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Some Like It Hot: Assessing Longer-Term Labor Market Benefits from a High-Pressure Economy

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Abstract: This paper finds that both "hot" and "cold" economic environments affect current and future labor market outcomes (such as time spent unemployed and out of the labor force and hourly pay) differentially between advantaged and disadvantaged groups. Using longitudinal data, we find that while disadvantaged workers reap greater benefits from exposure to hot economies, that benefit alone is not enough to offset the greater cost of exposure to cold economic environments. This suggests that an overexpansive policy is limited in its ability to achieve lasting reductions in labor market gaps, which would likely be better served by a policy prioritizing reduced economic volatility.

JEL classification: E60, E24, J64, J31

Key words: hysteresis, labor force participation, labor market gaps, unemployment, wage gaps

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Some Like it Hot: Assessing Longer-term Labor Market Benefits from a High-Pressure Economy

1 Introduction and Background

The fundamental question posed in this paper is to what extent exposure to a high-pressure economic environment improves current and future labor market outcomes and how the impact of that exposure differs across different demographic groups. The importance of both intensity and duration of "hot" and "cold" economic environments is explored. Using the 1979 and 1997 National Longitudinal Surveys of Youth (NLSY), the analysis is at the individual worker level allowing us to observe individuals across multiple business cycles, to identify when individuals move between high-pressure and high-unemployment periods, and to control for individual fixed effects. Labor market outcomes examined here are unemployment, labor force participation, and real hourly wages.

A high-pressure, or hot, economic environment is one in which the unemployment rate is below the natural, or sustainable or long-term, unemployment rate -- that level of unemployment that can be maintained without putting too much pressure on inflation (Condon and Torres 2016). There is general agreement that a high-pressure economy has potential risks, including financial instability, vulnerability to adverse shocks that could lead to recession, and could generally be a signal that an economy's long-run growth prospects are dim (Fischer 2016). In fact, since 1960, there has never been a period of high-pressure in the U.S. that isn't followed by a recession (Bostic 2018). If the demand for resources (including labor) expands beyond the economy’s capacity to supply them, the risk of undesirable inflation, financial imbalances, and other negative developments may grow.[1]

[1] The natural tension between low unemployment and low inflation is reflected in the well-known Phillips Curve (Fisher 1926; Phillips 1958), which, of course, is not without its critics (e.g., Atkeson and Ohanian 2001; Gordon 2011; King and Watson 1994; Lucas and Sargent 1978).

High-pressure economies, however, have also been found to have significant contemporaneous benefits to workers. Okun et al. (1973) describe the environment as one in which disadvantaged workers experience upward mobility as increased demand makes employers dig deeper into their available labor pool (also see Krause and Lubik 2006). Rose et al. (1988) explain that the ability of workers to easily switch jobs during a high-pressure episode allows them to find better job matches in both the pecuniary and non-pecuniary dimensions.[2] And, as might seem obvious, greater demand bids up the price of labor so workers experience greater wage growth during high-pressure periods (Holzer et al. 2006). The antithesis of this, of course, is that we would see lower wages, at least at the entry-level, during recessions (Carneiro et al. 2012; Martins et al. 2012). While these findings would suggest a strong relationship between real wages and the business cycle, Otrok and Pourpourides (2017) conclude otherwise and Schmieder and von Wachter (2010) find that expansionary wage boosts do not persist once someone loses their job. However, Jefferson (2005) provides evidence that high-pressure economies improve the relative unskilled-to-skilled unemployment experience. As workers' wages are bid up from employers' efforts to meet demand hiring during high-pressure economies, we might expect these gains to be expressed as better outcomes in the future.

There is evidence of significant disparities in labor market outcomes, generally, across the business cycle. Cajner et al. (2017) finds that not only are blacks (and Hispanics) hit harder by recessions, their experience is more volatile across the business cycle (also see Zavodny and Zha 2000; and Jefferson 2008, who finds a similar result among the less educated; and Engemann and Wall 2010 who show the differential impact of recessions across a variety of demographics). Aaronson et al. (2019) identify what they refer to as the "high-beta" experience of disadvantaged groups who are both hit harder during recessions and benefit more during

[2] Also see Hagedorn and Manovskii (2013) who attribute all of the history dependence in wages on better job matches during tight labor markets.

expansions than their more advantaged counterparts. The identification of "large unemployment disparities" has a long history as a "social issue," dating back at least to Perry's (1970) identification of structural factors playing a role in the relationship between what level of unemployment can be attained at a given level of inflation, and Hall's (1970) consideration of whether the notion of "normal" unemployment differs by race and gender.

The disproportional benefit accruing to disadvantaged groups during particularly strong economic periods have led some to suggest that extending these high-pressure environments can go a long way to diminishing the economic disparities of disadvantaged groups (also see Couch and Fairlie 2010; Engemann and Wall 2010). Bernstein and Bentele (2019) demonstrate that if the world had an unemployment rate *always* below the natural rate, labor market gaps today would be considerably smaller than they actually are. However, the empirical evidence as to whether high-pressure economies have a lasting, longer-term positive impact on labor market outcomes of workers (i.e., positive hysteresis) is thin and varied. In the aggregate, Fleischman and Gallin (2001) find that positive aggregate economic shocks do not translate into persistently higher employment rates, however, there is more of a positive impact on younger workers compared with older workers. Schmieder and von Wachter (2010) find that expansionary wage boosts do not persist once someone loses their job, and Fallick and Krolikowski (2018) find that the positive influence of local labor market conditions on employment-to-population ratios among less-educated individuals dissipates within three years. Aaronson et al. (2019) present evidence of persistence in labor force participation, but not, generally, in unemployment. However, their analysis does not distinguish between weak and strong economic environments, and others (e.g., Hotchkiss 2019) find that identified impacts of past economic conditions on current labor market outcomes are dominated by weak economic periods.

Evidence of negative hysteresis, or, at least, persistence, however, is more prevalent. Kahn (2010) provides evidence that wages of white men who graduate from college during a recession experience lower wages for decades after graduating. The long-term implications of economic conditions upon labor market entry are also documented by Altonji et al. (2016), Cockx and Ghirelli (2016), Fernández-Kranz and Rodríguez-Planas (2018), Kondo (2015), Liu et al. (2016), Oreopoulos et al. (2012), Oyer (2006, 2008), Stevens (2008), and von Wachter and Bender (2006). Other evidence suggests that the lasting effects of recessions also affect health (Maclean 2013) and self-esteem (Maclean and Hill 2015). Yagan (2017) also attributes most of the employment decline between 2007 and 2015 to local unemployment shocks during the great recession. Of course, these studies follow on a long literature of the scaring effects more generally of unemployment (e.g., see Ellwood 1982; Schmillen and Umkehrer 2017) and employment instability (e.g., Neumark 2002).

This paper provides evidence for a strong economic environment impacting labor market outcomes two to four years out, and that disadvantaged workers often experience an even greater benefit than their advantaged counterparts. However, weak economic environments have a similarly long reach, and the negative impact is even stronger than that left over from a strong economy. While all workers benefit from exposure to a high-pressure environment, there is no evidence here that the distribution of economic impact on labor market outcomes across the business cycle, alone, will be effective in putting a dent in labor market disparities across demographic groups.

2 Quantifying State-level Labor Market Gaps and Hot and Cold Economic Periods

We quantify the economic environment of state, *s*, in year, *t*, based on how the state's unemployment rate ($UR_{s,t}$) relates to its long-term unemployment rate ($LTUR_{s,t}$). That difference is the unemployment rate gap:

$$GAP_{s,t} = UR_{s,t} - LTUR_{s,t} \; . \quad (1)$$

Use of the unemployment rate to quantify the economic environment dates back at least to Okun et al. (1973), which builds on the assumption made explicit in Okun (1962, 6) that, "idle labor is a satisfactory measure of all idle resources." So, while there are many other statistics one may draw upon to characterize current conditions of the labor market (for example, Faberman et al. 2020), we take our lead from U.S. Monetary Policymakers' focus on the relationship between the unemployment rate and the LTUR in characterizing how far the economy is from full employment.

Whether this unemployment rate gap is positive or negative will further classify the economic environment as either "cold" (the current unemployment is higher than the long-term average) or "hot", respectively. The estimate of the LTUR for the United States is provided by the Congressional Budget Office (CBO) based on a set of Philips curve equations, which describe an inverse relationship between the rate of unemployment and the rate of inflation (Arnold 2008; CBO 1994).[3] Since the notion of state-specific inflationary pressures isn't realistic, the CBO does not construct a LTUR for each state separately. However, employment conditions can vary widely across states. Therefore, we construct state-specific LTURs based on the CBO's estimation of the national LTUR and a state's long-term employment condition relative to the national condition.

Economic conditions experienced by workers have been found to vary dramatically and persistently across states (Partridge and Rickman 1997; Walden 2012). Therefore, each state's LTUR ($LTUR_{s,t}$) is constructed by adjusting the CBO's national LTUR ($LTUR_{US,t}$) by the difference between the average state ($\overline{UR}_{s,7615}$) and national ($\overline{UR}_{US,7615}$) unemployment rates between 1976 and 2015 -- a state-specific shift in the LTUR as reported by the CBO:

$$LTUR_{s,t} = LTUR_{US,t} + \left(\overline{UR}_{s,7615} - \overline{UR}_{US,7615}\right) . \tag{2}$$

[3] We make use of the CBO's LTUR, rather than the "Natural" unemployment rate since the CBO did not make explicit adjustments to the natural rate for structural factors before the Great Recession. CBO's estimates of potential GDP are based on the underlying LTUR. See "Potential GDP and Underlying Inputs" on the CBO's web page for historical estimates for the underlying long-term national unemployment rate: https://www.cbo.gov/about/products/budget-economic-data#6.

If labor market conditions at the state level exhibit different dynamics than those at the national level, this intercept shift may not fully capture the difference in exposure of workers across states. However, while one study concludes, "there is no long-run co-movement between the aggregate US unemployment rate and individual state unemployment rates," (Payne et al. 1999), another finds, "evidence for a strong national component in disaggregate [state] unemployment rate series," (Hotchkiss 1991b). Certainly, our construction of a state-specific measure of labor market conditions is a first-order improvement over relying on a national indicator of the economic environment to which someone is exposed.

We make use of monthly Current Population Survey (CPS) data between 1976 and 2015 to calculate each state's average annual unemployment rate. The CPS is administered each month by the U.S. Bureau of Labor Statistics to roughly 60,000 households. This is the nationally representative cross-sectional survey from which we get reports of the unemployment rate and the labor force participation rate, among other monthly labor market statistics.

As an example, Figure 1 illustrates the LTUR along with the actual annual unemployment rate for two states — North Dakota and Mississippi. The black dashed line reflects the national LTUR. Note that North Dakota's actual unemployment rate is almost always below the national LTUR and Mississippi's actual unemployment rate is almost always above the national LTUR. The gray bars reflect years in which the U.S. economy was in a recession. The unemployment gap is measured by the difference between a state's annual unemployment rate and the state's LTUR. When the annual unemployment rate falls below the LTUR, the state is in a high-pressure (hot) economy. When the annual unemployment rate is above the LTUR, the state is in a cold economy. As can be seen in these figures, sometimes the national recession corresponds to a state-level cold economy (e.g., during the 1983 recession for Mississippi), and sometimes it does not (e.g., during the 2001 recession, also for Mississippi).

[Figure 1 about here]

Adjusting for the consistently low unemployment experience of North Dakota and the consistently high unemployment experience of Mississippi produces much lower overall high-pressure exposure for North Dakota residents, relative to those living in Mississippi. An online data appendix contains graphs analogous to Figure 1 for all states in the U.S. On average, during hot periods workers experience an unemployment rate that is 0.78 percentage points below their state's LTUR, and during cold periods an unemployment rate that is 1.2 percentage points above their state's LTUR. In other words, cold economic environments are typically more intense than hot economic environments. In addition, on average, each person in the sample is exposed to a hot economic environment for only 27 percent of their time in the sample. The analysis below not only accounts for the intensity of the exposure to a hot and cold economic environments (through the size of the gap at any given time), but also the duration of exposure to each type of environment by measuring how long the hot or cold period has lasted.

One might argue that constructing state-specific LTURs to determine workers' exposure to a hot economy will understate the relationship between a high-pressure environment and labor market outcomes. For example, if one were to compare each state's unemployment rate to the national LTUR in order to define a high-pressure environment in that state, we would conclude that North Dakota is nearly always in high-pressure environment and Mississippi is almost never in one; these are, of course, extreme cases. As a robustness check we use the national LTUR to define high-pressure environments in each state. This produces very similar, but less precise, results, both in terms of magnitude and patterns across demographic groups (discussed below along with additional robustness results).

3 The National Longitudinal Surveys of Youth (1979 and 1997)

The National Longitudinal Surveys of Youth (NLSY79 and NLSY97) are nationally representative annual surveys started in 1979 and 1997 of young people born between 1957 and

1964 (NLSY79) and young people born between 1980 and 1984 (NLSY97).[4] The NLSY79 started with 12,686 respondents and NLSY97 started with 8,984. The annual NLSY79 surveys became biennial after 1994. Figure 2 illustrates the oldest and youngest ages we have from each survey in each year, along with recessionary bars. The last year of data that we have for the 1979 cohort is 2014 and for the 1997 cohort is 2013. In creating consistent demographic comparison groups across cohorts, only three racial groups are identified for the NLSY79 cohort, requiring all racial groups other than black, non-Hispanic and Hispanics to be grouped with white, non-Hispanics. Figure 2 illustrates that identification of the impact the economic environment on various labor market outcomes are derived from being able to observe individuals across multiple recessions and expansions.

[Figure 2 about here]

Estimating samples differ across labor market outcome analyses due to missing values and analysis-specific selection criteria. An online data appendix describes all of the restrictions producing the estimating samples and the impact of those restrictions on sample sizes. We restrict the sample to include individuals 18 and older; the maximum age in the sample is 57. The higher share of black and Hispanic observations than one might expect reflects the oversampling of these groups by the NLSY.[5] Table 1 provides a comparison of demographic characteristics across cohorts and by age using the sample for the unemployment outcome. Note that the cohorts overlap in two of the age groups in the table. Various long-term trends are reflected in the sample averages. For example, the rise in average educational attainment over time can be seen comparing cohorts within an age group – the share with less than a high school degree is lower and the share with college or more is higher among the NSLY97 cohort.

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[4] See https://www.bls.gov/nls/nlsy79.htm and https://www.bls.gov/nls/nlsy97.htm
[5] For more information on oversampling in the NLSY see: https://www.nlsinfo.org/content/cohorts/nlsy97/using-and-understanding-the-data/sample-weights-design-effects/page/0/0/#practical

[Table 1 about here]

4 Modeling the Long-term Impact of Hot and Cold Economic Environments

The share of time during the year in the labor force spent unemployed, the share of time spent out of the labor force, and real log hourly pay are the labor market outcomes analyzed here.[6] Comparing the impact of high-pressure exposure on labor market outcomes of advantaged and disadvantaged workers will provide evidence as to how effective such environments might be in putting a dent in existing labor market gaps (Antecol and Bedard 2004).

Labor market outcome $LMoutcome_{ist}$, of person *i*, in year, *t*, in state, s, is expressed as a function of the person's individual demographics; current and lagged values of the labor market gap (GAP_{ist-j}), where *j=0,2,4*;[7] the gap interacted with an indicator (0/1) for a "hot" labor market ($HotDum_{t-j}$); and, the year of either the hot or cold episode ($Hotyr_{t-j}$ or $Coldyr_{s,t-j}$), which captures the impact of the duration of the respective economic environment:

$$LMoutcome_{i,s,t} = \alpha + MALE_i + \sum_{k=2}^{4} AGE_{i,t}^{k}\,\delta_k + \sum_{k=2}^{3} RACE_i^{k}\,\beta_k + \sum_{k=2}^{3} EDUC_{i,t}^{k}\,\varphi_{1k}$$

$$+ \sum_{j=0,2,4} \left[GAP_{s,t-j}\left(\theta_{1j} Coldyr_{s,t-j} + \theta_{2j} Coldyr_{s,t-j}^{2}\right)\right]$$

$$+ \sum_{j=0,2,4} \left[GAP_{s,t-j} HotDum_{s,t-j}\left(\rho_{1j} Hotyr_{s,t-j} + \rho_{2j} Hotyr_{s,t-j}^{2}\right)\right]$$

$$+ \tau_t + \sigma_s + \pi_i + \varepsilon_{i,s,t}\ .^{8} \qquad (3)$$

Note that in this specification, "cold" actually corresponds to the typical economic environment. Over this time period, states spent an average of 70 percent of the time in a cold

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[6] Weekly hours of work as an outcome was also investigated, but there is not enough within-person variation in hours to identify any significant relationships across the business cycle.
[7] Longer lags generally were not found to be statistically significant. Lags enter in two-year intervals because of the every-other-year sampling for the 1979 cohort that began after 1994.
[8] This specification is akin to one estimated by (Aaronson et al. 2019), although they estimate their model using aggregated cross-sectional data and do not include a measure of the hot period duration.

environment. Additionally, $Hotyr_{i,t-j}$ and $Coldyr_{s,t-j}$ can be thought of as the "age" of hot and cold periods, respectively, and will capture the importance of duration of a particular type of economic environment, as opposed to the intensity of the economic environment, which is captured by $GAP_{i,s,t-j}$. The squared terms allow the potential impact of duration to be non-linear.[9]

The average impact of a change in the gap at time *t-j* on the labor market outcome of interest is given by the partial derivative $\partial LMoutcome_{i,s,t}/\partial GAP_{i,s,t-j} = \hat{\theta}_{1j}\overline{Coldyr}_{i,t-j}+\hat{\theta}_{2j}\overline{Coldyr}^2_{i,t-j} + \hat{\rho}_{2j}\overline{HotDum}_{i,t-j}\left(\overline{Hotyr}_{i,t-j} + \hat{\rho}_{3j}\overline{Hotyr}^2_{i,t-j}\right)$; the marginal impact of each additional hot or cold year are similarly estimated. This specification explicitly allows for a differential impact of the current and lagged economic environment on the labor market outcome depending on whether the person is in a hot or cold period. It is almost certainly the case that current and lagged economic environments are correlated. But the goal here is to elicit the <u>additional</u> influence the gap from two (or four) years ago has on outcomes <u>over and above</u> the influence of the contemporaneous economic conditions; we want to isolate the impact of each period's influence by also controlling for surrounding periods' economic conditions. We find that if the model is estimated including each economic period by itself (i.e., current or 2-year or 4-year lag by themselves), the point estimates are further from zero (larger in absolute value) supporting our marginal interpretation of the results.

We allow for full interaction of all of the regressors with each demographic variable by estimating equation (3) separately for each demographic group. This not only allows each of the regressors of interest to impact labor market outcomes differently, but also allows the error structure to vary by demographic group. The regression includes year (τ_t), state (σ_s), and person (π_i) fixed effects. Of course, the race and gender indicators are not identified when the individual

[9] Replacing the continuous duration regressors with dummy variables does not change any conclusions about the importance of duration.

fixed effect is included as a regressor, but all of the demographic groups for which we estimate separate regressions are listed in the equation for completeness. Individual fixed effects will capture unobserved time-invariant, person-specific contributions to the observed labor market outcomes. For example, a high-ability person will likely be observed with relatively high earnings across all economic environments, and someone with a high disutility of work will be observed with relatively low participation or hours of work regardless of the economic environment.

For each outcome, estimation is performed using Ordinary Least Squares (OLS) and standard errors are robust to cross-sectional heteroskedasticity and within-panel serial correlation (for example, see Arellano 2003; Stock and Watson 2008). Identification of the impact of the gap (and whether the person is observed during a hot or cold period) comes from observing individuals across multiple hot and cold economies. Overall, the median contribution will vary across sub-sample. For the full sample, the median number of cold periods an observation contributes is eleven (min=0, max=25) and the median number of hot periods is six (min=0, max=15). However, for the youngest age demographic group, the median contribution is four cold periods (min=0, max=7) and two hot periods (min=0, max=12).

Differences in marginal effects across demographic groups (which is the focus of this analysis) derive from the separate estimation of equation 3 by demographic group (e.g., black, high school grads, 18-24 year-olds, etc.), while controlling for the other characteristics of each individual within that group (e.g., individuals' age and education). Predicted outcomes will not only be a function of these demographic-specific parameter estimates, but also the characteristics of the individuals in that group. We will illustrate below the importance of those characteristics relative to the structural influences of different parameter estimates and unobservables in determining labor market outcomes.

Results from three labor market outcomes are presented here: (1) the share of time in the labor force during the year that a person spends unemployed -- this can be thought of as a personal unemployment rate (conditional on labor force participation); (2) the share of time during the year spent out of the labor force; and (3) the log real hourly wage on a person's main job during the year -- estimated on workers only.[10] Since wages are observed for workers only, that analysis will be augmented by controlling for individual selection into employment.[11]

Robustness specifications are estimated and detailed below. Additionally, depending on the outcome, additional sample considerations are made, such as labor market attachment and other sample selection issues. Details of the construction of each sample used to estimate each outcome are provided in an online data appendix.

5 Results

We will focus in detail on the marginal effects for the share of time spent unemployed since these results are the most precisely estimated among the outcomes considered. Some results for the share of time spent out of the labor force and log real hourly pay are contained in Appendix A and discussed briefly below, with additional results available in an online data appendix. Appendix B contains results from various robustness tests that will be discussed after presentation of the main results.

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[10] For the 1979 cohort, hourly pay is collected for up to 5 jobs during the year. The person's "main" job is defined as the one on which they worked the most number of hours. It is for that job that hourly pay is used for those analyses. For the 1997 cohort, hourly pay is collected for up to 7 jobs during the year. The person's "main" job during the year is identified by NLSY and the hourly pay corresponding to that job is used for those analyses.

[11] A standard two-step Heckman-correction methodology (Heckman 1974) is used, where the first stage is to estimate the probability of employment. Spouse earnings (if married) and number of children are used as identifying regressors. Parameter estimates from this probit are then used to construct an "inverse mills ratio." This mills ratio, designed to capture unobserved determinants of observed hours or wages that may be correlated with the probability of employment, is then included as an additional regressor in the second stage outcome regression, theoretically resulting in unbiased marginal effects for the regressors of interest that are generalizable to the un-selected population.

5.1 Share of Time in the Labor Force Spent Unemployed

5.1.a Estimated Marginal Effects

Table 2 contains the marginal effects of the state-specific unemployment gap on the share of time during the year that an individual in the labor force spent unemployed, differentiated by hot and cold periods. The positive marginal effects across the board indicate that the larger the unemployment gap (the weaker the economy), the greater share of time spent unemployed. For example, for the full sample (all demographic groups combined), a one percentage-point increase in the current unemployment rate gap (t) increases the share of time spent unemployed, on average, by 0.42 of a percentage point. The largest impact comes with a two-year lag (t-2) and the impact of a change in the current and two-year lagged gap is slightly larger during a hot economic period than during a cold economic period.[12] This is observed generally and across demographic groups -- except for men, as might be expected, whose unemployment experience has been historically more dramatically impacted during cold economic periods. However, the four-year lagged gap reached more consistently and significantly across cold periods than hot periods for both men and women.

[Table 2 about here]

The results in Table 2 illustrate well what is meant by disadvantaged demographic groups experiencing a "higher-beta" impact of changes in economic conditions (for example, see Aaronson et al. 2019; Hotchkiss 2019). In other words, generally, the marginal impact of an increase in the gap is larger for racial/ethnic minorities and those with less than a college degree than for their more advantaged counterparts. The evidence is not as strong for the youngest age group of 18-24 year-olds. While the marginal effects for 25-34 year-olds are the most precisely estimated (likely because of their largest sample size), the point estimates are often smaller than

[12] Note that even during a "hot" economic period, an increasing gap is indicative of a weakening labor market.

those for older cohorts. The negative contemporaneous effect estimated for 35-44 year-olds is an outlier suggesting that 35-44 year-olds, on average, experience a *decrease* in the amount of time they spend unemployed during a current cold period. However, this age group is harder hit than other age groups within two years.

The results for racial/ethnic minorities and the less educated are consistent with the literature that suggests that particularly strong growth can help to narrow labor market disparities between advantaged and disadvantaged workers (Bradbury 2000; Couch and Fairlie 2010), and that disadvantaged groups face worse labor market outcomes during recessions (Cajner et al. 2017; Engemann and Wall 2010; Hoynes et al. 2012).

The results in Table 2 speak specifically to the question of positive hysteresis by illustrating that disadvantaged groups -- blacks, for example -- benefit by a greater amount, but with a lag, than their advantaged counterpart. For example, the lingering benefit from a hotter economic period two years ago for blacks (1.1 percentage point decline in share of time spent unemployed for each percentage-point decline in the gap) is larger than for whites (0.49), and is larger than the two-year lagged affect from exposure to a cold economic environment (0.93). However, the hit that blacks get during cold economic periods, contemporaneously and at both lags, is larger than the hit experienced by whites.[13] This result is consistent with Jefferson (2005, 2008) who finds that economic downturns are fundamentally worse events for disadvantaged workers (i.e., blacks and the less educated).

Across the board, those with less than a college degree are impacted much more dramatically, both in hot and cold economic periods, than those with a college degree. Additionally, those with the lowest education levels (less-than-high-school and high school) are hit harder by cold periods than their more educated counterparts. Additionally, the benefit from a

[13] These differences are statistically significantly different from one another at a 99 percent confidence level based on a standard Z-test.

hot period two years ago is larger for those with a high school degree (0.65 percentage point decline in the share of time spent unemployed for a one percentage point increase in the gap) than for those with some college (0.59 marginal effect).

Table 3 addresses the question of the importance of duration of both cold and hot economic periods on the share of time spent unemployed. In addition to the current period's marginal effect, the table contains the estimated marginal effect of one additional year of a low-pressure or high-pressure period that occurred two and four years ago.

[Table 3 about here]

Very few of the marginal effects of an additional year of a hot period, either contemporaneously or lagged, significantly affect the share of time spent unemployed. However, there seems to be more of a cumulative effect of a cold period, both contemporaneously and lagged, on the share of time spent unemployed. Additionally, the effect is larger for men, racial/ethnic minorities, the less educated, and the young, relative to each of their demographic counterparts. Taking the results in Tables 2 and 3 at face value, we can compare the relative importance of intensity and duration of an economic period. For example, for the full sample, whereas an additional percentage point increase in the contemporaneous gap (holding duration constant) is associated with a 0.42 percentage point (1.6 standard deviation) increase in the share of time spent unemployed, on average, an additional year in a cold period (holding intensity constant) is associated with a 0.07 percentage point (0.3 standard deviation) increase point increase in the share of time spent unemployed. In other words, additional duration is less than 20 percent as impactful as additional intensity on the share of time workers spend unemployed.

Robustness results for all outcomes are presented and discussed in Section 6. One robustness test specific to the unemployment outcome estimation worth mentioning here excludes those who spend one hundred percent of their time employed. These results are included with the other robustness results in Appendix B and indicate that current and lagged economic environments are more impactful (larger marginal effects) for individuals who spend at least some of their time during the year unemployed. This is likely because disadvantaged workers are disproportionally represented in this sample and we have already established the higher-beta experience of individuals from disadvantaged demographic groups.

5.1.b Predicted Outcomes: The role of demographics vs. systemic factors

Since each of the demographic characteristics in the group-specific estimation (e.g., age and education when estimating equation 3 by race/ethnicity) are not interacted with the gap regressors, the marginal impact will not vary depending on those characteristics. However, the predicted outcome will differ depending on the group for which the outcome is estimated. The reason for estimating equation (3) by demographic group is to allow the mechanism (and unobservables) by which the economic environment is related to the outcome to differ across demographic groups. So, for example, in the presence of systemic racism, we would expect to see the share of time spent unemployed to differ across race/ethnic groups not only because of their different age and education characteristics, but also because of the different estimated parameters, fixed effects, and unobservables in the error term

To get an idea of how important differential mechanisms might be relative to differences in characteristics for shaping outcomes across race/ethnicity, for example, Figure 3 plots the expected share of time spent unemployed for each race/ethnic group using (a) their own group characteristics (age and education) and (b) the same characteristics (25-34 years and high school education).

[Figure 3 about here]

There is hardly any difference, other than estimation precision, in the predicted outcomes in panel (a) and panel (b) of Figure 3. The implication is that the mechanisms and unobservables determining a worker's share of time spent unemployed is more related to within-group race/ethnicity than it is to differences in characteristics (i.e., age and education) across groups. Of course, one factor that could be affecting both the mechanisms (estimated parameter estimates) and unobservables is systemic racism (Powell 2008).

5.1.c Predicted Outcomes: Illustration using COVID-19 Pandemic Recession

In addition to the possible presence of systemic factors, the consistently longer duration and greater intensity of cold periods relative to hot periods throughout the past decades has resulted in the persistence of labor market gaps between disadvantaged and their advantaged counterparts. We can illustrate this point by applying the parameter estimates from this analysis to address the following question: How long will it take for the COVID-19 recession that began in 2020 to erase any gains black workers, for example, made during the 2017-2019 hot period in closing unemployment gaps?

Figure 4 (panel a) plots the actual national unemployment rate, the national LTUR through 2019, and their projections for 2020 through 2025. From this figure we can see that the U.S. was in a cold period prior to 2017, then spent three years in a hot economic environment. With the onset of the COVID-19 pandemic, the economy again, very quickly re-entered a cold economic period.[14]

[Figure 4 about here]

Panel (b) of Figure 4 reports, over each time period indicated, the average share of time during the year spent unemployed for both white and black labor force participants. During the 2010-2016 cold economic period, the unemployment gap between whites and blacks averaged 9.14 percentage points. The high-beta experience of blacks during the following hot economic period of 2017-2019 helped to reduce that gap to 7.84 percentage points. With the onset of the COVID-19 pandemic in 2020, the unemployment gap shrunk slightly to 7.81 percentage point --

[14] Projections of the unemployment rate and the LTUR from 2020 onward are from the Congressional Budget Office (CBO) 10-year economic projects released in July 2020. Using non-public Blue Chip Consensus Forecasts released in October 2020 does not change the conclusions from analysis here.

bolstered by the lingering benefits of exposure to the preceding hot economic environment. However, extending the period of time for comparison just out to 2025, the unemployment gap between black and white workers once again widens, to 8.37 percentage points -- it doesn't take long for a cold economic environment to reverse the gains made during a hot economic environment.

5.2 Share of Time Out of the Labor Force

Appendix Table A1 contains the marginal effects for the non-participation outcome. Across demographic groups, labor market conditions four years ago are most strongly associated with current non-participation in the labor market, with hot economic environments being more impactful than cold economic environments. Disadvantaged demographic groups benefiting (statistically significantly at the 99 percent confidence level) more than their advantaged counterparts from exposure to a hot economic environment include blacks, high school graduates, and the relatively young (25-34 year-olds). Additionally, women's participation decisions are more affected than those of men by a lagged hot economic environment, but not a cold one.

Taken together, the larger impact of hot economic environments than cold environments on both participation and share of time spent unemployed is consistent with Hotchkiss and Robertson (2012) who find evidence that participation decisions are more responsive to improvements in the economy than to declines in the economy. This asymmetric response of labor supply behavior is consistent with the widely noted asymmetric movement of the unemployment rate across the business cycle (for example, see Koop and Potter 1999; Neftçi 1984).

Although not estimated with much precision, we find some evidence (results available in an online data appendix) that longer periods of hot economic environments generally increase non-participation. While perhaps unexpected, this is consistent with recent findings of Higgins et al. (2019), who find evidence of what they call a "negative added worker" effect -- when an expansion becomes especially strong/long, labor force participation responses become weaker, even to the extent that a lower unemployment rate *decreases* participation.[15] Also, while not very precise, longer cold economic periods mostly (when statistically significant) increase non-participation, which is consistent with a discouraged worker effect during weak economies.

5.3 Log Real Hourly Wages

The marginal effects of changes in the unemployment gap on log real hourly pay are found in Appendix Table A2. Since much of a worker's labor market pay is related to the industry and occupation in which they work (Bayer and Charles 2018; Cajner et al. 2017), equation (3) is modified for this outcome to include both occupation and industry dummy variables.

Having controlled for potential sample selection into employment (see footnote 11), these marginal effects should be generalizable to the population. Generally, larger unemployment gaps (weaker labor markets) are associated with lower wages (as seen from the negative marginal effects), although the effect takes a while to manifest itself, as the economic condition of two and four years ago are more strongly associated with current wages than is the current economic condition. This suggests that current wages are more heavily influenced by employment contracts, rather than by the spot market (Beaudry and DiNardo 1991; Devereux and Hart 2007). In other words, if wages are solely determined by the spot market (current labor market conditions), then past economic conditions should not affect current wages. Additionally, the relationship is stronger during hot economic periods than during cold economic periods, suggesting stickier wages during a weaker economy (for example, see Kahn 1997).

Unlike the determination of unemployment and labor force (non-) participation the

[15] A negative added worker effect might mean that if one family member is doing particularly well in the labor market (because of high demand reflected in the low unemployment rate), other family members will leave the labor market and specialize in home production.

impact of past economic conditions (of four years ago) on wages is stronger among whites than blacks, with wages among whites benefiting more from hot economies than suffering from cold economies.[16] This suggests that whites are better able to parlay a high-pressure economic environment into longer-term gains in terms of wages than are blacks, although black workers do benefit more than white workers from hot economic environments of two years ago. The same is true for those with some college education (with a two-year and four-year lag) and a high school education (with a four-year lag). However, wages of those with some college or less do suffer more from exposure to a cold economy than wages of college graduates. Wages of the relatively young (25-34 year-olds), with a lag, both benefit more from past exposure to a hot economy and suffer more from a cold economy than wages of their older counter-parts.

Similar to the impact on non-participation, duration of the economic environment is rarely a factor in wage determination. This is the case for both cold and hot period durations.

6 Robustness

Appendix B contains the marginal effects for a variety of robustness checks reflecting various alternative specifications. Four robustness specifications are estimated for each labor market outcome plus some outcome-specific alternatives; these results are for the full sample only. The bottom line from these robustness estimations is that the baseline conclusions are consistent across alternative specifications.

6.1 Replace the state-specific unemployment gap with the national unemployment gap

One might argue that using state-specific employment gaps to determine workers' exposure to a hot economy will understate the relationship between a high-pressure environment and labor market outcomes. However, we find very similar results (not consistently larger or smaller than the baseline) and similar patterns when the national unemployment gap replaces the

[16] All comparisons of marginal effects mentioned here, within and between racial groups, are statistically significantly significant at the 99 percent confidence level.

state-specific gap for quantifying the current and lagged economic environment.[17] This is consistent with (Hotchkiss 1991b) who finds a very strong national component in state labor market conditions.

6.2 Exclude individual fixed-effects

We expect the individual fixed effects to be capturing unobserved time-invariant, individual-specific characteristics related to an individual's "tendency" to be unemployed, highly-paid, etc. We find that excluding individual fixed effects marginally increases the lagged impact of the unemployment gap on unemployment and non-participation, suggesting the fixed-effects are performing as expected. When the individual fixed effect is excluded as a regressor, unobserved individual characteristics are left in the error term, allowing for the remaining regressors to pick up some of the fixed effect. The degree to which excluding the individual fixed effect biases parameter estimates depends on how correlated the fixed effect is with the remaining regressors. In this case, there appears to be some correlation, but the estimated relationship between the economic environment and the outcomes is not entirely due to unobserved individual-specific factors. In other words, excluding the fixed effect magnifies the importance of the gap, but including it doesn't erase its importance.

The effect of excluding individual fixed effects from the hourly pay estimation is more mixed, but also does not produce results materially different from the baseline.

6.3 Include lagged values of the outcome variables

Current labor market outcomes are likely correlated with lagged values of those outcomes. This is the primary reason we include an individual fixed effect. However, if the correlation is time-varying, and correlated with lagged values of the gap, exclusion of lagged labor market outcomes could bias the estimated relationship of interest. To test the extent this

[17] While the pattern of point estimates is similar in the non-participation analysis using the national unemployment gap, there is a significant reduction in precision, likely as a result of less variation across observations.

exclusion might bias the estimated coefficients, we estimate the model including two- and four-year lagged values of the labor market outcome (the lagged dependent variable). Because of Nickell's (1981) warning of bias that arises with the presence of the lagged dependent variable in fixed effects models, this specification also requires excluding individual fixed-effects. Therefore, these results should be compared (for robustness purposes) to the baseline estimation excluding individual fixed effects. Including lagged outcomes primarily reduces the impact of past economic environments, suggesting we should interpret the case for hysteresis presented by the baseline results as an upper-bound.

6.4 Restrict sample to active labor force participation

It is possible that exposure to a high-pressure economy will only have an impact on those who are more attached to the labor market. This robustness specification restricts the sample to those with at least 32 weeks in the labor force during each of the previous four years. Patterns of marginal effects are the same, but slightly smaller. One reason for these smaller marginal effects is, as we might expect, those with stable labor market attachment are less impacted by business cycle fluctuations. Additionally, through this restriction we have eliminated younger observations for which the marginal effects are typically larger.

6.5 Additional robustness check for non-participation outcome

One additional robustness exercise performed for explaining labor force non-participation was the inclusion of two additional regressors typically significant in explaining labor supply behavior -- number of children and spouse's earnings (if married). Greater number of children and spouse's earnings both contribute to a statistically significant increase in non-participation, as expected, but their inclusion as regressors did not alter the estimated impact of the gap on participation, suggesting those regressors are not particularly correlated with the unemployment gap.

6.6 Additional robustness checks for hourly pay

Three additional robustness exercises were undertaken for consideration of the hourly pay analysis. First, keeping the sample the same, the final wage equation was re-estimated not controlling for sample selection; the marginal effects are nearly identical to the baseline (this is in spite of the fact that the "excluded regressors" in the first stage are statistically significant). Second, because of the potential correlation between wages and hours of work (for example, see Hotchkiss 1991a), hours worked per week was included as an additional regressor in the hourly pay regression; the marginal effects were, again, nearly identical to the baseline. And, third, the baseline specification was re-estimated excluding occupation and industry indicators. While not much different from the baseline, the marginal effects with a two-year lag are larger than when occupation and industry are included. This suggests that some of the workers' labor market experiences across the business cycle are, not surprisingly, industry and/or occupation specific (Bayer and Charles 2018; Cajner et al. 2017).

6.7 The role of migration

The greater benefit that disadvantaged workers experience during hot economies is typically interpreted as employers digging deeper into the labor pool and giving opportunities to disadvantaged workers they would not normally employ. In other words, a hot economy results in, or causes, disproportionately better outcomes among disadvantaged workers. However, if disadvantaged workers have better outcomes simply because they are more likely to "chase" better economic environments, the argument to prolong a high-pressure economy in order to improve the long-term outcomes of disadvantaged workers would not be justified -- the better outcomes are not "caused" by a hot economy, but, rather, by the self-selection of workers moving to better opportunity.

However, if disadvantaged workers are able to chase good economic environments, one might argue that they would also be more likely to "flee" bad economic environments, which is inconsistent with the results in Table 2 showing an even stronger negative impact on outcomes during weak economies for disadvantage workers. There is a long literature showing that economic conditions have a stronger "pull" factor than "push" factor (for example, see Boyd 2002; Hotchkiss et al. 2008), suggesting the stronger impact of hot economic environments still might be the result of selection, rather than causal.

To take a closer look at the evidence for selective behavior, we estimate the model separately for movers (those who were living in a different state 4 years ago than currently) and non-movers (those who have been in the same state for the past 4 years).[18] The marginal effects are mostly stronger and more statistically significant for non-movers than for those living in a different state four years ago. This is not consistent with movers driving the results in the baseline.[19] Additionally, if selection were driving the larger marginal impact of changes in the gap during hot economic environments among the disadvantaged, then we should see *greater* migration among the disadvantaged. However, consistent with other literature on migration (for example, see Burns and Hotchkiss 2019; Greenwood 1975), migration is higher among the advantaged (i.e., white, non-Hispanics and college educated). This suggests that the extra benefit black workers and the less educated reap from exposure to a hot economy derives not from self-selection through migration, but from the exposure to that environment itself.

7 Summary and Policy Implications

The main conclusions from the analyses in this paper can be summarized as follows:

(a) some labor market outcomes are impacted more from exposure to a hot economic environment than other labor market outcomes;

(b) disadvantaged workers are impacted more dramatically by both hot and cold economic environments than their "advantaged" counterparts;

[18] There are roughly half as many people having moved within the last two years versus the last four years, so we use the last four years to get as many movers as possible.

[19] The only exception are the results for the share of time spent unemployed lagged two years.

(c) the impact of exposure to hot economic environments on labor market outcomes is typically larger than the impact of cold economic environments; and
(d) the duration of a particular economic period is typically not as important for labor market outcomes as the intensity of the environment exposed to.

These results suggest that progress might be made in shrinking labor market gaps between advantaged and disadvantaged workers by policy makers orchestrating dramatic high-pressure economic periods. However, additional evidence suggests that sustained progress in closing labor market gaps is unlikely to be achieved through exposure to hot economic environments alone. While disadvantaged groups benefit more from hot periods, they also suffer more from cold periods -- what has been called the "high-beta" experience of disadvantaged demographic groups (also see Aaronson et al. 2019). And, since cold economic environments are typically more intense and last longer than hot economic environments, the net result is a lack of sustained progress in closing labor market gaps.

The importance of the underlying labor market structure in impeding progress across the business cycle was also illustrated by finding that worse outcomes across both hot and cold economies are observed among racial/ethnic minorities with the same characteristics as their white counterparts. This suggest that the mechanisms and unobservables (such as, systemic racism) play a much larger role in determining labor market outcomes than observed characteristics.

Among all groups, the duration of a high-pressure economic environment has little influence in addition to its intensity, whereas the duration of a low-pressure economic environment does marginally negatively impact labor market outcomes, but not as dramatically as the intensity of that environment. In other words, while the size of the unemployment gap significantly influences labor market outcomes, those outcomes are essentially the same, all else equal, for someone who experienced a hot economic environment that lasted one year as someone exposed to a hot economic environment that lasted four years. The duration of cold economic environments, however, have more of an impact on the share of time spent unemployed than on other outcomes -- but, again, the impact of a longer cold period is only a fraction of the impact of a more intense cold period.

The two main conclusions from the analysis in this paper -- that current and future labor market outcomes of disadvantage workers benefit more from exposure to a hot economy, but also suffer more from a weak economic environment, relative to their advantaged counterparts, and that duration of hot periods is not as important as being in one -- have at least three important policy implications. First, they suggest that merely prolonging high-pressure economic environments, ceteris paribus, will not, alone, effectively closing labor market gaps. The expectation by some that hot economies can reduce labor market gaps originates with Okun's (1973) notion of cyclical upgrading, and is buoyed by empirical evidence of the high-beta experience of disadvantaged groups during particularly strong economic environments. However, a careful reading of Okun (1973) -- specifically, his rebuttal to comments on his research -- reveals that he was not suggesting that a "high-pressure policy" will, *by itself*, permanently reduce labor market gaps between advantaged and disadvantaged workers. Just creating more good jobs is not enough. He literally calls for "manpower programs" to take advantage of hot-economic environments to, "incorporate a major effort to instill training and the basis for upgrading [skills], rather than merely create more [good] jobs" (Okun 1973,p. 245). The identification of the need for coordinated effort between training programs and fiscal or monetary policies directed at creating good jobs is consistent with Chetty et al. (2018) who present evidence of deep roots for ongoing racial disparities, particularly among men -- disparities of a more structural rather than cyclical nature.

The second implication is that policies that can reduce the volatility of the economy (e.g., fewer and less severe recessions) will likely benefit disadvantaged workers more than attempting to prolong a high-pressure economic environment alone. Understanding why every high-pressure economic period since 1960 has ended in recession (Bostic 2018) would be useful in addressing what seems like that inevitability, and perhaps have a chance of making a dent in observed labor market disparities. However, successfully reducing cyclical volatility is complicated by an environment in which monetary policy is bounded from below -- an environment in which the U.S. found itself in the aftermath of the Great Recession. As Coibion et al. (2017) point out, interest rates bounded by zero effectively become contractionary if economic conditions say they should be lower. Consequently, appealing to non-traditional monetary policy strategies may be required in order to avoid the consequences of a contraction in such an environment (for example, see Feiveson et al. 2020).

And the third implication is that in periods of unforeseen negative shocks to the economy, as was experienced by the COVID-19 pandemic, it doesn't take long for gains made in reducing labor market disparities during a preceding hot period to be erased by a sudden and dramatic downturn. If policies aren't undertaken to enable disadvantaged workers to better take advantage of hot periods, or to eliminate structural contributors to the determination of labor market outcomes, it will be highly unlikely that there will be a significant reduction in labor market disparities.

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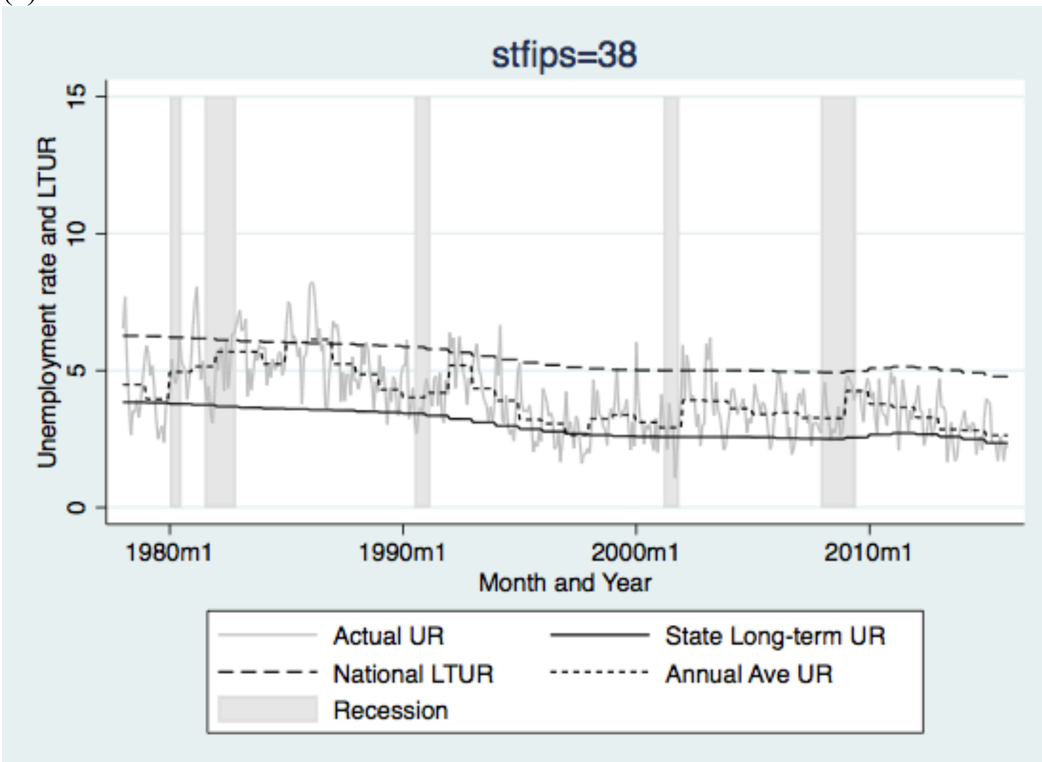
Figure 1 Actual and natural rate of unemployment for North Dakota and Mississippi.

(a) North Dakota



(b) Mississippi

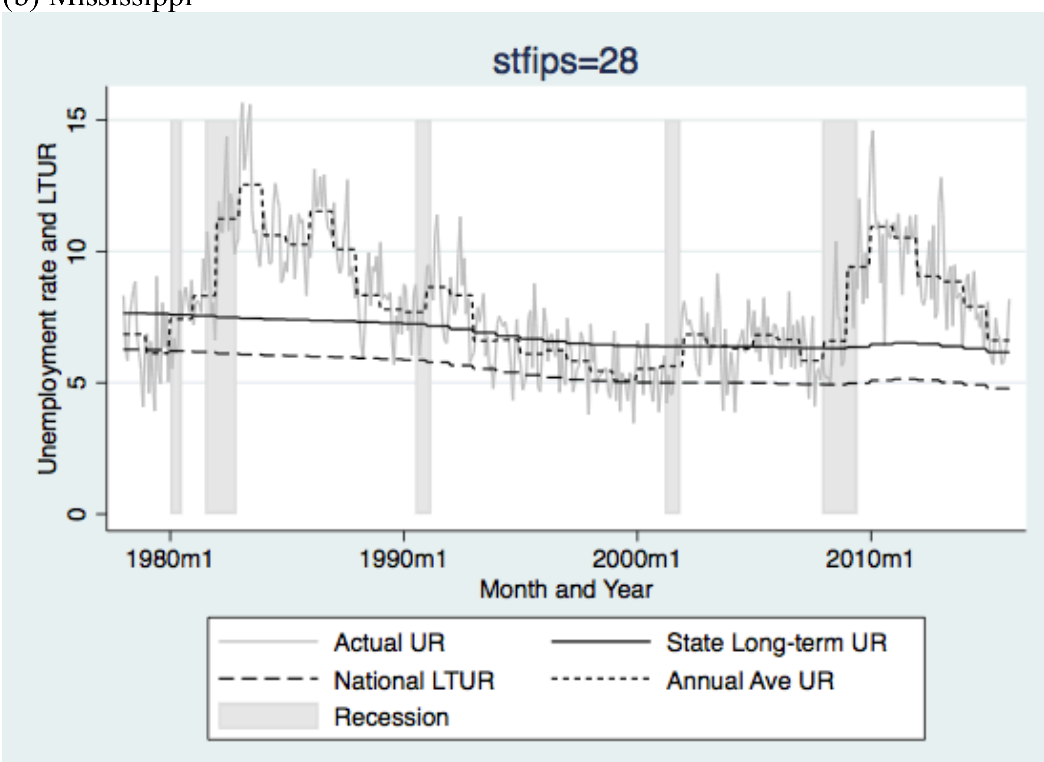
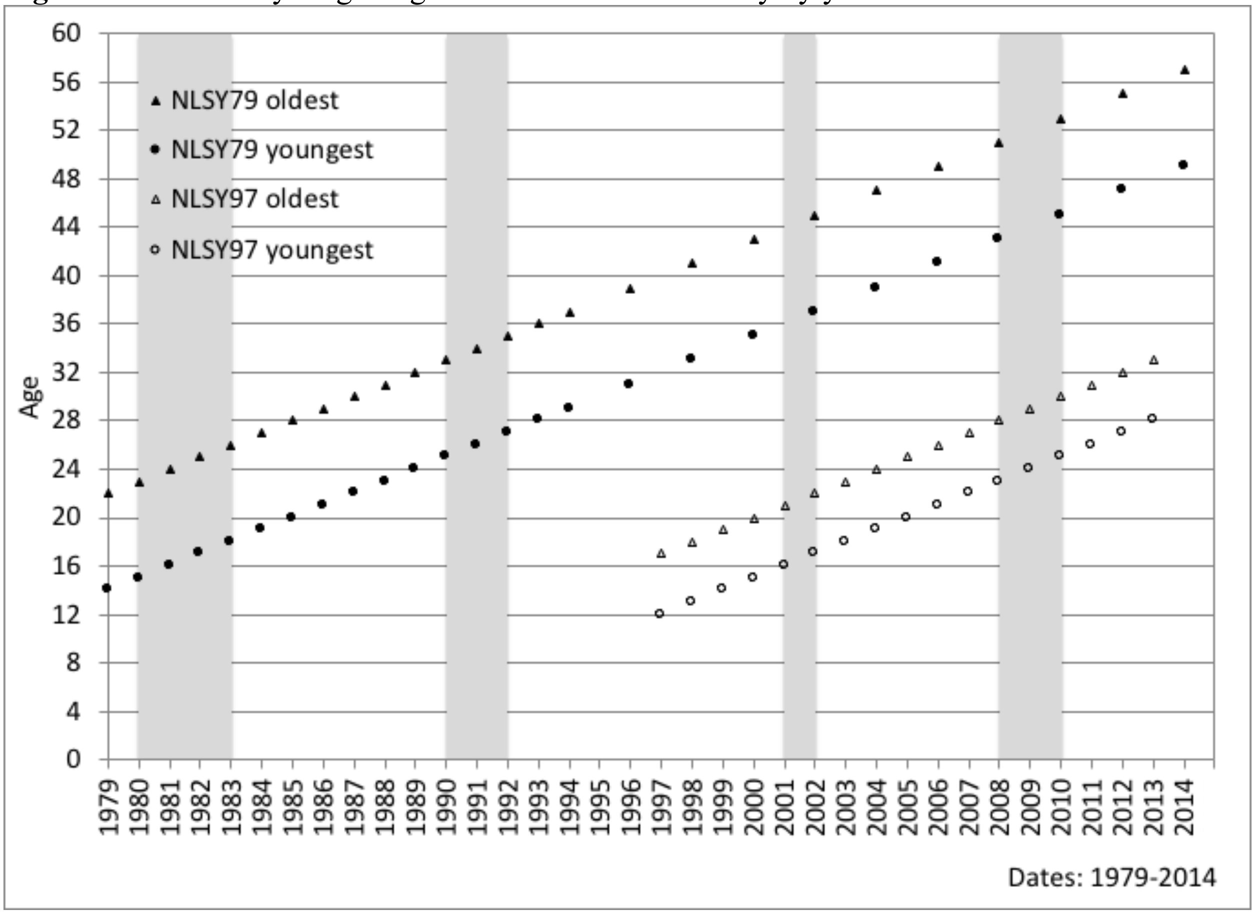


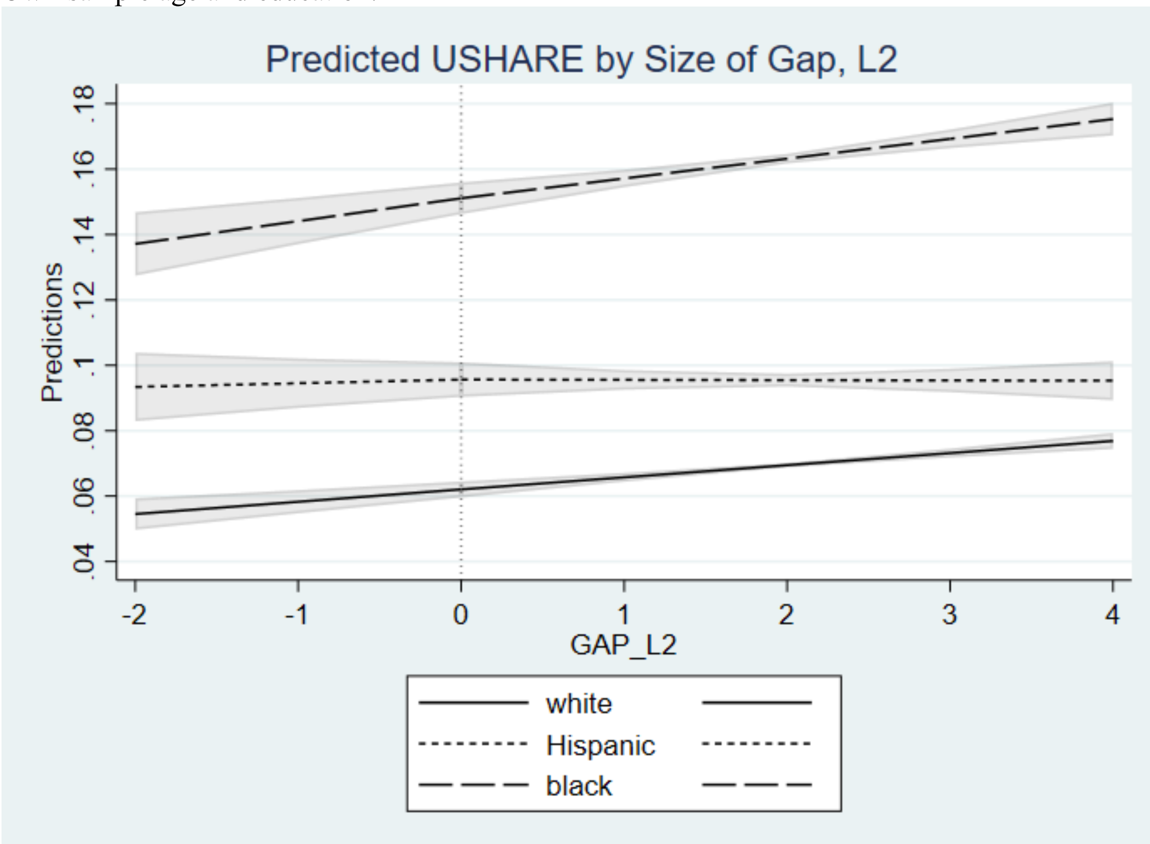
Figure 2 Oldest and youngest ages from each NLSY survey by year.



Note: Recessionary years shaded in gray

Figure 3 Predicted share of time in the labor force spent unemployed by size of gap.

(a) Own-sample age and education.



(b) Median values (25-34 years, HS education)

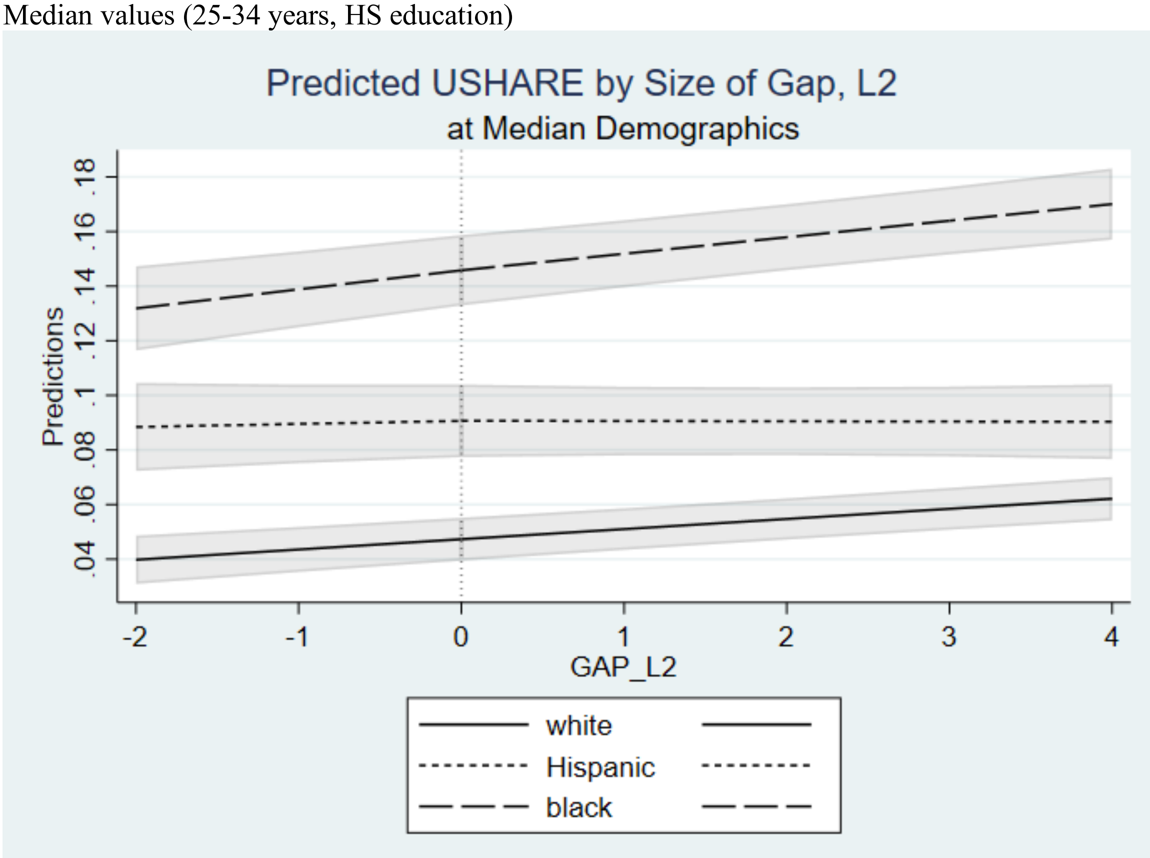
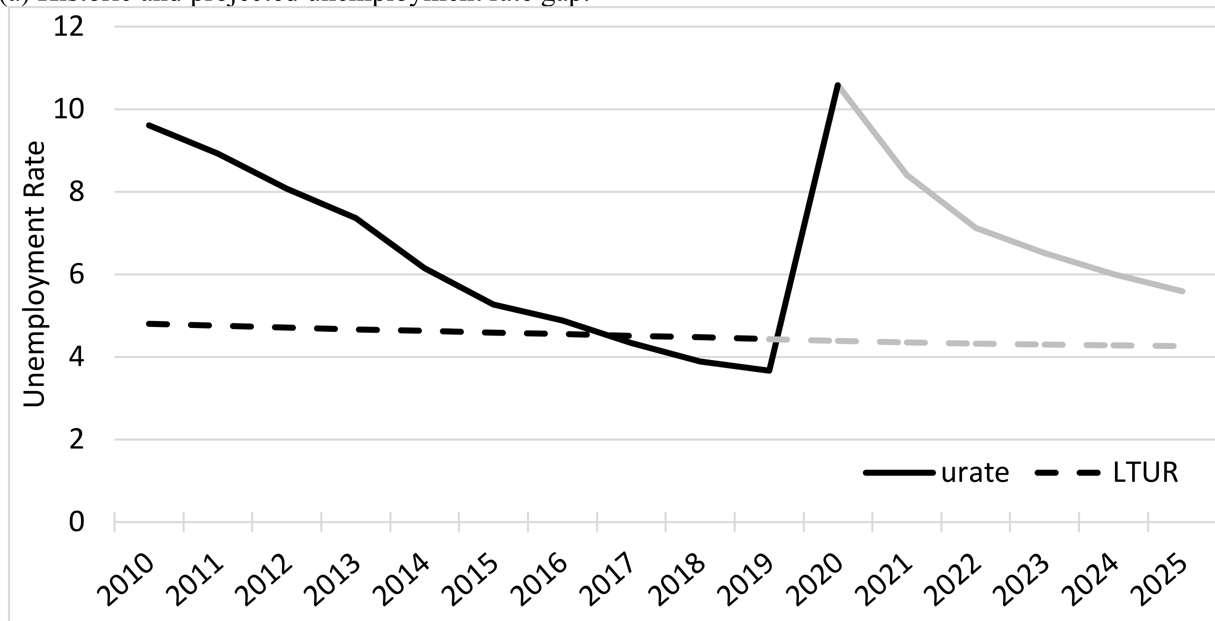


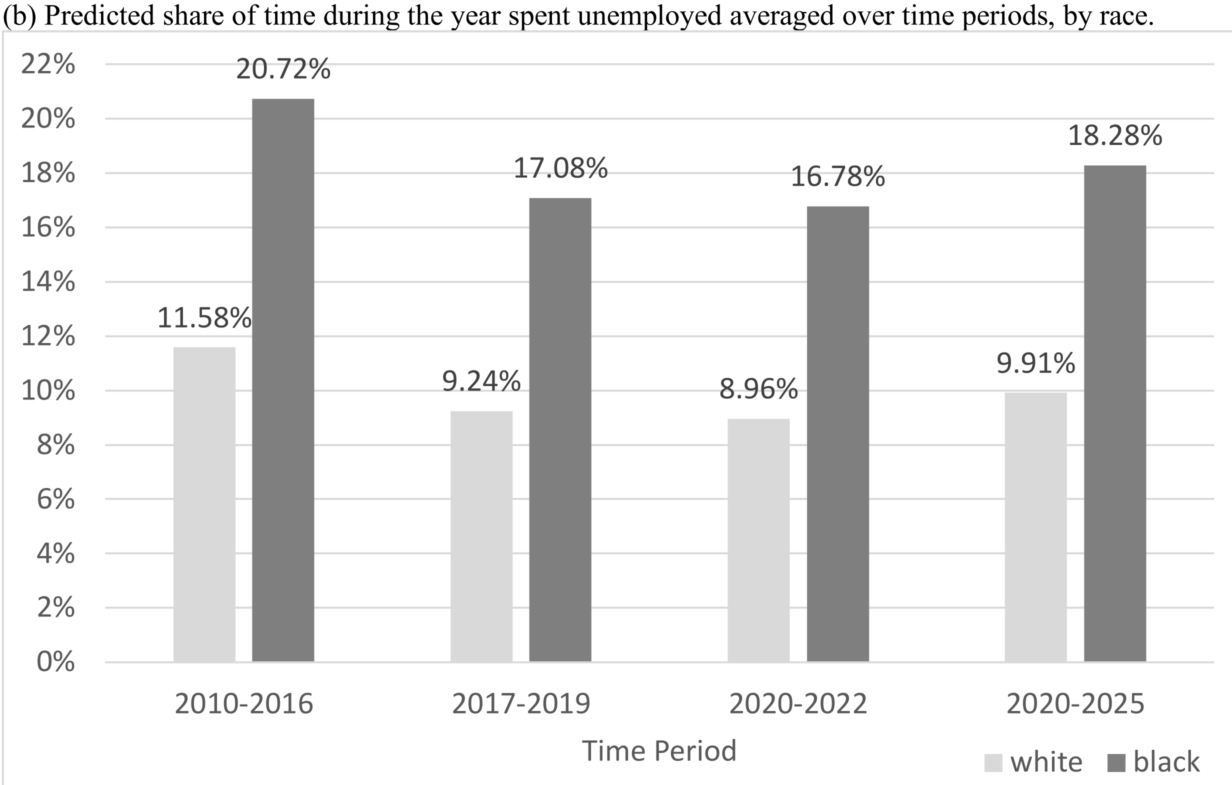
Figure 4 Historical and projected economic environment and predicted average share of time spent unemployed by race.

(a) Historic and projected unemployment rate gap.



Source: U.S. Bureau of Labor Statistics, Unemployment Rate [UNRATE], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/UNRATE, October 3, 2020. CBO 10-year Economic Projections; https://www.cbo.gov/data/budget-economic-data (July 2020).

(b) Predicted share of time during the year spent unemployed averaged over time periods, by race.



Source: Authors calculations using estimated paramters from equation (3) and NLSY data.

Table 1 Unweighted sample means of NLSY of unemployment estimating sample by cohort and age group.

	All Ages		18-24 year olds		25-34 year olds		35-44 year olds	45-64 year olds
Variable	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY79
Age 45-64 = 1	0.1756							
Age 35-44 = 1	0.2258							
Age 25-34 = 1	0.4694	0.6628						
Age 18-24 = 1	0.1292	0.3372						
College or more = 1	0.2122	0.2923	0.1397	0.2488	0.2053	0.3144	0.2234	0.2697
Some College = 1	0.2392	0.3155	0.2281	0.3273	0.2228	0.3096	0.2466	0.2814
High School = 1	0.3599	0.2658	0.3793	0.2839	0.3643	0.2565	0.3542	0.3411
Less than HS = 1	0.1887	0.1264	0.253	0.14	0.2075	0.1195	0.1758	0.1078
White & Other = 1	0.5448	0.5159	0.581	0.5246	0.5601	0.5115	0.5171	0.5127
Hispanic = 1	0.1734	0.2125	0.1643	0.2108	0.1682	0.2134	0.183	0.1816
Black = 1	0.2818	0.2715	0.2547	0.2646	0.2717	0.2751	0.2999	0.3057
Male = 1	0.5051	0.5029	0.5021	0.4985	0.5076	0.5051	0.5068	0.4988
Share of time in LF spent unemployed	0.095 (0.2452)	0.1128 (0.2652)	0.1724 (0.3031)	0.1065 (0.2454)	0.0999 (0.246)	0.116 (0.2746)	0.0605 (0.2054)	0.0692 (0.2284)
Person/year Observations	155,059	59,399	20,028	20,029	72,784	39,370	35,011	27,236

Note: Details of sample construction are contained in an online data appendix. Samples include NLSY oversample of the poor and racial/ethnic minorities. Standard deviations in parentheses. Racial groups other than "Black" are not distinguished in the 1979 cohort so are combined with "White" for the full sample.

Table 2 Marginal impact of a one percentage point change in the unemployment gap on the share of time spent unemployed.

	Current Gap (t)	Gap (t-2)	Gap (t-4)	Current Gap (t)		Gap (t-2)		Gap (t-4)	
Outcome/Group	Gap marginal effect average across both hot and cold periods			positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)
Full Sample	**0.0042*****	**0.0052*****	**0.0023****	**0.0041*****	**0.0043*****	**0.0051*****	**0.0055*****	**0.0025*****	0.0018
(214,458)	[0.0008]	[0.0008]	[0.0007]	[0.0008]	[0.0010]	[0.0008]	[0.0010]	[0.0006]	[0.0010]
Women	**0.0035****	**0.0043*****	**0.0027****	**0.0031****	**0.0043****	**0.0040*****	**0.0050*****	**0.0028****	0.0027
(106,263)	[0.0012]	[0.0011]	[0.0010]	[0.0012]	[0.0014]	[0.0011]	[0.0014]	[0.0010]	[0.0014]
Men	**0.0048*****	**0.0061*****	0.0017	**0.0050*****	**0.0043*****	**0.0061*****	**0.0060*****	**0.0021***	0.0009
(108,195)	[0.0011]	[0.0011]	[0.0009]	[0.0011]	[0.0013]	[0.0010]	[0.0013]	[0.0008]	[0.0013]
White, NH	**0.0036*****	**0.0053*****	**0.0019***	**0.0032*****	**0.0044*****	**0.0055*****	**0.0049*****	**0.0023****	0.0011
(115,117)	[0.0010]	[0.0010]	[0.0008]	[0.0009]	[0.0011]	[0.0009]	[0.0011]	[0.0008]	[0.0011]
Hispanic	**0.0060****	-0.0002	0.003	**0.0057****	**0.0070****	-0.0004	0.0004	0.0026	0.0037
(39,512)	[0.0019]	[0.0019]	[0.0018]	[0.0019]	[0.0025]	[0.0019]	[0.0028]	[0.0017]	[0.0025]
Black, NH	0.0033	**0.0098*****	**0.0043***	**0.0041***	0.0011	**0.0093*****	**0.0111*****	**0.0046****	0.0036
(59,829)	[0.0019]	[0.0020]	[0.0017]	[0.0019]	[0.0024]	[0.0019]	[0.0024]	[0.0015]	[0.0024]
College Plus	0.0015	0.001	0.0001	0.0015	0.0015	0.0012	0.0004	0.0008	-0.0013
(50,270)	[0.0012]	[0.0011]	[0.0010]	[0.0012]	[0.0014]	[0.0011]	[0.0013]	[0.0010]	[0.0013]
Some College	**0.0046****	**0.0059*****	0.0006	**0.0044****	**0.0049****	**0.0059*****	**0.0059*****	0.0006	0.0007
(55,826)	[0.0015]	[0.0015]	[0.0013]	[0.0015]	[0.0018]	[0.0014]	[0.0018]	[0.0013]	[0.0018]
High School	**0.0042****	**0.0053*****	**0.0041****	**0.0040****	**0.0046****	**0.0048*****	**0.0065*****	**0.0039*****	**0.0045***
(71,593)	[0.0015]	[0.0015]	[0.0013]	[0.0014]	[0.0018]	[0.0014]	[0.0018]	[0.0012]	[0.0018]
LT High School	**0.0068****	**0.0109*****	0.0029	**0.0073****	0.0059	**0.0100*****	**0.0128*****	0.0035	0.0017
(36,769)	[0.0026]	[0.0026]	[0.0021]	[0.0025]	[0.0032]	[0.0025]	[0.0031]	[0.0020]	[0.0030]
45-64 years old	-0.003	**0.0056***	0.0016	-0.0029	-0.004	**0.0057***	0.0049	0.0023	-0.0006
(27,236)	[0.0025]	[0.0022]	[0.0020]	[0.0025]	[0.0026]	[0.0022]	[0.0026]	[0.0019]	[0.0026]
35-44 years old	**-0.0053***	**0.0088*****	0.0023	**-0.0053****	-0.0054	**0.0067****	**0.0111****	0.0024	0.0022
(35,011)	[0.0023]	[0.0026]	[0.0025]	[0.0019]	[0.0032]	[0.0021]	[0.0035]	[0.0021]	[0.0033]
25-34 years old	**0.0050*****	**0.0046*****	**0.0030****	**0.0047*****	**0.0058*****	**0.0042*****	**0.0056*****	**0.0028****	**0.0032***
(112,154)	[0.0012]	[0.0011]	[0.0010]	[0.0012]	[0.0014]	[0.0011]	[0.0013]	[0.0009]	[0.0013]
18-24 years old	0.0047	0.0034	-0.0005	0.0054	0.0032	0.0036	0.0023	-0.0004	-0.0007
(40,057)	[0.0031]	[0.0027]	[0.0026]	[0.0030]	[0.0036]	[0.0026]	[0.0035]	[0.0023]	[0.0043]

Note: Data are the 1979 and 1997 NLSY cohorts covering years 1982 through 2014. Unemployment is measured as the share of time during the year in the labor market spent unemployed. Demographic-specific results are estimated by a fully-interactive model, allowing the impact for all demographics, in addition to the impact of the gap and hot period, to differ by demographic group (controlling for the rest of the demographics). Sample sizes for each of the groups are noted below the group label. Time, state, and individual fixed effects are included and standard errors are robust to cross-sectional heteroskedasticity and within-panel (serial) correlation. The year in each hot and cold period (and their squared term) are also interacted with the gap to account for duration of each period. Parameter coefficients are found in an online data appendix.

Table 3 Marginal impact of a one additional year of exposure to a high-pressure and cold-pressure economic environment on the share of time spent unemployed.

	Year in Hot Period			**Year in Cold Period**		
Outcome/Group	HOTyr(t)	HOTyr (t-2)	HOTyr (t-4)	COLDyr(t)	COLDyr(t-2)	COLDyr(t-4)
Full Sample	0.0004	0.0006	-0.0005	**0.0007***	**0.0012***	**0.0006***
	[0.0007]	[0.0006]	[0.0005]	[0.0002]	[0.0002]	[0.0001]
Women	0.0016	0.0013	-0.0001	**0.0006**	**0.0009***	**0.0006**
	[0.0010]	[0.0010]	[0.0007]	[0.0002]	[0.0003]	[0.0002]
Men	-0.0006	-0.0001	-0.0009	**0.0009***	**0.0015***	**0.0005**
	[0.0009]	[0.0009]	[0.0007]	[0.0002]	[0.0002]	[0.0002]
White, NH	**0.0015***	-0.0006	-0.0009	**0.0005**	**0.0012***	**0.0005***
	[0.0007]	[0.0007]	[0.0006]	[0.0002]	[0.0002]	[0.0002]
Hispanic	0.0026	0.0014	0.0008	**0.0012**	-0.0001	0.0005
	[0.0029]	[0.0028]	[0.0012]	[0.0005]	[0.0005]	[0.0003]
Black, NH	-0.0032	0.0018	-0.0007	**0.0008***	**0.0022***	**0.0011***
	[0.0017]	[0.0015]	[0.0011]	[0.0004]	[0.0004]	[0.0003]
College Plus	0.0003	-0.0011	**-0.0016***	0.0003	0.0003	0.0002
	[0.0011]	[0.0010]	[0.0007]	[0.0002]	[0.0003]	[0.0002]
Some College	0.001	0	0.0001	**0.0008***	**0.0016***	0.0002
	[0.0015]	[0.0013]	[0.0008]	[0.0003]	[0.0004]	[0.0003]
High School	0.0006	0.002	0.0004	**0.0007***	**0.0010**	**0.0008***
	[0.0011]	[0.0012]	[0.0009]	[0.0003]	[0.0003]	[0.0002]
LT High School	-0.001	0.0027	-0.0013	**0.0012**	**0.0022***	0.0008
	[0.0017]	[0.0017]	[0.0017]	[0.0004]	[0.0005]	[0.0004]
45-64 years old	-0.0074	-0.0026	-0.0036	0.0003	0.0003	0.0002
	[0.0075]	[0.0048]	[0.0022]	[0.0002]	[0.0003]	[0.0002]
35-44 years old	0	**0.0001***	0	**0.0008***	**0.0016***	0.0002
	[0.0000]	[0.0001]	[0.0001]	[0.0003]	[0.0004]	[0.0003]
25-34 years old	0.0019	0.0019	0.0004	**0.0007***	**0.0010**	**0.0008***
	[0.0014]	[0.0011]	[0.0009]	[0.0003]	[0.0003]	[0.0002]
18-24 years old	-0.0023	-0.0028	-0.0004	**0.0012**	**0.0022***	0.0008
	[0.0020]	[0.0042]	[0.0022]	[0.0004]	[0.0005]	[0.0004]

Note: Data are the 1979 and 1997 NLSY cohorts covering years 1982 through 2014. Unemployment is measured as the share of time during the year in the labor market spent unemployed. Demographic-specific results are estimated by a fully-interactive model, allowing the impact for all demographics, in addition to the impact of the gap and hot period, to differ by demographic group (controlling for the rest of the demographics). Sample sizes for each of the groups are noted below the group label. Time, state, and individual fixed effects are included and standard errors are clustered at the state level. Hot periods are also interacted with the year of the of the high-pressure episode and its squared term.

APPENDICES
Additional Tables

for

Some Like it Hot: Assessing Longer-term Labor Market Benefits from a High-Pressure Economy

Appendix A. Marginal Effects Tables for Share of Time Spent out of the Labor Force and Log Real Hourly Wage

This appendix contains marginal effects for the impact of the size of the unemployment rate gap (contemporaneous and lagged) on time spent out of the labor force and log real hourly wage. These results are discussed in the text.

Notes: Data are the 1979 and 1997 NLSY cohorts covering years 1982 through 2014. Dependent variable for Table A1 is the share of time during a year spent out of the labor force (neither employed nor unemployed). Dependent variable for Table A2 is log real ($2014) hourly pay. Demographic-specific results are estimated by a fully-interactive model, allowing the impact for all demographics, in addition to the impact of the gap and hot period, to differ by demographic group (controlling for the rest of the demographics). Sample sizes for each of the groups are noted below the group label. Time, state, and individual fixed effects are included and standard errors are robust to cross-sectional heteroskedasticity and within-panel (serial) correlation. The year in each hot and cold period (and their squared term) are also interacted with the gap to account for duration of each period. Parameter coefficients are found in an online data appendix. Estimation of hourly pay, selection into employment is controlled for using standard Heckman correction (spouse earnings and number of children are identifying regressors in the first stage probit), and observations in top and bottom one percent of real hourly pay distribution are excluded from analysis.

Table A1 Marginal impact of a one percentage point change in the unemployment gap on the **share of time spent out of the labor force**.

	Current Gap (t)	Gap (t-2)	Gap (t-4)	Current Gap (t)		Gap (t-2)		Gap (t-4)	
Outcome/Group	Gap marginal effect average across both hot and cold periods			positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)
Full Sample	**0.0020***	0.001	**0.0029*****	**0.0020***	0.002	0.0012	0.0007	**0.0018***	**0.0050*****
(237,288)	[0.0010]	[0.0008]	[0.0008]	[0.0010]	[0.0012]	[0.0008]	[0.0011]	[0.0008]	[0.0012]
Women	0.0024	0.0015	**0.0027***	0.0021	0.003	0.0015	0.0015	0.0013	**0.0054****
(123,077)	[0.0016]	[0.0013]	[0.0013]	[0.0015]	[0.0019]	[0.0013]	[0.0017]	[0.0012]	[0.0019]
Men	0.0014	0.0004	**0.0030****	0.0017	0.0007	0.0007	-0.0004	**0.0023***	**0.0046*****
(114,211)	[0.0012]	[0.0010]	[0.0010]	[0.0012]	[0.0014]	[0.0010]	[0.0013]	[0.0009]	[0.0014]
White, NH	**0.0040****	0.0005	**0.0037****	**0.0040****	**0.0040***	0.0009	-0.0005	**0.0023***	**0.0067*****
(125,511)	[0.0014]	[0.0011]	[0.0011]	[0.0014]	[0.0017]	[0.0011]	[0.0014]	[0.0011]	[0.0016]
Hispanic	-0.0024	0.0018	-0.0003	-0.0018	-0.004	0.0013	0.0031	-0.0005	-0.0001
(44,438)	[0.0025]	[0.0021]	[0.0022]	[0.0024]	[0.0032]	[0.0020]	[0.0029]	[0.0020]	[0.0033]
Black, NH	-0.0001	0.0026	**0.0047****	-0.0001	-0.0001	0.0026	0.0026	**0.0035***	**0.0069****
(67,339)	[0.0020]	[0.0018]	[0.0016]	[0.0020]	[0.0025]	[0.0017]	[0.0023]	[0.0015]	[0.0023]
College Plus	0.002	0	0.0025	0.0024	0.001	0.0002	-0.0005	0.0015	**0.0045***
(52,689)	[0.0019]	[0.0016]	[0.0015]	[0.0019]	[0.0022]	[0.0016]	[0.0019]	[0.0015]	[0.0021]
Some College	0.001	0.0022	0.0021	0.0012	0.0005	0.0023	0.002	0.0018	0.0028
(60,165)	[0.0018]	[0.0016]	[0.0016]	[0.0018]	[0.0023]	[0.0016]	[0.0021]	[0.0014]	[0.0023]
High School	0.0005	-0.0006	**0.0040****	0.0002	0.0013	-0.0006	-0.0005	**0.0031***	**0.0059****
(79,525)	[0.0017]	[0.0014]	[0.0015]	[0.0017]	[0.0021]	[0.0014]	[0.0019]	[0.0014]	[0.0021]
LT High School	**0.0055***	0.001	0.0012	**0.0053***	0.0059	0.0011	0.0009	-0.0007	0.0049
(44,909)	[0.0026]	[0.0022]	[0.0022]	[0.0025]	[0.0032]	[0.0021]	[0.0029]	[0.0020]	[0.0032]
45-64 years old	-0.0033	0	0.0023	-0.0033	-0.0033	0.0005	-0.0032	0.0027	0.0012
(31,542)	[0.0027]	[0.0022]	[0.0022]	[0.0026]	[0.0030]	[0.0022]	[0.0026]	[0.0021]	[0.0029]
35-44 years old	-0.0024	-0.0004	0.006	-0.0016	-0.0034	-0.0013	0.0006	0.0037	0.0083
(39,345)	[0.0029]	[0.0032]	[0.0032]	[0.0024]	[0.0040]	[0.0026]	[0.0043]	[0.0027]	[0.0043]
25-34 years old	0.0024	0.0007	**0.0022***	0.0023	0.0027	0.0007	0.0005	0.0015	**0.0035***
(123,092)	[0.0013]	[0.0011]	[0.0010]	[0.0013]	[0.0016]	[0.0011]	[0.0014]	[0.0010]	[0.0014]
18-24 years old	-0.0018	-0.0011	0.0003	-0.001	-0.0035	-0.0009	-0.0017	-0.0017	0.0048
(43,309)	[0.0031]	[0.0026]	[0.0025]	[0.0030]	[0.0036]	[0.0025]	[0.0035]	[0.0022]	[0.0043]

Table A2 Marginal impact of a one percentage point change in the unemployment gap on **log real hourly pay**.

	Current Gap (t)	Gap (t-2)	Gap (t-4)	Current Gap (t)		Gap (t-2)		Gap (t-4)	
Outcome/Group	Gap marginal effect average across both hot and cold periods			positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)
Full Sample	-0.0021	**-0.0059****	**-0.0075*****	-0.0022	-0.002	**-0.0045****	**-0.0091*****	**-0.0065*****	**-0.0092****
(101,326)	[0.0019]	[0.0018]	[0.0020]	[0.0018]	[0.0025]	[0.0017]	[0.0026]	[0.0018]	[0.0029]
Women	-0.0038	**-0.0060***	**-0.0057***	-0.0038	-0.0038	**-0.0048***	**-0.0090***	-0.0048	-0.0072
(49,881)	[0.0026]	[0.0026]	[0.0029]	[0.0026]	[0.0035]	[0.0024]	[0.0036]	[0.0026]	[0.0042]
Men	0.0011	**-0.0052***	**-0.0090*****	0.0009	0.0014	-0.0038	**-0.0085***	**-0.0076****	**-0.0115****
(51,445)	[0.0027]	[0.0026]	[0.0027]	[0.0027]	[0.0036]	[0.0025]	[0.0036]	[0.0025]	[0.0039]
White, NH	0.0013	-0.0052	**-0.0093****	0.0012	0.0015	-0.0044	**-0.0074***	**-0.0074****	**-0.0126****
(53,966)	[0.0029]	[0.0027]	[0.0029]	[0.0028]	[0.0037]	[0.0025]	[0.0037]	[0.0026]	[0.0043]
Hispanic	-0.005	-0.0052	-0.0076	-0.0058	-0.0028	-0.0054	-0.0046	-0.0076	-0.0075
(19,158)	[0.0045]	[0.0048]	[0.0049]	[0.0042]	[0.0064]	[0.0046]	[0.0061]	[0.0044]	[0.0069]
Black, NH	-0.0035	-0.0053	-0.0063	-0.0028	-0.005	-0.0025	**-0.0114***	-0.0052	-0.0081
(28,202)	[0.0036]	[0.0037]	[0.0036]	[0.0036]	[0.0047]	[0.0034]	[0.0051]	[0.0033]	[0.0051]
College Plus	0.001	-0.0007	-0.0036	0.0005	0.0023	0.002	-0.0075	-0.0015	-0.0073
(27,076)	[0.0043]	[0.0040]	[0.0047]	[0.0042]	[0.0057]	[0.0038]	[0.0056]	[0.0042]	[0.0069]
Some College	**-0.0067***	**-0.0080***	**-0.0068***	**-0.0067***	-0.0069	**-0.0069***	**-0.0105***	-0.0048	**-0.0104***
(28,681)	[0.0034]	[0.0032]	[0.0033]	[0.0033]	[0.0042]	[0.0030]	[0.0045]	[0.0030]	[0.0048]
High School	0.0017	-0.0053	**-0.0080****	0.0028	-0.001	-0.0052	-0.0055	**-0.0072****	**-0.0092***
(31,911)	[0.0029]	[0.0029]	[0.0031]	[0.0028]	[0.0039]	[0.0027]	[0.0041]	[0.0027]	[0.0044]
LT HS	-0.0026	-0.004	-0.0094	-0.0022	-0.0032	-0.0009	-0.0106	**-0.0104***	-0.0077
(13,658)	[0.0051]	[0.0054]	[0.0052]	[0.0049]	[0.0064]	[0.0051]	[0.0070]	[0.0048]	[0.0069]
45-64 years old	0.0048	-0.0024	0.0004	0.0051	0.001	-0.002	-0.0049	0.0006	-0.0004
(19,471)	[0.0055]	[0.0043]	[0.0047]	[0.0055]	[0.0063]	[0.0043]	[0.0049]	[0.0042]	[0.0077]
35-44 years old	0.0015	0.0003	-0.0003	0.0005	0.0027	0.0053	-0.0046	-0.0009	0.0004
(25,354)	[0.0058]	[0.0062]	[0.0065]	[0.0045]	[0.0080]	[0.0049]	[0.0083]	[0.0054]	[0.0089]
25-34 years old	-0.0017	-0.0045	**-0.0130*****	-0.0015	-0.0022	-0.0033	**-0.0080***	**-0.0124*****	**-0.0140****
(38,466)	[0.0034]	[0.0029]	[0.0033]	[0.0034]	[0.0041]	[0.0028]	[0.0038]	[0.0032]	[0.0045]
18-24 years old	-0.0053	-0.0136	-0.0097	-0.0031	-0.0093	-0.0093	-0.0259*	-0.0041	-0.0184
(18,035)	[0.0077]	[0.0096]	[0.0090]	[0.0074]	[0.0096]	[0.0093]	[0.0124]	[0.0075]	[0.0133]

Appendix B. Marginal Effects for Robustness Tests - all outcomes

This appendix provides the marginal effects for the impact of the unemployment gap each labor market outcome. Results are presented for full sample (men, women, and all demographic groups combined). These results are discussed in the text.

Notes for the tables: Data are the 1979 and 1997 NLSY cohorts covering years 1982 through 2014. Dependent variable is stated in each table's title. Sample sizes for each specification are noted below the specification.

Details of the robustness specifications:
Baseline: Estimates reported in Table 2 and tables in Appendix A.
National GAP: Baseline specification using national measure of gap rather than state-specific gap.
No individual FE: Baseline excluding individual fixed effects.
Lagged Outcome & no FE: Baseline specification including two-year and four-year lagged values of the outcome variable, but excluding the fixed effects because of Nickell's (1988) warning of bias if both are included.
Active LM sample: Baseline specification, restricting sample to those with at least 32 weeks in the labor force during each of the previous four years.

Specific to share of time in the labor force spent unemployed:
This specification test excludes those who spend 100% of their time employed (a significant portion of the ushare sample).

Specific to share of time spent out of the labor force:
Addt'l regressors: This specification includes regressors typically important for labor supply decisions -- spouse's income (if married) and the presence of children.

Specific to hourly pay:
No Occ/Ind FE: Excludes occupation and industry fixed effects in order to see how much of the GAP effect on wages is occupation/industry specific.
Include Hours: Baseline regression including weekly hours of work in order to see whether correlation between hours and wages left unaccounted for biases results on GAP marginal effects. There is hardly any different at all in the marginal effects from the baseline. Where there is a difference, the marginal effects including hours are marginally smaller (closer to zero), as might be expected since wages and hours are positively correlated.

Table B1 Robustness specifications, marginal effect of gap on **share of time spent unemployed**.

	Current Gap (t)	Gap (t-2)	Gap (t-4)	Current Gap (t)		Gap (t-2)		Gap (t-4)	
Specification/LM Outcome	Gap marginal effect averaged across both hot and cold periods			positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)
Baseline	**0.0042*****	**0.0052*****	**0.0023****	**0.0041*****	**0.0043*****	**0.0051*****	**0.0055*****	**0.0025*****	0.0018
(214,458)	[0.0008]	[0.0008]	[0.0007]	[0.0008]	[0.0010]	[0.0008]	[0.0010]	[0.0006]	[0.0010]
National GAP	**0.0027*****	**0.0032*****	0.0008	**0.0021*****	**0.0039*****	**0.0027*****	**0.0043*****	**0.0009***	0.0006
(214,458)	[0.0005]	[0.0005]	[0.0004]	[0.0005]	[0.0007]	[0.0005]	[0.0006]	[0.0004]	[0.0006]
No individual FE	**0.0039*****	**0.0060*****	**0.0027*****	**0.0038*****	**0.0040*****	**0.0057*****	**0.0066*****	**0.0028*****	**0.0023***
(214,458)	[0.0008]	[0.0008]	[0.0007]	[0.0008]	[0.0009]	[0.0008]	[0.0011]	[0.0006]	[0.0010]
Lagged & noFE	**0.0033*****	**0.0043*****	-0.0008	**0.0034*****	**0.0031*****	**0.0041*****	**0.0049*****	-0.0004	-0.0016
(182,373)	[0.0007]	[0.0008]	[0.0006]	[0.0007]	[0.0009]	[0.0008]	[0.0010]	[0.0006]	[0.0009]
Active LM	**0.0023****	**0.0036*****	0.0012	**0.0021****	**0.0028****	**0.0036*****	**0.0036*****	**0.0016****	0.0004
(140,021)	[0.0007]	[0.0007]	[0.0006]	[0.0007]	[0.0009]	[0.0007]	[0.0009]	[0.0006]	[0.0008]
Exclude ushare=0	**0.0084*****	**0.0126*****	**0.0046***	**0.0089*****	**0.0070***	**0.0120*****	**0.0144*****	**0.0054****	0.0028
(49,792)	[0.0023]	[0.0022]	[0.0020]	[0.0023]	[0.0028]	[0.0021]	[0.0029]	[0.0018]	[0.0030]
Non-movers	**0.0052*****	**0.0047*****	**0.0024****	**0.0052*****	**0.0053*****	**0.0047*****	**0.0049*****	**0.0024*****	**0.0023***
(195,043)	[0.0009]	[0.0009]	[0.0008]	[0.0009]	[0.0011]	[0.0009]	[0.0011]	[0.0007]	[0.0011]
Different state t-4	-0.0015	**0.0069*****	0.0001	-0.0011	-0.0023	**0.0066****	**0.0076****	0.0015	-0.0032
(19,039)	[0.0024]	[0.0020]	[0.0019]	[0.0023]	[0.0031]	[0.0020]	[0.0025]	[0.0019]	[0.0028]

Table B2 Robustness specifications, marginal effect of gap on **share of time spent out of the labor force**.

	Current Gap (t)	Gap (t-2)	Gap (t-4)	Current Gap (t)		Gap (t-2)		Gap (t-4)	
Specification/LM Outcome	Gap marginal effect averaged across both hot and cold periods			positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)
Baseline	**0.0020***	0.001	**0.0029*****	**0.0020***	0.002	0.0012	0.0007	**0.0018***	**0.0050*****
(237,288)	[0.0010]	[0.0008]	[0.0008]	[0.0010]	[0.0012]	[0.0008]	[0.0011]	[0.0008]	[0.0012]
National GAP	0.0006	0.0008	0.001	0.0004	0.001	**0.0011***	0.0004	0.0005	**0.0017***
(237,288)	[0.0006]	[0.0005]	[0.0006]	[0.0006]	[0.0009]	[0.0005]	[0.0007]	[0.0005]	[0.0008]
No individual FE	0.0013	**0.0021***	**0.0035*****	0.0015	0.0007	**0.0023***	0.0016	**0.0025****	**0.0055*****
(237,288)	[0.0009]	[0.0010]	[0.0009]	[0.0009]	[0.0012]	[0.0010]	[0.0013]	[0.0008]	[0.0013]
Lagged & noFE	0.0008	0.0015	0.0007	0.001	0.0005	0.0015	0.0016	0	**0.0023***
(218,833)	[0.0008]	[0.0009]	[0.0007]	[0.0008]	[0.0010]	[0.0008]	[0.0011]	[0.0007]	[0.0010]
Active LM	0.0005	-0.0001	**0.0011*****	0.0004	0.0006	0	-0.0003	**0.0007*****	**0.0017*****
(145,115)	[0.0003]	[0.0003]	[0.0002]	[0.0003]	[0.0003]	[0.0003]	[0.0004]	[0.0002]	[0.0003]
Addt'l Regressors	**0.0021***	0.0007	**0.0032*****	**0.0020***	0.0023	0.0009	0.0002	**0.0021***	**0.0055*****
(215,020)	[0.0010]	[0.0009]	[0.0009]	[0.0010]	[0.0013]	[0.0009]	[0.0011]	[0.0008]	[0.0012]
Non-movers	**0.0030****	0	**0.0036*****	**0.0031****	**0.0030***	0.0003	-0.0006	**0.0024****	**0.0061*****
(216,012)	[0.0011]	[0.0009]	[0.0009]	[0.0011]	[0.0013]	[0.0009]	[0.0012]	[0.0008]	[0.0013]
Different state t-4	-0.0047	0.0037	-0.0023	-0.0043	-0.0056	0.0035	0.0042	-0.0023	-0.0021
(20,861)	[0.0032]	[0.0023]	[0.0026]	[0.0032]	[0.0041]	[0.0023]	[0.0031]	[0.0025]	[0.0037]

Table B3 Robustness specifications, marginal effect of gap on **log real hourly pay**.

	Current Gap (t)	Gap (t-2)	Gap (t-4)	Current Gap (t)		Gap (t-2)		Gap (t-4)	
Specification/LM Outcome	Gap marginal effect averaged across both hot and cold periods			positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)	positive gap (cold)	negative gap (hot)
Baseline	-0.0021	**-0.0059****	**-0.0075*****	-0.0022	-0.002	**-0.0045****	**-0.0091*****	**-0.0065*****	**-0.0092****
(101,326)	[0.0019]	[0.0018]	[0.0020]	[0.0018]	[0.0025]	[0.0017]	[0.0026]	[0.0018]	[0.0029]
National GAP	-0.0021	**-0.0044*****	**-0.0050*****	-0.0016	-0.0031	**-0.0036*****	**-0.0060*****	**-0.0029****	**-0.0079*****
(101,326)	[0.0012]	[0.0011]	[0.0013]	[0.0011]	[0.0018]	[0.0010]	[0.0018]	[0.0010]	[0.0020]
No individual FE	0.0006	-0.0045	**-0.0055***	0.0007	0.0002	-0.0031	**-0.0079***	-0.0037	**-0.0086****
(101,326)	[0.0021]	[0.0023]	[0.0022]	[0.0021]	[0.0027]	[0.0022]	[0.0033]	[0.0020]	[0.0033]
Lagged & noFE	-0.0029	-0.0038	-0.0011	-0.0023	-0.0046	-0.0022	**-0.0072***	-0.0008	-0.0015
(67,309)	[0.0021]	[0.0022]	[0.0022]	[0.0021]	[0.0027]	[0.0020]	[0.0032]	[0.0019]	[0.0034]
Active LM	-0.0009	**-0.0068*****	**-0.0058****	-0.0008	-0.0011	**-0.0055****	**-0.0100*****	**-0.0051***	**-0.0072***
(63,440)	[0.0022]	[0.0020]	[0.0022]	[0.0021]	[0.0029]	[0.0019]	[0.0028]	[0.0020]	[0.0033]
No Selection	-0.0041*	**-0.0057****	**-0.0075*****	**-0.0040***	-0.0044	**-0.0044***	**-0.0087*****	**-0.0065*****	**-0.0091****
(101,195)	[0.0019]	[0.0018]	[0.0020]	[0.0018]	[0.0024]	[0.0017]	[0.0026]	[0.0018]	[0.0029]
Include Hours	-0.0021	**-0.0059****	**-0.0074*****	-0.0022	-0.0019	**-0.0045****	**-0.0091*****	**-0.0065*****	**-0.0091****
(101,195)	[0.0019]	[0.0018]	[0.0020]	[0.0019]	[0.0025]	[0.0017]	[0.0026]	[0.0018]	[0.0029]
No Occ/Ind FE	-0.0009	**-0.0081*****	**-0.0071*****	-0.001	-0.0005	**-0.0066*****	**-0.0117*****	**-0.0064*****	**-0.0083****
(116,686)	[0.0018]	[0.0018]	[0.0019]	[0.0018]	[0.0024]	[0.0017]	[0.0025]	[0.0017]	[0.0027]
Non-movers	-0.0025	**-0.0064*****	**-0.0076*****	-0.0026	-0.0021	**-0.0053****	**-0.0092*****	**-0.0067*****	**-0.0093****
(92,848)	[0.0020]	[0.0019]	[0.0021]	[0.0019]	[0.0026]	[0.0018]	[0.0027]	[0.0019]	[0.0030]
Different state t-4	0.0045	-0.0009	0.0066	0.0081	-0.0037	0.0046	-0.0143	0.0081	0.0035
(8,301)	[0.0078]	[0.0061]	[0.0086]	[0.0075]	[0.0105]	[0.0062]	[0.0087]	[0.0078]	[0.0130]

"Some Like it Hot: Assessing Long-term Labor Market Benefits from a High-pressure Economy"

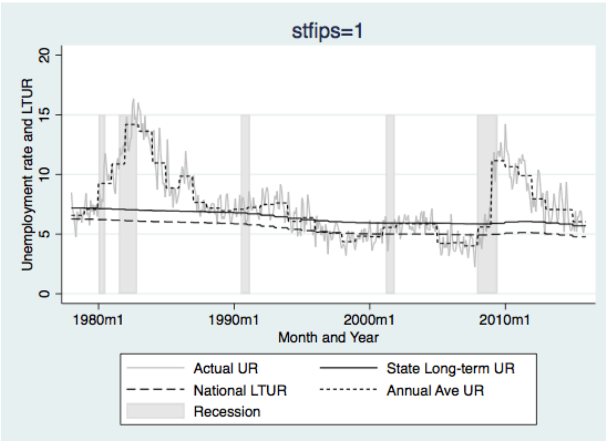
Data appendix

Table of Contents

I. Actual and natural rate of unemployment for all states

Supplemental Appendix
Illustration of state natural unemployment rates for each state

Alabama



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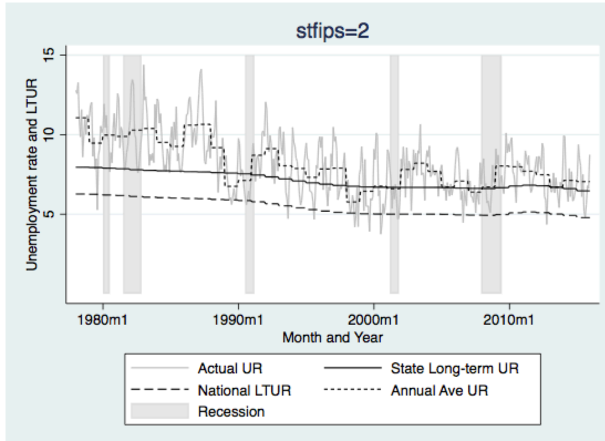

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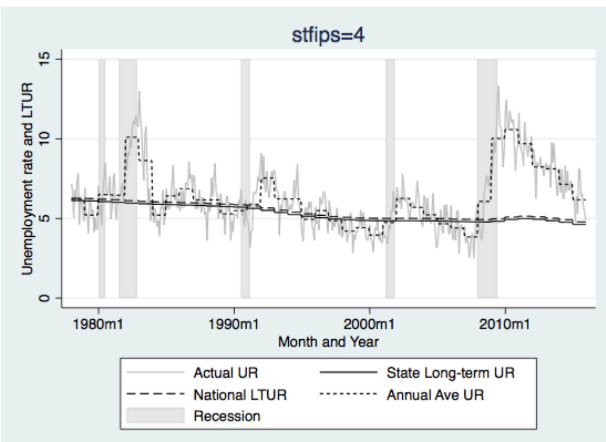

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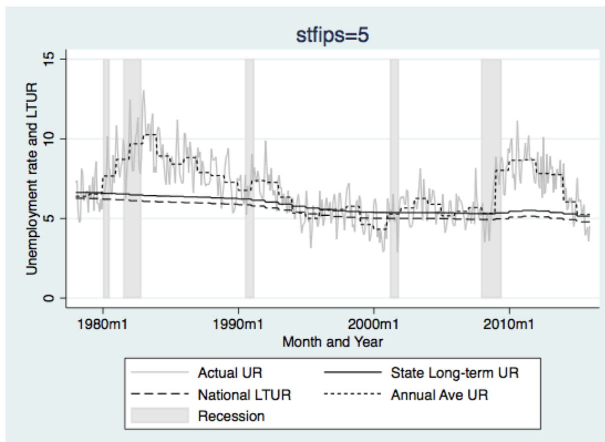

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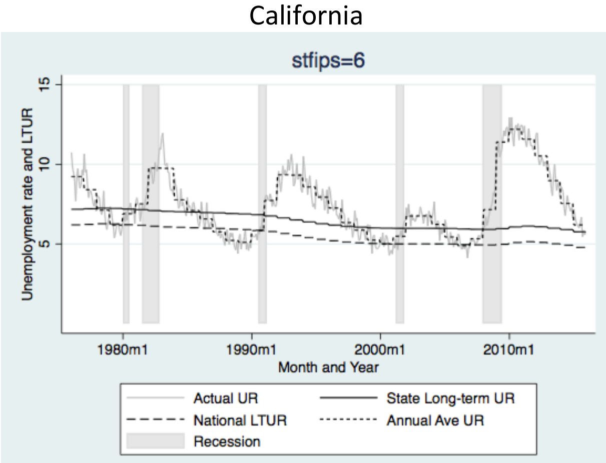

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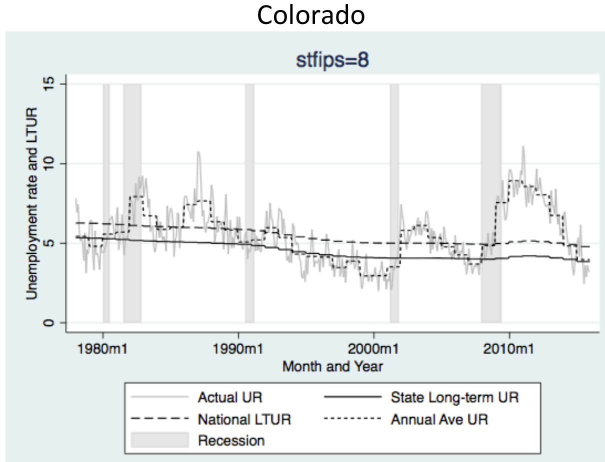

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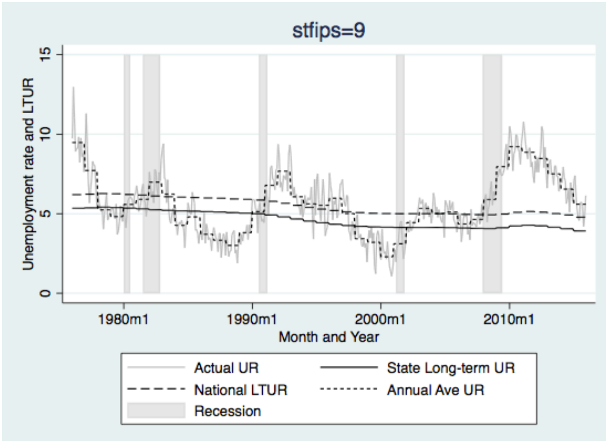

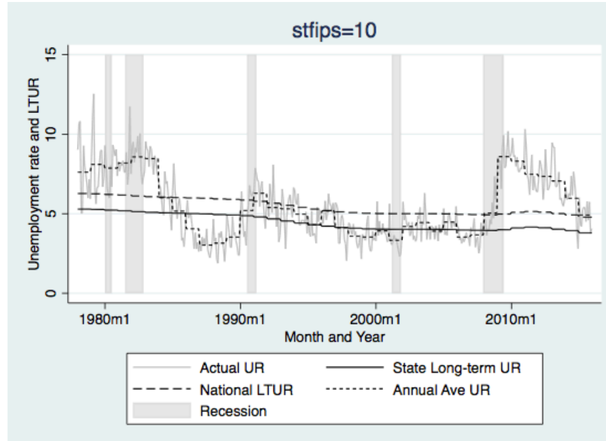

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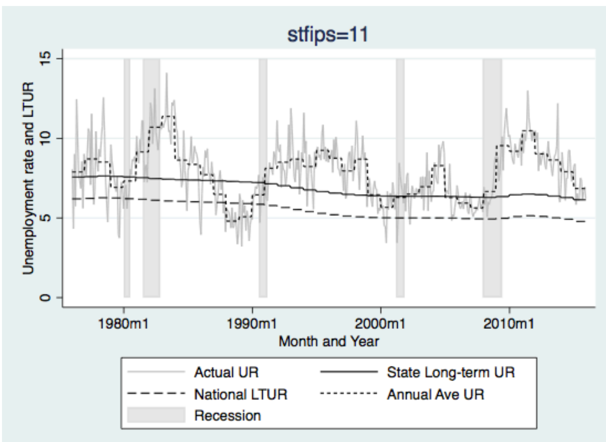

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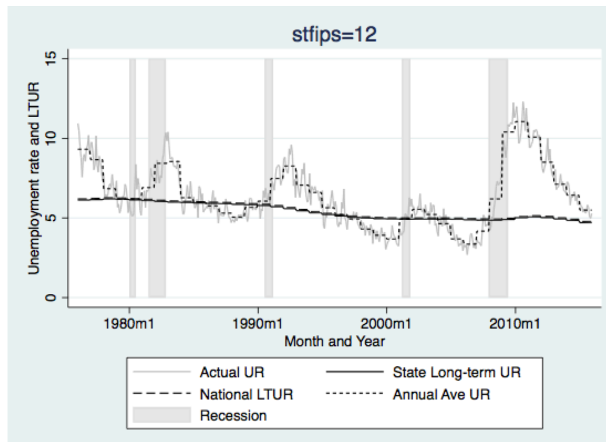

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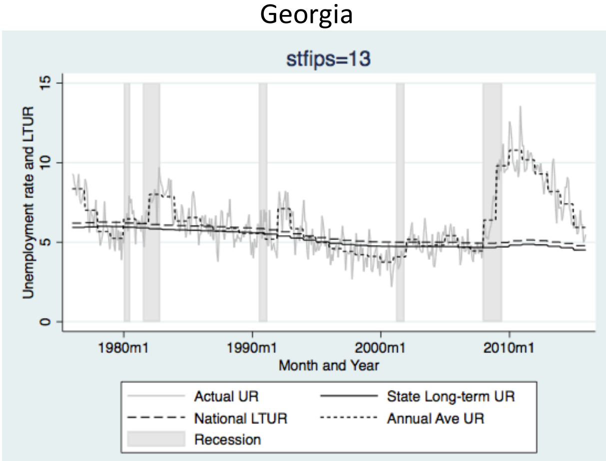

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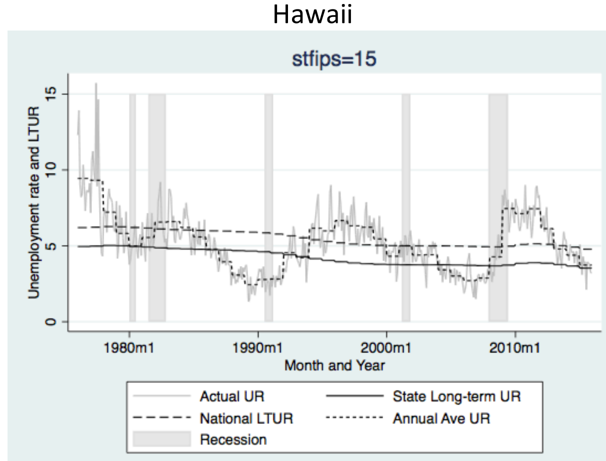

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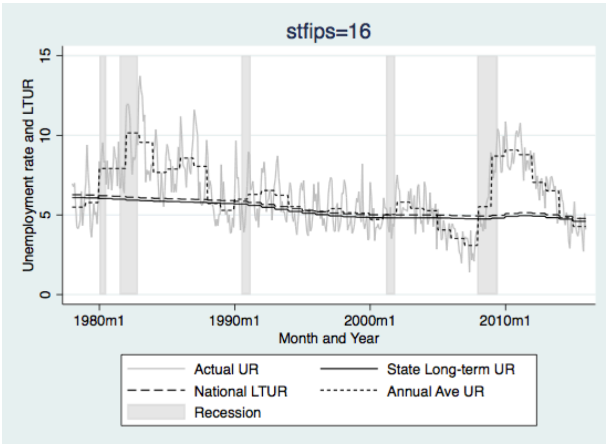

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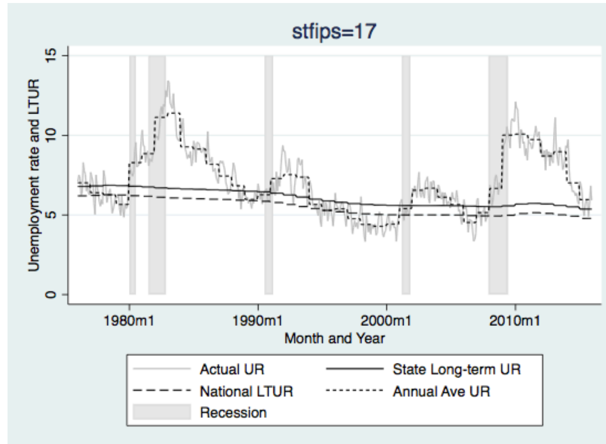

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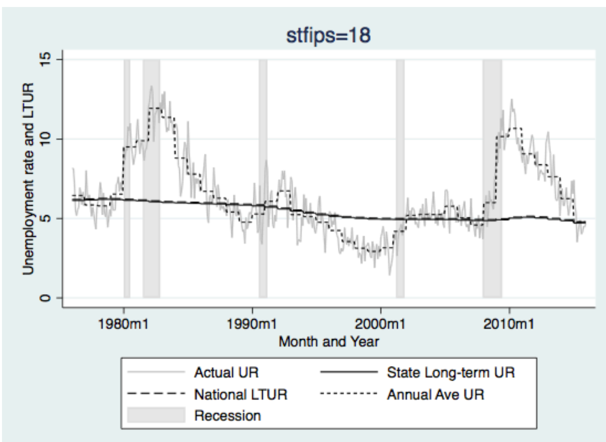

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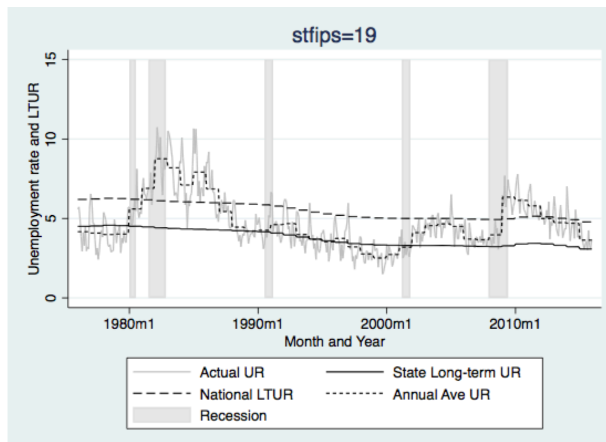

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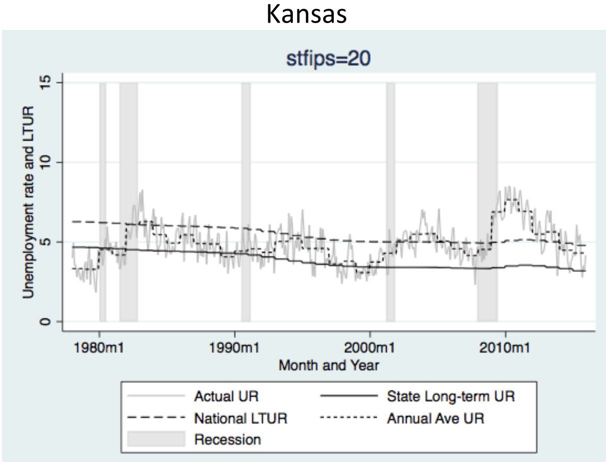

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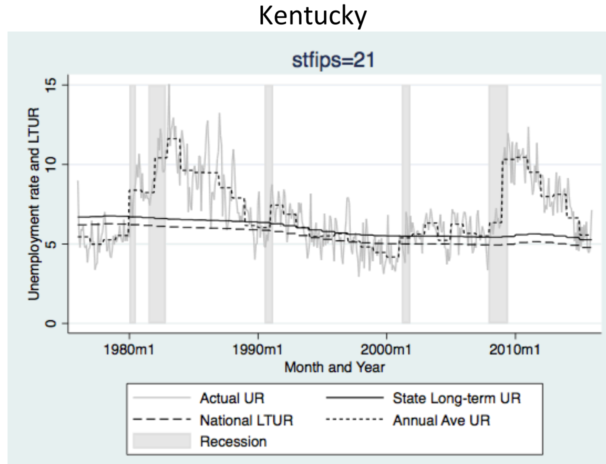

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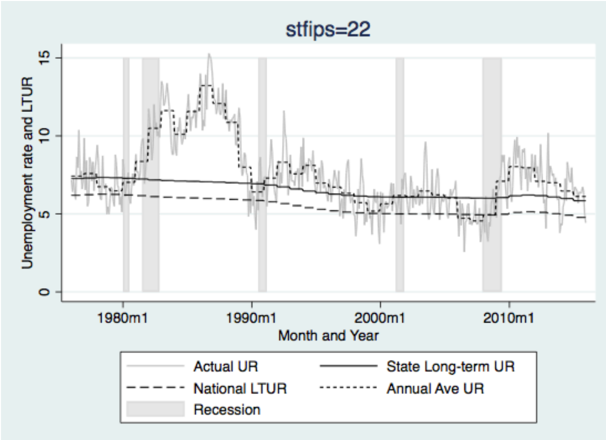

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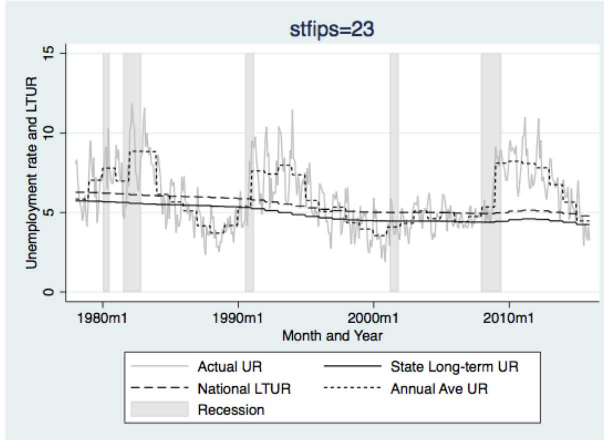

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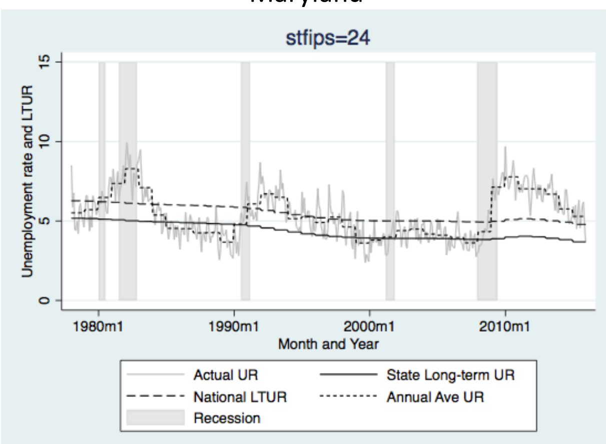
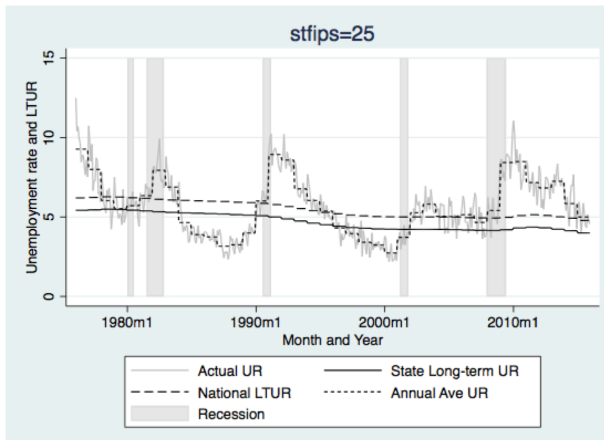


Massachusetts



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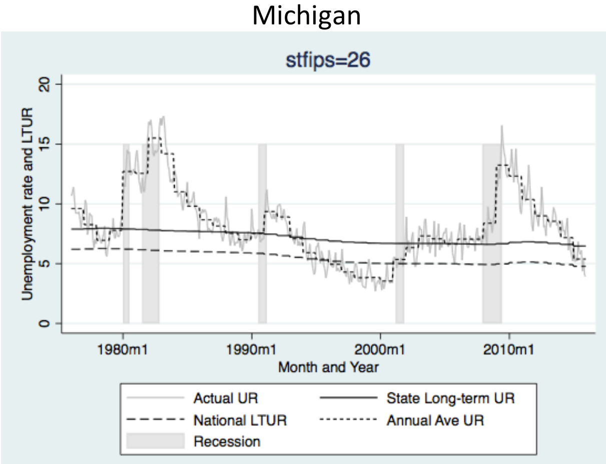

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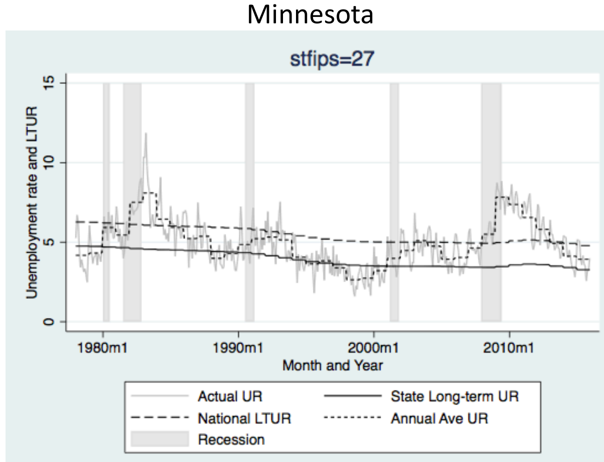

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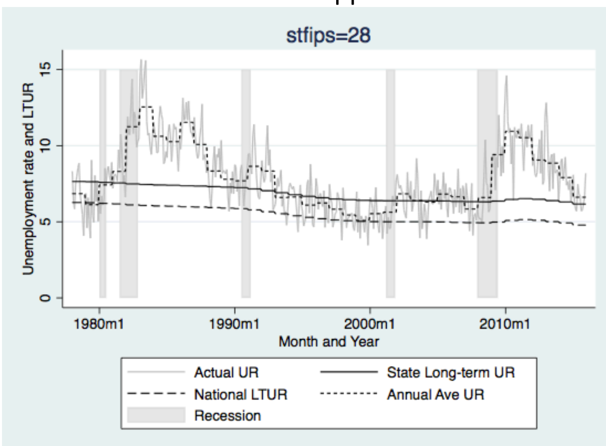

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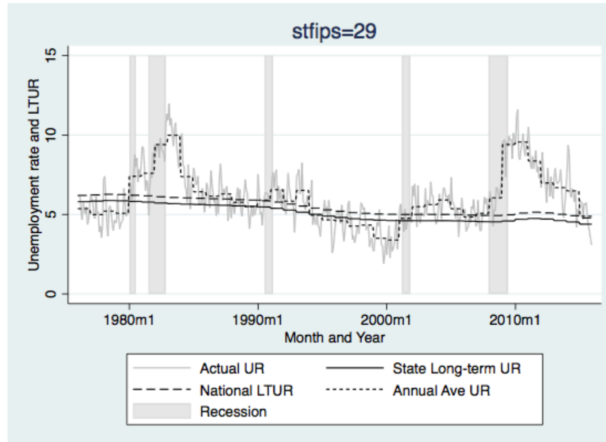

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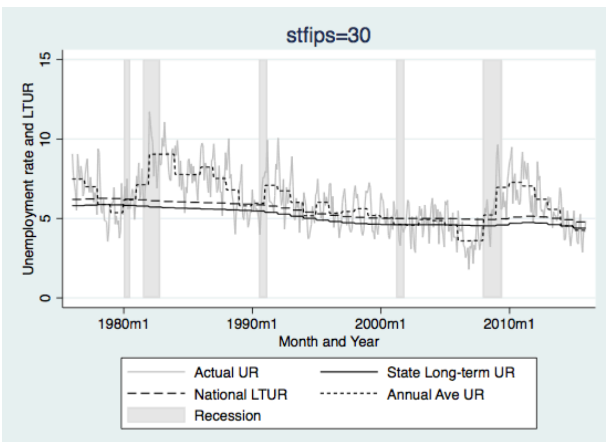

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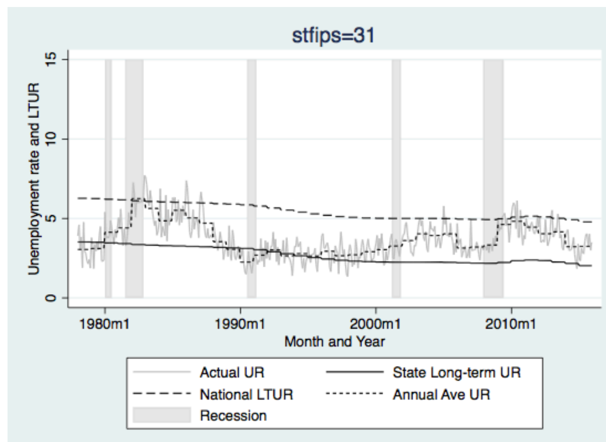

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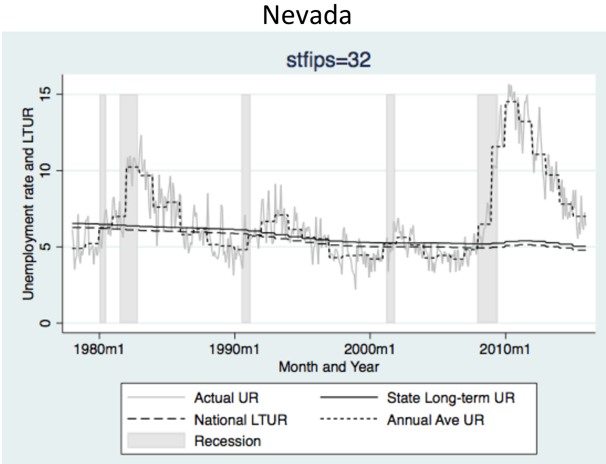

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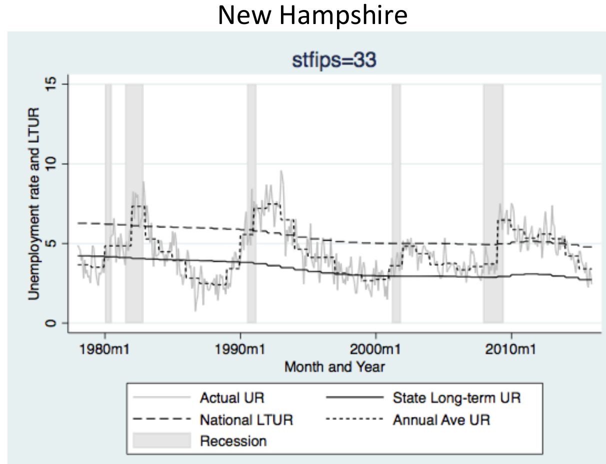

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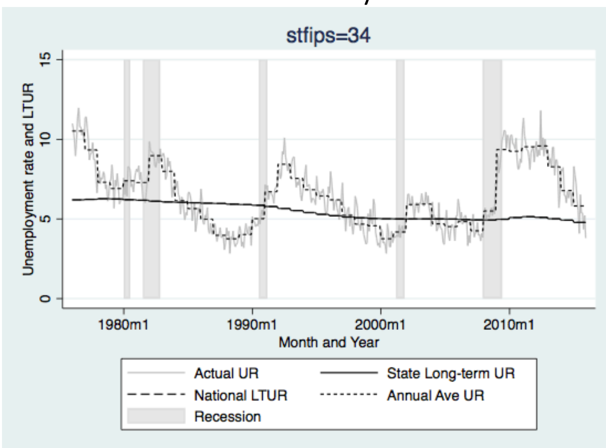

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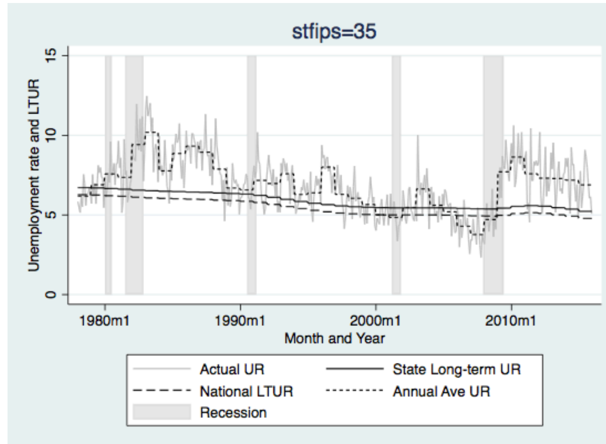

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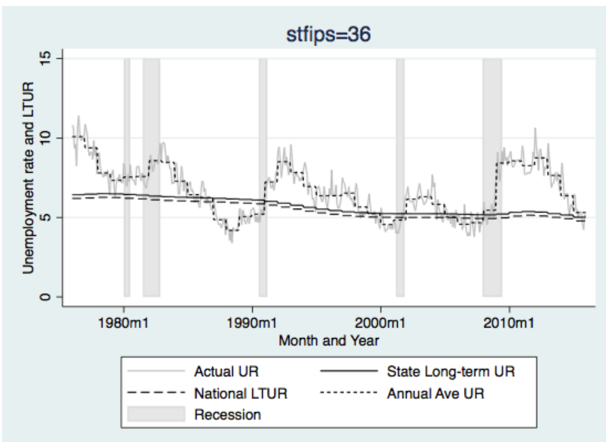

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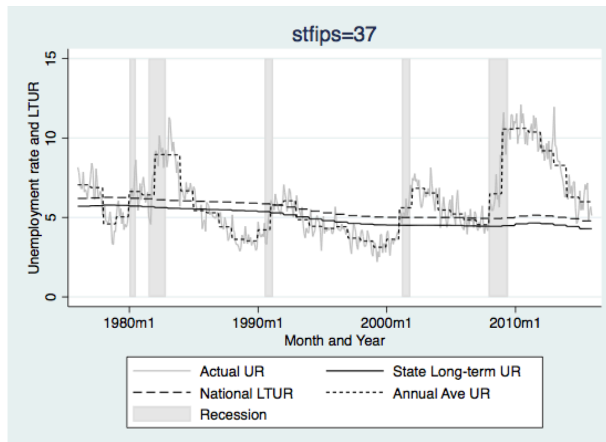

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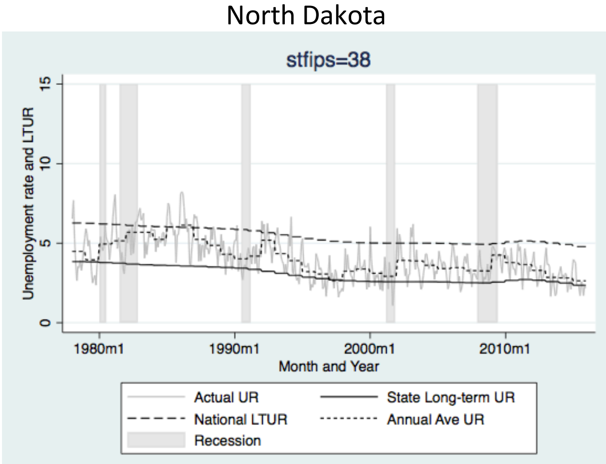

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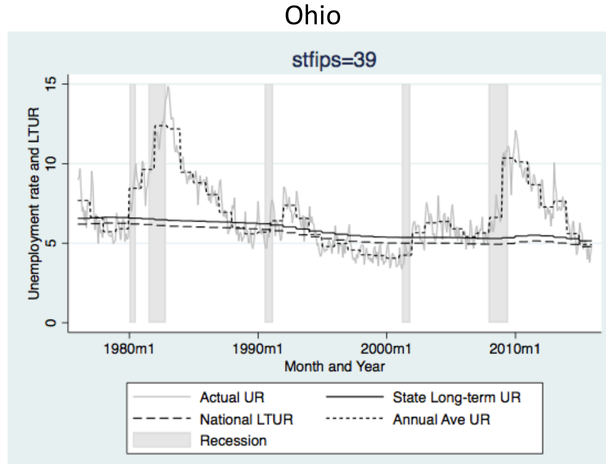

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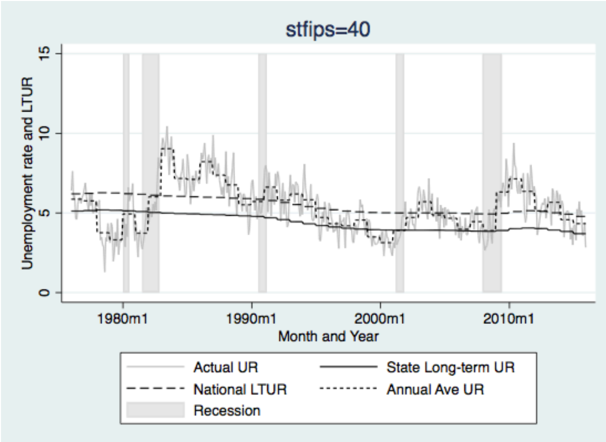

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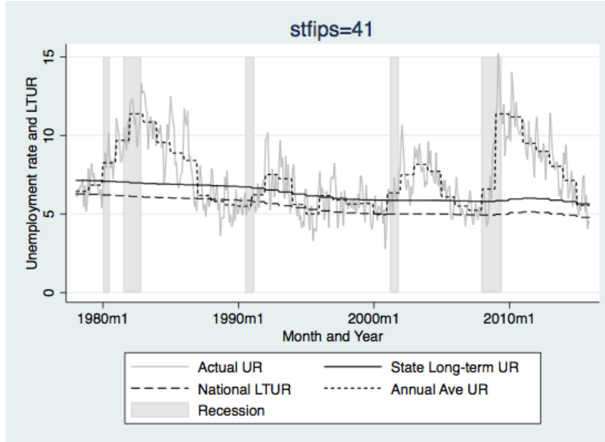

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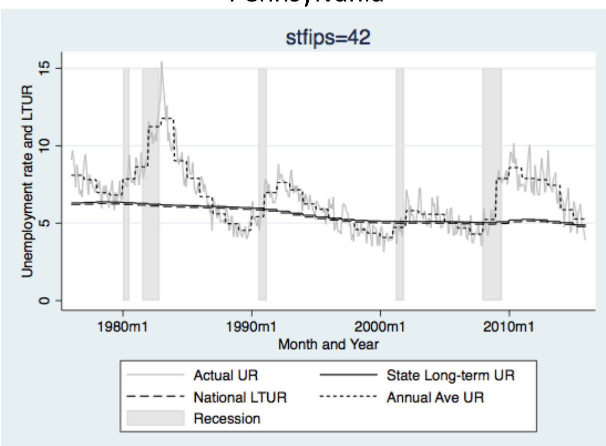
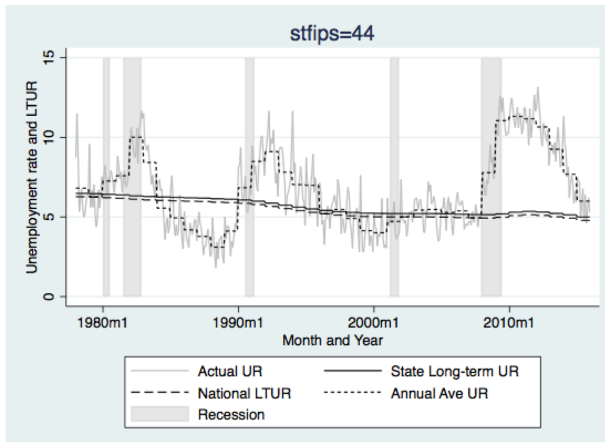
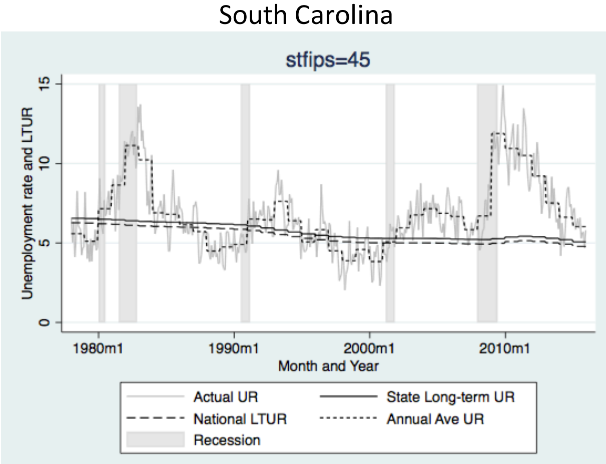


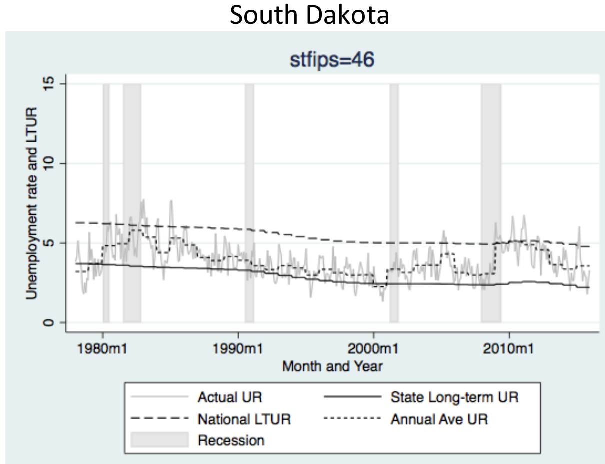
Rhode Island



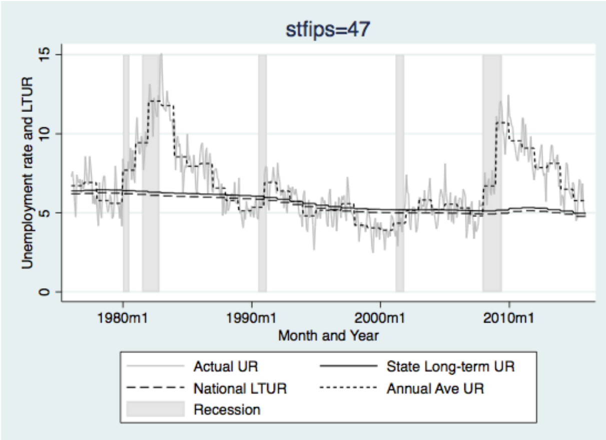
South Carolina



South Dakota



Tennessee



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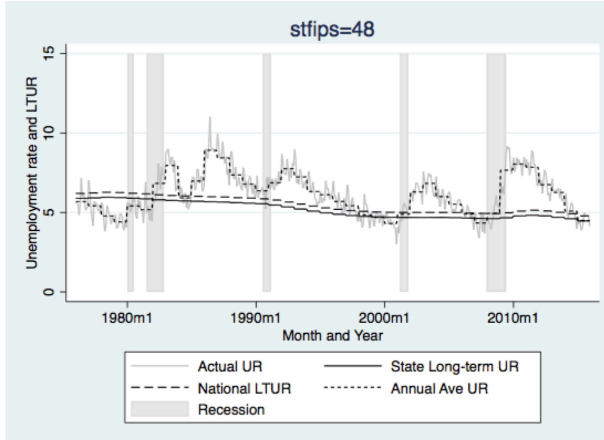
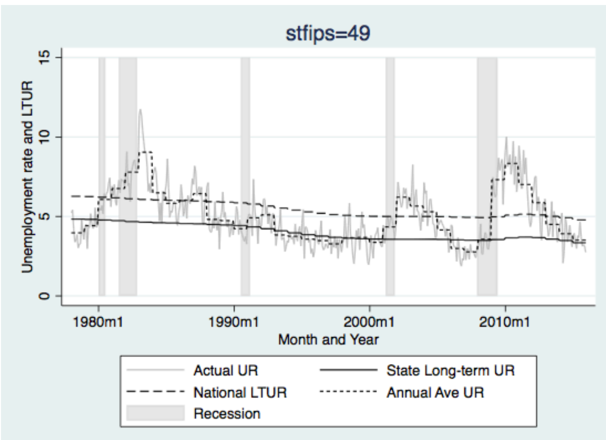
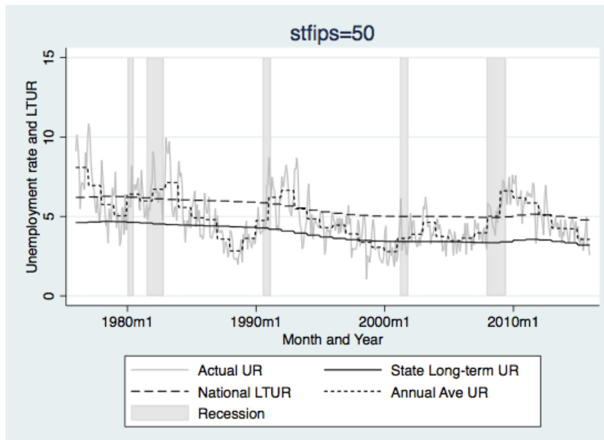


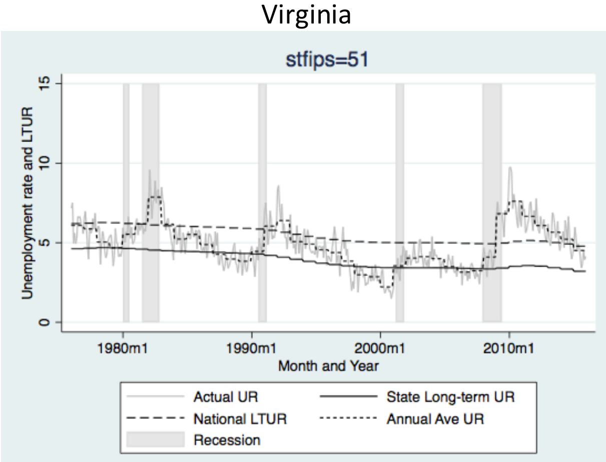
Utah



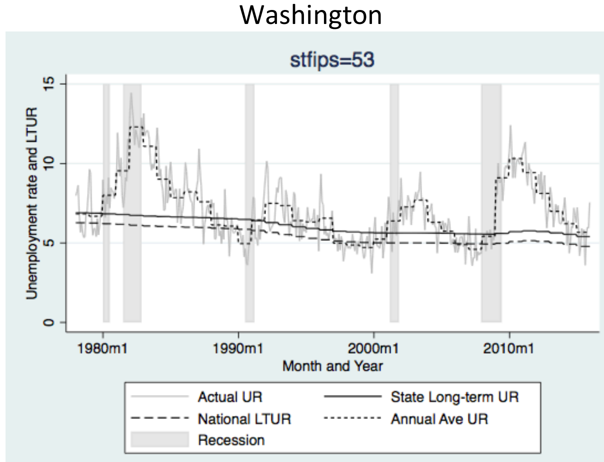
Vermont



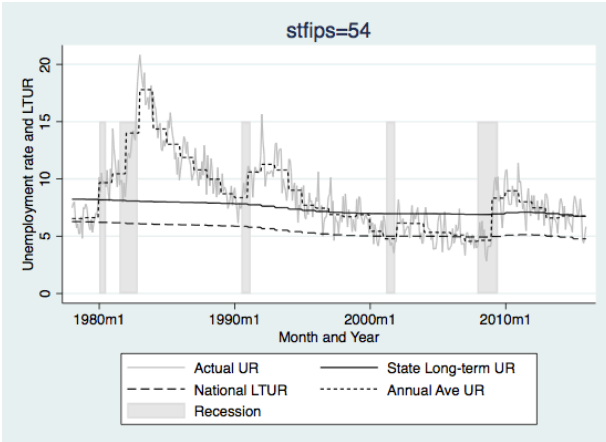
Virginia



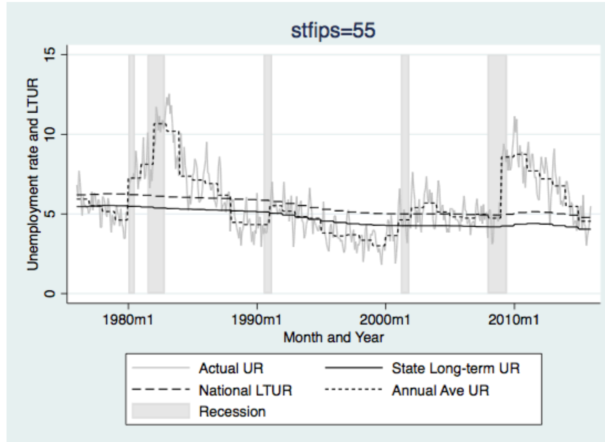
Washington



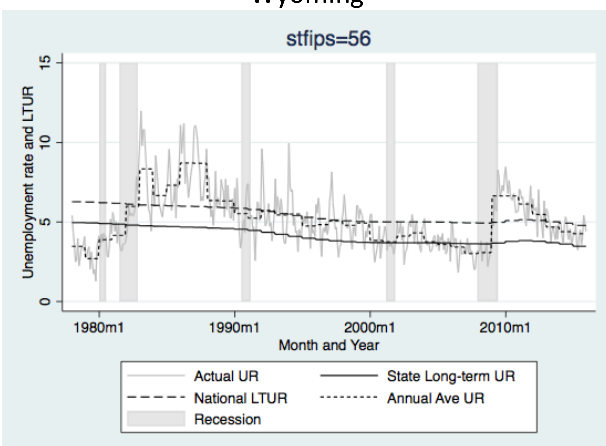
West Virginia



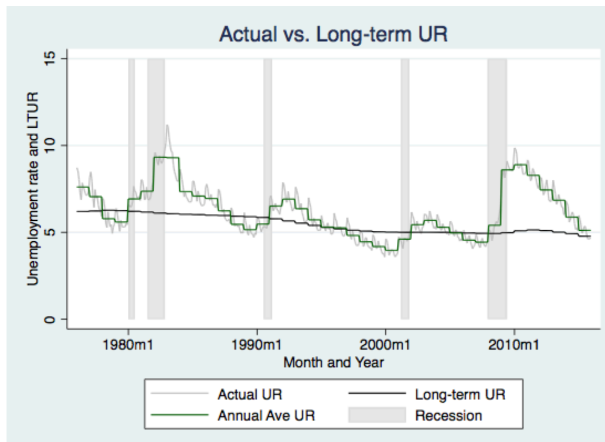
Wisconsin



Wyoming



United States



II. Description of sample construction

Public data are obtained from the National Longitudinal Survey of Youth (NLSY) Investigator page: https://www.nlsinfo.org/investigator/pages/login.jsp Data from the 1979 and 1997 surveys are pulled separately. Differences in variable definitions (such as race), are synthesized and the two survey observations are merged together.

Restricted state identifiers are obtained through an application process with the Bureau of Labor Statistics. Details can be found here: https://www.bls.gov/rda/restricted-data.htm

The NLSY records weekly activity from which the annual number of weeks unemployed, out of the labor force, and employed are constructed.

For the 1979 cohort, hourly pay and weekly hours of work are collected for up to 5 jobs during the year. The person's "main" job is defined as the one on which he/she worked the most number of hours. It is for that job that hourly pay and hours of work are used for those analyses.

For the 1997 cohort, hourly pay and weekly hours of work are collected for up to 7 jobs during the year. The person's "main" job during the year is identified by NLSY and the hourly pay and hours of work corresponding to that job are used for those analyses.

There are a total of 335,501 potential observations with non-missing state identifiers between the ages of 18 and 57 (the oldest among the respondents from NLSY1979). There are 110,165 person/year observations missing a state identifier (76 percent of those missing observations are from the NLSY1979).

Restricting the sample to those with non-missing demographics brings the number of person/year observations to 335,372.

Additional restrictions for ushare and olfshare analysis:
Restricting the sample to those who report at least 44 weeks of activity during the year decreases the potential sample size to 315,987.
Non-missing ushare (requires some weeks in the LF, in order to interpret as personal unemployment rate) and non-missing 2 and 4 year lagged values of gap = 214,458
Non-missing olfshare and non-missing 2 and 4 year lagged values of gap = 237,288

Additional restrictions for hourlypay analysis:
Non-missing and non-zero total weeks of activity (less restrictive than ushare and olfshare analysis) = 320,064
Non-military = 319, 674
Non-missing and non-zero hourlypay (at least one week of work and reported hourlypay) and non-missing 2 and 4 year lagged values of gap = 130,065
Non-outlier hourlypay (not in the bottom 1% or top 99%) = 127,366
Non-missing identifiers for selection equation (spouse earnings if married and number of children) = 116,686
Non-missing occupation and industry codes = 101,326

III. Estimating samples means for out of the labor force and log real hourly pay

Notes: Estimating samples means for share of time in the labor force spent unemployed is in the paper. Samples include NLSY oversample of the poor and racial/ethnic minorities. Standard deviations in parentheses. Racial groups other than "Black" are not distinguished in the 1979 cohort so are combined with "White" for the full sample. Sample means are unweighted.

Out of the Labor Force Analysis Sample

	All Ages		18-24 year olds		25-34 year olds		35-44 year olds	45-64 year olds
Variable	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY79
Age 45-64 = 1	0.1822	0	0	0	0	0	0	1
Age 35-44 = 1	0.2273	0	0	0	0	0	1	0
Age 25-34 = 1	0.4637	0.6673	0	0	1	1	0	0
Age 18-24 = 1	0.1268	0.3327	1	1	0	0	0	0
College plus = 1	0.2008	0.2794	0.1332	0.2404	0.1931	0.2989	0.2135	0.2514
Some College = 1	0.2326	0.3102	0.2197	0.3211	0.2155	0.3047	0.2403	0.2752
High School = 1	0.3583	0.2728	0.3732	0.2876	0.363	0.2654	0.3513	0.3447
Less than HS = 1	0.2084	0.1376	0.2739	0.1509	0.2284	0.131	0.1949	0.1287
White & Other = 1	0.5356	0.5109	0.571	0.5171	0.5528	0.5078	0.5085	0.5013
Hispanic = 1	0.1777	0.2132	0.1685	0.2119	0.1729	0.2138	0.1871	0.1844
Black = 1	0.2867	0.2759	0.2605	0.2709	0.2743	0.2784	0.3044	0.3143
Male = 1	0.4776	0.4915	0.4765	0.4933	0.476	0.4905	0.4815	0.4773
Share of time in LF	0.1927	0.1714	0.2591	0.1851	0.1933	0.1646	0.1682	0.1755
spent unemployed	(0.3465)	(0.3188)	(0.3548)	(0.3148)	(0.3392)	(0.3206)	(0.3417)	(0.3587)
Person/year Observations	173101	64187	21954	21355	80260	42832	39345	31542

Log Real Hourly Earnings Analysis Sample

	All Ages		18-24 year olds		25-34 year olds		35-44 year olds	45-64 year olds
Variable	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY97	NLSY79	NLSY79
Age 45-64 = 1	0.3161							
Age 35-44 = 1	0.4116							
Age 25-34 = 1	0.2361	0.6022						
Age 18-24 = 1	0.0363	0.3978						
College plus = 1	0.2457	0.3006	0.1764	0.264	0.2274	0.3248	0.2337	0.2829
Some College = 1	0.2571	0.3233	0.2614	0.3387	0.2305	0.3132	0.2491	0.2868
High School = 1	0.3479	0.2638	0.333	0.277	0.3482	0.255	0.3558	0.3392
Less than HS = 1	0.1493	0.1123	0.2292	0.1203	0.1939	0.107	0.1613	0.0912
White & Other = 1	0.5389	0.5229	0.6253	0.5332	0.5554	0.5161	0.5294	0.5289
Hispanic = 1	0.1775	0.207	0.1531	0.2025	0.1748	0.21	0.1797	0.1795
Black = 1	0.2836	0.2701	0.2216	0.2644	0.2698	0.274	0.291	0.2915
Male = 1	0.5147	0.4969	0.5631	0.4967	0.5497	0.497	0.5122	0.4862
Share of time in LF	20.9888	15.6413	13.2818	14.0177	17.9245	16.7136	21.5795	23.3923
spent unemployed	(13.9119)	(8.6027)	(6.3206)	(7.3104)	(10.8924)	(9.2033)	(13.9882)	(15.6297)
Person/year Observations	61601	39725	2234	15801	14542	23924	25354	19471

IV. Marginal impact of a one additional year of exposure: share of time spent out of the labor force

	Year in Hot Period			Year in Cold Period		
Outcome/Group	HOTyr(t)	HOTyr (t-2)	HOTyr (t-4)	COLDyr(t)	COLDyr(t-2)	COLDyr(t-4)
Full Sample	0	-0.0007	**0.0023*** **	0.0002	0.0003	**0.0004***
	[0.0009]	[0.0009]	[0.0006]	[0.0002]	[0.0002]	[0.0002]
White, NH	0	-0.0018	**0.0036*** **	**0.0005***	0.0003	**0.0005***
	[0.0011]	[0.0011]	[0.0010]	[0.0002]	[0.0002]	[0.0002]
Hispanic	-0.0035	0.0022	0.0003	-0.0004	0.0002	-0.0001
	[0.0037]	[0.0030]	[0.0017]	[0.0006]	[0.0005]	[0.0004]
Black, NH	0	-0.0001	0.0021	-0.0002	0.0007	0.0008*
	[0.0018]	[0.0016]	[0.0011]	[0.0004]	[0.0004]	[0.0003]
College Plus	-0.002	-0.0011	**0.0023***	0.0002	0.0002	0.0004
	[0.0019]	[0.0017]	[0.0011]	[0.0004]	[0.0004]	[0.0003]
Some College	-0.0011	-0.0006	0.0006	-0.0001	0.0006	0.0004
	[0.0021]	[0.0017]	[0.0012]	[0.0004]	[0.0004]	[0.0003]
High School	0.0012	0	0.002	0.0001	-0.0002	0.0007*
	[0.0014]	[0.0015]	[0.0012]	[0.0003]	[0.0003]	[0.0003]
LT High School	0.0006	-0.0003	0.0042*	0.0008	0.0004	-0.0002
	[0.0018]	[0.0020]	[0.0018]	[0.0004]	[0.0004]	[0.0004]
45-64 years old	-0.0003	**-0.0124***	-0.0017	**-0.0015***	0.0001	0.001
	[0.0087]	[0.0057]	[0.0026]	[0.0006]	[0.0007]	[0.0007]
35-44 years old	0	0	0.0003	0	0	0.0001
	[0.0000]	[0.0001]	[0.0002]	[0.0000]	[0.0000]	[0.0001]
25-34 years old	0.0006	-0.0006	0.0022*	0.0002	0.0003	0.0003
	[0.0016]	[0.0013]	[0.0010]	[0.0003]	[0.0003]	[0.0002]
18-24 years old	-0.0026	-0.0017	0.0042	0.0001	0.0001	-0.0005
	[0.0021]	[0.0044]	[0.0023]	[0.0004]	[0.0007]	[0.0008]
Women	0.0011	0	**0.0031** **	0.0002	0.0003	0.0002
	[0.0015]	[0.0014]	[0.0010]	[0.0003]	[0.0003]	[0.0003]
Men	-0.0012	-0.0014	**0.0016***	0.0003	0.0003	**0.0006** **
	[0.0011]	[0.0010]	[0.0007]	[0.0002]	[0.0002]	[0.0002]

Notes for Tables: Data are the 1979 and 1997 NLSY cohorts covering years 1982 through 2014. Dependent variable is t share of time during a year spent out of the labor force (neither employed nor unemployed). Demographic-specific resul estimated by a fully-interactive model, allowing the impact for all demographics, in addition to the impact of the gap an period, to differ by demographic group (controlling for the rest of the demographics). Sample sizes for each of the grou noted below the group label. Time, state, and individual fixed effects are included and standard errors are clustered at th level. Hot and cold periods are also interacted with the year of the of the economic episode and its squared term.

V. Marginal impact of a one additional year of exposure: log real hourly pay

	Year in Hot Period			Year in Cold Period		
Outcome/Group	HOTyr(t)	HOTyr (t-2)	HOTyr (t-4)	COLDyr(t)	COLDyr(t-2)	COLDyr(t-4)
Full Sample	0.0001	**-0.0042***	-0.0012	-0.0005	**-0.0011****	**-0.0013*****
	[0.0022]	[0.0017]	[0.0009]	[0.0004]	[0.0004]	[0.0003]
White, NH	0.0002	-0.0027	-0.0021	-0.0001	-0.0009	**-0.0014****
	[0.0029]	[0.0023]	[0.0013]	[0.0005]	[0.0005]	[0.0004]
Hispanic	0.0055	0.0007	0.0005	-0.0014	-0.0017	-0.0015
	[0.0093]	[0.0058]	[0.0029]	[0.0013]	[0.0013]	[0.0008]
Black, NH	-0.0024	**-0.0067***	-0.0013	-0.0006	-0.0006	-0.0011
	[0.0035]	[0.0027]	[0.0014]	[0.0008]	[0.0008]	[0.0006]
College Plus	0.0026	**-0.0106***	-0.0028	-0.0003	0.0004	-0.0005
	[0.0069]	[0.0046]	[0.0024]	[0.0010]	[0.0010]	[0.0008]
Some College	-0.0003	-0.0037	-0.0024	-0.0014	-0.0018*	-0.0009
	[0.0041]	[0.0032]	[0.0016]	[0.0008]	[0.0007]	[0.0005]
High School	-0.0041	-0.0003	-0.001	0.0004	**-0.0011***	**-0.0013****
	[0.0027]	[0.0023]	[0.0013]	[0.0006]	[0.0006]	[0.0005]
LT High School	-0.0008	**-0.0067***	0.0008	-0.0001	-0.0004	**-0.0017***
	[0.0031]	[0.0030]	[0.0018]	[0.0010]	[0.0010]	[0.0008]
45-64 years old	-0.0306	-0.0101	-0.0012	-0.0006	-0.0002	0
	[0.0199]	[0.0103]	[0.0067]	[0.0012]	[0.0013]	[0.0013]
35-44 years old	0	-0.0001	0	0	0	-0.0001
	[0.0000]	[0.0000]	[0.0004]	[0.0000]	[0.0000]	[0.0002]
25-34 years old	-0.0021	-0.009	-0.0011	-0.0005	-0.0012	**-0.0024*****
	[0.0070]	[0.0049]	[0.0022]	[0.0010]	[0.0007]	[0.0006]
18-24 years old	-0.0033	**-0.0101***	-0.0022	-0.0006	-0.0028	-0.0011
	[0.0031]	[0.0046]	[0.0016]	[0.0009]	[0.0017]	[0.0016]
Women	-0.0002	-0.0039	-0.0011	-0.0007	**-0.0014***	**-0.0010***
	[0.0032]	[0.0024]	[0.0013]	[0.0006]	[0.0006]	[0.0004]
Men	0.0004	-0.0044	-0.0016	-0.0001	-0.0007	**-0.0014****
	[0.0029]	[0.0023]	[0.0012]	[0.0006]	[0.0006]	[0.0004]

VI. Parameter estimates for marginal effects reported in the paper - unemployment

Notes for Tables: Robust standard errors in brackets. Regressions include state, time, and individual fixed effects. Excluded categorical regressors are ages 45-64 and GTE to college education; race indicators are absorbed by the individual fixed effect. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Parameter estimates, share of time spent unemployed, for full sample and by race group.

			By Race	
Sample:	Full Sample	White,NH	Hispanic	Black,NH
Ages 45-64	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 35-44	0.0070*	0.0039	0.0144	0.0068
	[0.0032]	[0.0035]	[0.0077]	[0.0074]
Ages 25-34	0.0044	-0.0015	0.0110	0.0092
	[0.0046]	[0.0052]	[0.0112]	[0.0106]
Ages 18-24	0.0208***	0.0134*	0.0225	0.0304*
	[0.0055]	[0.0062]	[0.0131]	[0.0126]
GECOLL	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
SCOLL	-0.0081*	-0.0164***	0.0052	0.0031
	[0.0038]	[0.0042]	[0.0094]	[0.0090]
HS	-0.0113*	-0.0233***	-0.0014	0.0104
	[0.0057]	[0.0069]	[0.0127]	[0.0130]
LTHS	0.0110	-0.0069	0.0045	0.0471**
	[0.0085]	[0.0110]	[0.0179]	[0.0180]
GAP_L0*COLDyr_L0	0.0015***	0.0012***	0.0021**	0.0016*
	[0.0003]	[0.0004]	[0.0007]	[0.0007]
GAP_L2*COLDyr_L2	0.0019***	0.0021***	-0.0002	0.0038***
	[0.0003]	[0.0004]	[0.0007]	[0.0008]
GAP_L4*COLDyr_L4	0.0010***	0.0009*	0.0012	0.0019**
	[0.0003]	[0.0003]	[0.0007]	[0.0007]
GAP_L0*COLDyr_L0* COLDyr_L0	-0.0001***	-0.0001**	-0.0002**	-0.0001
	[0.0000]	[0.0000]	[0.0001]	[0.0001]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0001***	-0.0001***	0.0000	-0.0003***
	[0.0000]	[0.0000]	[0.0001]	[0.0001]

GAP_L4*COLDyr_L4*COLDyr_L4	-0.0001*	-0.0000	-0.0001	-0.0001
	[0.0000]	[0.0000]	[0.0001]	[0.0001]
GAP_L0_hot=1*GAP_L0*HOTyr_L0	0.0002	0.0014	0.0020	-0.0038*
	[0.0008]	[0.0008]	[0.0029]	[0.0018]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	0.0005	-0.0009	0.0010	0.0021
	[0.0007]	[0.0008]	[0.0035]	[0.0017]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	-0.0007	-0.0013	0.0013	-0.0010
	[0.0007]	[0.0008]	[0.0023]	[0.0017]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0	0.0001	-0.0000	0.0001	0.0006**
	[0.0001]	[0.0001]	[0.0005]	[0.0002]
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2	0.0000	0.0002*	0.0002	-0.0002
	[0.0001]	[0.0001]	[0.0007]	[0.0002]
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4	0.0001	0.0002	-0.0001	0.0001
	[0.0001]	[0.0001]	[0.0004]	[0.0002]
Constant	0.1089***	0.1059***	-0.1584	0.1314***
	[0.0163]	[0.0175]	[0.1192]	[0.0291]
Observations	214458	115117	39512	59829

Parameter estimates, share of time spent unemployed, by education group.

Sample:	GECOLL	SCOLL	HS	LTHS
Ages 45-64	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 35-44	0.0007	0.0107	0.0118*	0.0126
	[0.0042]	[0.0058]	[0.0058]	[0.0116]
Ages 25-34	-0.0003	0.0185*	0.0066	-0.0081
	[0.0063]	[0.0084]	[0.0080]	[0.0159]
Ages 18-24	0.0267***	0.0333***	0.0130	0.0100
	[0.0077]	[0.0101]	[0.0096]	[0.0182]
GECOLL	0.0000			
	[.]			
SCOLL	0.0005	0.0017**	0.0015**	0.0028**
	[0.0004]	[0.0006]	[0.0006]	[0.0010]
HS	0.0005	0.0022***	0.0019**	0.0037***
	[0.0004]	[0.0006]	[0.0006]	[0.0010]
LTHS	0.0003	0.0002	0.0016**	0.0014
	[0.0004]	[0.0006]	[0.0005]	[0.0009]
GAP_L0*COLDyr_L0	-0.0000	-0.0001**	-0.0001*	-0.0002*
	[0.0000]	[0.0001]	[0.0000]	[0.0001]
GAP_L2*COLDyr_L2	-0.0000	-0.0001*	-0.0001*	-0.0002*
	[0.0000]	[0.0001]	[0.0001]	[0.0001]
GAP_L4*COLDyr_L4	-0.0000	0.0000	-0.0001**	-0.0001
	[0.0000]	[0.0001]	[0.0000]	[0.0001]
GAP_L0*COLDyr_L0* COLDyr_L0	-0.0002	0.0005	0.0006	-0.0017
	[0.0010]	[0.0015]	[0.0013]	[0.0023]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0011	0.0000	0.0020	0.0033
	[0.0010]	[0.0013]	[0.0013]	[0.0022]
GAP_L4*COLDyr_L4* COLDyr_L4	-0.0023*	-0.0000	0.0007	-0.0021
	[0.0010]	[0.0013]	[0.0014]	[0.0024]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0	0.0002*	0.0001	-0.0000	0.0003

	[0.0001]	[0.0002]	[0.0001]	[0.0003]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	0.0001	-0.0000	-0.0000	-0.0003
	[0.0001]	[0.0002]	[0.0002]	[0.0003]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	0.0002	0.0001	-0.0001	0.0003
	[0.0001]	[0.0001]	[0.0002]	[0.0003]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0		0.0000		
		[.]		
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2			0.0000	
			[.]	
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4				0.0000
				[.]
Constant	0.0067	0.0962***	0.1478***	0.1762**
	[0.0162]	[0.0251]	[0.0324]	[0.0550]
Observations	50270	55826	71593	36769

Parameter estimates, share of time spent unemployed, by age group.

Sample:	Age 45-64	Age 35-44	Age 25-34	Age 18-24
Ages 45-64	0.0000			
	[.]			
Ages 35-44	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 25-34	-0.0100	-0.0120	-0.0016	-0.0361***
	[0.0123]	[0.0139]	[0.0088]	[0.0079]
Ages 18-24	-0.0362*	-0.0171	-0.0094	-0.0777***
	[0.0166]	[0.0205]	[0.0124]	[0.0170]
GECOLL	-0.0605**	-0.0167	0.0056	-0.0699*
	[0.0217]	[0.0275]	[0.0210]	[0.0293]
SCOLL	-0.0007	-0.0027**	0.0018***	0.0022
	[0.0008]	[0.0010]	[0.0004]	[0.0014]
HS	0.0020*	0.0030**	0.0016***	0.0014
	[0.0009]	[0.0010]	[0.0004]	[0.0013]
LTHS	0.0009	0.0011	0.0011**	-0.0004
	[0.0009]	[0.0009]	[0.0004]	[0.0013]
GAP_L0*COLDyr_L0	0.0000	0.0001	-0.0001***	-0.0002
	[0.0001]	[0.0001]	[0.0000]	[0.0002]
GAP_L2*COLDyr_L2	-0.0001	-0.0001	-0.0001**	-0.0001
	[0.0001]	[0.0001]	[0.0000]	[0.0002]
GAP_L4*COLDyr_L4	-0.0000	-0.0001	-0.0001	0.0001
	[0.0001]	[0.0001]	[0.0000]	[0.0001]
GAP_L0*COLDyr_L0* COLDyr_L0	-0.0036	-0.0000	0.0016	-0.0036
	[0.0037]	[0.0016]	[0.0013]	[0.0027]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0016	0.0029	0.0020	-0.0022
	[0.0028]	[0.0017]	[0.0011]	[0.0038]
GAP_L4*COLDyr_L4* COLDyr_L4	-0.0036	-0.0001	0.0005	-0.0000
	[0.0022]	[0.0018]	[0.0012]	[0.0033]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0	0.0004	-0.0000	-0.0001	0.0006*

	[0.0003]	[0.0002]	[0.0002]	[0.0003]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	0.0002	-0.0002	-0.0002	-0.0000
	[0.0002]	[0.0002]	[0.0002]	[0.0004]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	0.0004	-0.0000	-0.0001	-0.0002
	[0.0002]	[0.0002]	[0.0002]	[0.0004]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0		0.0000		
		[.]		
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2			0.0000	
			[.]	
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4				0.0000
				[.]
Constant	0.0542	0.0340	0.1007***	0.3347***
	[0.0682]	[0.0479]	[0.0258]	[0.0443]
Observations	27236	35011	112154	40057

Parameter estimates, share of time spent unemployed, by gender group.

Sample:	Women	Men
Ages 45-64	0.0000	0.0000
	[.]	[.]
Ages 35-44	0.0083	0.0053
	[0.0047]	[0.0043]
Ages 25-34	0.0109	-0.0019
	[0.0068]	[0.0062]
Ages 18-24	0.0269***	0.0152*
	[0.0080]	[0.0074]
GECOLL	0.0000	0.0000
	[.]	[.]
SCOLL	-0.0162**	-0.0018
	[0.0053]	[0.0054]
HS	-0.0257**	-0.0032
	[0.0080]	[0.0080]
LTHS	0.0028	0.0157
	[0.0123]	[0.0117]
GAP_L0*COLDyr_L0	0.0011*	0.0019***
	[0.0004]	[0.0004]
GAP_L2*COLDyr_L2	0.0015***	0.0023***
	[0.0005]	[0.0004]
GAP_L4*COLDyr_L4	0.0012**	0.0008*
	[0.0004]	[0.0004]
GAP_L0*COLDyr_L0*COLDyr_L0	-0.0001*	-0.0001***
	[0.0000]	[0.0000]
GAP_L2*COLDyr_L2*COLDyr_L2	-0.0001*	-0.0001***
	[0.0000]	[0.0000]
GAP_L4*COLDyr_L4*COLDyr_L4	-0.0001*	-0.0000
	[0.0000]	[0.0000]
GAP_L0_hot=1*GAP_L0*HOTyr_L0	0.0015	-0.0010
	[0.0011]	[0.0010]

GAP_L2_hot=1*GAP_ L2*HOTyr_L2	0.0013	-0.0003
	[0.0011]	[0.0010]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4	-0.0002	-0.0012
	[0.0011]	[0.0010]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0*HOTyr_ L0	-0.0000	0.0003*
	[0.0001]	[0.0001]
GAP_L2_hot=1*GAP_ L2*HOTyr_L2*HOTyr_ L2	-0.0001	0.0001
	[0.0001]	[0.0001]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4*HOTyr_ L4	0.0000	0.0001
	[0.0001]	[0.0001]
Constant	0.1485***	0.0704**
	[0.0224]	[0.0225]
Observations	106263	108195

VII. Parameter estimates for marginal effects reported in the paper - out of the labor force

Notes for Tables: Robust standard errors in brackets. Regressions include state, time, and individual fixed effects. Excluded categorical regressors are ages 45-64 and GTE to college education; race indicators are absorbed by the individual fixed effect. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Parameter estimates, share of time spent out of the labor force, for full sample and by race group.

			By Race	
Sample:	Full Sample	White,NH	Hispanic	Black,NH
Ages 45-64	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 35-44	-0.0022	0.0030	0.0010	-0.0111
	[0.0042]	[0.0057]	[0.0099]	[0.0080]
Ages 25-34	0.0065	0.0154*	0.0004	-0.0032
	[0.0058]	[0.0076]	[0.0142]	[0.0112]
Ages 18-24	0.0387***	0.0430***	0.0192	0.0465***
	[0.0066]	[0.0085]	[0.0161]	[0.0130]
GECOLL	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
SCOLL	0.0711***	0.0667***	0.0953***	0.0691***
	[0.0065]	[0.0088]	[0.0159]	[0.0121]
HS	0.0656***	0.0511***	0.0878***	0.0806***
	[0.0095]	[0.0132]	[0.0226]	[0.0174]
LTHS	0.0857***	0.0591**	0.1044***	0.1165***
	[0.0131]	[0.0187]	[0.0288]	[0.0242]
GAP_L0*COLDyr_L0	0.0009*	0.0016**	-0.0007	0.0002
	[0.0004]	[0.0005]	[0.0009]	[0.0008]
GAP_L2*COLDyr_L2	0.0004	0.0003	0.0006	0.0010
	[0.0003]	[0.0004]	[0.0008]	[0.0008]
GAP_L4*COLDyr_L4	0.0008*	0.0010*	-0.0001	0.0016*
	[0.0003]	[0.0005]	[0.0009]	[0.0007]
GAP_L0*COLDyr_L0* COLDyr_L0	-0.0001**	-0.0002***	0.0001	-0.0001
	[0.0000]	[0.0000]	[0.0001]	[0.0001]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0000	0.0000	-0.0001	-0.0000

	[0.0000]	[0.0000]	[0.0001]	[0.0001]
GAP_L4*COLDyr_L4*COLDyr_L4	-0.0001	-0.0001	-0.0000	-0.0001
	[0.0000]	[0.0000]	[0.0001]	[0.0001]
GAP_L0_hot=1*GAP_L0*HOTyr_L0	-0.0000	-0.0000	-0.0037	0.0000
	[0.0010]	[0.0013]	[0.0036]	[0.0019]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	-0.0005	-0.0016	0.0031	0.0000
	[0.0009]	[0.0012]	[0.0035]	[0.0018]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	0.0035***	0.0048***	0.0004	0.0033
	[0.0010]	[0.0013]	[0.0032]	[0.0018]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0	-0.0000	0.0000	0.0007	-0.0000
	[0.0001]	[0.0001]	[0.0006]	[0.0002]
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2	-0.0001	0.0000	-0.0007	-0.0001
	[0.0001]	[0.0001]	[0.0006]	[0.0002]
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4	-0.0004**	-0.0005**	-0.0000	-0.0003
	[0.0001]	[0.0001]	[0.0005]	[0.0002]
Constant	0.1217***	0.1400***	0.3623*	0.0964*
	[0.0246]	[0.0308]	[0.1515]	[0.0401]
Observations	237288	125511	44438	67339

Parameter estimates, share of time spent out of the labor force, by education group.

Sample:	GECOLL	SCOLL	HS	LTHS
Ages 45-64	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 35-44	0.0084	0.0010	0.0022	-0.0177
	[0.0074]	[0.0079]	[0.0073]	[0.0131]
Ages 25-34	-0.0169	0.0188	0.0135	-0.0051
	[0.0106]	[0.0113]	[0.0098]	[0.0164]
Ages 18-24	0.0683***	0.0454***	0.0179	0.0145
	[0.0121]	[0.0128]	[0.0111]	[0.0179]
GECOLL	0.0000			
	[.]			
SCOLL	0.0010	0.0007	0.0000	0.0022*
	[0.0007]	[0.0007]	[0.0006]	[0.0010]
HS	0.0000	0.0009	-0.0002	0.0002
	[0.0007]	[0.0006]	[0.0006]	[0.0009]
LTHS	0.0006	0.0008	0.0013*	-0.0003
	[0.0007]	[0.0007]	[0.0006]	[0.0009]
GAP_L0*COLDyr_L0	-0.0001	-0.0001	0.0000	-0.0002*
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
GAP_L2*COLDyr_L2	0.0000	-0.0001	0.0000	0.0000
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
GAP_L4*COLDyr_L4	-0.0000	-0.0001	-0.0001	0.0000
	[0.0001]	[0.0001]	[0.0001]	[0.0001]
GAP_L0*COLDyr_L0*COLDyr_L0	-0.0020	-0.0009	0.0014	0.0008
	[0.0018]	[0.0020]	[0.0016]	[0.0024]
GAP_L2*COLDyr_L2*COLDyr_L2	-0.0009	-0.0004	0.0002	0.0001
	[0.0017]	[0.0018]	[0.0017]	[0.0024]
GAP_L4*COLDyr_L4*COLDyr_L4	0.0030	0.0011	0.0031	0.0061*
	[0.0016]	[0.0018]	[0.0017]	[0.0026]
GAP_L0_hot=1*GAP_L0*HOTyr_L0	0.0003	0.0000	-0.0002	-0.0001
	[0.0002]	[0.0002]	[0.0002]	[0.0003]

GAP_L2_hot=1*GAP_L2*HOTyr_L2	0.0000	-0.0001	-0.0001	-0.0002
	[0.0002]	[0.0002]	[0.0002]	[0.0003]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	-0.0001	-0.0002	-0.0004*	-0.0006*
	[0.0002]	[0.0002]	[0.0002]	[0.0003]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0		0.0000		
		[.]		
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2			0.0000	
			[.]	
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4				0.0000
				[.]
Constant	0.0954*	0.2667***	0.1486***	0.3223***
	[0.0471]	[0.0582]	[0.0392]	[0.0604]
Observations	52689	60165	79525	44909

Parameter estimates, share of time spent out of the labor force, by age group.

Sample:	Age 45-64	Age 35-44	Age 25-34	Age 18-24
Ages 45-64	0.0000			
	[.]			
Ages 35-44	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 25-34	0.0209	0.0005	0.0217	0.0501***
	[0.0164]	[0.0259]	[0.0114]	[0.0097]
Ages 18-24	0.0009	-0.0194	-0.0028	0.0068
	[0.0205]	[0.0308]	[0.0156]	[0.0194]
GECOLL	-0.0386	0.0088	-0.0467*	0.0017
	[0.0269]	[0.0360]	[0.0230]	[0.0282]
SCOLL	-0.0006	-0.0007	0.0010*	-0.0007
	[0.0008]	[0.0013]	[0.0005]	[0.0013]
HS	0.0002	-0.0006	0.0002	-0.0007
	[0.0008]	[0.0012]	[0.0004]	[0.0012]
LTHS	0.0012	0.0014	0.0006	-0.0010
	[0.0010]	[0.0012]	[0.0004]	[0.0012]
GAP_L0*COLDyr_L0	-0.0000	0.0000	-0.0001*	0.0001
	[0.0001]	[0.0001]	[0.0000]	[0.0002]
GAP_L2*COLDyr_L2	-0.0000	0.0000	0.0000	0.0001
	[0.0001]	[0.0001]	[0.0000]	[0.0002]
GAP_L4*COLDyr_L4	-0.0001	-0.0000	-0.0001	0.0001
	[0.0001]	[0.0001]	[0.0000]	[0.0001]
GAP_L0*COLDyr_L0* COLDyr_L0	-0.0003	-0.0010	0.0008	-0.0041
	[0.0042]	[0.0020]	[0.0014]	[0.0029]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0071*	0.0014	-0.0002	-0.0013
	[0.0032]	[0.0022]	[0.0013]	[0.0040]
GAP_L4*COLDyr_L4* COLDyr_L4	-0.0018	0.0034	0.0027*	0.0062
	[0.0025]	[0.0023]	[0.0012]	[0.0033]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0	0.0002	0.0000	-0.0002	0.0007*
	[0.0004]	[0.0002]	[0.0002]	[0.0003]

GAP_L2_hot=1*GAP_ L2*HOTyr_L2	0.0006*	-0.0001	-0.0002	-0.0000
	[0.0003]	[0.0003]	[0.0002]	[0.0004]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4	0.0002	-0.0004	-0.0002	-0.0008
	[0.0002]	[0.0003]	[0.0001]	[0.0004]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0*HOTyr_ L0		0.0000		
		[.]		
GAP_L2_hot=1*GAP_ L2*HOTyr_L2*HOTyr_ L2			0.0000	
			[.]	
GAP_L4_hot=1*GAP_ L4*HOTyr_L4*HOTyr_ L4				0.0000
				[.]
Constant	0.2471***	0.1839***	0.1808***	0.2012***
	[0.0591]	[0.0448]	[0.0364]	[0.0471]
Observations	31542	39345	123092	43309

Parameter estimates, share of time spent out of the labor force, by gender group.

Sample:	Women	Men
Ages 45-64	0.0000	0.0000
	[.]	[.]
Ages 35-44	0.0097	-0.0156**
	[0.0067]	[0.0050]
Ages 25-34	0.0252**	-0.0131
	[0.0092]	[0.0069]
Ages 18-24	0.0451***	0.0332***
	[0.0102]	[0.0080]
GECOLL	0.0000	0.0000
	[.]	[.]
SCOLL	0.0377***	0.1086***
	[0.0094]	[0.0085]
HS	0.0370**	0.0747***
	[0.0134]	[0.0122]
LTHS	0.1024***	0.0503**
	[0.0189]	[0.0165]
GAP_L0*COLDyr_L0	0.0010	0.0007
	[0.0006]	[0.0004]
GAP_L2*COLDyr_L2	0.0006	0.0001
	[0.0005]	[0.0004]
GAP_L4*COLDyr_L4	0.0006	0.0009*
	[0.0005]	[0.0004]
GAP_L0*COLDyr_L0*COLDyr_L0	-0.0001*	-0.0001
	[0.0001]	[0.0000]
GAP_L2*COLDyr_L2*COLDyr_L2	-0.0000	0.0000
	[0.0000]	[0.0000]
GAP_L4*COLDyr_L4*COLDyr_L4	-0.0001	-0.0000
	[0.0001]	[0.0000]
GAP_L0_hot=1*GAP_L0*HOTyr_L0	0.0012	-0.0013
	[0.0016]	[0.0011]

GAP_L2_hot=1*GAP_ L2*HOTyr_L2	0.0001	-0.0013
	[0.0015]	[0.0011]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4	0.0043**	0.0026*
	[0.0015]	[0.0011]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0*HOTyr_ L0	-0.0001	0.0001
	[0.0002]	[0.0001]
GAP_L2_hot=1*GAP_ L2*HOTyr_L2*HOTyr_ L2	-0.0001	-0.0000
	[0.0002]	[0.0001]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4*HOTyr_ L4	-0.0004*	-0.0003*
	[0.0002]	[0.0001]
Constant	0.1681***	0.1041**
	[0.0341]	[0.0326]
Observations	123077	114211

VIII. Parameter estimates for marginal effects reported in the paper - log real hourly pay

Notes for Tables: Robust standard errors in brackets. Regressions include state, time, occupation & industry, and individual fixed effects (not reported). Excluded categorical regressors are ages 45-64 and GTE to college education; race indicators are absorbed by the individual fixed effect.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Parameter estimates, log real hourly pay, for full sample and by race group.

			By Race	
Sample:	Full Sample	White,NH	Hispanic	Black,NH
mills	-0.1713***	-0.1648***	-0.2117***	-0.1563***
	[0.0263]	[0.0430]	[0.0553]	[0.0415]
Ages 45-64	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 35-44	0.0398***	0.0490***	0.0691**	0.0033
	[0.0091]	[0.0136]	[0.0223]	[0.0135]
Ages 25-34	0.0384**	0.0423*	0.0978***	-0.0034
	[0.0117]	[0.0169]	[0.0274]	[0.0196]
Ages 18-24	-0.0173	-0.0203	0.0578	-0.0512*
	[0.0142]	[0.0205]	[0.0339]	[0.0238]
GECOLL	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
SCOLL	-0.1170***	-0.1176***	-0.1227***	-0.1068***
	[0.0126]	[0.0182]	[0.0288]	[0.0209]
HS	-0.1031***	-0.0854***	-0.1209**	-0.1135***
	[0.0168]	[0.0247]	[0.0372]	[0.0279]
LTHS	-0.0175	0.0271	-0.0886	-0.0411
	[0.0229]	[0.0344]	[0.0483]	[0.0391]
GAP_L0*COLDyr_L0	-0.0008	0.0008	-0.0024	-0.0012
	[0.0007]	[0.0011]	[0.0016]	[0.0015]
GAP_L2*COLDyr_L2	-0.0018*	-0.0018	-0.0020	-0.0011
	[0.0007]	[0.0011]	[0.0019]	[0.0016]
GAP_L4*COLDyr_L4	-0.0029***	-0.0033**	-0.0032	-0.0024
	[0.0009]	[0.0012]	[0.0020]	[0.0017]
GAP_L0*COLDyr_L0* COLDyr_L0	0.0001	-0.0001	0.0002	0.0001
	[0.0001]	[0.0001]	[0.0001]	[0.0001]

GAP_L2*COLDyr_L2* COLDyr_L2	0.0001	0.0001	0.0001	0.0001
	[0.0001]	[0.0001]	[0.0001]	[0.0002]
GAP_L4*COLDyr_L4* COLDyr_L4	0.0002*	0.0002	0.0002	0.0001
	[0.0001]	[0.0001]	[0.0001]	[0.0002]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0	0.0004	0.0006	0.0056	-0.0024
	[0.0021]	[0.0029]	[0.0083]	[0.0036]
GAP_L2_hot=1*GAP_ L2*HOTyr_L2	-0.0052*	-0.0034	0.0017	-0.0089*
	[0.0021]	[0.0030]	[0.0066]	[0.0036]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4	-0.0023	-0.0045	-0.0005	-0.0021
	[0.0020]	[0.0030]	[0.0062]	[0.0032]
GAP_L0_hot=1*GAP_ L0*HOTyr_L0*HOTyr_ L0	-0.0002	-0.0002	-0.0013	0.0002
	[0.0002]	[0.0003]	[0.0014]	[0.0003]
GAP_L2_hot=1*GAP_ L2*HOTyr_L2*HOTyr_ L2	0.0004*	0.0002	-0.0007	0.0008*
	[0.0002]	[0.0003]	[0.0011]	[0.0003]
GAP_L4_hot=1*GAP_ L4*HOTyr_L4*HOTyr_ L4	0.0002	0.0004	0.0006	0.0000
	[0.0002]	[0.0003]	[0.0011]	[0.0003]
Constant	2.6978***	2.7088***	2.8131***	2.6606***
	[0.0471]	[0.0641]	[0.1801]	[0.0711]
Observations	101326	53966	19158	28202

Parameter estimates, log real hourly pay, by education group.

Sample:	GECOLL	SCOLL	HS	LTHS
mills	0.0477	-0.1581**	-0.2044***	-0.1512**
	[0.1032]	[0.0523]	[0.0405]	[0.0477]
Ages 45-64	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 35-44	0.0828**	0.0468***	0.0116	0.0240
	[0.0296]	[0.0116]	[0.0094]	[0.0170]
Ages 25-34	0.0303	0.0529**	0.0346*	0.0275
	[0.0343]	[0.0191]	[0.0149]	[0.0238]
Ages 18-24	-0.0147	-0.0124	-0.0086	-0.0004
	[0.0406]	[0.0229]	[0.0184]	[0.0300]
GECOLL	0.0000			
	[.]			
SCOLL	0.0005	-0.0027*	0.0012	-0.0013
	[0.0017]	[0.0013]	[0.0011]	[0.0021]
HS	0.0009	-0.0028*	-0.0021	-0.0001
	[0.0016]	[0.0013]	[0.0011]	[0.0022]
LTHS	-0.0005	-0.0022	-0.0032*	-0.0048*
	[0.0020]	[0.0015]	[0.0013]	[0.0023]
GAP_L0*COLDyr_L0	-0.0001	0.0002*	-0.0001	0.0002
	[0.0002]	[0.0001]	[0.0001]	[0.0002]
GAP_L2*COLDyr_L2	-0.0001	0.0002	0.0001	-0.0001
	[0.0001]	[0.0001]	[0.0001]	[0.0002]
GAP_L4*COLDyr_L4	-0.0001	0.0001	0.0002	0.0004
	[0.0002]	[0.0001]	[0.0001]	[0.0002]
GAP_L0*COLDyr_L0* COLDyr_L0	0.0026	-0.0003	-0.0041	-0.0011
	[0.0056]	[0.0036]	[0.0030]	[0.0042]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0119*	-0.0040	-0.0001	-0.0103*
	[0.0051]	[0.0039]	[0.0033]	[0.0047]
GAP_L4*COLDyr_L4* COLDyr_L4	-0.0054	-0.0051	-0.0015	0.0028
	[0.0047]	[0.0035]	[0.0030]	[0.0044]

GAP_L0_hot=1*GAP_L0*HOTyr_L0	-0.0005	0.0000	0.0002	0.0001
	[0.0005]	[0.0004]	[0.0003]	[0.0004]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	0.0011*	0.0002	-0.0001	0.0009
	[0.0005]	[0.0004]	[0.0004]	[0.0005]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	0.0004	0.0005	-0.0001	-0.0006
	[0.0005]	[0.0004]	[0.0004]	[0.0005]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0		0.0000		
		[.]		
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2			0.0000	
			[.]	
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4				0.0000
				[.]
Constant	2.7119***	2.7074***	2.4579***	2.4534***
	[0.1007]	[0.1002]	[0.0753]	[0.0912]
Observations	27076	28681	31911	13658

Parameter estimates, log real hourly pay, by age group.

Sample:	Age 45-64	Age 35-44	Age 25-34	Age 18-24
mills	-0.0973	-0.0616	-0.0985	-0.1717
	[0.0933]	[0.0618]	[0.0528]	[0.0898]
Ages 45-64	0.0000			
	[.]			
Ages 35-44	0.0000	0.0000	0.0000	0.0000
	[.]	[.]	[.]	[.]
Ages 25-34	-0.0149	0.0228	-0.0623*	-0.0664**
	[0.0315]	[0.0641]	[0.0267]	[0.0240]
Ages 18-24	0.0160	-0.0363	-0.0293	-0.0193
	[0.0426]	[0.0693]	[0.0364]	[0.0390]
GECOLL	0.0932	-0.0026	0.0327	0.1031
	[0.0660]	[0.0801]	[0.0607]	[0.0677]
SCOLL	0.0022	0.0002	-0.0005	-0.0011
	[0.0018]	[0.0025]	[0.0012]	[0.0038]
HS	-0.0010	0.0026	-0.0011	-0.0028
	[0.0016]	[0.0023]	[0.0011]	[0.0054]
LTHS	0.0004	-0.0003	-0.0054***	-0.0021
	[0.0019]	[0.0023]	[0.0015]	[0.0051]
GAP_L0*COLDyr_L0	-0.0002	0.0000	0.0000	-0.0000
	[0.0002]	[0.0002]	[0.0001]	[0.0004]
GAP_L2*COLDyr_L2	0.0001	-0.0002	0.0000	-0.0004
	[0.0001]	[0.0002]	[0.0001]	[0.0008]
GAP_L4*COLDyr_L4	-0.0001	-0.0000	0.0004*	-0.0002
	[0.0002]	[0.0002]	[0.0001]	[0.0004]
GAP_L0*COLDyr_L0* COLDyr_L0	-0.0144	0.0017	-0.0012	-0.0079
	[0.0095]	[0.0039]	[0.0041]	[0.0074]
GAP_L2*COLDyr_L2* COLDyr_L2	-0.0057	-0.0069	-0.0077	-0.0210*
	[0.0059]	[0.0040]	[0.0043]	[0.0093]
GAP_L4*COLDyr_L4* COLDyr_L4	-0.0011	0.0019	-0.0018	-0.0108
	[0.0065]	[0.0049]	[0.0037]	[0.0072]

GAP_L0_hot=1*GAP_L0*HOTyr_L0	0.0011	-0.0003	0.0000	0.0006
	[0.0008]	[0.0004]	[0.0004]	[0.0007]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	0.0004	0.0008	0.0005	0.0022*
	[0.0005]	[0.0005]	[0.0004]	[0.0010]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	0.0001	-0.0007	0.0001	0.0014
	[0.0005]	[0.0006]	[0.0004]	[0.0009]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0		0.0000		
		[.]		
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2			0.0000	
			[.]	
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4				0.0000
				[.]
Constant	2.7796***	2.9678***	2.5128***	2.6055***
	[0.0964]	[0.1121]	[0.0998]	[0.1752]
Observations	19471	25354	38466	18035

Parameter estimates, log real hourly pay, by gender group.

Sample:	Women	Men
mills	-0.0548	-0.3817***
	[0.0435]	[0.0446]
Ages 45-64	0.0000	0.0000
	[.]	[.]
Ages 35-44	0.0352*	0.0335**
	[0.0142]	[0.0117]
Ages 25-34	0.0188	0.0352*
	[0.0189]	[0.0151]
Ages 18-24	-0.0409	-0.0054
	[0.0224]	[0.0183]
GECOLL	0.0000	0.0000
	[.]	[.]
SCOLL	-0.1100***	-0.1198***
	[0.0176]	[0.0183]
HS	-0.1090***	-0.0996***
	[0.0245]	[0.0238]
LTHS	-0.0590	0.0045
	[0.0378]	[0.0311]
GAP_L0*COLDyr_L0	-0.0016	0.0006
	[0.0010]	[0.0010]
GAP_L2*COLDyr_L2	-0.0017	-0.0017
	[0.0010]	[0.0010]
GAP_L4*COLDyr_L4	-0.0020	-0.0035**
	[0.0012]	[0.0012]
GAP_L0*COLDyr_L0*COLDyr_L0	0.0001	-0.0001
	[0.0001]	[0.0001]
GAP_L2*COLDyr_L2*COLDyr_L2	0.0000	0.0002
	[0.0001]	[0.0001]
GAP_L4*COLDyr_L4*COLDyr_L4	0.0000	0.0002*
	[0.0001]	[0.0001]

GAP_L0_hot=1*GAP_L0*HOTyr_L0	0.0002	0.0006
	[0.0030]	[0.0029]
GAP_L2_hot=1*GAP_L2*HOTyr_L2	-0.0048	-0.0054
	[0.0030]	[0.0029]
GAP_L4_hot=1*GAP_L4*HOTyr_L4	-0.0019	-0.0037
	[0.0029]	[0.0027]
GAP_L0_hot=1*GAP_L0*HOTyr_L0*HOTyr_L0	-0.0002	-0.0001
	[0.0003]	[0.0003]
GAP_L2_hot=1*GAP_L2*HOTyr_L2*HOTyr_L2	0.0004	0.0004
	[0.0003]	[0.0003]
GAP_L4_hot=1*GAP_L4*HOTyr_L4*HOTyr_L4	0.0000	0.0004
	[0.0003]	[0.0003]
Constant	2.5898***	2.8346***
	[0.0666]	[0.0658]
Observations	49881	51445