w o r k i n g

p a p e r

18 01R

Excess Persistence in Employment of Disadvantaged Workers

Bruce Fallick and Pawel Krolikowski

FEDERAL RESERVE BANK OF CLEVELAND

ISSN: 2573-7953

Working Paper 18-01R | August 2019*

Excess Persistence in Employment of Disadvantaged Workers

Bruce Fallick and Pawel Krolikowski

We examine persistence in employment-to-population ratios in excess of that implied by persistence in aggregate labor market conditions, among less-educated individuals using state-level data for the United States. Dynamic panel regressions and local projections indicate a moderate degree of excess persistence, which dissipates within three years. We find no significant asymmetry between the excess persistence of high vs. low employment rates. The cumulative effect of excess persistence in the business cycle surrounding the 2001 recession was mildly positive, while the effect in the cycle surrounding the 2008-09 recession was decidedly negative. Simulations suggest that the lasting employment benefits of temporarily running a "high-pressure" economy are small.

JEL codes: E24, J21, J24.

Keywords: persistence, labor market tightness, unemployment, employment.

Suggested citation: Fallick, Bruce, and Pawel Krolikowski, 2019. "Excess Persistence in Employment of Disadvantaged Workers." Federal Reserve Bank of Cleveland, Working Paper no. 18-01R. https://doi.org/10.26509/frbc-wp-201801r.

Bruce Fallick is at the Federal Reserve Bank of Cleveland (bruce.fallick@clev.frb.org), and Pawel Krolikowski is also at the Bank (pawel.krolikowski@clev.frb.org). The authors thank seminar participants at the Federal Reserve Bank of Cleveland, the Midwest Macroeconomic meetings, the Southern Economic Association meetings, and the American Economic Association meetings for helpful comments. Anne Chen, Emily Dohrman, and Meifeng Yang provided excellent research assistance.

*First version February 2018 under the title "Hysteresis in Employment among Disadvantaged Workers."

1 Introduction

The importance of employment experience for individuals' future labor market outcomes has long been recognized (Mincer, 1974). Experience provides human and market capital that enhance future employability. Such capital includes "hard" skills that contribute directly to production, as well as "soft" skills (Almlund et al., 2011), job contacts or networks that facilitate employment after job loss (Cingano and Rosolia, 2012; Glitz, 2017) or improve match quality (Dustmann et al., 2017), and better job matches through opportunities for job-to-job moves (Jovanovic, 1979, 1984). These observations suggest that, by affecting past employment experience, past macroeconomic states of the labor market may affect subsequent employment outcomes even conditional on subsequent macroeconomic conditions (Okun, 1973; Hagedorn and Manovskii, 2013). We define this lasting effect of past employment conditional on macroeconomic conditions as excess persistence in employment.

In this paper, we estimate excess persistence in employment among less-educated individuals using state-level data for the United States. We find a moderate but ephemeral degree of excess persistence: For the group with the greatest excess persistence among those we examine – prime-age men with no more than a high school education – the effects of past employment rates on subsequent employment rates can be substantial but essentially dissipate within three years. We find little evidence for asymmetric effects of high or low past employment on present employment. Our estimates imply that the cumulative effect of excess persistence in the business cycle surrounding the 2001 recession was mildly positive, while the effect in the cycle surrounding the 2008-09 recession was decidedly negative. Our simulations suggest that the employment benefits of temporarily running a "high-pressure" economy are small.

We focus our analysis on individuals with no more than a high school education, which we refer to as the disadvantaged population, for four reasons. First, this education group has seen its relative earnings (Acemoglu and Autor, 2011) and employment (Juhn, 1992; Council of Economic Advisers, 2017) decline markedly since the 1970s, which has made it a frequent focus of concern. Second, the mechanisms (noted above) posited to underlie possible excess persistence would seem to be more important for this population, whose lower employment rates in general mean that they may benefit less from households and neighborhoods that provide human and market capital independent of an individual's own employment history (Conley and Topa, 2002). Third, the employment of these populations tends to be more procyclical, so any change in overall labor market conditions can be expected to have a larger effect on their employment (Devereux, 2002; Hoynes et al., 2012; Aaronson et al., 2019), making any degree of excess persistence more important for this group. Fourth, blacks and Hispanics are more likely to be less educated (Stoops, 2004) and if these groups face discrimination in the labor market, higher levels of employment among the less educated mean greater direct exposure of employers to this group, which may reduce discrimination (Boisjoly et al., 2006; Miller, 2017). We find similar results for several definitions of disadvantaged populations that vary education levels and age.

Policymakers have recently expressed heightened interest in the relationship between employment experience and future employment outcomes, especially for disadvantaged populations. In particular, there is interest in the possibility that temporarily running a "high-pressure economy," with robust aggregate demand and a tight labor market, may produce long-run benefits to workers with weak workforce attachment even after the economy as a whole returns to a more "normal" state (Stockhammer and Sturn, 2012; Ball, 2015; Reifschneider et al., 2015; Yellen, 2016).[1]

The notion of excess persistence in employment may seem to be supported by evidence from microeconomic research. This evidence includes findings that macroeconomic conditions at the time a person completes his or her education and embarks upon a career have lasting effects on relative individual earnings,[2] that the state of the labor market earlier in one's tenure at an employer influences one's subsequent wage rate at that employer,[3] and that persons' early employment experience may affect their later employment.[4]

However, such evidence on how conditions at an early point in one's labor market experience affect individual outcomes does not establish the existence of excess persistence in aggregate employment. This is so for two reasons: First, the effects on those who, say, initially enter the labor force during a tight labor market are measured relative to the effects on those who enter during a slack labor market. This form of comparative excess persistence at the individual level does not imply excess persistence at an aggregate level: More employment in my history may enhance my chances of being employed today at the expense of reducing the chances of a competing person (with less employment in her history) being employed today.[5]

[1] A related literature addresses persistence in aggregate conditions themselves. This literature has found that in at least some (mostly European) countries, loose labor markets appear to have had adverse long-run effects (e.g., Blanchard and Summers, 1986; Ball, 2009).

[2] For recent evidence, see Kahn (2010), Oreopoulos et al. (2012), Gutierrez and Wenger (2017), Schwandt and von Wachter (2018), Shvartsman (2018), van den Berge (2018), and Rothstein (2019).

[3] See, for example, Beaudry and DiNardo (1991) and Schmieder and von Wachter (2010)

[4] Ellwood (1982) and Mroz and Savage (2006) find evidence for this last connection, but Gardecki and Neumark (1998) and Kletzer and Fairlie (2003) find otherwise. Burgess et al. (2003) find heterogeneous effects depending on a worker's skill level.

[5] In the context of trade policy, Abraham and Kearney (2018, p.8) write, "as Pierce and Schott (Pierce

Second, given the great heterogeneity across jobs and persons and the multiplicity of mechanisms through which employment experience may affect future employment probabilities, the dynamic effects of employment at the microeconomic level may depend on the source of the variation in employment. That is, the microeconomic evidence on the dynamic effects of more employment in general does not imply that greater employment achieved through tighter macroeconomic conditions, as opposed to other causes, will have lasting effects on overall employment rates.

In addition, the micro literature has mostly concentrated on excess persistence in wage rates or earnings, which need not imply excess persistence in employment. Indeed, depending on the mechanism at work, persistence in wage rates may work against persistence in employment. For example, Schmieder and von Wachter (2010) find that lower unemployment rates during a worker's job spell, which are associated with higher wage premiums, significantly increase the probability of job loss.

To measure the excess persistence in aggregate employment, we estimate a dynamic panel model in the detrended employment-to-population ratio (e/p) of disadvantaged workers, while controlling for aggregate labor market conditions using the unemployment rate (UR) gap among all workers. Within this framework we also use local projections (Jordà, 2005) to quantify excess employment persistence at different horizons. We use variation among states over time for identification in these regressions. The overall UR gap in a state is, of course, likely endogenous to the e/p of disadvantaged workers in that state. Therefore, as in Blanchard and Quah (1989) we use transitory movements in overall economic activity as a measure of demand disturbances and use it to instrument for the UR gap. Our results are robust to other relevant instruments (Section 5.1).

Previous research directly addressing the question of excess persistence in aggregate employment in the United States is thin. We follow the general approach of Fleischman and Gallin (2001) and Fleischman et al. (2018), who estimate a dynamic model to extract the persistence of the e/p in excess of that implied by the persistence of the macroeconomic conditions themselves, as measured by overall labor market tightness. Their evidence is not consistent with a large degree of persistence in cohort-level e/p in response to fluctuations in macroeconomic conditions. However, they use variation among synthetic birth cohorts over time to identify possible excess employment persistence in the national data, as opposed to

and Schott, 2016) acknowledge, their difference-in-differences identification strategy precludes an estimate of the effect of the policy change on overall U.S. employment. This is because the estimated effects are all about relative job losses and there is not an obvious way to translate their findings into an estimate of overall absolute job losses." Similarly, see Gautier et al. (2018) for an example of how microeconomic and aggregate welfare evaluation of job search assistance may differ.

variation among states over time. Our approach is also related to that of Blanchard and Katz (1992), a topic we explore further in Section 3.3.

Hotchkiss and Moore (2018) use state-level variation to compare individual outcomes in recessions following expansions of varying intensities. They find that, for some demographic groups, a person is likely to experience better outcomes during a period of high unemployment if that period was preceded by a tighter labor market. Yagan (2017) finds that individuals in localities that experienced greater increases in URs during the Great Recession were less likely to be employed in subsequent years. However, as Yagan (2017) notes, the results from his study may be driven by the effects of persistence in labor demand itself, rather than the result of excess persistence as we define it here. Using employer survey data from the 90s, Holzer et al. (2006) find that the relative demand for disadvantaged workers rose during the expansion and that racial discrimination likely declined. Unfortunately, their data cover only the period 1992 to 2001 and so cannot separate the contemporaneous implications of cyclical conditions from their longer-term effects. Finally, we do not address the possibility of persistence generated by *long-term* unemployment in particular, as in Kallenberg and von Wachter (2017) and Song and von Wachter (2014).

The paper proceeds as follows. Section 2 describes our data. Section 3 describes the dynamic panel model analysis and how it relates to Blanchard and Katz (1992). Section 4 presents our baseline estimates, including results using a local projections approach. Section 5 explores variations on our baseline specification, including alternative instruments, and addresses the issue of interstate migration. Section 6 simulates the implications of our excess persistence estimates for employment over the business cycle and their implications for temporarily running an economy above potential. Section 7 concludes.

2 Baseline sample

In this section we discuss our data, detrending approaches, and our baseline sample.

2.1 Data, definitions, and detrending

Our analysis uses annual data for the e/p and URs at the state level in the United States. We calculate the e/p for particular demographic groups for 1978 on, from individual data in the basic monthly Current Population Survey (CPS).[6] We use published data on state

[6]CPS state-level data (NBER, 2019) are also available for 1976 and 1977, but due to confidentiality restrictions, some states are not identified in those years.

URs. For both series, we use data through 2018. We include only the 50 states, omitting Washington DC and territories.

In this paper we concentrate on the prime-age population, ages 25 to 54, in order to abstract from education and ordinary retirement decisions. Moreover, as discussed above, we focus on persons with no more than a high school education, an education group that has faced substantial deterioration in labor market opportunities over the past 50 years. (See Section 5.3 for alternative definitions of the disadvantaged group.) We show our baseline results separately for prime-age men and prime-age women.

There are secular trends in the e/p of all groups of workers. To isolate the cyclical component, we detrend the e/p of each group in each state using the method recommended by Hamilton (2018).[7] Except where noted, all of the results reported below use these detrended e/p.[8]

In addition to the reasons proposed by Hamilton (2018), we prefer this detrending method because it is backward looking; detrending methods that use subsequent data are not suitable for our purposes, as they may include the effects of excess persistence in the estimates of trend, thereby understating the amount of excess persistence in the data. That said, our estimates of excess employment persistence rely on our estimate of trend so we also investigate alternative detrending methods in Section 5.2.

Figure 1 shows the actual e/p and trend e/p for prime-age male and female workers with no more than a high school education (the disadvantaged group), in which both series have been aggregated from the state to the national level for ease of display. Table 1 provides summary statistics for the state-level (actual and detrended) e/p used in the regression analysis, for disadvantaged men and women. Not surprisingly, there is more variation in the state-level data than is evident in the aggregate data in Figure 1.

We measure labor market tightness by the UR gap, the difference between the overall UR in the state and an estimate of the state's trend UR. For our baseline specification we use estimates of trend URs developed in unpublished work that adapts and extends the model of Tasci (2012) to the state context (the "Tasci-Fallick model").[9] In Section 5.1.1 we examine

[7]This method derives the trend in a variable as the predicted value from a regression of the variable at date $t + h$ on the four most recent values as of date t. We set the horizon parameter, h, at five years. The results are not sensitive to other reasonable choices for h.

[8]Removing the trend in the e/p allows us to concentrate on persistence stemming from cyclical fluctuations, which is our focus. Notice that this detrended e/p will move fairly closely with (the negative of) the unemployment-population ratio in each state, since $e/p = L/p - u/p$ and removing the trend in the e/p primarily removes the secular movements in the labor force participation rate. However, movements in the participation rate caused by cyclical fluctuations ought to remain in the detrended e/p if not too persistent.

[9]Tasci (2012) estimates trends in flow rates across labor force statuses as well as output in an unobserved components model, which then imply a trend UR. See Appendix A for a description of the extension to the

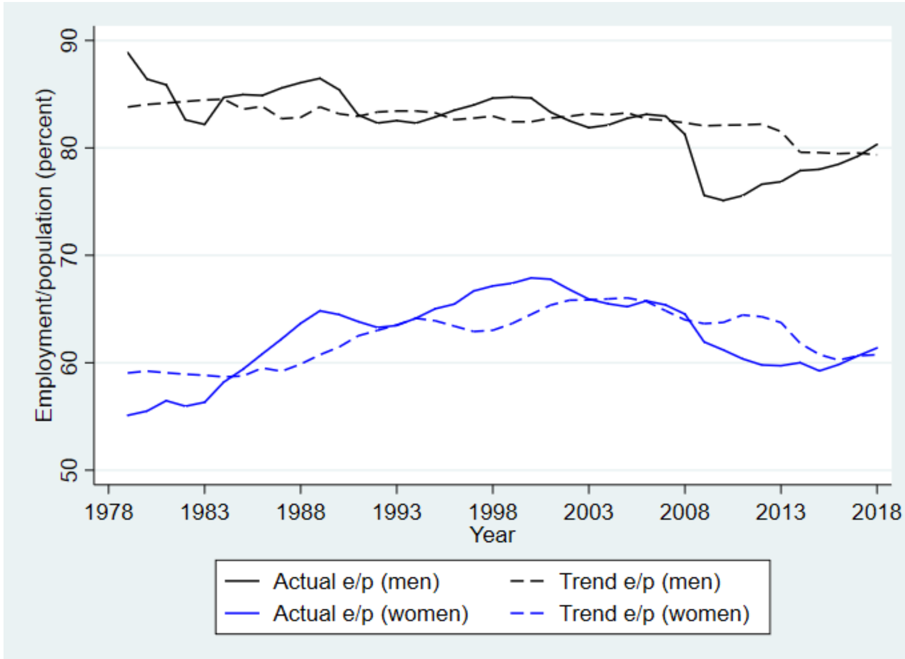

Figure 1: Actual e/p and Trend e/p of Disadvantaged Group, Aggregated

Note: State-level actual and trend e/p for prime-age men and women with no more than a high school education aggregated to the national level. Trend e/p is calculated separately for each state using the method in Hamilton (2018).

	Women				Men			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
e/p$_{s,t}$, actual (%)	62.3	6.8	37.9	81.8	82.4	5.1	62.6	94.4
e/p$_{s,t}$, detrended (pp)	0.0	3.3	-10.6	10.5	-0.3	3.4	-14.0	9.7

Table 1: Summary Statistics for Baseline Samples, State-Level Data

Note: Summary statistics for prime-age men and women with no more than a high school education for the years 1978 to 2018. Means and standard deviations are weighted by the population of the state. "e/p$_{st}$, actual" is the employment-to-population ratio of prime-age women or men with no more than a high school education in state s at time t. "e/p$_{st}$, detrended" is "e/p$_{st}$, actual" less the estimated trend for each state and is measured in percentage points (pp). Trend e/p is calculated using the method in Hamilton (2018). The detrended e/p will be the dependent variable in our baseline specification (Section 3).

the sensitivity of our results to this choice by comparing it to a selection of univariate filters.

The Tasci-Fallick model also provides estimated trends for overall economic activity, in addition to the UR, at the state level. We use these to instrument for the UR gap, as described in Section 3.1. (See Section 5.1.1 for summary statistics for the UR gap and our

state level.

baseline measure of economic activity.)

2.2 Disjoint samples

Measuring employment status in the CPS is subject to measurement error from at least two sources. The first is sampling error, which makes any particular sample imperfectly representative of the population. The second is misreporting, due to misunderstanding, proxy responses, etc. (Poterba and Summers, 1986; Elsby et al., 2015). Sampling error, in particular, is positively correlated over time due to the repeated sampling of individuals in the monthly CPS (Tiller, 1992), which would induce upward bias of our estimates of excess employment persistence.

To avoid this bias, we use "disjoint" samples from one year to the next. That is, we calculate the e/p in state s in a given year for use on the left-hand side (LHS) of our regression equation (equation 1 in Section 3.1 below) from a sample of individuals who are distinct from those used to calculate the e/p in previous years for use on the right-hand side (RHS) of this equation.[10] Since the disjoint samples still provide an unbiased estimate of the population e/p in each year, we obtain consistent estimates of excess employment persistence.

Such disjoint samples could be constructed in a number of ways. For simplicity and to balance the sample sizes used for the LHS and RHS measures, we choose to calculate the LHS e/p from a sample that includes only observations in the CPS that are in rotation groups 1 to 4, and the RHS e/p from a sample that includes only observations in rotation groups 5 to 8. These samples are disjoint because an individual in rotation groups 5 to 8 in year $t-1$ cannot be in rotation groups 1 to 4 in year t. Other schemes would provide slightly larger samples, but would involve a more complicated interaction between rotation group and calendar year. Summary statistics similar to those in Figure 1 and Table 1 for the full sample, but for our disjoint samples, are provided in Appendix B.

[10] Indeed, as expected, estimation with the full sample suggests a larger amount of excess persistence than with the disjoint samples, although our conclusions in Section 6, in which we use simulations to assess the magnitude of our estimates, are not materially affected. We recognize that the smaller estimates from the disjoint samples could be due to attenuation bias from the smaller sizes of the disjoint samples. However, experimentation with random subsamples of the full sample that mimic the size of our disjoint samples indicates that attenuation bias is not a serious concern in this case.

3 Methodology

We present and explain our baseline specification in Sections 3.1 and 3.2, respectively. We also relate our work to Blanchard and Katz (1992) in Section 3.3.

3.1 The dynamic panel approach

Equation (1) is our baseline estimating equation, in which the e/p is the detrended employment-to-population ratio, DA denotes the disadvantaged group, s denotes state, t denotes year, the α are state fixed effects, the γ are year fixed effects, $Ugap$ is the UR gap, β and δ are coefficients, and ϵ is an error term:

$$(e/p)^{DA}_{s,t} = \alpha_s + \gamma_t + \beta_1 (e/p)^{DA}_{s,t-1} + \beta_2 (e/p)^{DA}_{s,t-2} + \delta_0 Ugap_{s,t} + \delta_1 Ugap_{s,t-1} + \delta_2 Ugap_{s,t-2} + \epsilon_{s,t}. \quad (1)$$

As described in Section 2.2, the e/p on the left-hand and right-hand sides of the equation are derived from disjoint samples. We present details about this choice of specification in Section 3.2.

In this equation, the general state of the labor market, represented by the overall UR gap, affects the detrended e/p of the disadvantaged group contemporaneously and with two lags. Persistence in the overall UR gap, therefore, imparts a degree of persistence to the detrended e/p of the disadvantaged. The coefficients β on the lagged detrended e/p terms capture persistence in the e/p *in excess of* that implied by the persistence in the overall UR gap. This excess persistence is the focus of our analysis. In Appendix C we show that this β parameter is a function of both individual effects on a person's employment, such as human capital accumulation and depreciation, as well as cross-individual effects, such as employment networks and competition.

Of course, we are concerned about the endogeneity of the overall UR gap with respect to the detrended e/p for the disadvantaged group, if for no other reason than that the disadvantaged group make up a sizable proportion of the labor force.

One way to address this issue is to instrument for the UR with a broader set of indicators used to represent overall labor market conditions. For this purpose, the TF model estimates gaps for the State Coincident Indexes (SCI) produced by the Federal Reserve Bank of Philadelphia (FRB Philadelphia, 2019), as we describe in Appendix A. In Section 5.1 we examine alternative instruments, including state GDP, and find that they do not change our conclusions.

A regression of squared residuals on the inverse of the number of observations, as suggested by Solon et al. (2015), indicates significant heteroskedasticity in our data. Therefore we weight the regressions by the number of observations in the disadvantaged group in each state in each year.

It is well known that the dynamic panel approach with fixed effects may lead to biased estimates if the panel is short. Using Monte Carlo experiments, Arellano (2003) argues that if the number of periods is at least 10, then this bias is likely small. Nickell (1981) shows that with reasonably long panels, the bias is around order $-(1+\beta)/T$, in which T is the length of the panel. As our data effectively span 38 years, under the reasonable assumption that there is employment persistence ($\beta > 0$), the downward bias in our coefficient is likely small.

We are also not concerned that the size of our cross-section (N) induces bias. Monte Carlo simulations by Nerlove (1967), in which $N = 25$, suggest that the approximate formula for bias in Nickell (1981) is more or less exact when β is not too large. We have 50 cross-section observations in our baseline sample and our estimates of β are well below unity.

Although our data for the e/p goes back to 1978, our estimates for trend UR from the TF model begin only in 1979 (the earliest year for which the SCI is available). Between these data and the lag structure in equation (1), the sample period for our baseline regressions is 1981 to 2018 (38 years), which, with 50 states, yields a total of 1,900 observations.

3.2 Specification choice

To arrive at the relatively simple estimating equation (1), we began by estimating a panel VAR in seven variables: the overall UR gap and the e/p for six demographic groups – male and female intersected with education groups less than equal to high school (LEHS), some college, and college graduates. In this initial specification, we instrumented for the UR gap with the SCI gap, using trends from the Tasci-Fallick model to define both of these gaps.

Our primary interest is in the outcomes for LEHS men and women. Moreover, these groups exhibited greater excess persistence in the panel VAR than did the higher education groups. Therefore, we concentrated our attention on the equations that have the two e/p of the LEHS groups as outcome variables when choosing the lag structure and when assessing the inclusion of other demographic groups in the estimation.

We investigated various lag lengths and, based on both formal tests and to avoid overfitting, settled on 2 lags.

We then compared these two equations from the panel VAR with a more parsimonious specification in which the RHS of the equation for LEHS men (women) includes the lagged e/p terms for only LEHS men (women), as opposed to including the lagged e/p for every demographic group, in addition to the UR gap terms. The coefficients on the own lags and on aggregate conditions in this more parsimonious specification were similar to the coefficients in the specification with every demographic group's lagged e/p on the RHS, and we judged that the coefficients on other demographic groups' lagged e/p were not large enough to have significant implications for our simulations. Therefore, we chose to omit other demographic groups' lagged e/p from the RHS, leaving us with the dynamic panel specification in equation (1) estimated separately for LEHS men and LEHS women.

3.3 Relation to Blanchard and Katz (1992)

Our analysis is related to Blanchard and Katz (1992) – henceforth BK – and Dao et al. (2017). BK are interested in how a state's labor market adjusts to unexpected changes in labor demand that cause its employment to differ from that of other states. Accordingly, they estimate a VAR in three state-level variables: the change in employment, the employment-to-labor-force rate (that is, one minus the UR), and the labor force participation rate (LFPR), and identify innovations in employment with shocks to labor demand.[11]

As in this previous work, we use state-level labor market data in a VAR framework. However, we focus on the persistence of employment among disadvantaged workers in excess of that implied by overall labor market conditions. This difference in the question we are asking leads to three important differences between our setup and BK's.

First, given their focus on aggregate adjustment mechanisms, they estimate equations in the change in employment. Because we do not emphasize adjustment, the change in employment does not enter into our system. Rather, the dependent variable in equation (1) is the *level* of the detrended e/p.[12] A corollary of this difference in emphasis is that whereas interstate migration is an important potential adjustment mechanism in BK, we treat migration as a source of potential bias in our estimated employment persistence (Section 5.5).

Second, we examine employment (e/p) of the disadvantaged group, rather than employment of the *overall* population. This allows us to examine the persistence of employment in this group in *excess* of the persistence in overall labor market conditions.[13]

Third, since our focus is on the possible lasting effects of past employment of the disad-

[11]BK use defense spending and predicted growth rates of employment using state industry shares and national growth rates as two observable and plausibly exogenous demand shocks.

[12]We do not separately address the LFPR, which is consistent with BK (footnote 35).

[13]Mechanically, focusing on the e/p of all workers in the BK setup would mean we would be interested in the coefficient of the lagged e/p on the RHS, but would also include the employment-to-labor-force rate and the LFPR, which imply e/p.

vantaged group on their current employment *conditional* on overall labor market conditions, we take overall labor market conditions as given. We neither model them in a separate equation nor attempt to identify unexpected changes in those conditions.

4 Estimates

We present our baseline estimates of excess employment persistence in Section 4.1. We use local projections (Jordà, 2005) to investigate this excess employment persistence at different horizons in Section 4.2.

4.1 Baseline estimates

Table 2 presents estimates for disadvantaged women (column 1) and disadvantaged men (column 2).[14] For comparison, columns 3 and 4 show OLS estimates for women and men, respectively.

The coefficients on the lagged detrended e/p are significantly positive, indicating some excess persistence. However, the employment persistence is far from permanent. The coefficients above and the results in Sections 4.2 and 6 indicate that within three years the effect of the lagged e/p has virtually no effect on the current e/p.

Note that the coefficients on $Ugap_{s,t}$ and its lags are of opposite signs in Table 2. This is similar to the results in Fleischman and Gallin (2001) and Fleischman et al. (2018), in which the coefficients on the GDP gap and the lagged GDP gap have opposite signs. One interpretation of this is that changes in the UR gap, in addition to the level, have a short-run effect on the detrended e/p of the disadvantaged group, as is common in models of wage growth (Blanchard and Gali, 2010). As we will see in Section 6.2, this property leads to the e/p "overshooting" its trend in some simulations.

4.2 Local projections

The dynamic panel model in the previous section does not allow employment persistence to vary by horizon, but rather imposes exponential decay. To allow the effect of past employ-

[14] Throughout the paper, we show Driscoll-Kraay standard errors, with a lag length of 3, to allow for both spatial and temporal dependence in our state-panel regressions (Driscoll and Kraay, 1998). As an alternative, we have also estimated standard errors clustered on year and state. There was no consistent pattern across the coefficients of which method yielded larger estimates of the standard errors, and our conclusions are not sensitive to this choice.

	IV		OLS	
	(1)	(2)	(3)	(4)
	Women	Men	Women	Men
$(e/p)_{s,t-1}$	0.18***	0.24***	0.18***	0.25***
	(0.02)	(0.02)	(0.03)	(0.03)
$(e/p)_{s,t-2}$	0.08***	0.15***	0.08**	0.14***
	(0.03)	(0.03)	(0.03)	(0.02)
$Ugap_{s,t}$	-0.38**	-1.34***	-0.40**	-1.24***
	(0.16)	(0.12)	(0.16)	(0.11)
$Ugap_{s,t-1}$	-0.22	0.29**	-0.11	0.36***
	(0.17)	(0.15)	(0.20)	(0.13)
$Ugap_{s,t-2}$	0.32**	0.52***	0.21	0.42***
	(0.15)	(0.15)	(0.14)	(0.13)
FS F-stat	339	245		
Observations	1,900	1,900	1,900	1,900
R-squared	0.075	0.283	0.505	0.677

Table 2: Baseline Estimates

Note: The degree of excess persistence among prime-age individuals with no more than a high school education is substantial, but not large. These are the estimated coefficients from equation (1). The dependent variable is the detrended employment-to-population ratio of disadvantaged workers, $(e/p)_{s,t}$. $Ugap_{s,t}$ is the UR gap in state s at time t. We instrument for the UR gap with the SCI gap using two-stage least squares. Weighted by number of observations of the disadvantaged group. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 3.1 for the specification and Section 4.1 for a discussion of the results.

ment to vary by horizon, we estimate local projections (Jordà, 2005):

$$(e/p)^{DA}_{s,t+h} = \alpha^h_s + \gamma^h_t + \beta^h_1 (e/p)^{DA}_{s,t-1} + \beta^h_2 (e/p)^{DA}_{s,t-2} + \delta^h_0 Ugap_{s,t} + \delta^h_1 Ugap_{s,t-1} + \delta^h_2 Ugap_{s,t-2} + \epsilon_{s,t}, \quad (2)$$

which is the same as equation (1), but allows the coefficients on the RHS to vary by the horizon, h.

Table 3 presents the results for men and women, by different horizons. The first column ($h = 0$) replicates our estimates in Table 2. Column 2 through 5 show how lagged employment affects employment at subsequent horizons.

The results suggest that the effect of past employment on current employment declines at less than an exponential rate. Nevertheless, after three years, past employment is not estimated to improve current employment.

The coefficients on the lags of the e/p indicate a greater degree of excess employment for

	(1) $(e/p)_{s,t}$	(2) $(e/p)_{s,t+1}$	(3) $(e/p)_{s,t+2}$	(4) $(e/p)_{s,t+3}$	(5) $(e/p)_{s,t+4}$
Panel A. Women					
$(e/p)_{s,t-1}$	0.18***	0.11***	0.09***	-0.10***	-0.04
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
$(e/p)_{s,t-2}$	0.08***	0.04	-0.11***	0.011	0.07***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)
R-squared	0.075	0.047	0.047	0.049	0.045
Observations	1,900	1,850	1,800	1,750	1,700
Panel B. Men					
$(e/p)_{s,t-1}$	0.24***	0.16***	0.11***	-0.05	-0.010
	(0.02)	(0.03)	(0.02)	(0.04)	(0.04)
$(e/p)_{s,t-2}$	0.15***	0.08***	-0.04	0.02	-0.04
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
R-squared	0.283	0.198	0.131	0.108	0.086
Observations	1,900	1,850	1,800	1,750	1,700

Table 3: Local Projections

Note: The amount of excess employment persistence dissipates within three years. These are the estimated coefficients from equation (2) for different horizons. The dependent variable is the detrended employment-to-population ratio of disadvantaged workers, $(e/p_{s,t+h})$, at different horizons, h. This specification also includes the UR gap, which we instrument for with the SCI gap using two stage least squares. Weighted by the number of observations of the disadvantaged group. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 4.2 for details.

men than for women at the one- to four-year horizons. Therefore, in the interests of brevity, in the remainder of the paper we will concentrate on the results for men.

5 Variations in specification

In this section we present estimates from several variations of our baseline approach, including alternative instruments, different definitions of the disadvantaged population, and asymmetric effects. We also address the issue of interstate migration. We find that our baseline estimates of employment persistence in Section 4.1 are robust to these alternatives.

5.1 Alternative Instruments

5.1.1 State GDP

The TF model uses the trend in the Federal Reserve Bank of Philadelphia's SCI to represent overall economic activity, and in our baseline specification we use the estimated SCI gap to instrument for the UR gap. However, one may be concerned that the SCI are derived from data that concentrate on the labor market, and so may not fully alleviate concerns about the endogeneity of the UR gap with respect to the e/p of the disadvantaged.

As an alternative, in this section we use state GDP (BEA, 2019), in the same spirit as Blanchard and Quah (1989), instead of the SCI to construct the instrument. We use a variety of univariate filters to estimate the trends in state GDP and thus the GDP gap. At the same time, as well as for consistency, we examine the sensitivity of our results to the choice of the Tasci-Fallick model for the UR gap by replacing the Tasci-Fallick UR gap with gaps estimated with the same set of filters.

These filters are a Hodrick-Prescott (HP) filter with a smoothing parameter of 1600; a Baxter-King band-pass filter with a period of two to eight years and three-year smoothing; and a trend derived from the procedure suggested by Hamilton (2018), with a five-year horizon parameter.

To give these filters a running start ahead of our sample period, we estimate the filters from 1970 onward. However, data on state GDP are available beginning only with 1977. In order to minimize end-of-sample bias, we augment the GDP series on both ends with univariate forecasts (Kaiser and Maravall, 1999; Stock and Watson, 1999).[15]

Figure 2 shows the gaps implied by these four trends for the SCI (from the Tasci-Fallick model) and the natural logarithm of GDP (for the three univariate trends), all aggregated from the state to the national level (excluding DC). Figure 3 shows the corresponding four gaps for the UR. The Baxter-King trend stands out as moving closely with actual log GDP or UR, producing gaps that vary relatively little with the business cycle.[16]

Table 4 provides summary statistics for these UR, SCI, and GDP gaps. As with the e/p ratios, there is much more variation in the state-level data than is evident in the aggregate data.

Table 5 explores the sensitivity of our results to using the GDP gap as an instrument

[15] We use second-order autoregressive models for this purpose, similar to Clark and Kozicki (2005) and Mise et al. (2005), and extend the GDP series back from 1977 to 1970 and forward from 2018 to 2026.

[16] A common rule of thumb for the HP filter would suggest a smoothing parameter on the order of 6 for annual data; had we adopted this convention, the HP filter would have moved as closely with the actual quantities as the Baxter-King filter shown here.

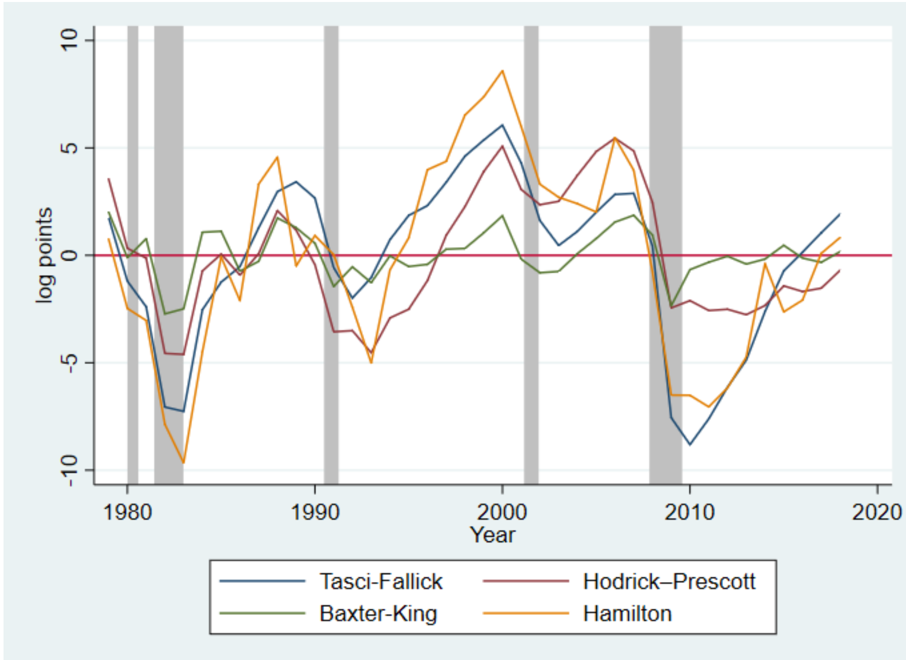

Figure 2: Estimates of State Activity and GDP Gaps, Aggregated

Note: Gaps estimated by four different approaches, aggregated to the national level. See Section 5.1.1 for details.

	Mean	Std Dev	Min	Max
$Ugap_{s,t}(TF)$	0.3	1.8	-4.6	7.7
$Ugap_{s,t}(HP)$	0.1	1.6	-3.1	7.6
$Ugap_{s,t}(BK)$	0.0	0.7	-2.0	3.7
$Ugap_{s,t}(Hamilton)$	0.1	1.7	-3.6	10.1
$SCIgap_{s,t}(TF)$	-0.3	4.8	-23.2	14.5
$GDPgap_{s,t}(HP)$	0.0	4.4	-15.4	21.2
$GDPgap_{s,t}(BK)$	0.0	1.6	-10.3	8.7
$GDPgap_{s,t}(Hamilton)$	-0.2	6.6	-25.0	32.1

Table 4: Summary Statistics for Aggregate Conditions, State-Level Data

Note: Summary statistics for state-level conditions, including the UR gap ($Ugap_{s,t}$), SCI gap ($SCIgap_{s,t}$), and GDP gap ($GDPgap_{s,t}$) measured in percentage points or log deviations from trend estimates.

and of these alternative methods of estimating the GDP and UR gaps. Column 1 repeats the baseline specification from column 2 of Table 2. The subsequent columns replace the Tasci-Fallick estimates with, respectively, the HP-filtered trends in column 2; the Baxter-King-filtered trends in column 3; and the Hamilton (2018) trends in column 4. These columns

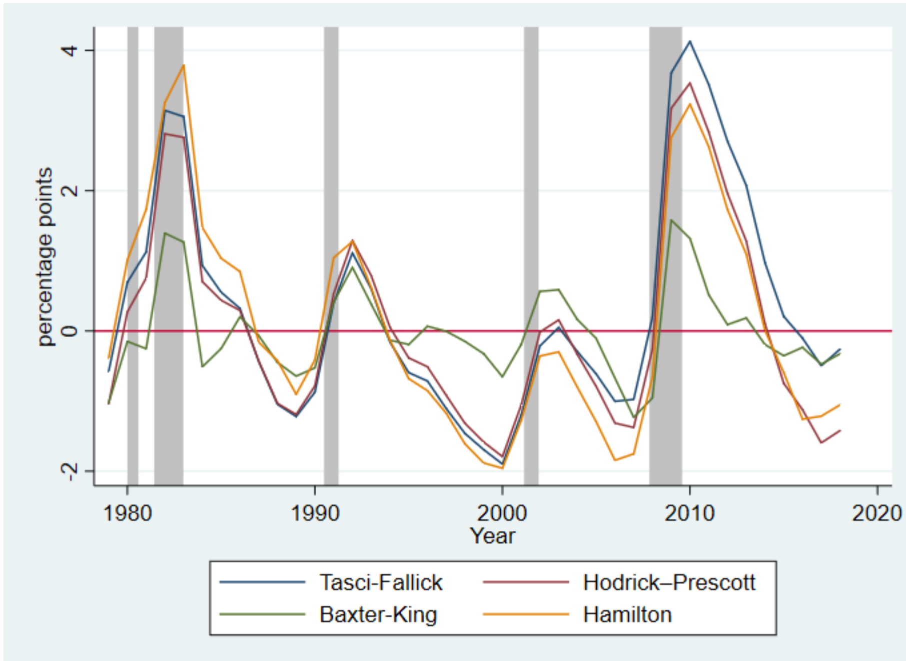

Figure 3: Estimates of State UR Gaps, Aggregated

Note: UR gaps estimated with four different approaches, aggregated to the national level. See Section 5.1.1 for details.

use the GDP gap as an instrument for the UR gap.

The coefficients on the lagged e/p using the HP trends are similar to the baseline in column 1, while the Baxter-King trend indicates somewhat more and the Hamilton (2018) trend somewhat less excess persistence than the first two. None of these differences are large enough to materially affect our characterization of excess persistence or our conclusions in the simulations in Section 6.

5.1.2 Regional and insured unemployment rates

It is difficult to find measures of overall economic activity that are convincingly free of potential endogeneity to the e/p of the disadvantaged within the state, and one may be concerned that neither the gap in the SCI or in GDP may entirely fit the bill. Therefore, in this section we explore two alternative instruments that may allay such concerns.

First, because business cycles are to some extent regional, the UR gaps of other states in a state's region, properly defined, are to a large extent a reflection of the same demand conditions as obtain in that state. Moreover, the UR gaps in these other states should be approximately exogenous to the e/p in the state in question. Therefore, as one alternative,

	(1) Tasci-Fallick	(2) Hodrick-Prescott	(3) Baxter-King	(4) Hamilton (2018)
$(e/p)_{s,t-1}$	0.24***	0.22***	0.32***	0.11***
	(0.019)	(0.024)	(0.044)	(0.041)
$(e/p)_{s,t-2}$	0.15***	0.15***	0.16***	0.15***
	(0.03)	(0.04)	(0.04)	(0.04)
$Ugap_{st}$	-1.34***	-1.8***	-1.79***	-0.97
	(0.12)	(0.30)	(0.65)	(0.97)
$Ugap_{s,t-1}$	0.29*	0.64	0.74	-1.60
	(0.15)	(0.54)	(0.72	(1.65)
$Ugap_{s,t-2}$	0.52***	0.38	0.52	1.55*
	(0.15)	(0.35)	(0.55)	(0.80)
Observations	1,900	1,900	1,900	1,900
R-squared	0.283	0.315	0.227	0.204

Table 5: Different Estimates of Trends in UR and GDP

Note: Using different estimates of trend unemployment and using the GDP gap to instrument for the UR gap makes little difference to the results. These are the estimated coefficients from equation (1). The dependent variable is the detrended employment-to-population ratio of disadvantaged workers, $(e/p)_{s,t}$. The disadvantaged group is prime-age men with no more than a high school education. $Ugap_{s,t}$ is the UR gap in state s at time t. The estimate of the trend UR and trend economic activity in each state varies by column. Weighted by the number of observations of the disadvantaged group. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.1.1 for details.

for each state we use the "leave-out" mean of the UR gap in the state's region, which we label the "regional Ugap". To define a state's region, we use the eight clusters of the 48 contiguous states identified by Crone (2005) as having similar business cycles. Column 2 of Table 2 presents the estimated coefficients when instrumenting with the SCI gap but using only the 48 contiguous states, and column 3 presents the results when instrumenting the UR gap with the regional UR gap, in which all gaps are estimated with the TF approach (as in the baseline).

Second, the number of individuals who receive unemployment insurance (UI) benefits are an indicator of the level of labor demand because benefits are designed to be paid only to individuals who lose a job through no fault of their own (e.g. laid off or position abolished), and not to individuals who are fired for cause or who quit (DOL, 2018). Therefore, we use the detrended insured unemployment rate (IUR), defined as the number of individuals receiving UI benefits over all covered employment, as another instrument for a state's UR gap. We detrend the IURs using the HP filter (with a smoothing parameter of 1600).[17] State-level insured unemployment data only start in 1986, so for comparison, in column 4 we present results using the SCI gap as an instrument for that date range. Column 5 presents the results using the detrended IUR as an alternative instrument.

The estimated excess employment persistence when we instrument for the UR gap with the regional UR gap or the IUR is no greater than in the baseline which uses the SCI gap. The overall effect of the UR (the sum of the contemporaneous and lag coefficients) is also similar with the three different instruments.

In addition to the estimated coefficients, Table 6 reports the first-stage F statistic to show that our instruments are all strongly correlated with the detrended e/p of the disadvantaged group.[18] Finally, despite relatively precise IV estimates, an over-identification test using all three instruments (Wooldridge, 2002, pp. 201) cannot reject the null hypothesis ($p = .19$) that the instruments are uncorrelated with the structural error term in equation (1).[19]

5.2 Time trends in the e/p

Our baseline estimates use the detrended e/p of the disadvantaged group in equation (1). We do this in order to concentrate on persistence stemming from cyclical fluctuations instead of lower-frequency (presumably more structural) phenomena. However, one may be concerned that the method we use to estimate the state-specific trends may capture some of the cyclical variation in which we are interested, especially because some secular movements, such as the number of persons receiving disability payments, may have their origins in phenomena that initially move with the business cycle (Aaronson et al., 2014). In this section, we investigate the sensitivity of our results to replacing the Hamilton (2018) trends with simple parametric time trends that are unlikely to be subject to such influences. In particular, Table 7 uses the actual e/p (i.e., not detrended) and includes state-specific linear and quadratic time trends on the right-hand side. Column 1 repeats our baseline specification (with the detrended e/p). Column 2 includes linear trends (with the actual e/p), and column 3 includes quadratic trends. The inclusion of the latter two trends results in smaller estimates of excess persistence than in the baseline – the opposite of our initial concern.

[17]As with GDP in Section 5.1.1, we augment the insured unemployment data on both ends using second-order regressive models to reduce endpoint bias.

[18]We report the conservative statistic proposed by Kleibergen and Paap (2006). Our test statistics are above conventional critical values presented in Stock and Yogo (2005), although the IUR instrument is somewhat weaker than the others.

[19]Over-identification restrictions test for several econometric issues simultaneously, including the exogeneity of the instruments and treatment effect heterogeneity (Angrist and Pischke, 2009).

	(1) SCIgap 1979-2018	(2) Exclude AK and HI	(3) Regional Ugap	(4) SCIgap 1986-2018	(5) IUR 1986-2018
$(e/p)_{s,t-1}$	0.24***	0.24***	0.14***	0.24***	0.16***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
$(e/p)_{s,t-2}$	0.15***	0.14***	0.08*	0.14***	0.06
	(0.03)	(0.03)	(0.04)	(0.03)	(0.05)
$Ugap_{s,t}$	-1.34***	-1.31***	-1.66***	-1.50***	-1.83***
	(0.12)	(0.12)	(0.32)	(0.12)	(0.27)
$Ugap_{s,t-1}$	0.29*	0.27*	-0.10	0.25	0.10
	(0.15)	(0.15)	(0.70)	(0.18)	(0.35)
$Ugap_{s,t-2}$	0.52***	0.50***	0.52	0.61***	0.22
	(0.15)	(0.15)	(0.47)	(0.20)	(0.31)
FS F-stat	245	225	67	99	19
Observations	1,900	1,824	1,824	1,650	1,650
R-squared	0.283	0.275	0.175	0.278	0.173

Table 6: Alternative Instruments

Note: The choice of instrument makes little difference to the results. These are the estimated coefficients from equation (1) with alternative instruments for the overall UR in state s at time t and its lags. The dependent variable is the detrended employment-to-population ratio of disadvantaged workers, $(e/p)_{s,t}$. The disadvantaged group is prime-age men with no more than a high school education. $Ugap_{s,t}$ is the UR gap in state s at time t, in which the trend is estimated using the Tasci-Fallick approach (Section 2). Column 1 reproduces the baseline regression in which we instrument the overall UR gap with the SCI gap. In column 2 we restrict the sample to the 48 contiguous states. In column 3 we instrument with the average UR of the other states in a state's region as defined by Crone (2005). In column 4 we use the SCI gap as an instrument but limited to years when the IUR is available. Column 5 instruments for the UR gap with the IUR gap. Weighted by number of observations of the disadvantaged group. "FS" stands for "First Stage". Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.1 for details.

5.3 Defining the disadvantaged population

The definition of the disadvantaged group is necessarily somewhat arbitrary. We have so far defined the disadvantaged group as prime-age persons with no more than a high school education because this group has seen substantial deterioration in relative earnings and employment in recent decades, has generally lower employment rates than other education groups, has more procyclical employment rates, and its members are more likely to be black or Hispanic. These characterizations are all the more apt for persons with less than a high school education. In addition, younger persons have had less opportunity for previous accumulation of human and market capital, and so may have more to gain from a bout of

	(1) Baseline	(2) Time Trends Linear	(3) Time Trends Quadratic
$(e/p)_{s,t-1}$	0.24***	0.13**	0.09***
	(0.019)	(0.024)	(0.025)
$(e/p)_{s,t-2}$	0.15***	0.08***	0.04
	(0.03)	(0.02)	(0.02)
$Ugap_{s,t}$	-1.34***	-1.45***	-1.56***
	(0.12)	(0.12)	(0.12)
$Ugap_{s,t-1}$	0.29*	0.48***	0.49***
	(0.15)	(0.13)	(0.14)
$Ugap_{s,t-2}$	0.52***	0.039	-0.18
	(0.15)	(0.12)	(0.11)
Observations	1,900	1,900	1,900
R-squared	0.283	0.277	0.264

Table 7: State-Specific Time Trends

Note: Using state-specific time trends reduces the estimates of excess persistence. These are the estimated coefficients from equation (1), in which we include linear and quadratic state-specific time trends instead of detrending the e/p with the Hamilton (2018) approach. The dependent variable is the employment-to-population ratio of disadvantaged workers, $(e/p)_{s,t}$. The disadvantaged group is prime-age men with no more than a high school education. $Ugap_{s,t}$ is the UR gap in state s at time t, in which we estimate the trend UR gap using the approach in Tasci (2012) (Section 2). We instrument for the UR gap with the SCI gap from the TF model. Weighted by number of observations of the disadvantaged group. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.2 for details.

employment and more to lose by missing out on employment.

Table 8 explores these possibilities by varying the definition of the disadvantaged population. Column 1 repeats our baseline specification, which treats prime-age (25 to 54) men with no more than a high school diploma as the disadvantaged group. Column 2 narrows the definition to prime-age men with less than a high school education. Column 3 narrows the sample to men ages 25 to 34 with no more than a high school education. (We also tried to narrow the sample to black men and to Hispanic men. Unfortunately, the samples in the CPS data were too small to allow reasonable estimation.)

In both cases, the coefficients indicate less excess persistence than in the baseline. We take these results with a grain of salt, because the smaller sizes of the samples in the CPS data may lead to noisier measures of the lagged e/p and therefore to attenuation of those

	(1) Baseline	(2) < HS	(3) $\leq$ HS, 25-34
$(e/p)_{s,t-1}$	0.24***	0.16***	0.14***
	(0.02)	(0.02)	(0.02)
$(e/p)_{s,t-2}$	0.15***	0.09***	0.10***
	(0.03)	(0.03)	(0.03)
$Ugap_{st}$	-1.34***	-1.23***	-1.83***
	(0.12)	(0.25)	(0.22)
$Ugap_{s,t-1}$	0.29*	0.45	0.34
	(0.15)	(0.37)	(0.32)
$Ugap_{s,t-2}$	0.52***	0.038	0.62**
	(0.15)	(0.32)	(0.24)
Observations	1,900	1,900	1,900
R-squared	0.283	0.085	0.199

Table 8: Different Definitions of Disadvantaged

Note: Different definitions of disadvantaged do not suggest greater excess persistence in employment. These are the estimated coefficients from equation (1). The dependent variable is the employment-to-population ratio of various definitions of disadvantaged workers, $(e/p)_{s,t}$. $Ugap_{s,t}$ is the UR gap in state s at time t, in which we estimate the trend UR gap using the approach in Tasci (2012) (Section 2). We instrument for the UR gap with the SCI gap. Weighted by number of observations of the disadvantaged group. Weighted by number of observations of the disadvantaged group. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.3 for details.

coefficients.[20]

5.4 Asymmetries

High and low detrended e/p may have asymmetric effects on future employment outcomes. For example, skills may be slower to deteriorate through non-use than they are to accrue through use, while the formation of networks may display the opposite pattern. To allow for such asymmetry, we split the lagged detrended e/p term into two components: one for the e/p above its trend (positive detrended e/p) and one for the e/p below its trend (negative detrended e/p).

Column 1 of Table 9 repeats the baseline specification. Column 2 introduces asymmetry.

[20] Attenuation bias is a potential concern with the baseline definition as well, of course. However, the sample sizes for that group are large. The smallest state averages 775 observations, whereas for the less-than-high-school group and the 25-34 group the smallest state averages 139 and 277, respectively. In contrast, for black men with no more than high school, the smallest state averages just 6 observations, and limiting the sample to only states with even 75 observations eliminates half of the states.

	(1) Baseline Baseline	(2) Linear Asymmetry	(3) Quadratic Asymmetry
$(e/p)_{s,t-1}$	0.24***		
	(0.02)		
$(e/p)_{s,t-2}$	0.15***		
	(0.03)		
$(e/p\ positive)_{s,t-1}$		0.24***	0.20*
		(0.05)	(0.11)
$(e/p\ positive\ squared)_{s,t-1}$			0.01
			(0.02)
$(e/p\ negative)_{s,t-1}$		0.24***	0.19***
		(0.03)	(0.06)
$(e/p\ negative\ squared)_{s,t-1}$			-0.01
			(0.01)
$(e/p\ positive)_{s,t-2}$		0.20***	0.25**
		(0.04)	(0.10)
$(e/p\ positive\ squared)_{s,t-2}$			-0.01
			(0.01)
$(e/p\ negative)_{s,t-2}$		0.11**	0.14**
		(0.04)	(0.06)
$(e/p\ negative\ squared)_{s,t-2}$			0.00
			(0.01)
$Ugap_{s,t}$	-1.34***	-1.35***	-1.35***
	(0.12)	(0.12)	(0.12)
$Ugap_{s,t-1}$	0.29*	0.31**	0.32**
	(0.15)	(0.15)	(0.15)
$Ugap_{s,t-2}$	0.52***	0.52***	0.51***
	(0.15)	(0.15)	(0.15)
Observations	1,900	1,900	1,900
R-squared	0.283	0.284	0.285

Table 9: Asymmetry

Note: Estimates do not indicate significant asymmetry. These are the estimated coefficients from versions of equation (1) in which we split the lagged detrended e/p term into two components: above and below trend. The dependent variable is the employment-to-population ratio of disadvantaged workers, $(e/p)_{s,t}$. The disadvantaged group is prime-age men with no more than a high school education. $Ugap_{s,t}$ is the UR gap in state s at time t, in which we estimate the trend UR gap using the approach in Tasci (2012) (Section 2). We instrument for the UR gap with the SCI gap. Weighted by number of observations of the disadvantaged group. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.4 for details.

The estimates do not indicate significant asymmetry. F-tests (not shown) cannot reject that the coefficients on the positive and negative e/p are equal at conventional significance levels. In column 3 we add quadratic terms in each asymmetric detrended e/p to allow for the possibility that extremely high employment or extremely low employment has a larger marginal effect than smaller deviations from trend. Here, too, one cannot reject symmetry.

5.5 Migration

The reasoning behind our empirical model assumes that the e/p of the disadvantaged group in a state in year $t-1$ represents the previous employment experience of an average disadvantaged person in that state in year t. Interstate migration may render this untrue. In particular, if migration responds to cyclical differences in labor market conditions across states, then the coefficients on the lagged e/p may reflect a combination of the effects on $(e/p)_t$ of migration into states with (presumably) higher $(e/p)_{t-1}$ and the excess persistence we are interested in measuring. However, in this section we find that migration of the disadvantaged group is not significantly cyclical, so migration is not a major concern.

To assess the importance of internal migration in response to cyclical conditions, we use data from the Annual Social and Economic Supplement (ASEC) to the CPS to compute net and gross migration rates for each state from 1982 to 2018. We focus on prime-age men with no more than a high school education to align with our baseline sample in Section 3. The migration data in the CPS ASEC have well-known imputation issues (Kaplan and Schulhofer-Wohl, 2012) so we use non-imputed migration data, as in Molloy et al. (2011) and Kaplan and Schulhofer-Wohl (2017). We also exclude the year 1985 because the migration question in that survey was not comparable to other years.

Using these CPS ASEC migration data, we estimate the following equation:

$$y^g_{s,t} = \alpha_s + \gamma_t + \xi_1 y^g_{s,t-1} + \xi_2 y^g_{s,t-2} + \delta_0 Ugap_{s,t} + \delta_1 Ugap_{s,t-1} + \delta_2 Ugap_{s,t-2} + \eta_{s,t}, \quad (3)$$

in which $y^g_{s,t}$ is either net in-migration or the sum of in- and out-migration ("gross migration") of group g in state s at time period t and the other notation follows our baseline specification in equation (1). Equation (3) follows our baseline specification closely in allowing for lags of the left-hand-side variable and for dynamic effects of the UR gap on migration rates. We use the Tasci-Fallick estimates of trend state-level URs, as in our baseline specification. The estimation period encompasses 31 years of data for each of 50 states resulting in 1,550 observations.

Table 10 presents the results. Column 1 suggests that a 1 pp increase in a state's UR decreases contemporaneous *net* migration by 0.16 pp. The average (absolute value of) net migration rates for this population over the 1982 to 2018 period was 1.3 percent, so the economic significance of this effect is modest. Moreover, the coefficient is not statistically significant. Column 2 suggests that a 1 pp increase in a state's UR decreases contemporaneous *gross* migration by 0.2 1pp. This response is also not statistically significant, and with average gross migration for this population at 3.9 percent over the relevant period, it is also not economically significant. In both columns 1 and 2, a test of whether the sum of the $Ugap$ coefficients is zero cannot be rejected, suggesting that, for less-educated prime-age men, the cumulative effect of labor market conditions on interstate migration is small. In sum, interstate migration among less-educated prime-age males does not respond significantly to cyclical labor market conditions. These findings are consistent with those of Bound and Holzer (2000) and Notowidigdo (2019).

	(1) Net Migration $\leq$ HS	(2) Gross Migration $\leq$ HS	(3) Net Migration $>$ HS	(4) Gross Migration $>$ HS
$Ugap_{st}$	-0.16	0.21	-0.20**	0.12
	(0.12)	(0.17)	(0.08)	(0.11)
$Ugap_{s,t-1}$	-0.10	-0.05	0.04	-0.002
	(0.19)	(0.20)	(0.16)	(0.19)
$Ugap_{s,t-2}$	0.18	-0.10	-0.07	-0.10
	(0.15)	(0.16)	(0.12)	(0.14)
$y_{s,t-1}$	-0.03	0.12*	0.07**	0.13***
	(0.04)	(0.07)	(0.03)	(0.04)
$y_{s,t-2}$	0.02	0.13**	0.004	0.08***
	(0.04)	(0.05)	(0.02)	(0.03)
Observations	1,550	1,550	1,550	1,550
p-value $\sum_i \delta_i = 0$	0.27	0.35	0.0001	0.86

Table 10: Migration in Response to Labor Market Conditions

Note: Interstate migration for less-educated prime-age men does not respond to cyclical labor market conditions. These are the estimated coefficients from equation (3). The dependent variable is either net or gross migration of less-educated prime-age men. $Ugap_{s,t}$ is the UR in state s at time t less the estimated trend UR, using the approach in Tasci (2012) (Section 2). Weighted by number of observations of each population in $t-1$. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.5 for details.

For comparison, we also examine interstate migration among more-educated prime-age men. Column 3 of Table 10 shows that the contemporaneous effect of labor market conditions on net migration for prime-age men with more than a high school education is larger than the effect for less-educated workers and is more precisely estimated. A test of whether the $Ugap$ coefficients sum to zero is rejected, suggesting that interstate net migration for more-educated workers responds negatively to increases in labor market slack. At the same time, column 4 shows that gross migration rates of more-educated prime-age men are not strongly affected by labor market conditions, as with less-educated prime-age men.[21]

These results are robust to using imputed data and focusing on larger states, as shown in Appendix D.

6 Simulations

In this section we provide two simulations to help interpret the magnitude of our baseline estimates of employment persistence (Section 4.1) and their implications for policymakers.

In both simulations we focus on prime-age men with no more than a high-school education to obtain an upper bound on the effects of employment persistence, as explained in Sections 3.2 and 4.2.[22]

6.1 Historical simulations

In this subsection we compare the simulated e/p of disadvantaged workers in a given state including the estimated degree of excess employment persistence to the simulated e/p of this group omitting the effects of employment persistence. We find that the cumulative effect of excess persistence in the business cycle surrounding the 2001 recession was mildly positive, while the effect in the cycle surrounding the 2008-09 recession was decidedly negative.

In these simulations, we allow the UR in each state to evolve as it actually did between the years 1985 and 2018 and, using equation (1), trace out the implied detrended e/p of the disadvantaged group for each year between 1987 and 2018. We do this once using all the estimated coefficients from our baseline regression, and once using the estimated coefficients for the $Ugap$ terms from equation (1) but replacing the coefficients on the lagged e/p terms with zeros, thus excluding the effects of excess employment persistence. We set the detrended e/p of the disadvantaged group to zero in the two years (1985 and 1986) before the simulation commences.[23]

[21]The evidence for the migration responses of working-age populations (as opposed to less-educated prime-age men) in response to local labor demand shocks is mixed. On the one hand, BK and Foote et al. (2019) find that migration can play an important role in local adjustment after a demand shock. On the other hand, Dao et al. (2017) suggest that interstate mobility is not as high as previously established.

[22]Our dynamic simulations condition on a full path for the UR gaps, so there is always an observed value for the lagged UR gap. Consequently, although Section 4.2 also presents results at different horizons using local projections, we only use estimates at the first horizon for our simulations.

[23]The outcomes of interest are not sensitive to this choice of the initial e/p. Nor are they sensitive to the choice of starting year.

For the year 1990, for example, we construct the e/p of the disadvantaged group in state s that includes persistence effects from the estimated state and calendar-year fixed effects, the β and δ coefficients as in Table 2 (column 2), the actual values of the UR gap in the years 1988 to 1990, and the previously simulated e/p of the disadvantaged group in years 1988 and 1989. We construct the e/p without the effect of employment persistence in the same way but replace the β coefficients with zeros.

The cumulative difference between these two simulations is a measure of the contribution of excess persistence to the e/p of the disadvantaged group over this period.[24] For ease of presentation, we aggregate this state-level measure of the effect of employment persistence to the national level.

Before turning to the contribution of excess persistence, we note that the e/p simulated using our estimated coefficients follows a similar trajectory to the actual e/p over the 1996 to 2018 period, suggesting that our dynamic panel model accounts reasonably well for the variations in the actual e/p. Figure 4 shows the simulated detrended e/p series along with the detrended actual e/p for the period 1996 to 2018, the first being a year in which the national UR was near the Congressional Budget Office's (CBO) estimate of the natural rate of unemployment.[25]

Figure 5 shows the estimated contribution of excess persistence to the e/p of the disadvantaged group as defined above. During the tight labor market toward the end of the 1990s expansion and before the 2001 recession, excess persistence served to buoy the e/p of the disadvantaged group by up to 1 percentage point. Following the recession, however, excess persistence pulled in the opposite direction, weighing on the e/p of this group by up to 1/2 percentage point. Cumulatively, the former benefit outweighed the latter cost.

The situation is, unfortunately, quite different in the subsequent business cycle. The labor market was not as tight toward the end of the 2000s expansion as it was in the previous cycle, so the contribution of excess persistence barely moved into positive territory. The severity of the 2008-09 recession, however, meant that excess persistence weighed on the e/p of this group by almost 3 percentage points in 2011 to 2012, and only in 2018, when

[24] An alternative would be to re-estimate the equation imposing the restriction that the coefficients on the lagged e/p be zero, and use the coefficients on the $Ugap$ terms from that regression in the counterfactual simulation. In that case, however, the coefficients on the $Ugap$ terms would reflect excess persistence in the e/p to the extent that it is correlated with the persistence in $Ugap$. In this case the difference would not measure the contribution of excess persistence under the assumption that some exists.

[25] To obtain the detrended actual e/p we use the full sample of the CPS as opposed to the disjoint samples we used for estimating the amount of employment persistence. We take this approach because the disjoint samples minimize correlated measurement error (Section 2.2), but using the full sample provides the best estimate of the e/p for any given year.

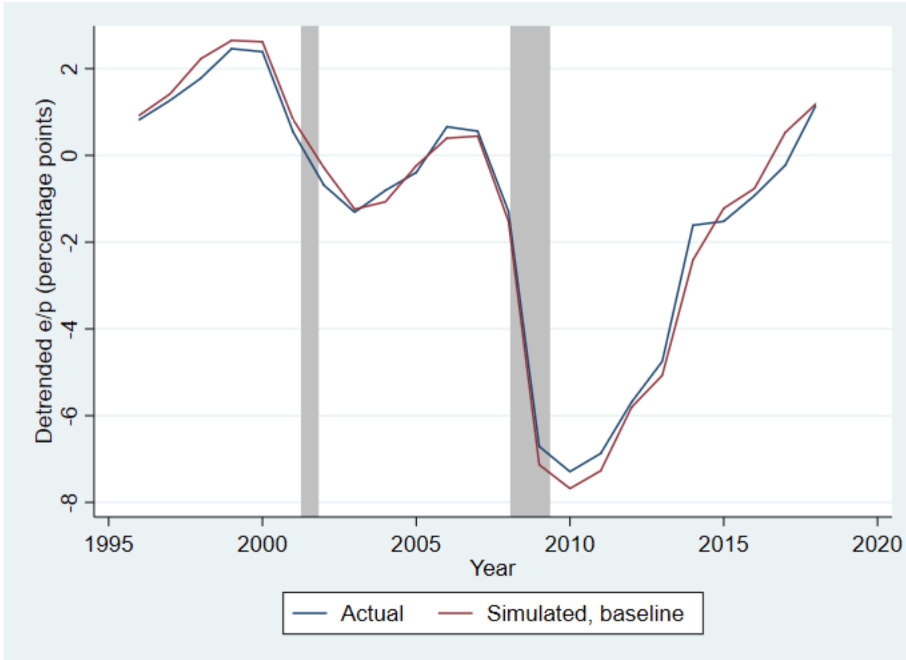

Figure 4: Detrended e/p of Disadvantaged Group: Actual and Historical Simulation

Note: The detrended e/p simulated using our estimated coefficients follows a similar trajectory to the detrended actual e/p over the 1996 to 2018 period. This shows the actual e/p over the 1996 to 2018 period along with the one-step-ahead dynamic simulation of equation (1) using our estimated coefficients in Table 2 (column 2). The simulation is done at the state level and then aggregated to the nation. For the UR gap we use the actual UR less the trend, in which we estimate the trend UR using the approach in Tasci (2012) (Section 2). See Section 6.1 for details.

the national UR was 0.7 percentage point below the CBO's natural rate of 4.6 percent, did excess persistence stop weighing on the e/p of disadvantaged workers.

6.2 Policy simulations

In running a "high-pressure economy" (Ball, 2015; Yellen, 2016), policymakers may face a trade-off between the possibility of engineering a "soft landing" and an increased risk of recession, either because of high inflation and subsequent policy response (Lacker, 2017; Bostic, 2018) or other business cycle dynamics (Beaudry et al., 2015, 2016; Feldstein, 2018; Kiley, 2018; Jackson and Tebaldi, 2019).[26] In this subsection, we assess the employment benefits of successfully engineering a soft landing relative to a recession and find that the lasting employment benefits of temporarily running a high-pressure economy are small.

[26] A "soft landing" is loosely defined as a high-pressure labor market followed by a gradual rise in the UR that comes to rest at a more sustainable level.

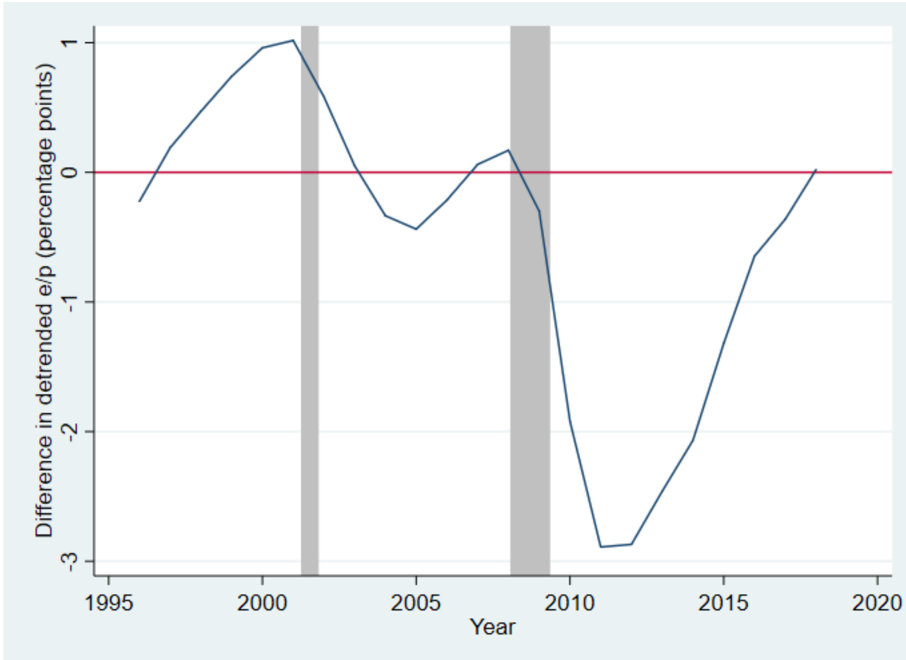

Figure 5: Contribution of Excess Persistence in Historical Simulation

Note: On net, excess persistence benefits disadvantaged workers during the business cycle around the 2001 recession but harms them during the cycle around the Great Recession. This figure plots the difference between the simulated employment-to-population ratio from equation (1) using the coefficients from Table 2 (column 2) and the estimated coefficients for the $Ugap$ terms but setting the coefficients on the lagged e/p terms to zero. This difference captures the contribution of excess persistence to the e/p of disadvantaged workers.

Policy discussions about soft landings most often refer to national conditions, so we simulate these scenarios directly at the national level using our baseline estimates of β and δ in Table 2, column 2. As in the historical simulations, we begin simulations for both scenarios in 1987 and we set the detrended e/p of the disadvantaged group to zero in the two years before the simulation commences.

Through the year 2000 the two scenarios are the same as we set the UR at the actual UR, and we use the CBO's estimate of the long-run natural rate to obtain the UR gap. In the year 2000 the national UR was as far below the CBO's estimate of its natural rate as occurred during the span of our data, suggesting a "high-pressure" economy.[27]

From 2005 on we set the UR to the natural rate in 2005 in both scenarios so that the UR

[27] In order to abstract from changes over time that are not due to the assumed paths for overall labor market conditions, we set the trend UR in every year of the simulation equal to the CBO's estimate of the long-run natural rate for 2005 (5.0 percent), and we set all of the year effects to the estimated year effect for 2005.

gap is zero.[28] What differs between the two scenarios is the path by which the UR moves from its trough in 2000 to this 2005 level.

We show the two paths for the UR in the upper panel of Figure 6. For the recession scenario, we set the UR at its actual value from 2001 (the year the recession commenced) through 2003 (the year in which the UR peaked during that cycle). We then set it to decline at a constant rate to trend in 2005. Thus this scenario includes something very like the 2001 recession. For the soft-landing scenario, we set the UR to rise at a constant rate from its low in 2000 to trend in 2005.

For ease of exposition, we show the simulated detrended e/p from the soft-landing and recession scenarios as the deviations from the "steady-state" detrended e/p implied by our baseline coefficients.[29] The lower panel of Figure 6 shows this deviated detrended e/p from these two scenarios.

Naturally, the e/p in both scenarios rises above the steady state (that is, it is positive in the graph) into the posited tight labor market of 2000. In the soft-landing scenario, the detrended e/p then falls toward the steady state as the UR reverts to trend. There is some small overshooting attributable to the difference in coefficients on the contemporaneous and lagged URs, as discussed in Section 4.1, which fades away by 2007.

The detrended e/p in the recession scenario, of course, falls relative to the soft-landing scenario during 2001 to 2003. By 2005, when the UR has returned to neutral, the detrended e/p has returned to its steady-state level except for a small amount of overshooting, which here, too, soon fades away.

In short, while a gap between the e/p in the two scenarios naturally opens up during the weak years of the recession posited in the recession scenario, this gap rapidly closes; once the UR reaches its trend level in 2005 there is little difference between the e/p in the two scenarios. The period of high pressure has no lasting effect on the detrended e/p of the disadvantaged group.

7 Conclusion

In this paper, we estimate a dynamic model on a panel of state-level data to quantify the persistence of the employment-to-population ratios of disadvantaged workers beyond that

[28] In 2005 the national UR was quite close to the CBO's estimate of the natural rate.

[29] We define a steady-state e/p as the solution for $(e/p)_t^{DA}$ in equation (1) when $(e/p)_t^{DA} = (e/p)_{t-1}^{DA} = (e/p)_{t-2}^{DA}$, $Ugap_t = Ugap_{t-1} = Ugap_{t-2} = 0$, and $\gamma_t = \gamma_{2005}$. There are no s subscripts because these policy simulations are performed at the aggregate level.

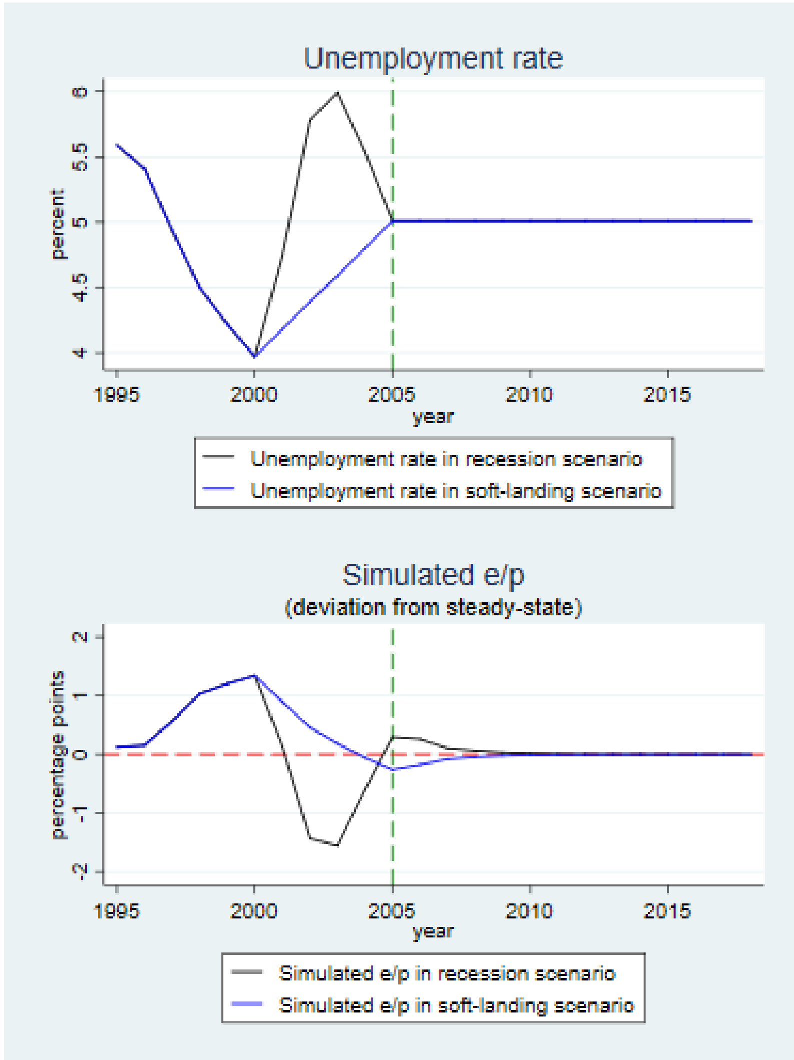

Figure 6: Soft-Landing and Recession Scenarios in Policy Simulation

Note: The lasting employment benefits of temporarily running a "high-pressure" economy are small. The top panel shows the trajectory of the UR for two scenarios: a "soft-landing" scenario and a "recession" scenario. The bottom panel shows the deviations of the employment-to-population ratio from steady state in these two scenarios. After 2005, when the UR returns to trend, there is little difference between the detrended e/p in the two scenarios.

implied by the persistence of aggregate labor market conditions, which we call excess persistence in employment. We find that the employment-to-population ratio of less-educated prime-age males exhibits a moderate degree of excess persistence, which dissipates within three years. This finding is robust to a number of variations in specification. Of particular interest, we find no substantial asymmetry in the excess persistence of high vs. low employment rates. The cumulative effect of excess persistence in the business cycle surrounding the 2001 recession was mildly positive, while the effect in the cycle surrounding the 2008-09 recession was, through 2016, decidedly negative. Our simulations also suggest that the lasting benefits to the employment rates of disadvantaged workers of temporarily running a "high-pressure" economy are small.

References

Aaronson, Stephanie, Tomaz Cajner, Bruce Fallick, Felix Galbis-Reig, Christopher Smith, and William Wascher (2014). "Labor Force Participation: Recent Developments and Future Prospects." *Brookings Papers on Economic Activity*, 2014(2), pp. 197–275. doi:10.1353/eca.2014.0015.

Aaronson, Stephanie R., Mary C. Daly, William Wascher, and David W. Wilcox (2019). "Okun Revisited: Who Benefits Most from a Strong Economy?" *Brookings Papers on Economic Activity*, 2019(1).

Abraham, Katherine G. and Melissa S. Kearney (2018). "Explaining the Decline in the U.S. Employment-to-Population Ratio: A Review of the Evidence." doi:10.3386/w24333. NBER Working Paper 24333.

Acemoglu, Daron and David Autor (2011). "Skills, Tasks and Technologies: Implications for Employment and Earnings." In David Card and Orley Ashenfelter, editors, *Handbook of Labor Economics*, volume 4, chapter 12, pp. 1043–1171. Elsevier. doi:10.1016/S0169-7218(11)02410-5.

Almlund, Mathilde, Angela Lee Duckworth, James Heckman, and Tim Kautz (2011). "Personality Psychology and Economics." In Richard B. Freeman and David A. Wise, editors, *Handbook of the Economics of Education vol. 4*, chapter 1, pp. 1–181. Elsevier. doi:10.3386/w16822.

Angrist, Joshua D. and Jörn-Steffen Pischke (2009). *Mostly Harmless Econometrics*. Princeton University Press.

Arellano, Manuel (2003). *Panel Data Econometrics*. Oxford: Oxford University Press. doi:10.1093/0199245282.001.0001.

Ball, Laurence M. (2009). "Hysteresis in Unemployment: Old and New Evidence." In Jeff Fuhrer et al., editor, *Understanding Inflation and the Implications for Monetary Policy: A Phillips Curve Retrospective*. Federal Reserve Bank of Boston. doi:10.7551/mitpress/9780262013635.003.0015.

Ball, Laurence M. (2015). "Monetary Policy for a High-Pressure Economy." Center on Budget and Policy Priorities, March 30. `https://www.cbpp.org/sites/default/files/atoms/files/3_30_15fe_ball.pdf`.

Barnichon, Regis and Geert Mesters (2018). "On the Demographic Adjustment of Unemployment." *The Review of Economics and Statistics*, 100(2), pp. 219–231. doi:10.1162/rest_a_00688.

Barnichon, Regis and Christopher J. Nekarda (2012). "The Ins and Outs of Forecasting Unemployment: Using Labor Force Flows to Forecast the Labor Market." *Brookings Papers on Economic Activity*, 2012(Fall), pp. 83–131. doi:10.1353/eca.2012.0018.

Barro, Robert J. (1988). "The Persistence of Unemployment." *American Economic Association Papers and Proceedings*, 78(2), pp. 32–37. https://www.jstor.org/stable/1818093.

BEA (2019). "GDP by State." https://www.bea.gov/data/gdp/gdp-state. Accessed: August 14, 2019.

Beaudry, Paul and John DiNardo (1991). "The Effect of Implicit Contracts on the Movement of Wages over the Business Cycle: Evidence from Micro Data." *Journal of Political Economy*, 99(4), pp. 665–688. doi:10.1086/261774.

Beaudry, Paul, Dana Galizia, and Franck Portier (2015). "Reviving the Limit Cycle View of Macroeconomic Fluctuations." doi:10.3386/w21241. NBER Working Paper 21241.

Beaudry, Paul, Dana Galizia, and Franck Portier (2016). "Putting the Cycle Back into Business Cycle Analysis." doi:10.3386/w22825. NBER Working Paper 22825.

Blanchard, Olivier and Jordi Gali (2010). "Labor Markets and Monetary Policy: A New Keynesian Model with Unemployment." *American Economic Journal: Macroeconomics*, 2(2), pp. 1–30. doi:10.1257/mac.2.2.1.

Blanchard, Olivier J. and Lawrence H. Summers (1986). "Hysteresis and the European Unemployment Problem." In Stanley Fischer, editor, *NBER Macroeconomics Annual*, volume 1, pp. 15–90. MIT Press. doi:10.1086/654013.

Blanchard, Olivier Jean and Lawrence F. Katz (1992). "Regional Evolutions." *Brookings Papers on Economic Activity*, 1992(1), pp. 1–75. doi:10.2307/2534556.

Blanchard, Olivier Jean and Danny Quah (1989). "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *American Economic Review*, 79(4), pp. 655–673. http://www.jstor.org/stable/1827924.

Boisjoly, Johanne, Greg J. Duncan, Michael Kremer, Dan M. Levy, and Jacque Eccles (2006). "Empathy or Antipathy? The Impact of Diversity." *American Economic Review*, 96(5), pp. 1890–1905. doi:10.1257/aer.96.5.1890.

Bostic, Raphael (2018). "Considerations on the Path from Extraordinary to Neutral." Speech, Global Interdependence Center, Madrid, Spain (November 15).

Bound, John and Harry J. Holzer (2000). "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s." *Journal of Labor Economics*, 18(1), pp. 20–54. doi:10.1086/209949.

Burgess, Simon, Carol Propper, Hedley Rees, and Arran Shearer (2003). "The Class of 1981: The Effects of Early Career Unemployment on Subsequent Unemployment Experiences." *Labour Economics*, 10, pp. 291–309. doi:10.1016/S0927-5371(02)00138-0.

Cingano, Federico and Alfonso Rosolia (2012). "People I Know: Job Search and Social Networks." *Journal of Labor Economics*, 30(2), pp. 291–332. doi:10.1086/663357.

Clark, Todd and Sharon Kozicki (2005). "Estimating Equilibrium Real Interest Rates in Real Time." *The North American Journal of Economics and Finance*, 16(3), pp. 395–413. doi:10.1016/j.najef.2005.04.002.

Conley, Timothy G. and Giorgia Topa (2002). "Socio-Economic Distance and Spatial Patterns in Unemployment." *Journal of Applied Econometrics*, 17(4), pp. 303–327. doi:10.1002/jae.670.

Council of Economic Advisers (2017). *Economic Report of the President*. Government Printing Office. Washington, January 2017, https://www.govinfo.gov/content/pkg/ERP-2017/pdf/ERP-2017.pdf.

Crone, Theodore M. (2005). "An Alternative Definition of Economic Regions in the United States Based on Similarities in State Business Cycles." *Review of Economics and Statistics*, 87(4), pp. 617–626. doi:10.1162/003465305775098224.

Crump, Richard K., Stefano Eusepi, Marc P. Giannoni, and Aysegul Sahin (2019). "A Unified Approach to Measuring u*." doi:10.2139/ssrn.3392998. FRB of New York Staff Report No. 889.

Dao, Mai, Davide Furceri, and Prakash Loungani (2017). "Regional Labor Market Adjustments in the United States: Trend and Cycle." *Review of Economics and Statistics*, 99(2), pp. 243–257. doi:10.1162/REST_a_00642.

Darby, Michael R., John C. Haltiwanger, and Mark W. Plant (1985). "Unemployment Rate Dynamics and Persistent Unemployment under Rational Expectations." *American Economic Review*, 75(4), pp. 614–637. https://www.jstor.org/stable/1821344.

Devereux, Paul J. (2002). "Occupational Upgrading and the Business Cycle." *LABOUR*, 16(3), pp. 423–452. doi:10.1111/1467-9914.00202.

DOL (2018). "State Unemployment Insurance Benefits." https://oui.doleta.gov/unemploy/uifactsheet.asp. Accessed: June 28, 2019.

Driscoll, John and Aart Kraay (1998). "Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data." *Review of Economics and Statistics*, 80(4), pp. 549–560. doi:10.1162/003465398557825.

Dustmann, Christian, Albrecht Glitz, Uta Schönberg, and Herbert Brücker (2017). "Factors Determining Callbacks to Job Applications by the Unemployed: An Audit Study." *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 3(3), pp. 168–201. doi:10.7758/rsf.2017.3.3.08.

Ellwood, David T. (1982). "Teenage Unemployment: Permanent Scars or Temporary Blemishes?" In Richard B. Freeman and David A. Wise, editors, *The Youth Labor Market Problem: Its Nature, Causes, and Consequences*, chapter 10, pp. 349–390. Chicago: University of Chicago Press.

Elsby, Michael W.L., Bart Hobijn, and Ayşegül Şahin (2015). "On the Importance of the Participation Margin for Labor market Fluctuations." *Journal of Monetary Economics*, 72, pp. 64 – 82. doi:10.1016/j.jmoneco.2015.01.004.

Feldstein, Martin (2018). "Normalizing Monetary Policy." *Cato Journal*, Spring/Summer. https://www.cato.org/cato-journal/springsummer-2018/normalizing-monetary-policy.

Fleischman, Charles and Joshua Gallin (2001). "Employment Persistence." Federal Reserve Board Finance and Economics Discussion Series 2001-25.

Fleischman, Charles A., Joshua Gallin, and Christopher L. Smith (2018). "Labor Market Persistence: A Cohort-level Analysis." Manuscript.

Foote, Andrew, Michel Grosz, and Ann Huff Stevens (2019). "Locate Your Nearest Exit: Mass Layoffs and Local Labor Market Response." *Industrial and Labor Relations Review*, 72(1), pp. 101–126. doi:10.1177/0019793917753095.

FRB Philadelphia (2019). “State Coincident Indexes.” https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident. Accessed: June 28, 2019.

Gardecki, Rosella and David Neumark (1998). “Order from Chaos? The Effects of Early Labor Market Experiences on Adult Labor Market Outcomes.” *Industrial and Labor Relations Review*, 51(2), pp. 299–322. doi:10.1177/001979399805100209.

Gautier, Pieter, Paul Muller, Bas van der Klaauw, Michael Rosholm, and Michael Svarer (2018). “Estimating Equilibrium Effects of Job Search Assistance.” *Journal of Labor Economics*, 36(4), pp. 1073–1125. doi:10.1086/697513.

Glitz, Albrecht (2017). “Coworker Networks in the Labour Market.” *Labour Economics*, 44, pp. 218–230. doi:10.1016/j.labeco.2016.12.006.

Gutierrez, Italo A. and Jennie Wenger (2017). “Long-Term Effects of Leaving Military Service in a Weak Economy.” doi:10.2139/ssrn.3105363. Michigan Retirement Research Center Research Paper No. 2017-369.

Hagedorn, Marcus and Iourii Manovskii (2013). “Job Selection and Wages over the Business Cycle.” *American Economic Review*, 103(2), pp. 771–803. doi:10.1257/aer.103.2.771.

Hamilton, James D. (2018). “Why You Should Never Use the Hodrick-Prescott Filter.” *Review of Economics and Statistics*, 100(5), pp. 831–843. doi:10.1162/rest_a_00706.

Holzer, Harry J., Steven Raphael, and Michael A. Stoll (2006). “Employers in the Boom: How Did Hiring of Less-Skilled Workers Change During the 1990s?” *Review of Economics and Statistics*, 88(1), pp. 283–299. doi:10.1162/rest.88.2.283.

Hotchkiss, Julie L. and Robert E. Moore (2018). “Some Like It Hot: Assessing Longer-Term Labor Market Benefits from a High-Pressure Economy.” Federal Reserve Bank of Atlanta Working Paper 2018-1.

Hoynes, Hilary, Douglas L. Miller, and Jessamyn Schaller (2012). “Who Suffers During Recessions?” *Journal of Economic Perspectives*, 26(3), pp. 27–48. doi:10.1257/jep.26.3.27.

Jackson, Matthew and Pietro Tebaldi (2019). “A Forest Fire Theory of the Duration of a Boom and the Size of a Subsequent Bust.” doi:10.2139/ssrn.2263501.

Jordà, Òscar (2005). "Estimation and Inference of Impulse Responses by Local Projections." *American Economic Review*, 95(1), pp. 161–182. doi:10.1257/0002828053828518.

Jovanovic, Boyan (1979). "Job Matching and the Theory of Turnover." *Journal of Political Economy*, 87, pp. 972–990. doi:10.1086/260808.

Jovanovic, Boyan (1984). "Matching, Turnover and Unemployment." *Journal of Political Economy*, 92(1), pp. 108–122. doi:10.1086/261210.

Juhn, Chinhui (1992). "Decline of Male Labor Market Participation: The Role of Declining Market Opportunities." *Quarterly Journal of Economics*, 107(1), pp. 79–121. doi:10.2307/2118324.

Kahn, Lisa B. (2010). "The Long-Term Consequences of Graduating from College in a Bad Economy." *Labour Economics*, 17(2), pp. 303–316. doi:10.1016/j.labeco.2009.09.002.

Kaiser, Regina and Agustin Maravall (1999). "Estimation of the Business Cycle: A Modified Hodrick-Prescott Filter." *Spanish Economic Review*, 1(2), pp. 175–206. doi:10.1007/s101080050008.

Kallenberg, Arne L. and Till von Wachter (2017). "The U.S. Labor Market During and After the Great Recession: Continuities and Transformations." *RSF: The Russell Sage Foundation Journal of the Social Sciences*, 3(3), pp. 1–19. doi:10.7758/rsf.2017.3.3.01.

Kaplan, Greg and Sam Schulhofer-Wohl (2012). "Interstate Migration Has Fallen Less Than You Think: Consequences of Hot Deck Imputation in the Current Population Survey." *Demography*, 49(3), pp. 1061–1074. doi:10.1007/s13524-012-0110-3.

Kaplan, Greg and Sam Schulhofer-Wohl (2017). "Understanding the Long-Run Decline in Interstate Migration." *International Economic Review*, 58(1), pp. 57–94. doi:10.1111/iere.12209.

Kiley, Michael T. (2018). "Unemployment Risk." doi:10.17016/FEDS.2018.067. Federal Reserve Board Finance and Economics Discussion Series 2018-067.

Kleibergen, Frank and Richard Paap (2006). "Generalized Reduced Rank Tests Using the Singular Value Decomposition." *Journal of Econometrics*, 133(1), pp. 97–126. doi:10.1016/j.jeconom.2005.02.011.

Kletzer, Lori G. and Robert W. Fairlie (2003). "The Long-Term Costs of Job Displacement For Young Adult Workers." *Industrial and Labor Relations Review*, 56(4), pp. 682–698. doi:10.1177/001979390305600408.

Lacker, Jeffrey M. (2017). "Economic Outlook." Speech, Maryland Bankers Association (January 6).

Meyer, Brent and Murat Tasci (2015). "Lessons for Forecasting Unemployment in the U.S.: Use Flow Rates, Mind the Trend." doi:10.26509/frbc-wp-201502. Federal Reserve Bank of Cleveland, Working Paper 15-02.

Miller, Conrad (2017). "The Persistent Effect of Temporary Affirmative Action." *American Economic Journal: Applied Economics*, 9(3), pp. 152–190. doi:10.1257/app.20160121.

Mincer, Jacob (1974). *Schooling, Experience and Earnings*. New York: Columbia University Press.

Mise, Emi, Tae-Hwan Kim, and Paul Newbold (2005). "On Suboptimality of the Hodrick–Prescott Filter at Time Series Endpoints." *Journal of Macroeconomics*, 27(1), pp. 53–67. doi:10.1016/j.jmacro.2003.09.003.

Molloy, Raven, Christopher L. Smith, and Abigail Wozniak (2011). "Internal Migration in the United States." *Journal of Economic Perspectives*, 25(3), pp. 173–196. doi:10.1257/jep.25.3.173.

Mroz, Thomas A. and Timothy H. Savage (2006). "The Long-Term Effects of Youth Unemployment." *Journal of Human Resources*, 41(2), pp. 259–293. doi:10.3368/jhr.XLI.2.259.

NBER (2019). "Current Population Survey (CPS) Basic Monthly Data." `http://data.nber.org/data/cps_basic.html`. Accessed: June 28, 2019.

Nerlove, Marc (1967). "Experimental Evidence on the Estimation of Dynamic Economic Relations from a Times Series of Cross-Sections." *Economic Studies Quarterly*, 18(3), pp. 42–74. doi:10.11398/economics1950.18.3_42.

Nickell, Stephen (1981). "Biases in Dynamic Models with Fixed Effects." *Econometrica*, 49(6), pp. 1417–1426. doi:10.2307/1911408.

Notowidigdo, Matthew J. (2019). "The Incidence of Local Labor Demand Shocks." *Journal of Labor Economics*. URL `http://faculty.wcas.northwestern.edu/noto/research/Notowidigdo_labor_demand_20190305.pdf`, forthcoming.

Okun, Arthur M. (1973). "Upward Mobility in a High-Pressure Economy." *Brookings Papers on Economic Activity*, 1973(1), pp. 207–261. doi:10.2307/2534087.

Oreopoulos, Philip, Andrew Heisz, and Till von Wachter (2012). "Short- and Long-Term Career Effects of Graduating in a Recession." *American Economic Journal: Applied Economics*, 4(1), pp. 1–29. doi:10.1257/app.4.1.1.

Pierce, Justin R. and Peter K. Schott (2016). "The Surprisingly Swift Decline of US Manufacturing Employment." *American Economic Review*, 106(7), pp. 1632–1662. doi:10.1257/aer.20131578.

Poterba, James M and Lawrence H Summers (1986). "Reporting Errors and Labor Market Dynamics." *Econometrica*, 54(6), pp. 1319–1338. doi:10.2307/1914301.

Reifscheider, David, William Wascher, and David Wilcox (2015). "Aggregate Supply in the United States: Recent Developments and Implications for the Conduct of Monetary Policy." *IMF Economic Review*, 63(1), pp. 71–109. doi:10.1057/imfer.2015.1.

Rothstein, Jesse (2019). "The Lost Generation? Scarring after the Great Recession." Manuscript.

Schmieder, Johannes F. and Till von Wachter (2010). "Does Wage Persistence Matter for Employment Fluctuations? Evidence from Displaced Workers." *American Economic Journal: Applied Economics*, 2(3), pp. 1–21. doi:10.1257/app.2.3.1.

Schwandt, Hannes and Till M. von Wachter (2018). "Unlucky Cohorts: Estimating the Long-Term Effects of Entering the Labor Market in a Recession in Large Cross-Sectional Data Sets." doi:10.3386/w25141. NBER Working Paper 25141.

Shvartsman, Elena (2018). "The State of the Economy at Graduation, Wages, and Catch-Up Paths: Evidence from Switzerland." IZA Discussion Paper No. 11622.

Solon, Gary, Seven J. Haider, and Jeffrey M. Wooldridge (2015). "What Are We Weighting For?" *Journal of Human Resources*, 2(50), pp. 301–316. doi:10.3368/jhr.50.2.301.

Song, Jae and Till von Wachter (2014). "Long-Term Nonemployment and Job Displacement." Proceedings from the Federal Reserve Bank of Kansas City's Economic Symposium, Jackson Hole, WY (August).

Stock, James and Mark Watson (1999). "Business Cycle Fluctuations in U.S. Macroeconomic Time Series." In J.B. Taylor and M.Woodford, editors, *Handbook of Macroeconomics*, volume 1, chapter 1, pp. 1–64. Elsevier. doi:10.1016/s1574-0048(99)01004-6.

Stock, James and Motohiro Yogo (2005). "Testing for Weak Instruments in Linear IV Regression." In Donald W.K. Andrews, editor, *Identification and Inference for Econometric Models*, pp. 80–108. Cambridge University Press, New York. doi:10.1017/CBO9780511614491.006.

Stockhammer, Englebert and Simon Sturn (2012). "The Impact of Monetary Policy on Unemployment Hysteresis." *Applied Economics*, 44(21), pp. 2743–2756. doi:10.1080/00036846.2011.566199.

Stoops, Nicole (2004). "Educational Attainment in the United States: 2003." `https://www.census.gov/prod/2004pubs/p20-550.pdf`. Accessed: June 28, 2019.

Tasci, Murat (2012). "The Ins and Outs of Unemployment in the Long Run: Unemployment Flows and the Natural Rate." doi:10.26509/frbc-wp-201224. Federal Reserve Bank of Cleveland, Working Paper 12-24.

Tiller, Richard B. (1992). "Time Series Modeling of Sample Survey Data from the Current Population Survey." *Journal of Official Statistics*, 8(2), pp. 149–166.

van den Berge, Wiljan (2018). "Bad Start, Bad Match? The Early Career Effects of Graduating in a Recession for Vocational and Academic Graduates." *Labour Economics*, 53, pp. 75–96. doi:10.1016/j.labeco.2018.05.011.

Wooldridge, Jeffrey M. (2002). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press.

Yagan, Danny (2017). "Employment Hysteresis in the Great Recession." doi:10.3386/w23844. NBER Working Paper 23844, September.

Yellen, Janet L. (2016). "Macroeconomic Research After the Crisis." Speech, Federal Reserve Bank of Boston (November 14).

A Tasci-Fallick estimates of trend URs

Several studies in the literature estimate trend or natural rates of unemployment by modeling trends in the labor force flows that drive the dynamics in the UR. These analyses then calculate the trend UR as the steady-state UR implied by these estimated trend flows (Darby et al., 1985; Barro, 1988; Barnichon and Nekarda, 2012; Tasci, 2012; Meyer and Tasci, 2015; Barnichon and Mesters, 2018; Crump et al., 2019). Among these studies, Tasci (2012), Meyer and Tasci (2015), and Crump et al. (2019) estimate the trends in the constituent flows in a state-space framework.

The Tasci-Fallick model adapts this method to the state level. Analyses of this sort for the United States as a whole generally abstract from movements into and out of scope for the CPS (such as international migration and aging into the survey universe), and thus include only flows among the three labor market statuses of employment (E), unemployment (U), and not in the labor force (NLF). This is reasonable at the national level. However, at the state level, there is the additional dimension of migration between states. Such migration is large, and may not be innocuous to ignore.

That said, the distinction between NLF and out-of-state turns out to be of little importance for estimates of trend, and collapsing them into a single status greatly reduces the data requirements as well as the computational complexity of the model. Call the collapsed state Q. Data requirements also make it desirable, as a practical matter, to model the net flows into E and U in each state rather than gross flows between Q and E and between Q and U separately.[30] This leaves a model with four flows, being the gross flow from U to E, the gross flow from E to U, the net flow between Q and E, and the net flow between Q and U.

As in the works cited above, the gross flows between E and U are represented by the corresponding hazard or transitions rates (r_{EU} and r_{UE}). Although the net flows involving Q cannot be represented as hazard rates (i.e., scaled by the size of the origin status), scaling the net flows by the size of the labor force in the state yields appropriate and analogous quantities for these net flows, Q (s_{QE} and s_{QU}).

As in Tasci (2012), the model also includes a measure of overall activity to help identify cyclical variation. Whereas Tasci (2012), being a model at the national level, uses real GDP as this measure, limitations on the frequency and timeliness make GDP data at the state level (BEA, 2019) less useful. The model therefore uses the SCI produced by the Federal

[30] Although one can back out estimates of the gross flows from available data, they are quite noisy, and net flows appear to yield more reliable estimates of the trends.

Reserve Bank of Philadelphia for this purpose (FRB Philadelphia, 2019).

After estimating trends in these four flows, denoted r^*_{EU}, r^*_{UE}, s^*_{QU} and s^*_{QE}, for each of the 50 states, the trend unemployent rate for each state is calculated as

$$u^* = \frac{r^*_{EU} + s^*_{QU}}{r^*_{EU} + r^*_{UE} + s^*_{QU} + s^*_{QE}}.$$

B Summary statistics for disjoint samples

Figure 1 in the main text shows the full-sample estimates of the e/p and the trend e/p for male and female disadvantaged workers, in which both series have been aggregated from the state to the national level. These full-sample estimates provide the best estimates of the actual e/p and trend e/p in the economy. However, as described in Section 2.2, for the estimation we use disjoint samples. Figures 7 and 8 replicate Figure 1 for those disjoint samples. Tables 11 and 12 do the same for Table 1. Clearly, on average the disjoint samples look much like the full sample, although there is more variability across states and years.

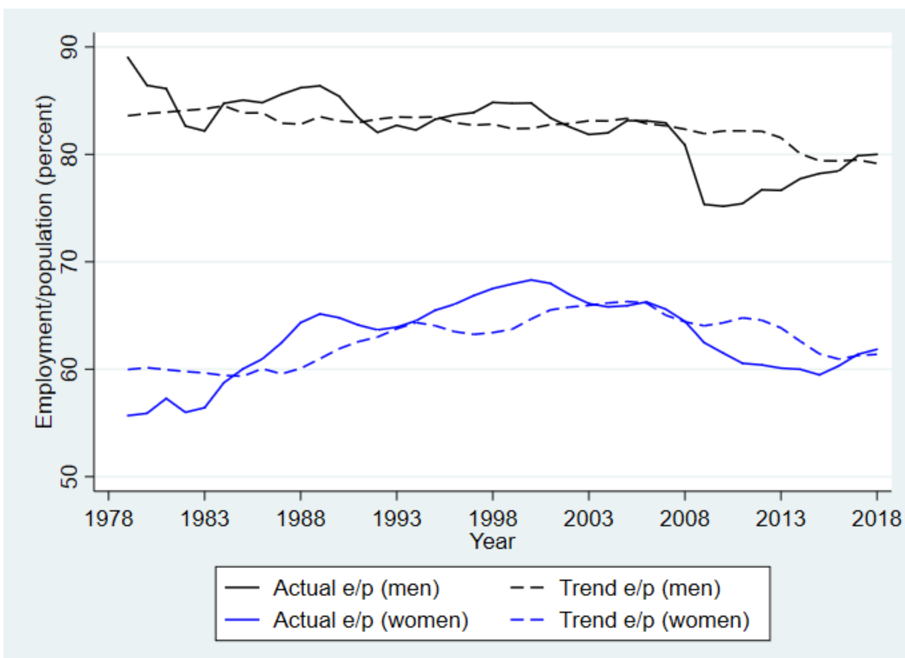

Figure 7: Actual e/p and Trend e/p of Disadvantaged Group, Aggregated, LHS Sample

Note: State-level actual and trend e/p for males and females aggregated to the national level. The trend e/p is calculated separately for each state using the method in Hamilton (2018). We use disjoint samples for the RHS and LHS employment-to-population ratio in the main analysis (Section 2.2). This presents the e/p ratios for the sample used in the LHS e/p. See Figure 1 for the e/p ratios using the full sample.

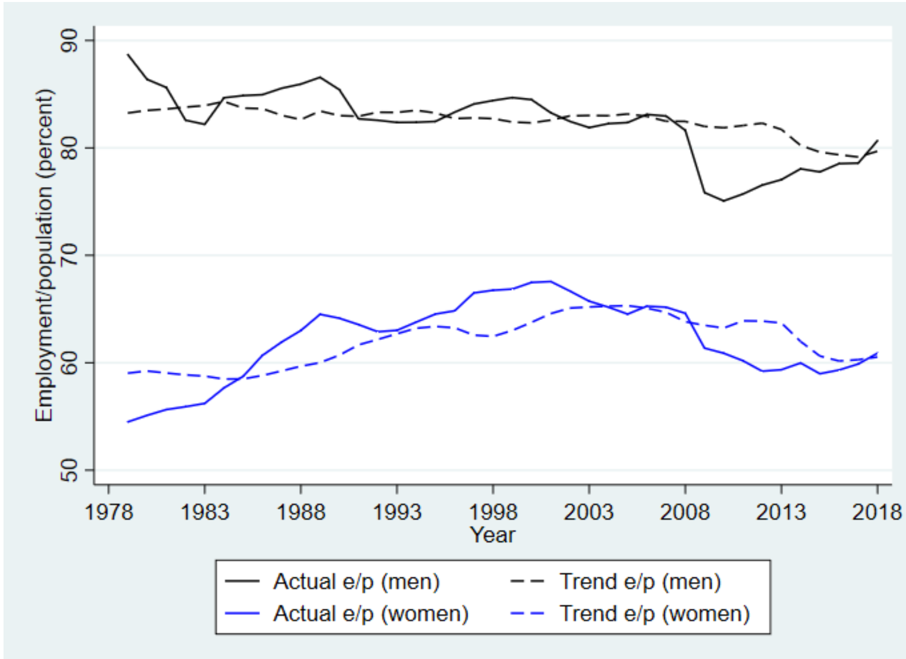

Figure 8: Actual e/p and Trend e/p of Disadvantaged Group, Aggregated, RHS Sample

Note: State-level actual and trend e/p for males and females aggregated to the national level. The trend e/p is calculated separately for each state using the method in Hamilton (2018). We use disjoint samples for the RHS and LHS employment-to-population ratio in the main analysis (Section 2.2). This presents the e/p ratios for the sample used in the RHS e/p. See Figure 1 for the e/p ratios using the full sample.

	Women				Men			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
e/p$_{s,t}$, actual (%)	62.7	7.0	37.7	83.2	82.4	5.2	61.4	95.6
e/p$_{s,t}$, detrended (pp)	-0.1	3.7	-12.9	13.0	-0.3	3.6	-14.0	9.7

Table 11: Summary Statistics for Baseline Groups, State-Level Data (LHS Sample)

Note: Summary statistics for baseline samples for the years 1978 to 2018. "e/p$_{st}$, actual" is the employment-to-population ratio of prime-age women or men with no more than a high school education in state s at time t. "e/p$_{st}$, detrended" is "e/p$_{st}$, actual" less the estimated trend for each state and is measured in percentage points (pp). The trend e/p is calculated using the method in Hamilton (2018). We use disjoint samples for the RHS and LHS employment-to-population ratio in the main analysis (Section 2.2). This table presents the summary statistics for the sample used in the LHS e/p. See Table 1 for the summary statistics using the full sample.

	Women				Men			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
e/p$_{s,t}$, actual (%)	61.9	7.0	37.8	85.4	82.3	5.2	59.2	95.6
e/p$_{s,t}$, detrended (pp)	0.0	3.8	-11.7	14.0	-0.3	3.6	-16.4	10.3

Table 12: Summary Statistics for Baseline Groups, State-Level Data (RHS Sample)

Note: Summary statistics for baseline samples for the years 1978 to 2018. "e/p$_{st}$, actual" is the employment-to-population ratio of prime-age women or men with no more than a high school education in state s at time t. "e/p$_{st}$, detrended" is "e/p$_{st}$, actual" less the estimated trend for each state and is measured in percentage points (pp). The trend e/p is calculated using the method in Hamilton (2018). We use disjoint samples for the RHS and LHS employment-to-population ratio in the main analysis (Section 2.2). This presents the summary statistics for the sample used in the RHS e/p. See Table 1 for the summary statistics using the full sample.

C Motivating our baseline equation

Our estimating equation (1) can be thought of as the aggregated version of an individual-level equation. Ignoring some lags and the state subscripts for ease of exposition, the individual-level equation is

$$(e/p)_{i,t} = \alpha_i + \gamma_t + \phi(e/p)_{i,t-1} + \lambda \sum_{j \neq i} (e/p)_{j,t-1} + \delta Ugap_t,$$

in which ϕ represents sources of persistence such as human capital accumulation and depreciation, and λ represents cross-individual effects of the sort we discussed in Section 1.

Summing across i,

$$\begin{aligned}\sum_i (e/p)_{i,t} &= \sum_i \alpha_i + N\gamma_t + \phi \sum_i (e/p)_{i,t-1} + \lambda \sum_i \sum_{j \neq i} (e/p)_{j,t-1} + N\delta Ugap_t \\ &= \sum_i \alpha_i + N\gamma_t + \phi \sum_i (e/p)_{i,t-1} + \lambda \sum_i \left[\sum_j (e/p)_{j,t-1} - (e/p)_{i,t-1} \right] + N\delta Ugap_t.\end{aligned}$$

Denote $(e/p)_t$ as the mean of $(e/p)_{i,t}$ across i to obtain

$$N(e/p)_t = \sum_i \alpha_i + N\gamma_t + N\phi(e/p)_{t-1} + \lambda \sum_i [N(e/p)_{t-1} - (e/p)_{i,t-1}] + N\delta Ugap_t,$$

and divide through by N to get

$$(e/p)_t = \frac{1}{N} \sum_i \alpha_i + \gamma_t + \phi(e/p)_{t-1} + \lambda[N(e/p)_{t-1} - (e/p)_{t-1}] + \delta Ugap_t$$

or

$$\begin{aligned}(e/p)_t &= \frac{1}{N} \sum_i \alpha_i + \gamma_t + [\phi + \lambda(N-1)](e/p)_{t-1} + \delta Ugap_t \\ &= \alpha + \gamma_t + \beta(e/p)_{t-1} + \delta Ugap_t.\end{aligned} \tag{4}$$

Equation (4) is our estimating equation, in which $\beta = \phi + \lambda(N-1)$ is the object of primary interest.

D Additional migration results

In this section we present the same results as in Table 10 of the main text, with two variations: First, we include imputed data in our analysis; second, we restrict our sample to larger states.

Table 13 presents the estimated coefficients from equation (3) using imputed migration data. The results are similar to those in Table 10 in the main text.

	(1) Net Migration $\leq$ HS	(2) Gross Migration $\leq$ HS	(3) Net Migration $>$ HS	(4) Gross Migration $>$ HS
$Ugap_{st}$	-0.18	0.17	-0.21**	0.14
	(0.15)	(0.15)	(0.10)	(0.13)
$Ugap_{s,t-1}$	-0.11	0.10	0.13	-0.18
	(0.23)	(0.18)	(0.19)	(0.25)
$Ugap_{s,t-2}$	0.14	-0.20	-0.23	0.09
	(0.17)	(0.16)	(0.14)	(0.18)
$y_{s,t-1}$	-0.02	0.13*	0.04	0.06*
	(0.04)	(0.06)	(0.03)	(0.04)
$y_{s,t-2}$	0.03	0.04	-0.03	-0.01
	(0.04)	(0.05)	(0.03)	(0.03)
Observations	1,550	1,550	1,550	1,550
p-value $\sum_i \delta_i = 0$	0.09	0.35	0.0000	0.63

Table 13: Migration in Response to Labor Market Conditions (Imputed Data)

Note: Interstate migration does not respond to cyclical labor market conditions for less-educated prime-age men. These are the estimated coefficients from equation (3) using imputed data. The dependent variable is either net or gross migration of less-educated prime-age men. $Ugap_{s,t}$ is the UR in state s at time t less the estimated trend UR, using the approach in Tasci (2012) (Section 2). Weighted by number of observations of each population in $t-1$. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.5 for details.

Table 14 presents the estimated coefficients from equation (3) using only the 37 most populous states as of 2018. We drop Wyoming, Vermont, DC, Alaska, North Dakota, South Dakota, Delaware, Rhode Island, Montana, Maine, New Hampshire, and Hawaii. The results are similar to those in Table 10 in the main text.

	(1) Net Migration $\leq$ HS	(2) Gross Migration $\leq$ HS	(3) Net Migration $>$ HS	(4) Gross Migration $>$ HS
$Ugap_{st}$	-0.09	0.13	-0.20*	0.14
	(0.11)	(0.14)	(0.11)	(0.11)
$Ugap_{s,t-1}$	-0.23	0.13	-0.08	0.07
	(0.17)	(0.21)	(0.17)	(0.23)
$Ugap_{s,t-2}$	0.32***	-0.18	0.07	-0.17
	(0.11)	(0.12)	(0.16)	(0.14)
$y_{s,t-1}$	0.03	0.19***	0.07*	0.11**
	(0.04)	(0.04)	(0.04)	(0.04)
$y_{s,t-2}$	0.02	0.18***	-0.007	0.09**
	(0.05)	(0.05)	(0.04)	(0.03)
Observations	1,209	1,209	1,209	1,209
p-value $\sum_i \delta_i = 0$	0.80	0.09	0.0019	0.58

Table 14: Migration in Response to Labor Market Conditions (Larger States)

Note: Interstate migration does not respond to cyclical labor market conditions for less-educated prime-age men. These are the estimated coefficients from equation (3) using only larger states. The dependent variable is either net or gross migration of less-educated prime-age men. $Ugap_{s,t}$ is the UR in state s at time t less the estimated trend UR, using the approach in Tasci (2012) (Section 2). Weighted by number of observations of each population in $t-1$. Driscoll-Kraay standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. See Section 5.5 for details.