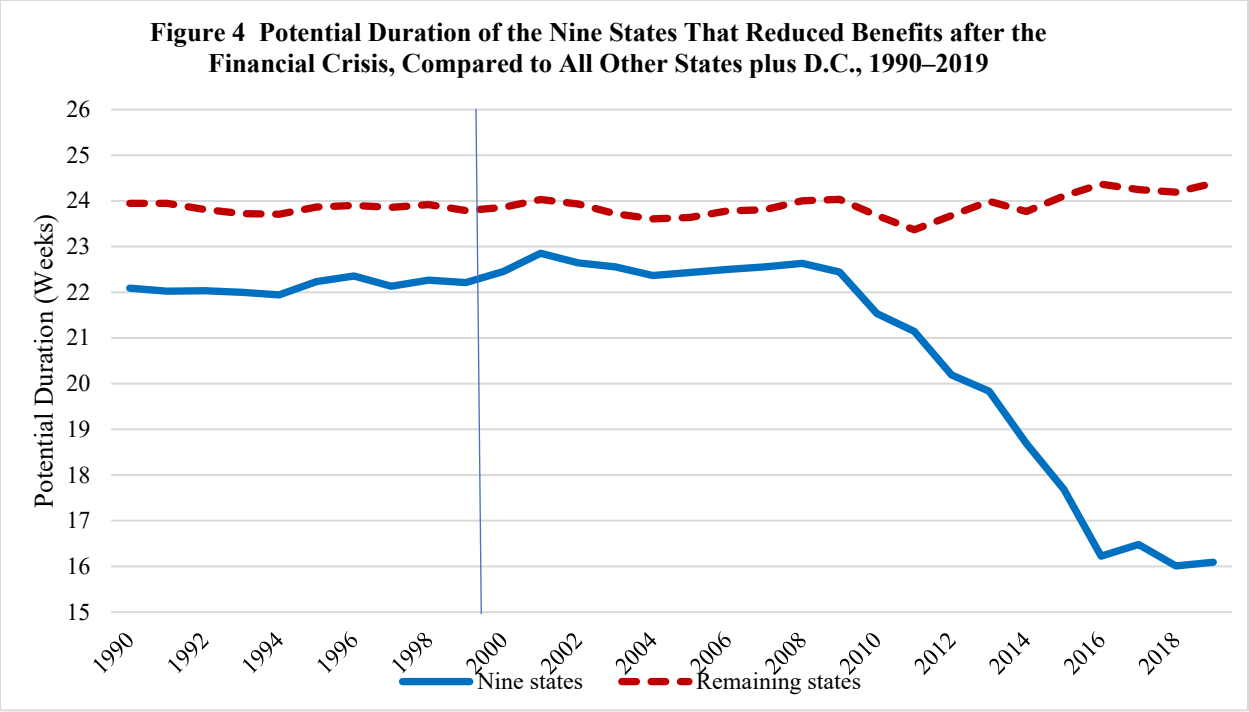
Figure 3 Wage Replacement Rate for the Nine States That Reduced Benefits after the Financial Crisis Compared to All Other States plus D.C., 1990–2019



SOURCE: Graphical summary of data from *The Unemployment Insurance Financial Data Handbook*, Employment and Training Handbook 394. Washington, DC: U.S. Department of Labor, Employment and Training Administration, Office of Unemployment Insurance. https://oui.doleta.gov/unemploy/hb394.asp.

The potential duration variable in the application equation (1) has a small but positive and significant parameter estimate. Figure 4 shows the dramatically sharp drop in the average potential duration in the nine states that cut potential durations after 2011, compared to the flat average potential duration in the remaining state programs.

Figure 4 Potential Duration of the Nine States That Reduced Benefits after the Financial Crisis, Compared to All Other States plus D.C., 1990–2019



SOURCE: Graphical summary of data from *The Unemployment Insurance Financial Data Handbook*, Employment and Training Handbook 394. Washington, DC: U.S. Department of Labor, Employment and Training Administration, Office of Unemployment Insurance. https://oui.doleta.gov/unemploy/hb394.asp.

The declines in average potential duration among the nine states are dramatic and contribute to the nationwide average decline in application rates, as illustrated in Figure 5. [11] We undertake a deeper investigation in Table 7 based on additional simulations.

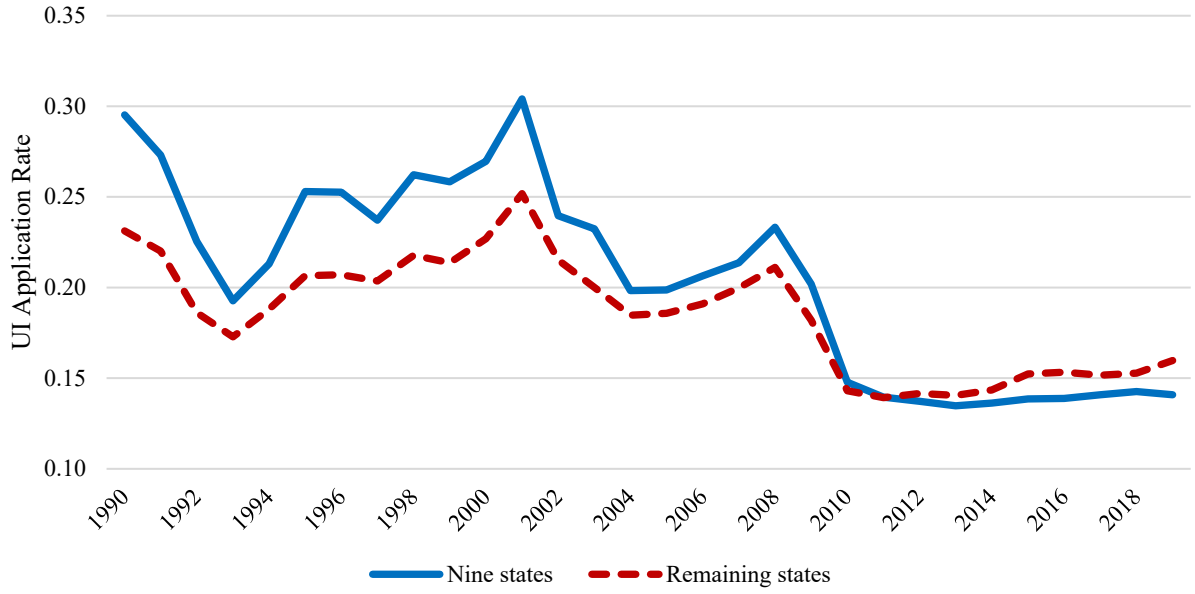
Table 7 Key Parameters from the Model of the Log of Initial Claims Reestimated to Include Controls for the Nine States That Cut UI Benefits after the Financial Crisis, *N* = 1,502

Description	Parameter estimate	Standard error	*t*-statistic
Wage replacement rate (mean = 0.361)	1.179	0.189	6.25
Potential UI duration (mean = 23.36)	0.006	0.004	1.35
Nine States in 2010–2019*Replace Rate	1.400	0.377	3.72
Nine States in 2010–2019*Potential Duration	0.006	0.007	0.80

NOTE: See Appendix B, Table B22, for the complete model.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

[11] In our analysis using state-year data, with each state receiving an equal weight, our graphs reflect simple weighted averages: that is, (9/51)*(change for 9 states) + (42/51)*(change for remaining states). The nine states account for 17.6 percent of the observed national change as the average of states in our analysis.

Figure 5 UI Application Rate in the Nine States That Reduced UI Benefits after the Financial Crisis Compared with All Other States plus D.C., 1990–2019



SOURCE: Based on initial claims data from U.S. Department of Labor, Employment and Training Administration, downloaded from https://oui.doleta.gov/unemploy/claimssum.asp; and on unemployment data from U.S. Department of Labor, Bureau of Labor Statistics, Local Area Unemployment Statistics, downloaded from https://www.bls.gov/lau/data.htm.

In Table 7 we present parameters of Equation (1) estimated over the full period, 1990–2019, for the 50 states plus D.C. To the model, we added a dummy variable that is "1" for the nine reduced potential duration states in the 2010–2019 period; "0" otherwise. We did not include a separate intercept-shift dummy variable for the late period (2010–2019).[12] The dummy variable for the short duration states in the 2010–2019 period is multiplied by the wage replacement rate and potential duration variables to measure impacts of the state policy changes in the later period.

Results in Table 7 suggest that the dominant factor driving results for the nine states, as well as the remaining states, is the wage replacement rate. However, there appears to be considerable collinearity between potential duration and the wage replacement rate over the

[12] The interaction term is (9 state dummy)*(dummy for 2010–2019) = 1, else 0. Note, a separate dummy variable for the later period (2010–2019) is not in the model.

2010–2019 period, particularly for the nine states that reduced benefits.[13] Therefore, potential duration appears to be an important explanatory variable for UI claims, particularly in the nine states that cut potential duration.

While declining replacement rates are an important factor for reducing UI claims in many states, they are a particularly strong factor in reducing claims in the nine states that cut potential duration. Indeed, the effect of the declining wage-replacement rate in the nine states is estimated to be more than double (1.179 + 1.400) the effect in the remaining states. The independent effect of shorter potential durations in the nine states should not be discounted, despite the lack of statistical leverage to produce statistically significant estimates.

Table 8 presents UI claims simulation results for the nine reduced potential duration states. We use the parameter estimates on the [(nine-state)*(late period)] dummy variable and the interactions of that variable with the replacement rate and potential duration. In other words, we assume that the nine states are like the other states in terms of the relationship between those two variables and initial claims. While it is tempting to attribute the 2019 simulated-claims levels in Table 8 to being precisely measured components of the total change in initial claims for all simulations summarized in Table 4, that should not be done. The models in Table 4 were estimated over two separate time intervals (1990–2001 and 2002–2019). The model underlying the results in Table 8 was estimated over the entire period, with separate parameters for the 2010–2019 period for the nine states that cut potential duration (Appendix Table B22).

[13] We tested the degree of collinearity between replacement rate and potential duration in this specification by dropping the wage replacement rate from the model. The parameter estimate on potential duration for the states that did not reduce benefits remains insignificant (parameter = 0.0024; se = 0.0044; t = 0.55). However, the interaction term for the nine states in the 2010–2019 period and potential duration becomes statistically significant (parameter = 0.0216; se = 0.0067; t = 3.22).

Table 8 Simulation of the Nine States Using Wage Replacement Rate and Potential Duration Coefficients or Means from 1990 to 2009 and Solving over 2010–2019

Year	Baseline prediction	Replacement rate and potential duration parameters, 1990–2009			Replacement rate and potential duration means, 1990–2009		
		Level	Change	Pct change	Level	Change	Pct change
2010	98,405	102,829	4,423	4.3	105,625	7,220	6.8
2011	88,024	94,148	6,125	6.5	98,550	10,527	10.7
2012	75,302	81,490	6,188	7.6	86,340	11,037	12.8
2013	66,010	71,970	5,960	8.3	76,865	10,855	14.1
2014	52,915	59,747	6,832	11.4	65,727	12,812	19.5
2015	44,127	50,236	6,109	12.2	55,748	11,621	20.8
2016	41,057	47,070	6,013	12.8	52,587	11,530	21.9
2017	39,062	44,848	5,786	12.9	50,153	11,092	22.1
2018	34,695	40,312	5,617	13.9	45,600	10,905	23.9
2019	33,991	39,417	5,426	13.8	44,558	10,567	23.7

NOTE: See Appendix B, Table B23, for more output from the simulations.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

OTHER FACTORS

In addition to results from the quantitative state-year analysis discussed so far, a few other possible explanations for declining UI claims merit discussion. Of particular importance are three: 1) availability of extended benefits, 2) a possible decline in the share of workers covered by UI, and 3) state fixed effects in our models.

We included variables for the availability of federally funded extended benefits in our regression models.[14] However, we did not discuss the estimated impacts on UI claims because of inconsistent results. When estimating our specification over the whole time period, the parameter estimate on extended benefits is zero (Table B.2). This is hard to interpret, since we know claims tend to be higher in recession periods when federal extended benefits are available. It may be the

[14] In our estimation period, federally funded extended benefits were available in several years. Emergency Unemployment Compensation (EUC) was payable from November 1991 to June 1994, Temporary Emergency Unemployment Compensation (TEUC) was payable from March 2002 to July 2004, and Emergency Unemployment Compensation (EUC08) was payable from July 2008 to December 2013. Extended Benefits (EB) under the federal-state extended benefits program (fully paid by the federal government in most years) were also available for many years in our period. Our extended benefits variable is the number of beneficiaries divided by the number of unemployed.

case that other variables in the model pick up the effects of recessions. However, in models estimated separately over our pre and post time periods, parameter estimates on extended benefits are significant but opposite in sign. Over the pre period (1990–2001), the parameter on extended benefits is –0.375 (for extended benefits in 1991–1994 and 2002–2004) (Table B.4). The parameter estimate during the financial crisis (2008–2013) is 0.134 (Table B.4). Taken together, these results suggest a questionable additional effect on UI claims. Manually doing the Oaxaca exercise, we insert the parameter on extended benefits from the early period into the data for the later period and simulate that UI claims would be 37,462 claims fewer than actual (Table B.20). Inserting federal extended benefits as a share of all benefits from the early period into the later period generates a decline in average annual claims in the later period of 6,825. We repeat the exercise for the early period based on the later period parameter and mean variable values (Table B.21). The simulations suggest that annual UI claims in the earlier period would have been nearly 8,500 higher if the parameters and mean values from the later period had prevailed in the earlier period.

Another possible explanation for the decline in claims over our analysis period is the suspected increasing reliance by employers on contract workers. Contract workers should be counted along with wage and salary workers in the labor force, but because employers do not directly make payroll tax payments, there could be slippage in the relationship between the labor force and UI claims for any given level of unemployment. New research by Abraham et al. (2023) suggests that workers responding to questions about employment status often claim employer attachment when they actually are contract workers. Indeed, the authors recommend that the Current Population Survey add prodding to their questions about work in the reference week to properly distinguish between employees and contract workers. Despite this possible

slippage, Garin, Jackson, and Koustas (2022, p. 799) report evidence that the share of the labor force in contract employment has remained in a range between 9 and 11 percent since the turn of the century. They do cite a slight increase in gig work but measure it at not more than 0.2 percent of the labor force. Contract work cannot explain the magnitude of the decline in UI claims over our analysis period.

We estimated all models of UI excluding time fixed effects so as not to remove the influence of changes in outcomes of variable values over time. We did, however, include a full set of state fixed effects, with state indicator variables estimated under the restriction that parameter estimates within the set of all states sum to zero, so that the parameter estimate for any state is interpreted relative to the dependent variable mean. As such, the parameters on the state indicators reflect the influence of variables omitted from our models on outcomes. Such omitted variables include things like differences in administrative access to UI—the difficulty of applying for benefits.[15]

State fixed effect estimates for the early (1990–2001) and later (2002–2019) periods are included in Appendix Table B4. Differences in parameter estimates between the two periods are given in Appendix Table B5, along with tests for significant differences. It should also be noted that our state indicators are not weighted by state size; each state indicator has equal weight in the models. After controlling for all variables in the model, parameter estimates on our state fixed effects suggest the biggest declines in UI applications occurred in some of the smallest states—Hawaii, Rhode Island, Maine, Indiana, Michigan, North Carolina, and Wyoming. (Michigan and North Carolina are not small states, but they did cut potential duration of benefits

[15] As discussed above, our models do include variables for monetary eligibility rates and claim denials as a share of determinations. We use the prior-year values of both these variables and estimate that they are a modest factor in explaining reductions in UI claims in the later period (Table 4).

in the later period.) State fixed-effect estimates also suggest that some of the biggest increases in UI claims occurred in some of the largest states—New York, Texas, California, and Florida, plus smaller states such as New Mexico, Arizona, and the District of Columbia.

Finally, we do not analyze data from the Covid-19 pandemic period or after. However, dramatic events happened in that period, and there may be lessons from that experience for understanding UI claims rates in the postpandemic period. The Pandemic Extended Unemployment Compensation (PEUC) program was not significantly different from earlier federal extensions of duration for exhaustees of regular state benefits. Indeed, PEUC extensions were much shorter than in the financial crisis under Emergency Unemployment Compensation in 2008. However, the availability of Federal Pandemic Unemployment Compensation (FPUC), which added $600 per week in benefits from April through July 2020 and $300 per week in benefits from March through September 2021, significantly increased the benefit replacement rate. Coombs et al. (2022) found that FPUC did not create significant return-to-work disincentives, but rather that the pool of UI applicants and beneficiaries mushroomed in this period. Certainly, UI work-search requirements being waived, the lack of business hiring, and the public efforts to promote social distancing had an influence, but the historically high UI wage replacement rates contributed to the enormous increase in UI claims. This is consistent with our simulation evidence that declining wage-replacement ratios are a prime factor in explaining the current low level of claims for UI benefits.

SUMMARY

In the 18 years after the 2001 dot-com recession, UI claims averaged nearly 5.0 percentage points lower than they had over the preceding 12 years. Claims dropped from a

weekly average of approximately 300,000 by nearly a third, to 220,000. In mid-March 2023, weekly UI claims were less than 200,000, despite the labor force being 20 percent larger than at the turn of the century, and also despite vigorous efforts by the Federal Reserve to raise interest rates and reduce inflation.[16]

Using state-year data from 1990–2019, we examined causes for the decline in UI claims. A Oaxaca-type decomposition suggests that neither changes in observable variables nor the way those variables affect claims explain the change, but does suggest that interactions between both sets of changes probably do explain the decline. Using a manual approach, we investigated the influence of six sets of state factors: 1) UI eligibility, 2) UI generosity, 3) the extent of part-time employment, 4) rates of new and re- entrants to the labor market, 5) demographic characteristics of the labor force, and 6) occupational and industrial proportions of employment. Among these, the three factors appearing to have the greatest effect of reducing UI claims are 1) UI generosity, 2) industry and occupation, and 3) labor force characteristics. There was also evidence that higher-than-average state denial rates of UI appeals in a prior year tend to depress rates of UI application. Our models of UI claims included two state UI-generosity variables—1) average wage-replacement rate and 2) potential weeks of duration of benefits—as well as shares of demographic groups in the labor force, and employment shares by industry and occupation.

Interactions between changes in labor force proportions and the UI-claiming behavior of workers in the groups contributed to declines in UI claims over the period. A dramatic decline in manufacturing employment (a traditionally high-UI-claim industry) and a rise in health-care employment (a traditionally low-claim industry) explain some of the decline. Declining benefit generosity also explains lower rates of UI application. Declining wage-replacement rates

[16] Seasonally adjusted UI claims for the week ending March 23, 2023, were 191,000 (OUI 2023).

emerged as a prime factor. Declines in UI wage replacement were particularly pronounced in the nine states that cut potential benefit durations to fewer than 26 weeks in response to the 2007–2009 financial crisis. The state-year analysis suggests that unemployed job seekers consider both the expected weekly rate of income replacement as well as the potential duration of benefit receipt before applying for benefits.

In addition to the factors that we examined for the prepandemic period, in the current period of labor shortages there appears to be a new attitude emerging among employers of increased concern for retaining workers. After years of having an abundant surplus labor pool, employers had difficulty filling job slots as the economy emerged from the Covid-19 pandemic. Persistent efforts by our central bank to slow the economy have resulted in fewer-than-expected layoffs. The increase in employer concern about employee retention suggests that the time might be right for the U.S. to place greater emphasis on an approach popular in Europe for retaining employees during periods of slack labor demand. Called k*urzarbeit* in Germany, short-time compensation, or work sharing, is a UI program feature available in most U.S. states. It allows employers to retain employees at reduced hours and lower payroll costs, with worker incomes partially made up by short-time compensation (STC) through unemployment insurance. Rather than immediately responding to rising unemployment with federal programs for extended or supplemental UI benefits, federal payment of STC benefits would be a timely response that should be welcomed by both business and labor.

Appendix A

Data Sources and Variable Definition Documentation

Current Population Survey (CPS), Bureau of Labor Statistics (BLS)

Select variables from the monthly CPS data files from January 1976 through June 2021 were downloaded from IPUMS CPS (https://cps.ipums.org/cps/).[17] The site has an interface that allows the user to select variables of interest and submit an extract request. Once processed, the variables for all months chosen are written onto a single file for the user to download. In the models discussed in this paper, these data were used to define variables for the characteristics of the labor force, including gender, race, ethnicity, and age. The data were also used to define variables for the occupation share of the employed and the share of employed persons aged 16 and older who were working part-time. In the extract, the variable "WTFINL," which is described as the "Final basic weight," was used to aggregate the sample to reflect population means.

The variables for the occupation shares of the employed also required a crosswalk to map the occupation (census) codes used in the CPS to the Standard Occupational Classification (SOC) system categories used in the models. The crosswalk is available from the Census Bureau and was downloaded from https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html. It is based on the 2010 census codes, which were derived from the 2010 SOC codes.

[17] Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, and Michael Westberry. 2022. *Integrated Public Use Microdata Series, Current Population Survey: Version 10.0 [Monthly CPS data files].* Minneapolis, MN: IPUMS. https://doi.org/10.18128/D030.V10.0.

Quarterly Census of Employment and Wages (QCEW), Bureau of Labor Statistics (BLS)

The QCEW provides coverage for 95 percent of the jobs in the United States and reports aggregate counts of employment and wages by industry at the county, metropolitan statistical area (MSA), state, and national levels. Annual data files were downloaded from the BLS website for 1990–2021 (https://www.bls.gov/cew/downloadable-data-files.htm).

These data were used to define variables for the share of employment by industry within each state. With the model estimation interval being 30 years in length (1990–2019) and having 50 states plus the District of Columbia, and 22 industry categories, one would expect a total of 33,660 observations in the QCEW data. However, because of missing data for local government in the District of Columbia for 1991, the initial count was 33,659. Of these, there were 139 observations that indicated zero employment in the state, industry, and year. These observations were interpolated linearly, provided there was a nonzero observation before and after the observation(s) where that state and industry's employment was zero. That is, no extrapolations were done. With only interpolation used, the number of records interpolated was 69.

Observations that were zero that could not be interpolated were set to missing. These included the following: 1) In Washington, D.C., the utilities industry for 1990–1998; 2) in Delaware, the agriculture and mining industries for 2008–2019; and 3) in Rhode Island, the agriculture and mining industries as well, but for the years 2013–2019. However, there were some observations for Washington, D.C., that were left with zero values. These were agriculture for 1990–1997 and mining for 2005–2019. Given the location (Washington, D.C.) and the industries involved (agriculture, forestry, fishing and hunting; and mining and oil and gas extraction) and the very small levels of associated nonzero observations that were available in remaining years, an arbitrary judgment was made that observations of zero were not out of the realm of possibility, and thus were not set to "missing."

The net result of the preceding was that the QCEW data would contribute 1,502 observations out of the total possible 1,530 (30 years times 50 states plus the District of Columbia).

Dependent Variable

The preliminary work for this paper used the regular UI application rate as the dependent variable. This variable for each state and year was defined as average monthly regular UI initial claims divided by average monthly unemployed. Monthly, UI initial claims data are from the U.S. Department of Labor, Employment and Training Administration, and were downloaded from https://oui.doleta.gov/unemploy/claimssum.asp.

The data for monthly unemployed for each state and territory are from Local Area Unemployment Statistics of the Department of Labor, Bureau of Labor Statistics, and were downloaded from https://www.bls.gov/lau/data.htm.

Further along in the analysis, the decision was made to model the application rate in log form but move the log of average monthly unemployed to the right side, leaving the log of average monthly initial claims as the dependent variable. For summary tables, the initial claims data were presented as annual average weekly initial UI claims for the U.S. These were imputed by first exponentiating actual and predicted average monthly initial claims, then multiplying by 12 for the 12 months in the year, dividing by 52 for the 52 weeks in the calendar year, and then multiplying by 51—the number of states (50) plus the District of Columbia.

Remaining Explanatory Variables

GDP per capita

All data that are needed to define the percentage change in gross domestic product (GDP) per capita at the state-year level are from the U.S. Department of Commerce, Bureau of

Economic Analysis (BEA). Real GDP data for each state and the District of Columbia from 1997 to the present are based on the NAICS industry classification system and written as millions of chained 2012 dollars. The series ID is SAGDP9N. Data from 1977 to 1997 are based on the SIC industry classification system and written as millions of chained 1997 dollars, and its series ID is SAGDP9S. Growth rates from this SIC-based series were used to extend the NAICS-based series from 1997 backward to 1977. The download process begins at https://apps.bea.gov/itable/?ReqID=70&step=1&acrdn=1.

The state population data for each year are part of the download of regional data focusing on personal income and employment by state and can be found at https://apps.bea.gov/iTable/?reqid=70&step=1&acrdn=4. The data series ID is SAINC1.

UI generosity: Wage replacement rate and potential UI duration

State-year data for the wage replacement rate and potential duration of regular UI benefits are from the ET Financial Data Handbook 394, from the Employment and Training Administration (ETA) at the U.S. Department of Labor. The data were downloaded from https://oui.doleta.gov/unemploy/DataDownloads.asp.

UI eligibility: Monetary eligibility and initial claims denial rates

Both the monetary eligibility rate and the proportion of initial claim determinations that led to denials due to issues with the job separation are also from ETA. Data for the number of monetary determinations and the total with sufficient earnings to qualify financially are from ETA Data Set 218, which deals with "Benefit Rights and Experience." Data for the share of initial claims of nonmonetary determinations denied for job-separation reasons are from ETA 207, the "Non-Monetary Determinations Activities Report." Both data sets (ETA 207 and ETA 218) were downloaded from https://oui.doleta.gov/unemploy/DataDownloads.asp.

Extended unemployment compensation availability

The variable for the availability of extended benefits is also based on ETA 394 data and is the sum of first payments under the federal-state extended benefits program or other federal emergency programs as a share of average monthly unemployed (from LAUS, as previously discussed).

Labor force, new and reentry

Persons newly or re-entering the labor force are unlikely to qualify for unemployment insurance due to insufficient recent earnings history. Data for these variables were compiled from the CPS data that was downloaded from https://cps.ipums.org/cps/. The CPS includes questions related to the reason for being unemployed, and choosing "new entrant" or "reentrant" to the labor force are two of the possible responses. The new and reentry rates used in the model are expressed as shares of the unemployed.

Appendix B

Detailed Tables Supporting Exhibits in the Main Body of the Paper

Table B1 Labor Force Size, Unemployment, and Annual Average of Weekly UI Claims: Comparison between 2000 and 2019

	Size in millions		Unemployment	Weekly
Year	Unemployed	Labor force	rate	UI claims[a]
2000	5.692	142.6	0.040	299,752
2019	6.001	163.5	0.037	216,249
2019 implied from 2000 rate				316,024

[a] Annual average of weekly UI claims from https://oui.doleta.gov/unemploy/claims.asp, excluding Puerto Rico and the Virgin Islands, since they are not included in the CPS geographic coverage for unemployed, labor force, and unemployment rate. https://www.bls.gov/cps/definitions.htm#geo.
SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B2 Model of the Log of Average Monthly Regular UI Initial Claims for the 50 States plus the District of Columbia for 1990–2019, $N = 1{,}502$

Variable description	Variable mean	Parameter estimate	Standard error	*t*-statistic
Intercept (dependent variable mean)	9.704	9.704	0.004	2743.50
Economic conditions				
Log, average monthly unemployed	170,094	0.524	0.028	18.63
Share of employed persons (16+) working part-time	0.193	–0.044	0.467	–0.10
GDP per capita, percent change	0.015	–1.592	0.175	–9.09
UI benefit generosity				
Wage replacement rate	0.361	1.396	0.184	7.60
Potential UI duration	23.356	0.014	0.003	4.90
Extended benefits/compensation availability				
EUC/TEUC first payments share of unemployed	0.139	0.016	0.027	0.60
New and re-entrants to the labor force				
New entrants' share of unemployed	0.080	–1.051	0.191	–5.50
Re-entrants' share of unemployed	0.305	–0.514	0.111	–4.64
UI Eligibility				
Monetary eligibility rate, *T*–1	0.881	–0.390	0.087	–4.47
Denial rate (separation), share of determinations, *T*–1	0.404	–0.422	0.045	–9.28
Characteristics of the labor force (CPS)				
Male	0.533	–1.420	0.301	–4.72
Female	0.467	1.617	0.343	4.72
American Indian/Alaskan Native	0.014	–1.133	0.595	–1.90
Asian, Native Hawaiian/Pacific Islander	0.042	1.547	0.474	3.26
Black, African American	0.100	–0.587	0.360	–1.63
White	0.844	0.012	0.045	0.27
Hispanic	0.086	0.051	0.238	0.21
Not Hispanic	0.914	–0.005	0.022	–0.21
Age 24 or less	0.153	–0.834	0.353	–2.36
Age 25–34	0.229	–0.618	0.217	–2.85
Age 35–54	0.448	0.827	0.121	6.85
Age 55–64	0.129	–0.095	0.359	–0.26
Age 65+	0.041	–2.151	0.786	–2.74
Industry shares of employment (QCEW)				
Agriculture, forestry, fishing	0.009	–8.731	2.875	–3.04
Mining	0.008	4.524	1.233	3.67
Utilities	0.005	–18.950	6.296	–3.01
Construction	0.050	5.785	0.967	5.98
Manufacturing	0.113	2.523	0.461	5.47
Wholesale trade	0.041	2.176	2.374	0.92
Retail trade	0.119	–1.330	1.270	–1.05
Transportation, warehousing	0.032	–3.035	1.630	–1.86
Information	0.021	–2.393	1.805	–1.33
Finance and insurance	0.041	1.281	1.472	0.87
Real estate, rental, leasing	0.014	–15.944	6.205	–2.57
Professional, scientific, technical	0.049	–0.236	1.139	–0.21
Company/enterprise management	0.013	–3.436	1.324	–2.60
Administration, support and waste mgmt	0.052	–2.618	0.803	–3.26
Educational services	0.015	9.791	2.749	3.56
Health care/social assistance	0.112	–1.036	0.754	–1.37
Art, entertainment, recreation	0.014	4.884	2.067	2.36
Accommodation and food services	0.089	–4.928	0.953	–5.17

Table B2 (Continued)

Variable description	Variable mean	Parameter estimate	Standard error	*t*-statistic
Other services (except public admin)	0.031	–6.405	1.934	–3.31
Public admin (CPS), federal gov't (QCEW)	0.028	0.855	1.413	0.61
State government	0.042	3.368	1.411	2.39
Local government	0.100	5.174	1.001	5.17
Occupation shares of employment (CPS)				
Management, business, financial	0.154	0.813	0.357	2.28
Computers, engineering, science	0.052	–1.460	0.742	–1.97
Education, legal, community service, arts, media	0.102	0.406	0.532	0.76
Health-care practitioners and technical	0.050	–1.388	0.837	–1.66
Service occupations	0.159	–1.288	0.422	–3.05
Sales and office occupations	0.242	0.206	0.324	0.64
Farming, fishing, forestry	0.009	–1.044	1.545	–0.68
Construction and extraction	0.057	0.233	0.737	0.32
Installation, maintenance, repair	0.037	2.534	1.057	2.40
Production, transportation, material moving	0.138	0.263	0.424	0.62
Alaska	0.020	–0.085	0.150	–0.57
Alabama	0.020	0.119	0.081	1.48
Arkansas	0.020	0.140	0.064	2.17
Arizona	0.020	0.201	0.082	2.44
California	0.020	1.585	0.123	12.84
Colorado	0.020	0.082	0.075	1.09
Connecticut	0.020	–0.044	0.082	–0.54
District of Columbia	0.014	–0.667	0.467	–1.43
Delaware	0.012	–0.270	0.122	–2.21
Florida	0.020	0.837	0.095	8.81
Georgia	0.020	0.631	0.102	6.18
Hawaii	0.020	–0.616	0.364	–1.69
Iowa	0.020	–0.366	0.073	–5.01
Idaho	0.020	–0.046	0.117	–0.39
Illinois	0.020	0.473	0.075	6.31
Indiana	0.020	–0.054	0.060	–0.90
Kansas	0.020	–0.464	0.061	–7.58
Kentucky	0.020	–0.036	0.058	–0.61
Louisiana	0.020	–0.150	0.095	–1.58
Massachusetts	0.020	0.160	0.093	1.71
Maryland	0.020	0.174	0.114	1.53
Maine	0.020	–0.615	0.088	–6.96
Michigan	0.020	0.745	0.062	12.03
Minnesota	0.020	–0.022	0.064	–0.35
Missouri	0.020	0.494	0.050	9.87
Mississippi	0.020	–0.226	0.123	–1.84
Montana	0.020	–0.355	0.089	–4.00
North Carolina	0.020	0.413	0.075	5.48
North Dakota	0.020	–0.736	0.109	–6.75
Nebraska	0.020	0.066	0.102	0.64
New Hampshire	0.020	–0.966	0.090	–10.71
New Jersey	0.020	0.449	0.081	5.55
New Mexico	0.020	–0.728	0.135	–5.38
Nevada	0.020	1.042	0.189	5.51
New York	0.020	0.799	0.110	7.23
Ohio	0.020	0.285	0.063	4.51
Oklahoma	0.020	–0.436	0.064	–6.82

Table B2 (Continued)

Variable description	Variable mean	Parameter estimate	Standard error	*t*-statistic
Oregon	0.020	0.543	0.081	6.74
Pennsylvania	0.020	0.792	0.079	10.05
Rhode Island	0.015	–0.504	0.101	–4.99
South Carolina	0.020	0.214	0.100	2.13
South Dakota	0.020	–1.387	0.098	–14.13
Tennessee	0.020	0.279	0.073	3.83
Texas	0.020	0.551	0.095	5.77
Utah	0.020	–0.694	0.078	–8.92
Virginia	0.020	0.207	0.084	2.46
Vermont	0.020	–0.952	0.099	–9.58
Washington	0.020	0.522	0.087	6.00
Wisconsin	0.020	0.490	0.061	8.06
West Virginia	0.020	–0.734	0.093	–7.85
Wyoming	0.020	–1.565	0.152	–10.32
Number of observations	1,502			
Adjusted *R*-squared	0.9853			

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B3 Oaxaca Summary for the Log of Initial Claims as the Dependent Variable

Description	- Coefficient	Standard error	z	P>|z|
Dependent variable mean, 2002–2019	9.68432	0.03822	253.39	0.000
Dependent variable mean, 1990–2001	9.73437	0.04507	216.00	0.000
Difference	–0.05006	0.05909	–0.85	0.397
Endowments	0.11473	0.08491	1.35	0.177
Coefficients	–0.01162	0.04220	–0.28	0.783
Interaction	–0.15317	0.07448	–2.06	0.040
	Endowments			
Log, average monthly unemployed	0.12673	0.03677	3.45	0.001
Share of employed persons (16+) working part-time	0.00126	0.00176	0.71	0.476
GDP per capita, percent change	0.01310	0.00271	4.84	0.000
Wage replacement rate	–0.00749	0.00369	–2.03	0.043
Potential UI duration	–0.01566	0.00689	–2.27	0.023
EUC/TEUC first payments share of unemployed	–0.02977	0.00486	–6.13	0.000
New entrants' share of unemployed	–0.00208	0.00154	–1.35	0.176
Reentrants' share of unemployed	0.01778	0.00391	4.54	0.000
Monetary eligibility rate, *T*—1	0.00077	0.00106	0.73	0.466
Denial rate (separation), share of determinations, *T*–1	–0.00781	0.00493	–1.58	0.113
Female	0.00193	0.00444	0.44	0.663
American Indian/Alaskan Native	–0.00004	0.00213	–0.02	0.986
Asian, Native Hawaiian/Pacific Islander	0.00097	0.01027	0.09	0.925
Black, African American	–0.00389	0.00598	–0.65	0.515
Hispanic	0.02310	0.01204	1.92	0.055
Age 24 or less	0.02308	0.03172	0.73	0.467
Age 25–34	0.03764	0.04168	0.90	0.366
Age 35–54	0.02435	0.03330	0.73	0.465
Age 55–64	–0.04919	0.09157	–0.54	0.591
Agriculture, forestry, fishing	–0.01160	0.00783	–1.48	0.139
Mining	–0.00026	0.00108	–0.24	0.810
Utilities	–0.03771	0.01486	–2.54	0.011
Construction	0.01351	0.00645	2.09	0.036
Manufacturing	–0.13045	0.08094	–1.61	0.107
Wholesale trade	–0.02727	0.01189	–2.29	0.022
Retail trade	–0.04334	0.02738	–1.58	0.113
Transportation, warehousing	0.00811	0.00539	1.51	0.132
Information	–0.02070	0.01307	–1.58	0.113
Finance and insurance	–0.00605	0.00467	–1.30	0.195
Real estate, rental, leasing	0.00168	0.00331	0.51	0.612
Professional, scientific, technical	0.05593	0.02608	2.14	0.032
Company/enterprise management	0.00231	0.00251	0.92	0.358
Admin, support, and waste mgmt	0.02775	0.02056	1.35	0.177
Educational services	0.10423	0.03106	3.36	0.001
Art, entertainment, recreation	0.00532	0.00266	2.00	0.046
Accommodation and food services	0.01780	0.02165	0.82	0.411
Other services (except public admin)	–0.00015	0.00138	–0.11	0.911
Public admin (CPS), federal gov't (QCEW)	–0.00531	0.01298	–0.41	0.683
State government	–0.01892	0.00935	–2.02	0.043
Local government	0.03392	0.01400	2.42	0.015
Management, business, financial	–0.00348	0.00670	–0.52	0.603
Computers, engineering, science	–0.00098	0.00826	–0.12	0.905
Education, legal, community service, arts, media	–0.02564	0.02262	–1.13	0.257
Service occupations	–0.03725	0.03284	–1.13	0.257

Table B3 (Continued)

Description	Coefficient	Standard error	z	P>|z|
Sales and office occupations	0.03064	0.02702	1.13	0.257
Farming, fishing, forestry	0.00572	0.00515	1.11	0.267
Construction and extraction	–0.00202	0.00203	–1.00	0.320
Installation, maintenance, repair	–0.00167	0.00464	–0.36	0.720
Production, transportation, material moving	0.04926	0.04933	1.00	0.318
Alaska	0.00001	0.00045	0.02	0.987
Alabama	0.00004	0.00244	0.02	0.987
Arkansas	0.00005	0.00286	0.02	0.987
Arizona	–0.00005	0.00294	–0.02	0.987
California	0.00010	0.00609	0.02	0.987
Colorado	–0.00004	0.00263	–0.02	0.987
Connecticut	0.00003	0.00194	0.02	0.987
District of Columbia	–0.02424	0.01491	–1.63	0.104
Delaware	0.00355	0.00291	1.22	0.223
Florida	0.00000	0.00016	0.02	0.987
Georgia	0.00004	0.00272	0.02	0.987
Hawaii	–0.00007	0.00396	–0.02	0.987
Iowa	–0.00001	0.00065	–0.02	0.987
Idaho	–0.00004	0.00256	–0.02	0.987
Illinois	0.00003	0.00211	0.02	0.987
Indiana	0.00007	0.00395	0.02	0.987
Kansas	–0.00004	0.00215	–0.02	0.987
Kentucky	0.00004	0.00258	0.02	0.987
Louisiana	–0.00003	0.00203	–0.02	0.987
Massachusetts	0.00001	0.00047	0.02	0.987
Maryland	–0.00004	0.00229	–0.02	0.987
Maine	0.00001	0.00055	0.02	0.987
Michigan	0.00015	0.00902	0.02	0.987
Minnesota	0.00002	0.00126	0.02	0.987
Missouri	0.00007	0.00436	0.02	0.987
Mississippi	–0.00000	0.00007	–0.02	0.987
Montana	–0.00007	0.00395	–0.02	0.987
North Carolina	0.00012	0.00731	0.02	0.987
North Dakota	–0.00007	0.00441	–0.02	0.987
Nebraska	–0.00003	0.00182	–0.02	0.987
New Hampshire	–0.00008	0.00512	–0.02	0.987
New Jersey	0.00002	0.00113	0.02	0.987
New Mexico	–0.00018	0.01088	–0.02	0.987
Nevada	0.00005	0.00315	0.02	0.987
New York	0.00004	0.00230	0.02	0.987
Ohio	0.00007	0.00449	0.02	0.987
Oklahoma	–0.00004	0.00245	–0.02	0.987
Oregon	0.00003	0.00203	0.02	0.987
Pennsylvania	0.00010	0.00596	0.02	0.987
Rhode Island	–0.00290	0.00289	–1.01	0.314
South Carolina	0.00006	0.00339	0.02	0.987
South Dakota	–0.00014	0.00849	–0.02	0.987
Tennessee	0.00009	0.00551	0.02	0.987
Texas	0.00002	0.00106	0.02	0.987
Utah	–0.00009	0.00524	–0.02	0.987
Virginia	0.00003	0.00197	0.02	0.987
Vermont	–0.00008	0.00489	–0.02	0.987
Washington	0.00002	0.00150	0.02	0.987

Table B3 (Continued)

Description	Coefficient	Standard error	z	P>|z|
Wisconsin	0.00012	0.00738	0.02	0.987
West Virginia	–0.00006	0.00336	–0.02	0.987
Wyoming	–0.00012	0.00716	–0.02	0.987
Log, average monthly unemployed	–1.32681	0.64963	—2.04	0.041
Share of employed persons (16+) working part-time	0.26994	0.16441	1.64	0.101
GDP per capita, % change	0.00901	0.00621	1.45	0.147
Wage replacement rate	0.66498	0.13942	4.77	0.000
Potential UI duration	–0.82754	0.27190	–3.04	0.002
EUC/TEUC first payments' share of unemployed	0.04673	0.00582	8.03	0.000
New entrants' share of unemployed	–0.00176	0.02594	–0.07	0.946
Reentrants' share of unemployed	0.09112	0.06242	1.46	0.144
Monetary eligibility rate, *T*–1	0.03309	0.15415	0.21	0.830
Denial rate (separation), share of determinations, *T*–1	–0.09009	0.03637	–2.48	0.013
Female	1.40742	0.55039	2.56	0.011
American Indian/Alaskan Native	–0.01806	0.01547	–1.17	0.243
Asian, Native Hawaiian/Pacific Islander	0.08563	0.03218	2.66	0.008
Black, African American	–0.03489	0.07714	–0.45	0.651
Hispanic	–0.14545	0.03854	–3.77	0.000
Age 24 or less	0.10397	0.29730	0.35	0.727
Age 25–34	0.50463	0.43050	1.17	0.241
Age 35–54	1.50352	0.78543	1.91	0.056
Age 55–64	0.14283	0.18803	0.76	0.448
Agriculture, Forestry, Fishing	–0.34696	0.07672	–4.52	0.000
Mining	0.03620	0.02891	1.25	0.210
Utilities	–0.29559	0.10748	–2.75	0.006
Construction	–0.27618	0.13138	–2.10	0.036
Manufacturing	–0.16139	0.32856	–0.49	0.623
Wholesale trade	–0.13905	0.25954	–0.54	0.592
Retail trade	–1.11389	0.50562	–2.20	0.028
Transportation, warehousing	–0.37716	0.14749	–2.56	0.011
Information	–0.23842	0.10685	–2.23	0.026
Finance and insurance	–0.52686	0.16790	–3.14	0.002
Real estate, rental, leasing	–0.03894	0.21320	–0.18	0.855
Professional, scientific, technical	–0.23148	0.14777	–1.57	0.117
Company/enterprise management	–0.08529	0.04785	–1.78	0.075
Admin, support and waste mgmt.	–0.33173	0.13846	–2.40	0.017
Educational services	–0.25864	0.09806	–2.64	0.008
Art, entertainment, recreation	0.00298	0.08575	0.03	0.972
Accommodation and food services	–0.74177	0.29760	—2.49	0.013
Other services (except publ admin)	–0.05226	0.14630	–0.36	0.721
Public admin (CPS), federal gov't (QCEW)	–0.41370	0.10240	–4.04	0.000
State government	–0.08228	0.16769	–0.49	0.624
Local government	–0.42061	0.32124	–1.31	0.190
Management, business, financial	0.51017	0.27146	1.88	0.060
Computers, engineering, science	0.04889	0.10100	0.48	0.628
Education, legal, community service, arts, media	0.45657	0.17033	2.68	0.007
Service occupations	0.43871	0.24460	1.79	0.073
Sales and office occupations	1.12277	0.43081	2.61	0.009
Farming, fishing, forestry	0.07703	0.03386	2.27	0.023
Construction and extraction	0.33506	0.11993	2.79	0.005
Installation, maintenance, repair	0.07280	0.09146	0.80	0.426
Production, transportation, material moving	0.60731	0.27928	2.17	0.030

Table B3 (Continued)

Description	Coefficient	Standard error	z	P>|z|
Alaska	–0.00532	0.00694	–0.77	0.443
Alabama	–0.00272	0.00360	–0.76	0.449
Arkansas	–0.00904	0.00423	–2.14	0.032
Arizona	0.02519	0.00820	3.07	0.002
California	0.02254	0.00880	2.56	0.010
Colorado	0.00764	0.00438	1.75	0.081
Connecticut	–0.00401	0.00401	–1.00	0.317
District of Columbia	0.01355	0.00938	1.44	0.149
Delaware	0.00223	0.00539	0.41	0.679
Florida	0.02399	0.00842	2.85	0.004
Georgia	0.00728	0.00485	1.50	0.133
Hawaii	–0.02603	0.01668	–1.56	0.119
Iowa	–0.00497	0.00357	–1.39	0.164
Idaho	0.00840	0.00626	1.34	0.180
Illinois	0.00528	0.00400	1.32	0.186
Indiana	–0.01514	0.00530	–2.86	0.004
Kansas	–0.00503	0.00313	–1.61	0.107
Kentucky	–0.01281	0.00462	–2.78	0.006
Louisiana	0.00076	0.00412	0.19	0.853
Massachusetts	0.00126	0.00444	0.28	0.776
Maryland	0.01343	0.00610	2.20	0.028
Maine	–0.01823	0.00650	–2.80	0.005
Michigan	–0.01420	0.00506	–2.81	0.005
Minnesota	–0.00795	0.00375	–2.12	0.034
Missouri	–0.00345	0.00252	–1.37	0.172
Mississippi	–0.00286	0.00557	–0.51	0.607
Montana	–0.00111	0.00435	–0.26	0.798
North Carolina	–0.01400	0.00518	–2.70	0.007
North Dakota	–0.01129	0.00643	–1.75	0.079
Nebraska	0.00570	0.00517	1.10	0.270
New Hampshire	–0.00465	0.00432	–1.08	0.282
New Jersey	0.00454	0.00438	1.04	0.299
New Mexico	0.02395	0.00896	2.67	0.007
Nevada	0.01325	0.01025	1.29	0.196
New York	0.01462	0.00658	2.22	0.026
Ohio	–0.00953	0.00403	–2.36	0.018
Oklahoma	–0.00203	0.00293	–0.69	0.488
Oregon	0.00564	0.00422	1.34	0.182
Pennsylvania	0.00114	0.00364	0.31	0.753
Rhode Island	–0.02188	0.00785	–2.79	0.005
South Carolina	–0.00486	0.00459	–1.06	0.290
South Dakota	–0.00587	0.00472	–1.24	0.214
Tennessee	–0.01094	0.00471	–2.32	0.020
Texas	0.01574	0.00640	2.46	0.014
Utah	0.00048	0.00337	0.14	0.886
Virginia	–0.00044	0.00378	–0.12	0.907
Vermont	–0.00929	0.00549	–1.69	0.091
Washington	0.00579	0.00469	1.23	0.217
Wisconsin	–0.01127	0.00438	–2.57	0.010
West Virginia	–0.01052	0.00546	–1.93	0.054
Wyoming	–0.01365	0.00855	–1.60	0.110
Intercept	0.03450	2.96959	0.01	0.991

Table B3 (Continued)

Description	Coefficient	Standard error	z	P>|z|
	Interaction			
Log, average monthly unemployed	–0.02425	0.01370	–1.77	0.077
Share of employed persons (16+) working part-time	–0.00360	0.00298	–1.21	0.226
GDP per capita, % change	–0.00442	0.00309	–1.43	0.153
Wage replacement rate	–0.01762	0.00668	–2.64	0.008
Potential UI duration	0.01201	0.00591	2.03	0.042
EUC/TEUC first payments' share of unemployed	0.04044	0.00654	6.18	0.000
New entrants' share of unemployed	–0.00014	0.00204	–0.07	0.946
Reentrants' share of unemployed	–0.00752	0.00522	–1.44	0.149
Monetary eligibility rate, *T*–1	–0.00011	0.00055	–0.21	0.836
Denial rate (separation), share of determinations, *T*–1	–0.01351	0.00664	–2.04	0.042
Female	0.01919	0.00781	2.46	0.014
American Indian/Alaskan Native	–0.00296	0.00304	–0.97	0.331
Asian, Native Hawaiian/Pacific Islander	0.04462	0.02089	2.14	0.033
Black, African American	–0.00379	0.00858	–0.44	0.659
Hispanic	–0.06606	0.01972	–3.35	0.001
Age 24 or less	–0.01358	0.03882	–0.35	0.727
Age 25–34	–0.06138	0.05244	–1.17	0.242
Age 35–54	–0.07616	0.04015	–1.90	0.058
Age 55–64	0.08459	0.11137	0.76	0.448
Agriculture, forestry, fishing	0.02906	0.01748	1.66	0.096
Mining	0.00113	0.00349	0.32	0.746
Utilities	0.07732	0.02862	2.70	0.007
Construction	–0.00862	0.00543	–1.59	0.112
Manufacturing	0.05220	0.10629	0.49	0.623
Wholesale trade	0.00883	0.01655	0.53	0.594
Retail trade	0.07569	0.03496	2.17	0.030
Transportation, warehousing	–0.01105	0.00711	–1.55	0.120
Information	0.03881	0.01771	2.19	0.028
Finance and insurance	0.01125	0.00836	1.35	0.178
Real estate, rental, leasing	0.00081	0.00444	0.18	0.856
Professional, scientific, technical	–0.05574	0.03593	–1.55	0.121
Company/enterprise management	–0.00626	0.00435	–1.44	0.150
Admin, support, and waste mgmt	–0.06458	0.02740	–2.36	0.018
Educational services	–0.10558	0.04112	–2.57	0.010
Art, entertainment, recreation	0.00017	0.00477	0.03	0.972
Accommodation and food services	–0.07068	0.03143	–2.25	0.025
Other services (except public admin)	–0.00008	0.00070	–0.11	0.915
Public admin (CPS), Federal gov't (QCEW)	0.00945	0.02302	0.41	0.681
State government	0.00434	0.00897	0.48	0.629
Local government	–0.01673	0.01369	–1.22	0.221
Management, business, financial	0.01621	0.00951	1.70	0.088
Computers, engineering, science	0.00552	0.01144	0.48	0.629
Education, legal, community service, arts, media	0.07940	0.02994	2.65	0.008
Service occupations	0.07735	0.04325	1.79	0.074
Sales and office occupations	–0.09481	0.03664	–2.59	0.010
Farming, fishing, forestry	–0.01617	0.00758	–2.13	0.033
Construction and extraction	0.00474	0.00403	1.17	0.240
Installation, maintenance, repair	–0.00508	0.00641	–0.79	0.428
Production, transportation, material moving	–0.14354	0.06634	–2.16	0.030
Alaska	–0.00003	0.00197	–0.02	0.987
Alabama	–0.00002	0.00101	–0.02	0.987
Arkansas	–0.00006	0.00335	–0.02	0.987

Table B3 (Continued)

Description	Coefficient	Standard error	z	P>|z|
Arizona	0.00015	0.00932	0.02	0.987
California	0.00014	0.00834	0.02	0.987
Colorado	0.00005	0.00283	0.02	0.987
Connecticut	–0.00002	0.00149	–0.02	0.987
District of Columbia	0.04099	0.02168	1.89	0.059
Delaware	–0.00148	0.00363	–0.41	0.683
Florida	0.00015	0.00888	0.02	0.987
Georgia	0.00004	0.00270	0.02	0.987
Hawaii	–0.00016	0.00963	–0.02	0.987
Iowa	–0.00003	0.00184	–0.02	0.987
Idaho	0.00005	0.00311	0.02	0.987
Illinois	0.00003	0.00196	0.02	0.987
Indiana	–0.00009	0.00560	–0.02	0.987
Kansas	–0.00003	0.00186	–0.02	0.987
Kentucky	–0.00008	0.00474	–0.02	0.987
Louisiana	0.00000	0.00028	0.02	0.987
Massachusetts	0.00001	0.00047	0.02	0.987
Maryland	0.00008	0.00497	0.02	0.987
Maine	–0.00011	0.00675	–0.02	0.987
Michigan	–0.00009	0.00526	–0.02	0.987
Minnesota	–0.00005	0.00294	–0.02	0.987
Missouri	–0.00002	0.00128	–0.02	0.987
Mississippi	–0.00002	0.00106	–0.02	0.987
Montana	–0.00001	0.00041	–0.02	0.987
North Carolina	–0.00009	0.00518	–0.02	0.987
North Dakota	–0.00007	0.00418	–0.02	0.987
Nebraska	0.00003	0.00211	0.02	0.987
New Hampshire	–0.00003	0.00172	–0.02	0.987
New Jersey	0.00003	0.00168	0.02	0.987
New Mexico	0.00015	0.00887	0.02	0.987
Nevada	0.00008	0.00491	0.02	0.987
New York	0.00009	0.00541	0.02	0.987
Ohio	–0.00006	0.00353	–0.02	0.987
Oklahoma	–0.00001	0.00075	–0.02	0.987
Oregon	0.00003	0.00209	0.02	0.987
Pennsylvania	0.00001	0.00042	0.02	0.987
Rhode Island	0.00843	0.00766	1.10	0.272
South Carolina	–0.00003	0.00180	–0.02	0.987
South Dakota	–0.00004	0.00217	–0.02	0.987
Tennessee	–0.00007	0.00405	–0.02	0.987
Texas	0.00010	0.00583	0.02	0.987
Utah	0.00000	0.00018	0.02	0.987
Virginia	–0.00000	0.00016	–0.02	0.987
Vermont	–0.00006	0.00344	–0.02	0.987
Washington	0.00004	0.00214	0.02	0.987
Wisconsin	–0.00007	0.00417	–0.02	0.987
West Virginia	–0.00006	0.00389	–0.02	0.987
Wyoming	–0.00008	0.00505	–0.02	0.987

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B4 Model of the Log of Average Monthly Initial UI Claims for the 50 States plus the District of Columbia, Estimated over 1990–2001 and 2002–2019

	1990–2001, $n = 603$				2002–2019, $n = 899$			
Variable description	Variable mean	Parameter estimate	Standard error	*t*-statistic	Variable mean	Parameter estimate	Standard error	*t*-statistic
Intercept (dependent variable mean)	9.734	9.734	0.004	2462.98	9.684	9.684	0.004	2435.12
Log of avg monthly unemployed	11.317	0.613	0.041	15.04	11.524	0.496	0.040	12.26
Share of employed persons (16+) working part-time	0.195	–0.483	0.621	–0.78	0.192	0.901	0.570	1.58
GDP per capita, percent change	0.021	–1.292	0.209	–6.18	0.011	–0.856	0.215	–3.98
Wage replacement rate	0.367	0.771	0.292	2.64	0.357	2.584	0.243	10.62
Potential UI duration	23.561	0.046	0.011	4.12	23.218	0.011	0.003	3.46
EUC/TEUC first-payments' share of unemployed	0.092	–0.375	0.037	–10.01	0.171	0.134	0.033	4.10
New entrants' share of unemployed	0.077	–0.346	0.242	–1.43	0.083	–0.369	0.237	–1.55
Reentrants' share of unemployed	0.321	–0.671	0.128	–5.23	0.295	–0.387	0.146	–2.65
Monetary eligibility rate, *T*–1	0.882	–0.252	0.137	–1.84	0.879	–0.215	0.108	–1.99
Denial rate (separation), share of determinations, *T*–1	0.371	–0.140	0.079	–1.77	0.427	–0.383	0.057	–6.71
Characteristics of the Labor Force (CPS)								
Male	0.536	–0.142	0.325	–0.44	0.530	–1.570	0.450	–3.49
Female	0.464	0.164	0.376	0.44	0.470	1.771	0.507	3.49
American Indian/Alaskan Native	0.013	0.016	1.021	0.02	0.015	–1.489	0.662	–2.25
Asian, Native Hawaiian/Pacific Islander	0.032	0.093	0.603	0.15	0.048	2.720	0.700	3.88
Black, African American	0.094	–0.346	0.500	–0.69	0.105	–0.784	0.541	–1.45
White	0.861	0.034	0.058	0.59	0.833	–0.033	0.073	–0.46
Hispanic	0.067	0.703	0.352	2.00	0.098	–1.266	0.376	–3.36
Not Hispanic	0.933	–0.051	0.025	–2.00	0.902	0.138	0.041	3.36
Age 24 or less	0.166	–0.012	0.508	–0.02	0.145	–1.612	0.490	–3.29
Age 25–34	0.247	–0.205	0.304	–0.68	0.217	–0.382	0.361	–1.06
Age 35–54	0.462	0.009	0.209	0.05	0.439	1.039	0.193	5.37
Age 55–64	0.095	0.176	0.642	0.27	0.151	–0.545	0.456	–1.20
Age 65+	0.030	1.050	1.354	0.78	0.049	–1.174	0.905	–1.30
Industry Share of Employment (QCEW)								
Agriculture, forestry, fishing	0.009	10.238	5.476	1.87	0.008	–21.942	5.896	–3.72
Mining	0.008	–6.080	2.852	–2.13	0.008	4.474	1.518	2.95
Utilities	0.006	17.928	9.077	1.98	0.005	–23.060	14.372	–1.60
Construction	0.049	3.745	1.783	2.10	0.051	4.281	1.163	3.68
Manufacturing	0.141	–2.198	0.788	–2.79	0.095	2.809	0.976	2.88
Wholesale trade	0.043	5.028	3.919	1.28	0.040	7.914	4.375	1.81

Table B4 (Continued)

Variable description	1990–2001, n = 603				2002–2019, n = 899			
	Variable mean	Parameter estimate	Standard error	t-statistic	Variable mean	Parameter estimate	Standard error	t-statistic
Retail trade	0.124	0.080	2.374	0.03	0.116	–2.750	2.134	–1.29
Transportation, warehousing	0.031	3.810	3.326	1.15	0.032	–2.126	2.565	–0.83
Information	0.023	0.411	3.259	0.13	0.019	–3.701	2.812	–1.32
Finance and insurance	0.042	1.713	1.952	0.88	0.041	–4.734	2.773	–1.71
Real estate, rental, leasing	0.014	–10.735	10.282	–1.04	0.014	–7.301	10.393	–0.70
Professional, scientific, technical	0.043	0.391	1.873	0.21	0.053	1.107	1.937	0.57
Company/enterprise management	0.012	–2.542	1.956	–1.30	0.013	–3.224	2.616	–1.23
Admin, support, and waste mgmt	0.047	–2.021	1.236	–1.63	0.056	–2.952	1.439	–2.05
Educational services	0.012	16.302	5.602	2.91	0.017	0.813	5.164	0.16
Health care/social assistance	0.096	–5.065	1.601	–3.16	0.123	1.089	1.154	0.94
Art, entertainment, recreation	0.014	1.894	2.189	0.87	0.015	8.266	5.354	1.54
Accommodation and food services	0.084	–2.847	1.804	–1.58	0.092	–5.500	1.781	–3.09
Other services (except public admin)	0.031	–8.460	3.565	–2.37	0.032	–3.966	2.454	–1.62
Public admin (CPS), federal gov't (QCEW)	0.028	3.095	2.214	1.40	0.028	–5.281	2.058	–2.57
State government	0.043	3.200	2.357	1.36	0.041	7.459	2.148	3.47
Local government	0.098	3.641	1.628	2.24	0.102	5.500	1.578	3.48
	Occupation Share of Employment (CPS)							
Management, business, financial	0.151	0.471	0.539	0.87	0.156	0.232	0.436	0.53
Computers, engineering, science	0.049	1.015	0.971	1.05	0.054	–1.585	0.939	–1.69
Education, legal, community service, arts, media	0.092	–0.407	0.715	–0.57	0.108	0.944	0.619	1.52
Health-care practitioners and technical	0.042	1.194	1.147	1.04	0.054	–2.413	0.980	–2.46
Service occupations	0.144	–0.275	0.591	–0.46	0.169	–0.832	0.476	–1.75
Sales and office occupations	0.255	–0.230	0.409	–0.56	0.233	0.570	0.410	1.39
Farming, fishing, forestry	0.011	–1.317	1.890	–0.70	0.009	2.174	2.076	1.05
Construction and extraction	0.057	–1.312	1.058	–1.24	0.058	0.966	0.844	1.14
Installation, maintenance, repair	0.038	1.818	1.316	1.38	0.036	0.113	1.261	0.09
Production, transportation, material moving	0.161	–0.101	0.508	–0.20	0.123	0.065	0.567	0.12
Alaska	0.020	0.036	0.243	0.15	0.020	–0.215	0.240	–0.89
Alabama	0.020	0.307	0.115	2.68	0.020	0.187	0.135	1.38
Arkansas	0.020	0.364	0.116	3.14	0.020	–0.074	0.117	–0.63
Arizona	0.020	–0.423	0.132	–3.22	0.020	0.859	0.142	6.03
California	0.020	0.802	0.212	3.78	0.020	1.952	0.211	9.25
Colorado	0.020	–0.381	0.132	–2.90	0.020	0.020	0.138	0.14
Connecticut	0.020	0.239	0.134	1.78	0.020	0.053	0.143	0.37
District of Columbia	0.005	–1.635	0.810	–2.02	0.020	1.105	0.674	1.64
Delaware	0.020	–0.293	0.180	–1.63	0.007	–0.164	0.204	–0.81

Table B4 (Continued)

Variable description	1990–2001, $n = 603$				2002–2019, $n = 899$			
	Variable mean	Parameter estimate	Standard error	*t*-statistic	Variable mean	Parameter estimate	Standard error	*t*-statistic
Florida	0.020	–0.003	0.163	–0.02	0.020	1.219	0.181	6.73
Georgia	0.020	0.345	0.152	2.26	0.020	0.727	0.161	4.52
Hawaii	0.020	–0.561	0.499	–1.12	0.020	–1.853	0.562	–3.30
Iowa	0.020	–0.113	0.105	–1.07	0.020	–0.346	0.122	–2.83
Idaho	0.020	–0.371	0.220	–1.68	0.020	0.068	0.182	0.37
Illinois	0.020	0.262	0.125	2.09	0.020	0.544	0.138	3.94
Indiana	0.020	0.512	0.094	5.41	0.020	–0.233	0.117	–1.98
Kansas	0.020	–0.317	0.095	–3.32	0.020	–0.553	0.097	–5.73
Kentucky	0.020	0.326	0.092	3.55	0.020	–0.302	0.103	–2.92
Louisiana	0.020	–0.300	0.142	–2.11	0.020	–0.245	0.148	–1.66
Massachusetts	0.020	0.040	0.175	0.23	0.020	0.120	0.143	0.83
Maryland	0.020	–0.335	0.182	–1.84	0.020	0.356	0.163	2.19
Maine	0.020	0.050	0.126	0.40	0.020	–0.849	0.148	–5.74
Michigan	0.020	1.201	0.100	12.01	0.020	0.504	0.112	4.49
Minnesota	0.020	0.147	0.096	1.52	0.020	–0.236	0.112	–2.10
Missouri	0.020	0.568	0.087	6.54	0.020	0.411	0.080	5.16
Mississippi	0.020	–0.033	0.175	–0.19	0.020	–0.161	0.213	–0.75
Montana	0.020	–0.560	0.140	–3.99	0.020	–0.600	0.164	–3.65
North Carolina	0.020	0.968	0.111	8.69	0.020	0.281	0.121	2.33
North Dakota	0.020	–0.623	0.207	–3.00	0.020	–1.173	0.184	–6.36
Nebraska	0.020	–0.271	0.190	–1.42	0.020	0.032	0.153	0.21
New Hampshire	0.020	–0.720	0.137	–5.26	0.020	–0.937	0.154	–6.08
New Jersey	0.020	0.129	0.137	0.94	0.020	0.373	0.159	2.35
New Mexico	0.020	–1.501	0.195	–7.70	0.020	–0.281	0.212	–1.33
Nevada	0.020	0.403	0.350	1.15	0.020	1.086	0.325	3.34
New York	0.020	0.288	0.187	1.54	0.020	1.038	0.177	5.87
Ohio	0.020	0.586	0.095	6.19	0.020	0.123	0.115	1.07
Oklahoma	0.020	–0.357	0.100	–3.57	0.020	–0.443	0.101	–4.37
Oregon	0.020	0.252	0.146	1.73	0.020	0.552	0.125	4.41
Pennsylvania	0.020	0.786	0.139	5.65	0.020	0.860	0.122	7.05
Rhode Island	0.020	0.355	0.176	2.02	0.012	–0.728	0.166	–4.39
South Carolina	0.020	0.436	0.154	2.83	0.020	0.208	0.157	1.33
South Dakota	0.020	–1.177	0.151	–7.81	0.020	–1.456	0.161	–9.05
Tennessee	0.020	0.723	0.123	5.88	0.020	0.190	0.126	1.51
Texas	0.020	0.120	0.143	0.84	0.020	0.928	0.175	5.31
Utah	0.020	–0.735	0.120	–6.13	0.020	–0.694	0.120	–5.78

Table B4 (Continued)

Variable description	1990–2001, n = 603				2002–2019, n = 899			
	Variable mean	Parameter estimate	Standard error	t-statistic	Variable mean	Parameter estimate	Standard error	t-statistic
Virginia	0.020	0.243	0.141	1.72	0.020	0.237	0.135	1.76
Vermont	0.020	–0.688	0.156	–4.40	0.020	–1.138	0.184	–6.18
Washington	0.020	0.179	0.156	1.15	0.020	0.486	0.151	3.21
Wisconsin	0.020	0.978	0.091	10.72	0.020	0.427	0.114	3.75
West Virginia	0.020	–0.481	0.162	–2.96	0.020	–0.993	0.159	–6.25
Wyoming	0.020	–0.996	0.272	–3.66	0.020	–1.665	0.264	–6.31
Number of observations	603				899			
Adjusted R-squared	0.9923				0.989			

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B5 Tests of Parameter Estimate Differences in Models of the Log of Average Monthly Initial UI Claims for the 50 States plus the District of Columbia between 2002–2019 and 1990–2001

	Difference in parameter estimates				Chi-square tests	
Variable description	Parameter difference	Standard error (*1)	*t*-statistic	*p*-value	Chi sq value	*p*-value
Intercept (dependent variable mean)	–0.050	0.006	–8.93	0.0000		
Log of average monthly unemployed	–0.117	0.057	–2.04	0.0416	3.859	0.0495
Share of employed (16+) working part-time	1.384	0.843	1.64	0.1012	3.06	0.0803
GDP per capita, percent change	0.436	0.300	1.45	0.1466	1.96	0.1619
Wage replacement rate	1.813	0.380	4.77	0.0000	23.30	0.0000
Potential UI duration	–0.035	0.012	–3.04	0.0025	7.72	0.0054
EUC/TEUC first payments' share of unemployed	0.509	0.050	10.24	0.0000	78.38	0.0000
New entrants' share of unemployed	–0.023	0.339	–0.07	0.9460	0.01	0.9428
Reentrants' share of unemployed	0.284	0.194	1.46	0.1449	2.08	0.1491
Monetary eligibility rate, *T*–1	0.037	0.175	0.21	0.8301	0.04	0.8322
Denial rate (separation), share of determinations, *T*–1	–0.243	0.098	–2.49	0.0132	6.86	0.0088
Characteristics of the labor force (CPS)						
Male	–1.429	0.555	–2.57	0.0104	6.38	0.0115
Female	1.607	0.632	2.54	0.0113	6.26	0.0124
American Indian/Alaskan Native	–1.506	1.217	–1.24	0.2165	1.86	0.1724
Asian, Native Hawaiian/Pacific Islander	2.627	0.924	2.84	0.0047	12.72	0.0004
Black, African American	–0.438	0.737	–0.59	0.5527	0.44	0.5095
White	–0.068	0.093	–0.73	0.4665	0.69	0.4058
Hispanic	–1.969	0.515	–3.82	0.0001	15.25	0.0001
Not Hispanic	0.188	0.048	3.91	0.0001	15.30	0.0001
Age 24 or less	–1.599	0.706	–2.27	0.0238	5.55	0.0185
Age 25–34	–0.177	0.471	–0.38	0.7071	0.15	0.6988
Age 35–54	1.030	0.285	3.61	0.0003	15.11	0.0001
Age 55–64	–0.721	0.787	–0.92	0.3601	0.89	0.3451
Age 65+	–2.224	1.629	–1.37	0.1727	2.08	0.1490
Industry share of employment (QCEW)						
Agriculture, forestry, fishing	–32.181	8.047	–4.00	0.0001	15.49	0.0001
Mining	10.554	3.230	3.27	0.0012	11.39	0.0007
Utilities	–40.988	16.998	–2.41	0.0163	6.61	0.0101
Construction	0.536	2.129	0.25	0.8013	0.07	0.7871
Manufacturing	5.007	1.254	3.99	0.0001	16.03	0.0001
Wholesale trade	2.886	5.873	0.49	0.6234	0.23	0.6336
Retail trade	–2.830	3.192	–0.89	0.3757	0.80	0.3706
Transportation, warehousing	–5.936	4.200	–1.41	0.1582	2.17	0.1405
Information	–4.112	4.304	–0.96	0.3399	0.87	0.3518
Finance and insurance	–6.447	3.391	–1.90	0.0578	3.55	0.0594
Real estate, rental, leasing	3.434	14.620	0.23	0.8144	0.06	0.8038
Professional, scientific, technical	0.716	2.695	0.27	0.7906	0.08	0.7758
Company/enterprise management	–0.681	3.266	–0.21	0.8348	0.05	0.8190
Admin, support, and waste mgmt	–0.931	1.897	–0.49	0.6240	0.26	0.6083
Educational services	–15.489	7.619	–2.03	0.0426	4.64	0.0312
Health care/social assistance	6.155	1.973	3.12	0.0019	9.46	0.0021
Art, entertainment, recreation	6.371	5.784	1.10	0.2712	1.27	0.2599
Accommodation and food services	–2.653	2.535	–1.05	0.2959	1.10	0.2935
Other services (except publ admin)	4.494	4.328	1.04	0.2996	1.35	0.2449
Public admin (CPS), fed gov't (QCEW)	–8.376	3.023	–2.77	0.0058	8.53	0.0035
State government	4.259	3.189	1.34	0.1823	2.20	0.1380

Table B5 (Continued)

Variable description	Difference in parameter estimates				Chi-square tests	
	Parameter difference	Standard error (*1)	*t*-statistic	*p*-value	Chi sq value	*p*-value
Local government	1.860	2.268	0.82	0.4125	0.80	0.3706
Occupation share of employment (CPS)						
Management, business, financial	–0.238	0.693	–0.34	0.7310	0.15	0.7009
Computers, engineering, science	–2.601	1.351	–1.93	0.0548	4.10	0.0429
Education, legal, community service, arts	1.351	0.946	1.43	0.1538	2.26	0.1330
Health-care practitioners and technical	–3.608	1.508	–2.39	0.0171	5.95	0.0147
Service occupations	–0.557	0.759	–0.73	0.4628	0.65	0.4214
Sales and office occupations	0.800	0.579	1.38	0.1679	2.18	0.1398
Farming, fishing, forestry	3.490	2.808	1.24	0.2144	1.84	0.1747
Construction and extraction	2.278	1.354	1.68	0.0930	3.65	0.0559
Installation, maintenance, repair	–1.705	1.822	–0.94	0.3498	1.13	0.2885
Production, transportation, material moving	0.166	0.761	0.22	0.8273	0.05	0.8172
Alaska	–0.251	0.341	–0.74	0.4621	0.62	0.4311
Alabama	–0.121	0.177	–0.68	0.4969	0.52	0.4721
Arkansas	–0.438	0.165	–2.66	0.0081	6.84	0.0089
Arizona	1.282	0.194	6.61	0.0000	44.72	0.0000
California	1.149	0.299	3.84	0.0001	14.01	0.0002
Colorado	0.400	0.190	2.10	0.0360	4.48	0.0344
Connecticut	–0.185	0.196	–0.95	0.3449	0.92	0.3380
District of Columbia	2.740	1.054	2.60	0.0096	7.40	0.0065
Delaware	0.129	0.272	0.47	0.6361	0.25	0.6172
Florida	1.222	0.244	5.01	0.0000	27.31	0.0000
Georgia	0.382	0.222	1.73	0.0850	3.37	0.0665
Hawaii	–1.292	0.751	–1.72	0.0862	3.81	0.0511
Iowa	–0.233	0.161	–1.45	0.1490	2.13	0.1441
Idaho	0.439	0.286	1.53	0.1254	2.63	0.1048
Illinois	0.282	0.186	1.51	0.1313	2.55	0.1102
Indiana	–0.744	0.151	–4.94	0.0000	24.68	0.0000
Kansas	–0.237	0.136	–1.74	0.0819	2.86	0.0909
Kentucky	–0.627	0.138	–4.54	0.0000	19.24	0.0000
Louisiana	0.055	0.206	0.27	0.7901	0.08	0.7729
Massachusetts	0.080	0.226	0.35	0.7242	0.13	0.7140
Maryland	0.691	0.244	2.83	0.0048	9.19	0.0024
Maine	–0.900	0.194	–4.63	0.0000	24.48	0.0000
Michigan	–0.697	0.150	–4.64	0.0000	23.82	0.0000
Minnesota	–0.383	0.148	–2.59	0.0100	7.08	0.0078
Missouri	–0.157	0.118	–1.33	0.1842	1.95	0.1629
Mississippi	–0.128	0.276	–0.46	0.6440	0.23	0.6304
Montana	–0.040	0.216	–0.18	0.8546	0.04	0.8446
North Carolina	–0.687	0.164	–4.19	0.0000	19.51	0.0000
North Dakota	–0.551	0.278	–1.98	0.0478	3.92	0.0477
Nebraska	0.303	0.244	1.24	0.2153	1.50	0.2205
New Hampshire	–0.218	0.206	–1.05	0.2921	0.89	0.3445
New Jersey	0.244	0.210	1.17	0.2444	1.37	0.2418
New Mexico	1.220	0.288	4.24	0.0000	21.92	0.0000
Nevada	0.682	0.478	1.43	0.1536	2.17	0.1403
New York	0.751	0.258	2.92	0.0037	9.39	0.0022
Ohio	–0.463	0.149	–3.11	0.0020	9.82	0.0017
Oklahoma	–0.086	0.142	–0.60	0.5468	0.40	0.5265
Oregon	0.300	0.192	1.56	0.1190	2.50	0.1138
Pennsylvania	0.074	0.185	0.40	0.6899	0.19	0.6650

Table B5 (Continued)

Variable description	Difference in parameter estimates				Chi-square tests	
	Parameter difference	Standard error (*1)	*t*-statistic	*p*-value	Chi sq value	*p*-value
Rhode Island	–1.083	0.242	–4.48	0.0000	23.14	0.0000
South Carolina	–0.228	0.220	–1.04	0.3005	1.15	0.2834
South Dakota	–0.279	0.220	–1.26	0.2066	1.66	0.1975
Tennessee	–0.533	0.176	–3.03	0.0026	9.29	0.0023
Texas	0.807	0.226	3.57	0.0004	14.38	0.0001
Utah	0.041	0.170	0.24	0.8108	0.06	0.8037
Virginia	–0.006	0.195	–0.03	0.9763	0.00	0.9754
Vermont	–0.450	0.242	–1.86	0.0629	3.94	0.0472
Washington	0.307	0.218	1.41	0.1587	1.88	0.1700
Wisconsin	–0.550	0.146	–3.77	0.0002	14.36	0.0002
West Virginia	–0.512	0.227	–2.25	0.0246	5.18	0.0228
Wyoming	–0.670	0.379	–1.77	0.0780	3.96	0.0465

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B6 Simulation of the Effect of UI Benefit Generosity Using the Model Estimated over the 2002–2019 Time Period, Then Inserting the Generosity Parameters from the Model Estimated over 1990–2001 or Means from the Same Interval

	Predicted 2002–2019	Insert generosity betas from model estimated 1990–2001			Insert generosity means from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
2002	417,350	503,385	86,034	20.6	396,327	–21,024	–5.0
2003	414,956	501,683	86,727	20.9	398,435	–16,521	–4.0
2004	353,211	435,465	82,254	23.3	351,748	–1,463	–0.4
2005	331,061	411,266	80,205	24.2	333,087	2,026	0.6
2006	314,964	395,022	80,058	25.4	319,336	4,372	1.4
2007	314,832	396,244	81,412	25.9	320,030	5,198	1.7
2008	387,750	484,920	97,171	25.1	389,927	2,177	0.6
2009	561,695	678,193	116,497	20.7	540,654	–21,042	–3.7
2010	492,247	609,232	116,985	23.8	502,561	10,314	2.1
2011	429,829	542,123	112,294	26.1	456,793	26,964	6.3
2012	373,938	474,608	100,670	26.9	401,782	27,844	7.4
2013	358,185	456,255	98,069	27.4	381,196	23,011	6.4
2014	299,280	381,186	81,906	27.4	325,717	26,437	8.8
2015	263,306	335,590	72,285	27.5	284,812	21,506	8.2
2016	256,369	321,853	65,484	25.5	271,393	15,024	5.9
2017	238,062	300,955	62,893	26.4	255,255	17,193	7.2
2018	219,142	280,725	61,582	28.1	239,211	20,069	9.2
2019	213,100	273,509	60,410	28.3	233,068	19,968	9.4
Overall	346,626	432,345	85,719	24.7	355,629	9,003	2.6

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B7 Simulation of the Effect of UI Benefit Generosity Using the Model Estimated over the 1990–2001 Time Period, Then Inserting the Generosity Parameters from the Model Estimated Over 2002–2019 or Means from the Same Interval

	Predicted 1990–2001	Insert generosity betas from model estimated 2002–2019			Insert generosity means from 2002–2019		
Year	model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	322,210	–68,844	–17.6	377,252	–13,801	–3.5
1991	433,459	358,851	–74,608	–17.2	415,837	–17,621	–4.1
1992	396,535	321,898	–74,637	–18.8	384,527	–12,008	–3.0
1993	372,163	304,292	–67,871	–18.2	359,313	–12,850	–3.5
1994	358,191	294,173	–64,018	–17.9	348,837	–9,354	–2.6
1995	352,564	287,041	–65,523	–18.6	339,329	–13,236	–3.8
1996	343,297	273,918	–69,379	–20.2	330,476	–12,821	–3.7
1997	320,923	254,671	–66,251	–20.6	313,395	–7,528	–2.3
1998	309,373	244,114	–65,259	–21.1	302,656	–6,718	–2.2
1999	299,909	239,730	–60,179	–20.1	292,802	–7,107	–2.4
2000	303,768	241,697	–62,071	–20.4	295,768	–8,000	–2.6
2001	388,696	315,047	–73,649	–18.9	369,477	–19,218	–4.9
Overall	355,828	288,137	–67,691	–19.0	344,139	–11,689	–3.3

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B8 Simulation of UI Eligibility from the Model Estimated over the 2002–2019 Time Period, Then Inserting the Eligibility Parameters from the Model Estimated over 1990–2001 or Their Means from the Same Interval

	Predicted 2002–2019	Insert UI eligibility parameters from the model estimated over 1990–2001			Insert UI eligibility means from1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
2002	417,350	434,577	17,227	4.1	420,202	2,852	0.7
2003	414,956	435,090	20,134	4.9	418,836	3,880	0.9
2004	353,211	370,271	17,060	4.8	356,172	2,962	0.8
2005	331,061	350,273	19,213	5.8	338,233	7,172	2.2
2006	314,964	333,229	18,265	5.8	322,300	7,336	2.3
2007	314,832	333,961	19,129	6.1	323,813	8,981	2.9
2008	387,750	410,347	22,598	5.8	396,924	9,174	2.4
2009	561,695	585,595	23,900	4.3	559,307	–2,388	–0.4
2010	492,247	508,376	16,129	3.3	479,833	–12,414	–2.5
2011	429,829	449,607	19,778	4.6	420,206	–9,622	–2.2
2012	373,938	392,270	18,332	4.9	368,644	–5,294	–1.4
2013	358,185	376,203	18,018	5.0	355,756	–2,429	–0.7
2014	299,280	314,939	15,659	5.2	298,341	–939	–0.3
2015	263,306	279,741	16,436	6.2	268,559	5,253	2.0
2016	256,369	271,886	15,518	6.1	262,307	5,938	2.3
2017	238,062	252,490	14,428	6.1	244,507	6,446	2.7
2018	219,142	232,882	13,740	6.3	225,898	6,756	3.1
2019	213,100	227,055	13,955	6.5	220,738	7,639	3.6
Overall	346,626	364,377	17,751	5.1	348,921	2,295	0.7

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B9 Simulation of UI Eligibility from the Model Estimated over the 1990–2001 Time Period, Then Inserting the Eligibility Parameters from the Model Estimated over 2002–2019 or Their Means from the Same Interval

	Predicted 1990–2001	Insert UI eligibility parameters from the model estimated over 2002–2019			Insert UI eligibility means from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	378,110	–12,944	–3.3	386,864	–4,189	–1.1
1991	433,459	420,385	–13,073	–3.0	428,720	–4,739	–1.1
1992	396,535	384,809	–11,726	–3.0	391,755	–4,780	–1.2
1993	372,163	359,794	–12,369	–3.3	365,955	–6,208	–1.7
1994	358,191	344,495	–13,696	–3.8	354,263	–3,928	–1.1
1995	352,564	338,519	–14,045	–4.0	349,918	–2,647	–0.8
1996	343,297	330,836	–12,461	–3.6	341,022	–2,275	–0.7
1997	320,923	308,658	–12,264	–3.8	319,712	–1,210	–0.4
1998	309,373	294,338	–15,035	–4.9	310,603	1,230	0.4
1999	299,909	285,813	–14,096	–4.7	301,731	1,822	0.6
2000	303,768	288,534	–15,234	–5.0	306,504	2,736	0.9
2001	388,696	369,094	–19,602	–5.0	392,568	3,872	1.0
Overall	355,828	341,949	–13,879	–3.9	354,135	–1,693	–0.5

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B10 Simulation of the Effect of Industry and Occupation Shares of Employment Using the Model Estimated for 2002—2019, Then Inserting the Industry and Occupation Parameters from the Model Estimated over 1990–2001 or Their Means from the Same Interval

	Predicted 2002–2019	Insert industry and occupation parameters from 1990–2001 model			Insert industry and occupation means from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
2002	417,350	422,622	5,271	1.3	385,901	–31,450	–7.5
2003	414,956	428,302	13,346	3.2	383,919	–31,037	–7.5
2004	353,211	366,874	13,663	3.9	325,603	–27,607	–7.8
2005	331,061	342,173	11,113	3.4	303,688	–27,373	–8.3
2006	314,964	324,892	9,928	3.2	288,592	–26,373	–8.4
2007	314,832	326,921	12,090	3.8	289,637	–25,195	–8.0
2008	387,750	405,531	17,781	4.6	359,337	–28,413	–7.3
2009	561,695	613,306	51,610	9.2	528,194	–33,501	–6.0
2010	492,247	556,955	64,708	13.1	461,544	–30,703	–6.2
2011	429,829	496,166	66,337	15.4	401,725	–28,104	–6.5
2012	373,938	447,191	73,253	19.6	347,567	–26,371	–7.1
2013	358,185	426,309	68,123	19.0	331,845	–26,340	–7.4
2014	299,280	357,690	58,410	19.5	276,243	–23,037	–7.7
2015	263,306	318,021	54,715	20.8	242,040	–21,266	–8.1
2016	256,369	315,855	59,486	23.2	236,266	–20,103	–7.8
2017	238,062	293,387	55,326	23.2	219,394	–18,668	–7.8
2018	219,142	269,925	50,782	23.2	201,737	–17,405	–7.9
2019	213,100	261,182	48,082	22.6	196,321	–16,779	–7.9
Overall	346,626	387,406	40,779	11.8	321,086	–25,540	–7.4

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B11 Simulation of the Effect of Industry and Occupation Shares of Employment Using the Model Estimated over 1990—2001, Then Inserting the Industry and Occupation Parameters from the Model Estimated over 2002–2019 or Their Means from the Same Interval

	Predicted 1990–2001	Insert industry and occupation parameters from 2002–2019 model			Insert industry and occupation means from 2002–2019		
Year	model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	499,848	108,794	27.8	363,726	–27,328	–7.0
1991	433,459	547,839	114,381	26.4	409,712	–23,746	–5.5
1992	396,535	484,002	87,467	22.1	382,156	–14,379	–3.6
1993	372,163	441,855	69,692	18.7	366,022	–6,141	–1.7
1994	358,191	424,887	66,696	18.6	353,991	–4,200	–1.2
1995	352,564	429,164	76,599	21.7	354,085	1,520	0.4
1996	343,297	417,470	74,173	21.6	346,383	3,086	0.9
1997	320,923	383,995	63,073	19.7	323,883	2,960	0.9
1998	309,373	377,372	67,999	22.0	312,623	3,250	1.1
1999	299,909	356,176	56,267	18.8	297,468	–2,441	–0.8
2000	303,768	362,325	58,557	19.3	298,658	–5,110	–1.7
2001	388,696	459,989	71,293	18.3	372,690	–16,006	–4.1
Overall	355,828	432,077	76,249	21.4	348,450	–7,378	–2.1

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B12 Simulation of the Effect of Rates of New and Re-Entry to the Labor Force Using the Model Estimated over the 2002–2019 Time Period, Then Inserting the New and Re-Entry Rate Parameters from the 1990–2001 Model or Their Means from the Same Interval

	Predicted 2002–2019	Insert new and re-entry rate parameters from the 1990–2001 model			Insert new and re-entry rate mean from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
2002	417,350	385,901	–31,450	–7.5	409,749	–7,602	–1.8
2003	414,956	383,919	–31,037	–7.5	408,595	–6,361	–1.5
2004	353,211	325,603	–27,607	–7.8	351,033	–2,177	–0.6
2005	331,061	303,688	–27,373	–8.3	331,575	514	0.2
2006	314,964	288,592	–26,373	–8.4	316,226	1,262	0.4
2007	314,832	289,637	–25,195	–8.0	314,528	–304	–0.1
2008	387,750	359,337	–28,413	–7.3	382,887	–4,863	–1.3
2009	561,695	528,194	–33,501	–6.0	540,992	–20,703	–3.7
2010	492,247	461,544	–30,703	–6.2	477,536	–14,712	–3.0
2011	429,829	401,725	–28,104	–6.5	420,836	–8,993	–2.1
2012	373,938	347,567	–26,371	–7.1	370,509	–3,429	–0.9
2013	358,185	331,845	–26,340	–7.4	357,207	–979	–0.3
2014	299,280	276,243	–23,037	–7.7	300,318	1,038	0.3
2015	263,306	242,040	–21,266	–8.1	264,799	1,493	0.6
2016	256,369	236,266	–20,103	–7.8	256,961	592	0.2
2017	238,062	219,394	–18,668	–7.8	238,054	–7	–0.0
2018	219,142	201,737	–17,405	–7.9	219,061	–81	–0.0
2019	213,100	196,321	–16,779	–7.9	213,209	109	0.1
Overall	346,626	321,086	–25,540	–7.4	343,004	–3,622	–1.0

Table B13 Simulation of the Effect of Rates of New and Re-Entry to the Labor Force Using the Model Estimated over the 1990–2001 Time Period, Then Inserting the New and Re-Entry Rate Parameters from the 2002–2019 Model or Their Means from the Same Interval

	Predicted 1990–2001	Insert new and re-entry rate parameters from the 2002–2019 model			Insert new and re-entry rate mean from 2002–2019		
Year	model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	421,819	30,765	7.9	389,694	–1,360	–0.3
1991	433,459	464,198	30,740	7.1	423,912	–9,546	–2.2
1992	396,535	423,330	26,795	6.8	385,809	–10,726	–2.7
1993	372,163	397,968	25,805	6.9	364,321	–7,842	–2.1
1994	358,191	394,647	36,456	10.2	371,793	13,601	3.8
1995	352,564	387,799	35,235	10.0	365,002	12,437	3.5
1996	343,297	378,307	35,010	10.2	356,939	13,642	4.0
1997	320,923	353,451	32,528	10.1	333,830	12,907	4.0
1998	309,373	339,861	30,488	9.9	319,774	10,401	3.4
1999	299,909	329,438	29,529	9.8	309,447	9,538	3.2
2000	303,768	334,127	30,359	10.0	313,726	9,957	3.3
2001	388,696	422,112	33,416	8.6	388,297	–398	–0.1
Overall	355,828	387,255	31,427	8.8	360,212	4,384	1.2

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B14 Simulation of the Effect of Labor Force Characteristics Using the Model Estimated over the 2002–2019 Time Period, Then Inserting the Labor Force Characteristic Parameters from the 1990–2001 Model or Their Means from the Same Interval

	Predicted 2002–2019	Inserting LF characteristic parameters from the 1990–2001 model			Inserting LF characteristic means from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
2002	417,350	452,876	35,525	8.5	402,199	–15,152	–3.6
2003	414,956	437,880	22,924	5.5	390,167	–24,789	–6.0
2004	353,211	377,745	24,535	6.9	335,444	–17,766	–5.0
2005	331,061	357,421	26,361	8.0	316,352	–14,708	–4.4
2006	314,964	342,439	27,474	8.7	302,758	–12,206	–3.9
2007	314,832	346,917	32,085	10.2	303,631	–11,201	–3.6
2008	387,750	433,179	45,429	11.7	374,846	–12,904	–3.3
2009	561,695	630,504	68,809	12.3	544,074	–17,621	–3.1
2010	492,247	562,878	70,631	14.3	481,848	–10,400	–2.1
2011	429,829	501,783	71,954	16.7	427,550	–2,279	–0.5
2012	373,938	441,391	67,453	18.0	372,989	–949	–0.3
2013	358,185	427,141	68,956	19.3	358,128	–58	–0.0
2014	299,280	363,742	64,461	21.5	303,167	3,887	1.3
2015	263,306	324,531	61,225	23.3	269,220	5,914	2.2
2016	256,369	317,938	61,569	24.0	262,429	6,061	2.4
2017	238,062	296,039	57,977	24.4	244,044	5,983	2.5
2018	219,142	274,056	54,914	25.1	224,563	5,421	2.5
2019	213,100	267,960	54,860	25.7	219,659	6,559	3.1
Overall	346,626	397,579	50,952	14.7	340,726	–5,900	–1.7

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B15 Simulation of the Effect of Labor Force Characteristics Using the Model Estimated over the 1990–2001 Time Period, Then Inserting the Labor Force Characteristic Parameters from the 2002–2019 Model or Their Means from the Same Interval

	Predicted 1990–2001	Inserting LF Characteristic Parameters from the 2002–2019 Model			Inserting LF Characteristic Means from 2002-2019		
Year	Model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	348,156	–42,897	–11.0	424,497	33,444	8.6
1991	433,459	394,370	–39,088	–9.0	469,659	36,200	8.4
1992	396,535	367,725	–28,810	–7.3	429,108	32,573	8.2
1993	372,163	348,046	–24,117	–6.5	401,908	29,745	8.0
1994	358,191	343,344	–14,847	–4.1	385,068	26,876	7.5
1995	352,564	347,649	–4,916	–1.4	380,610	28,046	8.0
1996	343,297	353,024	9,728	2.8	368,724	25,427	7.4
1997	320,923	331,395	10,473	3.3	342,232	21,309	6.6
1998	309,373	320,315	10,942	3.5	328,491	19,118	6.2
1999	299,909	312,383	12,474	4.2	316,599	16,690	5.6
2000	303,768	308,508	4,740	1.6	315,804	12,036	4.0
2001	388,696	390,287	1,591	0.4	401,655	12,959	3.3
Overall	355,828	347,100	–8,727	–2.5	380,363	24,535	6.9

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B16 Simulation of the Effect of the Part-Time Share of Employment Using the Model Estimated over 2002–2019, Then Inserting the Part-Time Share Parameter from the Model Estimated over 1990-2001 or Its Mean from the Same Interval

	Predicted 2002–2019	Insert part-time share parameters from 1990–2001 model			Insert part-time share mean from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
2002	417,350	323,362	–93,988	–22.5	419,367	2,017	0.5
2003	414,956	320,263	–94,693	–22.8	415,889	933	0.2
2004	353,211	272,393	–80,817	–22.9	353,924	713	0.2
2005	331,061	256,429	–74,631	–22.5	332,611	1,551	0.5
2006	314,964	245,170	–69,794	–22.2	317,521	2,557	0.8
2007	314,832	244,939	–69,892	–22.2	317,212	2,380	0.8
2008	387,750	298,479	–89,271	–23.0	387,869	119	0.0
2009	561,695	417,341	–144,354	–25.7	549,060	–12,635	–2.2
2010	492,247	367,622	–124,625	–25.3	482,694	–9,553	–1.9
2011	429,829	322,456	–107,373	–25.0	422,602	–7,227	–1.7
2012	373,938	281,777	–92,161	–24.6	368,764	–5,174	–1.4
2013	358,185	271,001	–87,184	–24.3	354,311	–3,875	–1.1
2014	299,280	227,573	–71,707	–24.0	297,105	–2,175	–0.7
2015	263,306	201,883	–61,423	–23.3	262,849	–457	–0.2
2016	256,369	196,761	–59,608	–23.3	256,126	–243	–0.1
2017	238,062	184,293	–53,769	–22.6	239,174	1,112	0.5
2018	219,142	170,223	–48,919	–22.3	220,719	1,576	0.7
2019	213,100	166,240	–46,860	–22.0	215,285	2,185	1.0
Overall	346,626	264,900	–81,726	–23.6	345,171	–1,455	–0.4

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B17 Simulation of the Effect of the Part-Time Share of Employment Using the Model Estimated over 1990—2001, Then Inserting the Part-Time Share Parameter from the Model Estimated over 2002–2019 or Its Mean from the Same Interval

	Predicted 1990–2001	Insert part-time share parameters from 2002–2019 model			Insert part-time share mean from 1990–2001		
Year	model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	508,557	117,503	30.0	390,387	–667	–0.2
1991	433,459	569,553	136,094	31.4	434,291	833	0.2
1992	396,535	520,824	124,289	31.3	397,274	739	0.2
1993	372,163	489,089	116,925	31.4	372,945	782	0.2
1994	358,191	471,140	112,948	31.5	359,097	906	0.3
1995	352,564	461,901	109,336	31.0	352,949	384	0.1
1996	343,297	447,436	104,139	30.3	343,078	–219	–0.1
1997	320,923	416,695	95,773	29.8	320,286	–637	–0.2
1998	309,373	400,483	91,110	29.4	308,392	–981	–0.3
1999	299,909	386,138	86,229	28.8	298,415	–1,494	–0.5
2000	303,768	388,703	84,935	28.0	301,602	–2,166	–0.7
2001	388,696	500,586	111,890	28.8	386,671	–2,024	–0.5
Overall	355,828	463,425	107,598	30.2	355,449	–379	–0.1

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B18 Total Effects of Incremental Simulations Inserting the Parameters or Means of Categories of Variables from 1990–2001 into the Model Estimated over the 2002–2019 Time Period

Year	Predicted 2002–2019 model	Inserting category: Parameters, 1990–2001	Inserting category: Means, 1990–2001	Net ccchange	Pct change
2002	417,350	18,620	–70,358	–51,738	–12.4
2003	414,956	17,401	–73,896	–56,495	–13.6
2004	353,211	29,088	–45,338	–16,251	–4.6
2005	331,061	34,886	–30,819	4,067	1.2
2006	314,964	39,558	–23,052	16,507	5.2
2007	314,832	49,629	–20,140	29,489	9.4
2008	387,750	65,295	–34,708	30,587	7.9
2009	561,695	82,962	–107,890	–24,928	–4.4
2010	492,247	113,124	–67,467	45,656	9.3
2011	429,829	134,885	–29,261	105,625	24.6
2012	373,938	141,175	–13,373	127,802	34.2
2013	358,185	139,643	–10,669	128,974	36.0
2014	299,280	125,692	5,211	130,903	43.7
2015	263,306	121,970	12,442	134,413	51.0
2016	256,369	122,345	7,270	129,615	50.6
2017	238,062	118,188	12,059	130,247	54.7
2018	219,142	114,695	16,335	131,030	59.8
2019	213,100	113,668	19,682	133,349	62.6
Overall	346,626	87,935	–25,221	62,714	18.1

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B19 Total Effects of Incremental Simulations Inserting the Parameters or Means of Categories of Variables from 2002–2019 into the Model Estimated over the 1990–2001 Time Period

Year	Predicted 1990–2001 model	Inserting category: Parameters, 2002–2019	Inserting category: Means, 2002–2019	Net change	Pct change
1990	391,053	132,378	–13,901	118,477	30.3
1991	433,459	154,445	–18,619	135,826	31.3
1992	396,535	123,378	–8,581	114,797	29.0
1993	372,163	108,065	–2,516	105,549	28.4
1994	358,191	123,539	23,901	147,440	41.2
1995	352,564	136,686	26,505	163,192	46.3
1996	343,297	141,209	26,840	168,049	49.0
1997	320,923	123,331	27,802	151,133	47.1
1998	309,373	120,243	26,300	146,543	47.4
1999	299,909	110,224	17,007	127,231	42.4
2000	303,768	101,285	9,451	110,737	36.5
2001	388,696	124,940	–20,816	104,124	26.8
Overall	355,828	124,977	7,781	132,758	37.3

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B20 Simulation of the Effect of Federal and State Extended Compensation/Benefit Program Continued Claims as a Share of the Unemployed, Estimated over 2002—2019, Then Inserting the Share Parameter from the Model Estimated over 1990–2001 or Its Mean from the Same Interval

	Predicted 2002–2019	Insert fed/state extended parameter from the 1990–2001 model			Insert fed/state extended share mean from 1990–2001		
Year	model	Level	Change	Pct Change	Level	Change	Pct Change
2002	417,350	325,840	–91,510	–21.9	395,507	–21,843	–5.2
2003	414,956	333,379	–81,577	–19.7	396,246	–18,710	–4.5
2004	353,211	350,322	–2,889	–0.8	356,673	3,462	1.0
2005	331,061	330,816	–245	–0.1	334,968	3,907	1.2
2006	314,964	314,309	–655	–0.2	318,555	3,591	1.1
2007	314,832	314,831	–1	–0.0	318,591	3,760	1.2
2008	387,750	332,874	–54,876	–14.2	376,790	–10,960	–2.8
2009	561,695	418,271	–143,424	–25.5	525,541	–36,154	–6.4
2010	492,247	374,931	–117,316	–23.8	463,039	–29,208	–5.9
2011	429,829	345,690	–84,139	–19.6	410,501	–19,328	–4.5
2012	373,938	319,661	–54,277	–14.5	363,001	–10,936	–2.9
2013	358,185	317,197	–40,988	–11.4	350,954	–7,231	–2.0
2014	299,280	296,905	–2,375	–0.8	302,161	2,881	1.0
2015	263,306	263,273	–33	–0.0	266,368	3,062	1.2
2016	256,369	256,359	–10	–0.0	259,362	2,993	1.2
2017	238,062	238,059	–3	–0.0	240,863	2,801	1.2
2018	219,142	219,140	–2	–0.0	221,711	2,569	1.2
2019	213,100	213,098	–2	–0.0	215,591	2,491	1.2
Overall	346,626	309,164	–37,462	–10.8	339,801	–6,825	–2.0

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B21 Simulation of the Effect of Federal and State Extended Compensation/Benefit Program Continued Claims as a Share of the Unemployed Estimated over 1990—2001, Then Inserting the Share Parameter from the Model Estimated over 2002–2019 or Its Mean from the Same Interval

	Predicted 1990–2001	Insert fed/state extended parameter from the 2002–2019 model			Insert fed/state extended share mean from 2002–2019		
Year	model	Level	Change	Pct change	Level	Change	Pct change
1990	391,053	391,802	749	0.2	365,118	–25,935	–6.6
1991	433,459	468,742	35,283	8.1	427,805	–5,654	–1.3
1992	396,535	485,354	88,819	22.4	428,794	32,259	8.1
1993	372,163	466,755	94,592	25.4	409,658	37,495	10.1
1994	358,191	370,465	12,274	3.4	342,369	–15,823	–4.4
1995	352,564	353,208	644	0.2	329,253	–23,312	–6.6
1996	343,297	343,649	352	0.1	320,417	–22,880	–6.7
1997	320,923	321,200	278	0.1	299,436	–21,487	–6.7
1998	309,373	309,679	305	0.1	288,686	–20,687	–6.7
1999	299,909	300,284	375	0.1	279,970	–19,939	–6.6
2000	303,768	304,031	263	0.1	283,513	–20,256	–6.7
2001	388,696	388,927	231	0.1	362,646	–26,050	–6.7
Overall	355,828	375,341	19,514	5.5	344,805	–11,022	–3.1

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B22 Model of the Log of Average Monthly Initial Claims for the 50 States plus D.C., Estimated over 1990–2019 and Including Controls for the Nine States That Reduced Benefits after the Financial Crisis

Description	Variable mean	Parameter estimate	Standard error	*t*-statistic
Intercept	9.704	3.843	0.347	11.07
Log, average monthly unemployed	170,094	0.532	0.028	18.98
Share of employed persons (16+) working part-time	0.193	–0.012	0.464	–0.03
GDP per capita, % change	0.015	–1.624	0.175	–9.30
Wage replacement rate	0.361	1.179	0.189	6.25
Potential UI duration	23.356	0.006	0.004	1.35
Nine states & 2010–2019 = 1	0.060	–0.650	0.161	–4.04
Nine states & 2010–2019, × replace rate	0.020	1.400	0.377	3.72
Nine states & 2010–2019, × potential duration	1.102	0.006	0.007	0.80
EUC/TEUC first payments' share of unemployed	0.139	0.016	0.026	0.61
New entrants' share of unemployed	0.080	–1.011	0.190	–5.31
Re-entrants' share of unemployed	0.305	–0.518	0.110	–4.71
Monetary eligibility rate, *T*–1	0.881	–0.390	0.088	–4.43
Denial rate (separation), share of determinations, *T*–1	0.404	–0.427	0.045	–9.43
Male	0.533	–1.383	0.299	–4.62
Female	0.467	1.575	0.341	4.62
American Indian/Alaskan Native	0.014	–1.054	0.592	–1.78
Asian, Native Hawaiian/Pacific Islander	0.042	1.390	0.474	2.93
Black, African American	0.100	–0.465	0.360	–1.29
White	0.844	0.004	0.045	0.09
Hispanic	0.086	0.077	0.240	0.32
Not Hispanic	0.914	–0.007	0.023	–0.32
Age 24 or less	0.153	–0.878	0.351	–2.50
Age 25–34	0.229	–0.721	0.218	–3.31
Age 35–54	0.448	0.849	0.120	7.06
Age 55–64	0.129	–0.120	0.357	–0.33
Age 65+	0.041	–1.581	0.793	–1.99
Agriculture, forestry, fishing	0.009	–9.648	2.883	–3.35
Mining	0.008	4.354	1.229	3.54
Utilities	0.005	–20.162	6.289	–3.21
Construction	0.050	5.434	0.967	5.62
Manufacturing	0.113	2.647	0.460	5.75
Wholesale trade	0.041	2.600	2.378	1.09
Retail trade	0.119	–1.081	1.263	–0.86
Transportation, warehousing	0.032	–3.315	1.637	–2.02
Information	0.021	–2.401	1.846	–1.30
Finance and insurance	0.041	1.376	1.465	0.94
Real estate, rental, leasing	0.014	–11.274	6.263	–1.80
Professional, scientific, technical	0.049	–0.119	1.132	–0.10
Company/enterprise management	0.013	–4.016	1.322	–3.04
Admin, support, and waste mgmt	0.052	–2.880	0.813	–3.54
Educational services	0.015	9.322	2.747	3.39
Health care/Social assistance	0.112	–1.360	0.757	–1.80
Art, entertainment, recreation	0.014	4.625	2.068	2.24
Accommodation and food services	0.089	–4.579	0.951	–4.81
Other services (except public admin)	0.031	–6.271	1.923	–3.26

Table B22 (Continued)

Description	Variable mean	Parameter estimate	Standard error	*t*-statistic
Public admin (CPS), Federal government (QCEW)	0.028	0.933	1.403	0.66
State government	0.042	3.093	1.413	2.19
Local government	0.100	4.657	1.001	4.65
Management, business, financial	0.154	0.914	0.355	2.57
Computers, engineering, science	0.052	–1.226	0.740	–1.66
Education, legal, community service, arts, media	0.102	0.381	0.529	0.72
Health-care practitioners and technical	0.050	–1.189	0.839	–1.42
Service occupations	0.159	–1.290	0.421	–3.06
Sales and office occupations	0.242	0.180	0.322	0.56
Farming, fishing, forestry	0.009	–1.086	1.542	–0.70
Construction and extraction	0.057	0.182	0.733	0.25
Installation, maintenance, repair	0.037	2.386	1.052	2.27
Production, transportation, material moving	0.138	0.120	0.423	0.28
Alaska	0.020	–0.081	0.150	–0.54
Alabama	0.020	0.097	0.080	1.21
Arkansas	0.020	0.168	0.065	2.58
Arizona	0.020	0.157	0.085	1.85
California	0.020	1.553	0.123	12.64
Colorado	0.020	0.039	0.076	0.51
Connecticut	0.020	–0.054	0.082	–0.66
District of Columbia	0.014	–0.819	0.465	–1.76
Delaware	0.012	–0.266	0.121	–2.19
Florida	0.020	0.787	0.097	8.13
Georgia	0.020	0.594	0.102	5.83
Hawaii	0.020	–0.504	0.365	–1.38
Iowa	0.020	–0.331	0.073	–4.53
Idaho	0.020	–0.016	0.117	–0.14
Illinois	0.020	0.464	0.074	6.23
Indiana	0.020	–0.069	0.060	–1.15
Kansas	0.020	–0.467	0.062	–7.55
Kentucky	0.020	0.000	0.059	0.00
Louisiana	0.020	–0.169	0.095	–1.78
Massachusetts	0.020	0.175	0.093	1.88
Maryland	0.020	0.113	0.114	0.99
Maine	0.020	–0.597	0.088	–6.77
Michigan	0.020	0.745	0.062	12.02
Minnesota	0.020	–0.015	0.064	–0.23
Missouri	0.020	0.505	0.051	10.00
Mississippi	0.020	–0.221	0.122	–1.81
Montana	0.020	–0.352	0.089	–3.98
North Carolina	0.020	0.419	0.075	5.57
North Dakota	0.020	–0.711	0.109	–6.49
Nebraska	0.020	0.098	0.101	0.97
New Hampshire	0.020	–0.966	0.090	–10.78
New Jersey	0.020	0.423	0.081	5.23
New Mexico	0.020	–0.691	0.135	–5.11
Nevada	0.020	0.960	0.190	5.06
New York	0.020	0.764	0.110	6.94
Ohio	0.020	0.293	0.063	4.67
Oklahoma	0.020	–0.425	0.064	–6.67
Oregon	0.020	0.567	0.081	7.03
Pennsylvania	0.020	0.816	0.079	10.39
Rhode Island	0.015	–0.490	0.101	–4.87

Table B22 (Continued)

Description	Variable mean	Parameter estimate	Standard error	*t*-statistic
South Carolina	0.020	0.198	0.100	1.99
South Dakota	0.020	–1.349	0.098	–13.77
Tennessee	0.020	0.231	0.074	3.13
Texas	0.020	0.496	0.097	5.09
Utah	0.020	–0.680	0.078	–8.68
Virginia	0.020	0.138	0.085	1.63
Vermont	0.020	–0.900	0.100	–9.01
Washington	0.020	0.555	0.089	6.26
Wisconsin	0.020	0.512	0.061	8.44
West Virginia	0.020	–0.657	0.095	–6.92
Wyoming	0.020	–1.505	0.151	–9.95
Number of observations	1,502			
Adjusted *R*-squared	0.9855			

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Table B23 Simulation of the Single Equation Model Estimated from 1990-2019 that Includes Interactions of the Nine States that Reduced Benefits after the Financial Crisis with UI Generosity Variables and Inserts those Parameters or Means from 2010-2019 Into the Solution from 1990—2009

Year	Baseline prediction	Insert the nine state parameters from 2010–2019			Insert the nine state means from 2010—2019		
		Level	Change	Pct change	Level	Change	Pct change
1990	77,735	78,392	657	0.8	70,303	–7,431	–10.6
1991	88,546	89,946	1,400	1.6	79,526	–9,020	–11.3
1992	84,709	84,131	–577	–0.7	77,491	–7,218	–9.3
1993	79,667	79,530	–137	–0.2	72,648	–7,019	–9.7
1994	67,198	66,660	–538	–0.8	61,593	–5,605	–9.1
1995	68,422	68,299	–123	–0.2	62,408	–6,014	–9.6
1996	69,872	68,624	–1,248	–1.8	64,612	–5,261	–8.1
1997	65,842	64,725	–1,117	–1.7	60,958	–4,883	–8.0
1998	64,012	62,772	–1,241	–2.0	59,360	–4,652	–7.8
1999	61,431	60,545	–886	–1.5	56,794	–4,637	–8.2
2000	63,695	62,858	–838	–1.3	58,789	–4,906	–8.3
2001	84,078	84,652	574	0.7	76,237	–7,841	–10.3
2002	88,728	90,044	1,316	1.5	79,808	–8,920	–11.2
2003	81,917	82,653	736	0.9	74,101	–7,816	–10.5
2004	78,290	77,204	–1,086	–1.4	72,246	–6,044	–8.4
2005	72,390	70,614	–1,775	–2.5	67,316	–5,074	–7.5
2006	72,246	70,254	–1,992	–2.8	67,402	–4,844	–7.2
2007	72,329	69,956	–2,373	–3.4	67,596	–4,734	–7.0
2008	87,332	84,791	–2,542	–3.0	81,176	–6,156	–7.6
2009	126,106	125,426	–680	–0.5	114,960	–11,146	–9.7

SOURCE: Tabulated results are based on state-year data described in Appendix A.

Appendix C

Table C1 States with Maximum Potential UI Duration Reduced to Less Than 26 Weeks in 2011 or 2012

States that have not cut potential duration since 2020	Maximum UI duration
Arkansas	9 to 16
Florida	9 to 12–23 (B, U)
Georgia	6 to 14–20 (B, U)
Idaho	10 to 20–26 (B, U)[a]
Kansas	10 to 16–26 (B, U)[a]
Michigan	20 (B)
Missouri	8 to 20 (B)
North Carolina	12 to 20 (U)
South Carolina	13 to 20 (B)

States cutting potential duration since 2020	Maximum UI duration
Alabama	14 (B, U)
Arizona	8 to 24 (B)
Oklahoma	16 in 2023[b]

NOTE: "B" means individual potential duration depends on base period earnings. "U" means the state maximum potential duration depends on the state level of unemployment. This list excludes Illinois and Massachusetts. Illinois cut potential duration to 25 weeks in 2011 and restored potential duration to 26 weeks in 2013. Massachusetts, which has a 30-week potential duration, passed a law to cut potential duration to 26 weeks whenever federal extended benefits are available.

[a] Can be less than 26 if low unemployment.

[b] Starting in 2025 it will vary from 16 to 20, depending on the unemployment rate.

SOURCE: Legislated state UI potential durations are listed in the following report, from 2022: *Significant Provisions of State Unemployment Insurance Laws*. Washington, DC: U.S. Department of Labor, Employment and Training Administration, Office of Unemployment Insurance. https://oui.doleta.gov/unemploy/content/sigpros/2020-2029/July2022.pdf (accessed April 12, 2023).

REFERENCES

Anderson, Patricia M., and Bruce D. Meyer. 1997. "Unemployment Insurance Take-Up Rates and the After-Tax Value of Benefits." *Quarterly Journal of Economics* 112(3): 913–937.

Auray, Stephane, David L. Fuller, and Nicolas Lepage-Saucier. 2018. "Why Do Half of Unemployment Benefits Go Unclaimed?" Paper presented at the sessions of the Labor and Employment Relations Association (LERA) at the annual meeting of the Allied Social Science Association (ASSA), held in Atlanta, Georgia, January 4–6.

Blank, Rebecca, and David Card. 1991. "Recent Trends in Insured and Uninsured Employment: Is There an Explanation?" *Quarterly Journal of Economics* 106(4): 1157–1189.

Bureau of Labor Statistics (BLS). 2023. *Labor Force Statistics from the Current Population Survey*. Washington, DC: U.S. Department of Labor, Bureau of Labor Statistics. https://www.bls.gov/cps/definitions.htm#geo (accessed April 6, 2023).

Burtless, Gary. 1983. "Why Is Insured Unemployment So Low?" *Brookings Papers on Economic Activity* 14(1): 225–254.

DeAntonio, Dante. 2018. *Why Are U.S. Unemployment Insurance Claims So Low?* Economic View Report No. 348474. New York: Moody's Analytics. https://www.economy.com/economicview/analysis/348474 (accessed April 6, 2023).

Ebenstein, Avraham, and Kevin Stange. 2010. "Does Inconvenience Explain Low Take-Up? Evidence from Unemployment Insurance." *Journal of Policy Analysis and Management* 29(1): 111–136.

Garin, Andrew, Emilie Jackson, and Dmitri Koustas. 2022. "Is Gig Work Changing the Labor Market? Key Lessons from Tax Data." *National Tax Journal* 75(4): 791–816.

Kitagawa, Evelyn M. 1955. "Components of a Difference between Two Rates." *Journal of the American Statistical Association* 50(272): 1168--1194.

Lachowska, Marta, Isaac Sorkin, and Stephen A. Woodbury. 2022. "Firms and Unemployment Insurance Take-Up." NBER Working Paper No. 30266. Cambridge MA: National Bureau of Economic Research. http://www.nber.org/papers/w30266 (accessed April 6, 2023).

Oaxaca, Ronald L. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review* 14(3): 693–709 https://doi.org/10.2307/2525981.

Oaxaca, Ronald L., and Michael R. Ransom. 1999. "Identification in Detailed Wage Decompositions." *Review of Economics and Statistics* 81(1): 154–157.

Office of Unemployment Insurance (OUI). 2023. "Unemployment Insurance Weekly Claims." News release, March 16. Washington, DC: U.S. Department of Labor, Employment and

Training Administration, Office of Unemployment Insurance. https://oui.doleta.gov/press/2023/031623.pdf (accessed April 6, 2023).

O'Leary, Christopher J., and Kenneth J. Kline. 2016."Are State Unemployment Insurance Reserves Sufficient for the Next Recession?" Upjohn Institute Working Paper No. 16-257. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research. https://doi.org/10.17848/wp16-257.

Reich, Robert B. 1997. *Locked in the Cabinet*. New York: Alfred A. Knopf.

U.S. Department of Labor (USDOL). 2022. *Comparison of State Unemployment Laws 2022*. Washington, DC: U.S. Department of Labor, Employment and Training Administration, Office of Unemployment Insurance. https://oui.doleta.gov/unemploy/comparison/2020-2029/comparison2022.asp (accessed April 6, 2023).

_____. 2023. *Monthly Program and Financial Data*. Washington, DC: U.S. Department of Labor, Employment and Training Administration, Office of Unemployment Insurance. https://oui.doleta.gov/unemploy/claimssum.asp (accessed April 6, 2023).

Vroman, Wayne. 2009. "Unemployment Insurance Recipients and Nonrecipients in the CPS." *Monthly Labor Review* 132(October): 44–53.

Wandner, Stephen A., and Andrew Stettner. 2000. "Why Are Many Jobless Workers Not Applying for Benefits?" *Monthly Labor Review* 123(6): 21–33.

Winsborough, H. H., and Peter Dickinson. 1971. "Components of Negro-White Income Differences." *Proceedings of the American Statistical Association, Social Statistics Section*, pp. 6–8. http://www.asasrms.org/Proceedings/y1971/Components%20Of%20Negro-White%20Income%20Differences.pdf (accessed April 6, 2023).