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Hysteresis in Employment among Disadvantaged Workers

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Hysteresis in Employment among Disadvantaged Workers

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We examine hysteresis in employment-to-population ratios among less-educated men using state-level data. Results from dynamic panel regressions indicate a moderate degree of hysteresis: The effects of past employment rates on subsequent employment rates can be substantial but essentially dissipate within three years. This finding is robust to a number of variations. We find no substantial asymmetry in the persistence of high vs. low employment rates. The cumulative effect of hysteresis 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. Additional simulations suggest that the employment benefits of temporarily running a "high-pressure" economy are small.

JEL codes: E24, J21, J24.

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

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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 may include, most obviously, "hard" skills that contribute directly to production, but also "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 past macroeconomic states of the labor market, by affecting employment experience, may affect subsequent employment outcomes even conditional on subsequent macroeconomic conditions (Okun, 1973; Hagedorn and Manovskii, 2013). We define this as hysteresis in employment.

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 (for example, Yellen, 2016; Ball, 2015; Reifscheider et al., 2015; Stockhammer and Sturn, 2012).[1]

The plausibility of this notion is enhanced by research 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 (Kahn, 2010; Oreopoulos et al., 2012), that the state of the labor market earlier in one's tenure at an employer influences one's subsequent wage rate at that employer (Beaudry and DiNardo, 1991; Schmieder and von Wachter, 2010), and that persons' early employment experience may affect their later employment.[2]

However, such evidence on individual outcomes, while valuable in its own right, does not establish the existence of hysteresis in aggregate employment. 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 hysteresis at the individual level does not imply hysteresis at an aggregate level: More employment in my history may enhance my chances of being employed today at the expense of reducing the

[1]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]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.

chances of a competing person being employed today. 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 *per se* 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 hysteresis in wage rates or earnings, which need not imply hysteresis in employment. Indeed, depending on the mechanism at work, persistence in wage rates may work against persistence in employment.[3] For these reasons, the question of hysteresis in aggregate employment is distinct and requires independent investigation.

Previous research directly addressing the question of hysteresis in aggregate employment is thin. Fleischman and Gallin (2001), whose general approach we follow, is the most relevant paper. As we do, Fleischman and Gallin (2001) estimate a dynamic model to extract the persistence of the employment-to-population ratio (e/p) in excess of that implied by the persistence of the macroeconomic conditions themselves, as measured by overall labor market tightness. The authors find little persistence in cohort-level employment rates. However, whereas they use variation among synthetic birth cohorts over time to identify possible hysteresis in the national data, we use variation among states over time for identification in state-panel regressions. Hotchkiss and Moore (2018) use a more discrete approach with state-level data and 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 unemployment rates 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 hysteresis as we define it here. Holzer et al. (2006) find that in employer survey data from the 90s, 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.

In this paper, we analyze the implications of labor market tightness (or looseness) for

[3] 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.

the future employment rates of disadvantaged populations conditional on subsequent overall labor market conditions.[4] Disadvantaged populations are of particular interest in this context. The mechanisms (noted above) posited to underlie possible hysteresis would seem to be more important for these populations, 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). In addition, the employment of these populations tends to be more procyclical, so any change in overall labor market conditions may have a larger effect on them (Hoynes, 2000; Hines et al., 2001; Devereux, 2002). Finally, if the disadvantaged population of interest is one that faces discrimination in the labor market, higher levels of employment mean greater direct exposure of employers to the disadvantaged group, which may reduce discrimination (Boisjoly et al., 2006; Miller, 2017).

Our baseline specifications define prime-age men with no more than a high school education as the disadvantaged population. We explore several other definitions, varying education, race, and age. In other variations, we allow for asymmetric effects of high or low past employment on present employment and for effects to depend on the duration of high or low past employment; we also address the issue of interstate migration with two distinct approaches.

Our dynamic panel approach indicates a moderate but ephemeral degree of hysteresis: The effects of past employment rates on subsequent employment rates can be substantial but essentially dissipate within three years. We find no substantial asymmetry in the persistence of high vs. low employment rates. Our estimates imply that the cumulative effect of hysteresis 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 also suggest that the employment benefits of temporarily running a "high-pressure" economy are small.

The paper proceeds as follows. Section 2 describes our data and definitions. Section 3 describes the dynamic panel model analysis. Section 4 describes the implications of our estimates for the effects of hysteresis over the business cycle. Section 5 concludes.

[4] We do not address the possibility of hysteresis generated by long-term unemployment in particular. See Kallenberg and von Wachter (2017) and Song and von Wachter (2014) for some discussion of this issue.

2 Data and Definitions

We base our analysis on annual data for unemployment rates (U) and the e/p at the state level.[5] We calculate these quantities for the entire population and for particular demographic groups from the individual data in the basic monthly Current Population Survey (CPS).[6]

We measure labor market tightness by a combination of the overall unemployment rate in the state and an estimate of the state's trend unemployment rate. For our baseline specification we use estimates of trend unemployment rates developed in unpublished work that adapts and extends the model of Tasci (2011) to the state context (the Tasci-Fallick model). As alternatives, we use a selection of univariate filters.

We confine our main analysis to prime-age (25-54) men with no more than a high school education, a group that has been a focus of concern about low employment rates over the past few decades (Juhn, 1992; Council of Economic Advisers, 2017). For comparison, we define an advantaged group as prime-age men with at least a four-year college degree.

There are secular trends in the e/p of both groups. We detrend the e/p using the method recommended by Hamilton (2017).[7] Except where noted, all of the results reported below use these detrended e/p.[8]

In addition to the reasons proposed by Hamilton (2017), 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 hysteresis in the estimates of trend, thereby understating the amount of hysteresis in the data. Figure 1 presents a graph for the original e/p and detrended e/p for disadvantaged workers where both series have been aggregated from the state to the national level.

Of course, there is a mechanical relationship between the e/p for the disadvantaged (or the advantaged) group and the overall unemployment rate, our measure of labor market tightness. We address this endogeneity by using the unemployment rate of prime-age men in neither the disadvantaged nor the advantaged group as an instrument for the overall

[5] We include only the 50 states, omitting Washington DC.

[6] The rates for the overall population closely match the estimates from the Bureau of Labor Statistics' Local Area Unemployment Statistics program.

[7] 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 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. We recognize that some elements of these secular movements, such as the number of persons receiving disability payments, may have their origins in initially cyclical phenomena.

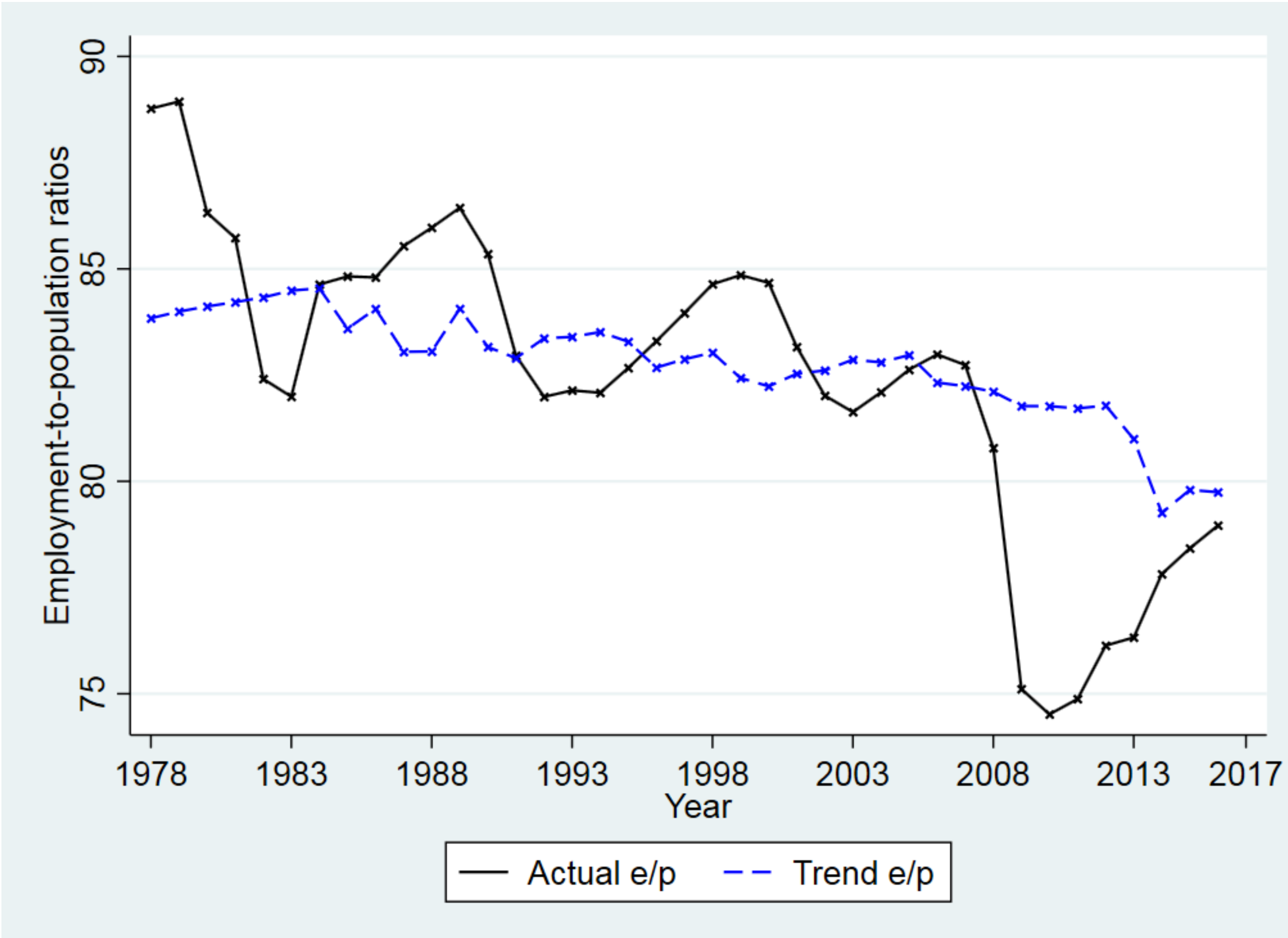

Figure 1: Actual e/p and Trend e/p of Disadvantaged Group, Aggregated

unemployment rate, on the assumption that the unemployment rate of this group is associated with the e/p of the other groups only through its association with overall tightness. This a reasonable assumption if labor markets are sufficiently segmented by education.[9] In addition, we examine as an alternative outcome variable the difference between the e/p of the disadvantaged group and the e/p of the advantaged group. Although the difference is procyclical, it bears no apparent mechanical relationship to the overall unemployment rate, thereby avoiding the endogeniety discussed above. This difference is of direct interest as well, addressing the question of how the posited enduring consequences of labor market tightness affect an important dimension of inequality.

[9]We have established that this instrument behaves well in that it has a strong first stage and affects the e/p for the disadvantaged in a reduced-form regression.

3 Dynamic Panel Approach

Our basic estimating equation is (1), where e/p is the 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, U is the overall unemployment rate, and TU is an estimate of the trend unemployment rate. β, δ, and θ are coefficients, and ϵ is an error term.

$$(e/p)_{s,t}^{DA} = \alpha_s + \gamma_t + \beta\,(e/p)_{s,t-1}^{DA} + \delta_0 U_{s,t} + \delta_1 U_{s,t-1} + \theta_0 TU_{s,t} + \theta_1 TU_{s,t-1} + \epsilon_{s,t} \qquad (1)$$

In this equation, the general state of the labor market, represented by the overall unemployment rate, affects the e/p of the disadvantaged group contemporaneously and with a lag. Persistence in the state of the overall labor market, therefore, imparts a degree of persistence to the e/p of the disadvantaged. The coefficient on the lagged e/p term captures persistence in the e/p in excess of that generated by that persistence in the overall labor market. This additional persistence is what we mean by hysteresis in employment.[10]

3.1 Baseline estimates

Table 1 presents estimates for the disadvantaged group using the trend unemployment rate estimated in the Tasci-Fallick model. Column 1 shows the estimates from an unweighted OLS regression. Column 2 instruments for the overall state unemployment rate with the unemployment rate for the "middle" group. We will instrument for the unemployment rate in this way in all subsequent regressions, except when we look at the difference in e/p between disadvantaged and advantaged workers.[11]

Column 3 shows the IV regression weighted by the number of observations in the disadvantaged group in each state. The results are not sensitive to weighting. However, a regression of squared residuals on the inverse of the number of observations, as suggested by Solon et al. (2015), indicates significant heteroskedasticity in the data, so we will concentrate on weighted regressions. We will treat the specification in column 3 as our baseline regression.

The coefficient on the lagged e/p is significantly positive, indicating some excess persis-

[10]This equation can be recast as a recursive VAR in $(e/p)_{s,t}^{DA}$, $U_{s,t}$ and $TU_{s,t}$ with the restriction that the e/p ratio of the disadvantaged group does not affect the aggregate or trend unemployment rates.

[11]It is well known that the dynamic panel approach with fixed effects may lead to biased estimates. Using Monte Carlo experiments, Arellano (2003) argues that if the number of periods is at least 10, then this is likely small. As our panel spans 40 years, this bias may not be a major concern. To check, we estimated the specification in column 2 using the methods of Arellano and Bond (1991) and Kiviet (1995), respectively. Neither method suggests bias in the ordinary IV estimates in our case.

Table 1: Basic Estimates

	(1) Disadv No IV Unweighted	(2) Disadv IV Unweighted	(3) Disadv IV Weighted	(4) Adv IV Weighted	(5) Disadv-Adv No IV Weighted
$(e/p)_{s,t-1}$	0.52***	0.52***	0.55***	0.35***	0.47***
	(0.019)	(0.020)	(0.024)	(0.024)	(0.031)
$U_{s,t}$	-1.39***	-2.17***	-1.97***	-0.63***	-0.89***
	(0.071)	(0.16)	(0.13)	(0.10)	(0.096)
$U_{s,t-1}$	0.82***	1.47***	1.39***	0.34***	0.50***
	(0.060)	(0.12)	(0.11)	(0.093)	(0.087)
$TU_{s,t}$	0.073	0.40**	0.27	0.22	0.041
	(0.14)	(0.18)	(0.18)	(0.17)	(0.37)
$TU_{s,t-1}$	-0.009	-0.25	-0.16	-0.11	0.087
	(0.15)	(0.19)	(0.18)	(0.16)	(0.34)
Observations	1,900	1,900	1,900	1,900	1,900
R-squared	0.804	0.789	0.818	0.563	0.623
	Illustration of "shock" to e/p equivalent to 1 pp decrease in U_{st}				
Impact	1.39	2.17	1.97	0.63	1.28
Impact+1	0.73	1.12	1.08	0.22	0.60
Impact+2	0.38	0.58	0.59	0.08	0.28
Impact+3	0.20	0.30	0.32	0.03	0.13

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. Where indicated, the unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Where indicated, weighted by number of observations of the disadvantaged group.

tence. The magnitude is substantial, but not large. To illustrate, in the bottom panel of the table we "shock" the e/p by an amount equivalent to the estimated reaction of the e/p to a 1 percentage point reduction in the unemployment rate, then allow the increase in the e/p to decay at the rate indicated by the coefficient β on lagged e/p.[12] In our baseline specification in column 3, this is an increase in the e/p of approximately 2 percentage points. The shock dissipates according to the estimate of β of 0.55. By the third year following the shock, only 0.3 percentage point of the elevated e/p remains out of the initial 2 percentage points.

For comparison, column 4 shows results for the e/p of the advantaged group. At 0.6 percentage point, the initial shock to the e/p equivalent to a 1 percentage point decrease in the overall unemployment rate for this group is considerably smaller than that for the disadvantaged group, as one would expect given the well-known greater procyclicality of

[12] The magnitude of this shock was chosen to approximate the difference between the Congressional Budget Office's estimate of the natural rate of unemployment and the national unemployment rate during the tightest labor market in our sample – the year 2000.

employment for the latter. The estimated coefficient β is smaller than that for the disadvantaged group in column 3 and does not imply any notable hysteresis. Column 5 replaces the e/p of either group with the difference between the e/p of the disadvantaged and the e/p of the advantaged group and does not instrument for the overall unemployment rate.[13] This formulation provides a direct test of hysteresis in the inequality between the two groups that may be induced by overall labor market tightness. The degree of excess persistence in this inequality is modest.

Note that the coefficients on $U_{s,t}$ and its lag are of opposite signs. One interpretation of this is that improvements in aggregate labor market conditions, in addition to their level, have a short-run positive effect on the e/p of the disadvantaged group. That is, another economic representation of equation (1) has $(\delta_0 + \delta_1)U_{s,t} - \delta_1(U_{s,t} - U_{s,t-1})$ rather than $\delta_0 U_{s,t} + \delta_1 U_{s,t-1}$.[14] As we will see in section 4.2 below, this property of our estimates leads to the e/p "overshooting" its trend in some simulated situations.

3.2 Alternative instruments

In our baseline specification we use the unemployment rate of the "middle" group to instrument for the overall state unemployment rate. However, if the labor market of this middle group is not sufficiently segmented from the labor market of those with at most a high school diploma, our instrument may not satisfy the exclusion restriction. In this section we address this concern by replacing the unemployment rate of the middle group with each of two alternative instruments for the overall state unemployment rate. The first is the unemployment rate of the advantaged group, which we can be more confident is sufficiently segmented from the disadvantaged group. The second is a state-level version of the Federal Reserve Bank of Atlanta's Wage Growth Tracker.[15]

The results are shown in Table 2. Column 1 repeats the baseline specification. Column 2 uses the unemployment rate of the advantaged group as an alternative instrument. For comparability, column 3 repeats the baseline specification over the shorter sample period for which the wage growth data are available (1983 on). Column 4 uses the wage growth data as the instrument.

The choice of instrument makes little difference to the results. The coefficient on lagged e/p is similar across all columns, as is the overall effect of the unemployment rate (the sum

[13]Results with the unemployment rate of the "middle" group as an instrument for the overall unemployment rate yield similar results.

[14]Analogously, it is not uncommon for models of wage growth to include a term in the change in unemployment. See, e.g., Blanchard and Gali (2010).

[15]Our thanks to John Robertson for this suggestion.

Table 2: Different Instruments

	(1) Baseline	(2) Advantaged	(3) Shorter Sample	(4) Wage Growth
$(e/p)_{s,t-1}$	0.55***	0.53***	0.53***	0.57***
	(0.024)	(0.030)	(0.026)	(0.042)
$U_{s,t}$	-1.97***	-0.97***	-2.22***	-2.38***
	(0.13)	(0.17)	(0.16)	(0.31)
$U_{s,t-1}$	1.39***	0.43*	1.57***	1.84***
	(0.11)	(0.21)	(0.14)	(0.34)
$TU_{s,t}$	0.27	-0.13	0.32	0.42
	(0.18)	(0.17)	(0.28)	(0.32)
$TU_{s,t-1}$	-0.16	0.18	-0.25	-0.37
	(0.18)	(0.18)	(0.25)	(0.31)
Observations	1,900	1,900	1,650	1,650
R-squared	0.818	0.824	0.807	0.795

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate in the baseline. Weighted by number of observations of the disadvantaged group.

of the contemporaneous and lag coefficients).

3.3 Trend unemployment rates

In order to examine the sensitivity of our results to the method of estimating the trend unemployment rate in each state, in addition to the Tasci-Fallick estimates, we calculated several univariate filters: a Hodrick-Prescott 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 (2017), with a five-year horizon parameter Figure 2 shows the four trends along with the actual unemployment rate, all aggregated from the state to the national level (excluding DC). The Baxter-King trend stands out as moving closely with the actual unemployment rate.[16]

Table 3 explores the sensitivity of our results to these alternative methods of estimating trend unemployment rates. Column 1 repeats the baseline specification from column 3 of Table 1. The subsequent columns replace the Tasci-Fallick estimates with, respectively, the HP-filtered trend in column 2; the Baxter-King-filtered trend in column 3; and the Hamilton

[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 unemployment rate as the Baxter-King filter shown here.

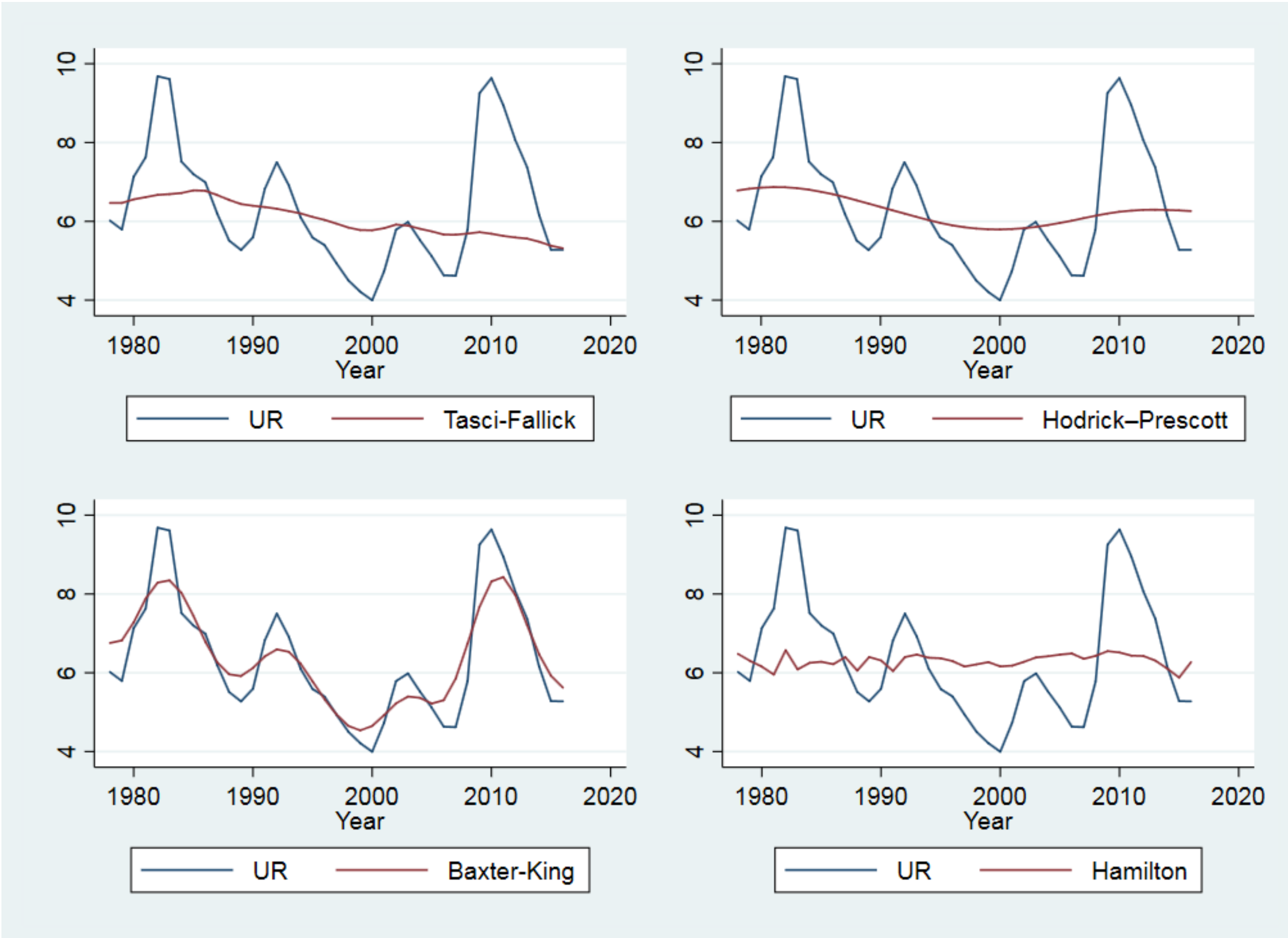

Figure 2: Estimates of State Trend Unemployment Rates, Aggregated

trend in column 4. The results are qualitatively similar across the different trends, with coefficients on lagged e/p in the vicinity of 0.5.

3.4 Time trends

As noted above, the estimates shown so far use a detrended e/p of the disadvantaged group on the left-hand side of equation (1). In this section, we investigate the sensitivity of our results to this choice. In particular, Table 4 uses the actual e/p and includes state-specific linear and quadratic time trends on the right-hand side. Column 1 repeats our baseline specification (with detrended e/p). Column 2 includes linear trends (with actual e/p), and column 3 includes quadratic trends. The inclusion of the latter two trends (which, in each case, are jointly statistically significant) results in smaller estimates of excess persistence

Table 3: Different Estimates of Trend Unemployment

	(1) Tasci-Fallick	(2) Hodrick-Prescott	(3) Baxter-King	(4) Hamilton (2017)
$(e/p)_{s,t-1}$	0.55***	0.51***	0.53***	0.53***
	(0.024)	(0.027)	(0.025)	(0.022)
U_{st}	-1.97***	-2.06***	-3.14***	-2.05***
	(0.13)	(0.12)	(0.25)	(0.15)
$U_{s,t-1}$	1.39***	1.22***	0.86***	1.36***
	(0.11)	(0.10)	(0.20)	(0.099)
TU_{st}	0.27	1.01	2.02***	0.68***
	(0.18)	(0.76)	(0.35)	(0.16)
$TU_{s,t-1}$	-0.16	0.0046	0.046	0.073
	(0.18)	(0.78)	(0.25)	(0.17)
Observations	1,900	1,900	1,900	1,900
R-squared	0.818	0.822	0.800	0.821

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

than in the baseline.

Table 4: State-Specific Time Trends

	(1) Baseline	(2) Linear Time Trends	(3) Quadratic Time Trends
$(e/p)_{s,t-1}$	0.55***	0.44***	0.38***
	(0.024)	(0.029)	(0.030)
$U_{s,t}$	-1.97***	-1.99***	-2.03***
	(0.13)	(0.11)	(0.11)
$U_{s,t-1}$	1.39***	1.12***	1.04***
	(0.11)	(0.10)	(0.11)
$TU_{s,t}$	0.27	0.23	0.25
	(0.18)	(0.20)	(0.23)
$TU_{s,t-1}$	-0.16	-0.095	-0.027
	(0.18)	(0.21)	(0.24)
Observations	1,850	1,850	1,850
R-squared	0.821	1.000	1.000

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

3.5 Defining the disadvantaged population

Table 5 varies the definition of the disadvantaged population.[17] Column 1 repeats our baseline specification, which treats prime-age men with no more than a high school diploma as the disadvantaged group. For definitions of disadvantaged that involve smaller populations, however, many states do not afford enough observations for reasonable estimation. Accordingly, column 2 repeats the baseline specification using only the 29 largest states.[18] The estimates are similar to those from the full sample, so we are comfortable restricting analysis to these states in order to examine other definitions of the disadvantaged group.

Table 5: Different Definitions of Disadvantaged

	Disadvantaged Group				
	(1)	(2)	(3)	(4)	(5)
	Baseline	Larger states	$\leq$ HS, Black	$<$ HS, Black	$\leq$ HS, 25-34
$(e/p)_{s,t-1}$	0.55***	0.55***	0.35***	0.33***	0.41***
	(0.024)	(0.031)	(0.031)	(0.028)	(0.047)
U_{st}	-1.97***	-2.00***	-2.30***	-1.99***	-2.34***
	(0.13)	(0.15)	(0.28)	(0.72)	(0.15)
$U_{s,t-1}$	1.39***	1.44***	1.20***	1.07*	1.36***
	(0.11)	(0.13)	(0.30)	(0.61)	(0.19)
TU_{st}	0.27	0.35	-0.16	0.038	0.80
	(0.18)	(0.25)	(0.52)	(0.89)	(0.56)
$TU_{s,t-1}$	-0.16	-0.28	0.26	-0.097	-0.28
	(0.18)	(0.25)	(0.57)	(1.05)	(0.58)
Observations	1,900	1,102	1,102	1,102	1,102
R-squared	0.818	0.843	0.586	0.440	0.859

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

Column 3 restricts the sample to prime-age black men with no more than a high school education, arguably a more disadvantaged group than the baseline. Column 4 narrows the definition further, to prime-age black men with less than a high school education. In both cases, we see no indication of greater hysteresis in employment than in the baseline.[19]

[17] In all cases we continue to use the unemployment rate of prime-age men with more education than a high school diploma and less than a four-year college degree as the instrument for the overall unemployment rate.

[18] More precisely, it uses the 29 states that average at least 30 observations of black men with less than a high school education aged 25-54.

[19] In results not shown, we also find smaller estimates of hysteresis for prime-age Hispanic men with no more than a high school education.

The degree of hysteresis may depend upon the age of the worker. In particular, having had less opportunity for previous accumulation of human and market capital, younger workers may have more to learn from a bout of employment and more to lose by missing out on employment. Column 5 restricts the sample to men ages 25-34 with no more than a high school education. Here, again, we see no indication of greater hysteresis than in the baseline.[20]

3.6 Asymmetries

High and low e/p may have asymmetric effects on future employment outcomes. For example, skills may be slower to deteriorate through nonuse 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 e/p term into two components: one for e/p above its trend (positive detrended e/p) and one for e/p below its trend (negative detrended e/p).

Column 1 of Table 6 repeats the baseline specification. Column 2 introduces asymmetry. The estimates do not indicate significant asymmetry. In column 3 we add quadratic terms in each asymmetric e/p, to allow for the possibility that extremely high employment or extremely low employment has a larger marginal effect than more modest deviations from trend. Here, there is some indication of asymmetry, with below-trend e/p exhibiting less persistence than above-trend e/p, to an increasing degree as the deviation from trend becomes larger in magnitude. As the illustration at the bottom of the table shows, however, in our "shock" experiment, even above-trend e/p does not exhibit noticeably more hysteresis than in the baseline specification.

3.7 Rotation groups

In section 1 we briefly argued that hysteresis in the aggregate is a mixture of direct hysteresis at the individual level and the indirect effects of one person's employment or employability on another's. And that partly for this reason, individual-level data, analyzed at the individual level, are not well-suited for estimating hysteresis in the aggregate. Even when the data are aggregated, however, it is possible that the sampling structure of the CPS causes our data to misstate the degree of hysteresis.

In the full population, a given person observed in year t represents only a small fraction of the population in year $t-1$ and so contributes only a small amount to the aggregate

[20]Restricting the sample to young black men of this education level would have required us to drop an impractical number of states from the regression.

Table 6: Asymmetry

	(1) Baseline	(2) Linear Asymmetry	(3) Quadratic Asymmetry
$(e/p)_{s,t-1}$	0.55***	–	–
	(0.024)		
$(e/p\ positive)_{s,t-1}$	–	0.54***	0.55***
	–	(0.034)	(0.089)
$(e/p\ positive\ squared)_{s,t-1}$	–	–	0.0018
	–	–	(0.017)
$(e/p\ negative)_{s,t-1}$	–	0.55***	0.45***
	–	(0.041)	(0.053)
$(e/p\ negative\ squared)_{s,t-1}$	–	–	-0.013***
	–	–	(0.0045)
$U_{s,t}$	-1.97***	-1.97***	-1.99***
	(0.13)	(0.13)	(0.13)
$U_{s,t-1}$	1.39***	1.39***	1.40***
	(0.11)	(0.11)	(0.11)
$TU_{s,t}$	0.27	0.28	0.29
	(0.18)	(0.18)	(0.18)
$TU_{s,t-1}$	-0.16	-0.16	-0.18
	(0.18)	(0.19)	(0.19)
Observations	1,900	1,900	1,900
R-squared	0.818	0.818	0.819
	Illustration of "shock" to e/p equivalent to 1 pp decrease in U_{st}		
Impact	1.97	1.97	1.99
Impact+1	1.08	1.06	1.09
Impact+2	0.59	0.57	0.60
Impact+3	0.32	0.30	0.33

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

e/p in year $t-1$. In the CPS (abstracting from attrition), a household is interviewed in 4 consecutive months ("month in sample," or MIS, 1-4) and again in 4 consecutive months 12 months later (MIS 5-8). Thus, in the CPS data, each person observed in year t represents a larger fraction of the calculated e/p in year $t-1$ than is the case in the full population. This could cause hysteresis at the individual level to contribute disproportionately to the estimated coefficient on the lagged e/p in our aggregated data. If individual hysteresis is large and the indirect effects are negative, this could cause our baseline estimate to overstate the degree of aggregate hysteresis.

We explore this possibility in Table 7. Column 1 repeats the estimates from our baseline specification. Column 2 restricts the sample to households in their first four-month rotation (MIS 1-4). Column 3 restricts the sample to households in their second four-month rotation (MIS 5-8). The coefficients on lagged e/p in the latter two columns are substantially smaller than in the baseline estimate, indicating a smaller degree of hysteresis.

Table 7: Rotation Groups

	(1) Baseline	(2) MIS 1-4	(3) MIS 5-8
$(e/p)_{s,t-1}$	0.55***	0.32***	0.28***
	(0.023)	(0.026)	(0.029)
$U_{s,t}$	-1.97***	-2.88***	-3.00***
	(0.13)	(0.29)	(0.28)
$U_{s,t-1}$	1.39***	1.92***	1.95***
	(0.11)	(0.23)	(0.23)
$TU_{s,t}$	0.27	0.35	0.93**
	(0.18)	(0.33)	(0.37)
$TU_{s,t-1}$	-0.16	-0.11	-0.63
	(0.18)	(0.33)	(0.36)
Observations	1,900	1,900	1,900
R-squared	0.818	0.67	0.65

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

While it is not clear whether the restricted samples are definitively superior to the full sample, these results suggest that our baseline estimates might be best interpreted as an upper bound on the degree of aggregate employment hysteresis.

3.8 Migration

The economic 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.

To put this possibility in perspective, interstate migration in the 2000s amounted to about 1.5 percent of the population each year, and a significant part of this may be driven by geographic differences in labor market conditions (Foote et al., 2015). Although disadvantaged workers are less likely to move in response to labor market conditions (Notowidigdo, 2011), whether migration is large enough to substantially bias our estimates is difficult to say a priori.[21]

We attempt to account for migration in two ways.

First, we estimate two spatial panel models, shown in Table 8. In one of these models, the e/p of the disadvantaged group in one state is permitted to affect the e/p of the disadvantaged group in other states (in the terminology of Elhorst (2014) a spatial autoregressive model, labeled SAR in the table). In the other, the unemployment rate (as well as the other regressors) in one state are permitted to affect the e/p of the disadvantaged group in other states (a spatial Durbin model, labeled SDM). In both models, the size of these cross-state effects are assumed to vary with a notion of the "distance" between the states. We estimated these models using, alternately, a first-order contiguity matrix and a matrix based on rates of total observed bilateral migration between states as a measure of that distance. For these models, we omitted Alaska and Hawaii because of their atypical geographic positions. The estimates are similar to the baseline regression, suggesting that migration may not be a significant problem for our model.

Second, we re-estimate the baseline specification on a sample comprising only nonmigrants. To construct this sample, we retain only individuals in year t who were present in the CPS 12 months previously.[22] Unfortunately, this restriction rules out any residential moves, not only the interstate migration with which we are concerned.[23]

When we estimate equation (1) with this nonmigrant sample, the estimated coefficient on lagged e/p is 0.22 (standard error 0.025), 0.33 smaller than our baseline estimate. However, the difference between these two estimates may result from at least two factors in addition to migration. First, the nonmigrant sample is about three-eighths the size of the baseline sample, which may make the data noisier and so exacerbate any attenuation bias. To gauge the possible extent of this, we estimated equation (1) using several three-eighth random samples of the full sample. This yielded a coefficient on lagged e/p of around 0.44. Thus, the smaller sample size can account for around a third of the difference between the nonmigrant and baseline estimates. Second, the nonmigrant sample is perforce limited to observations in

[21]Our empirical model also assumes that the coefficients are the same across states. Yagan (2017) raises the possibility that the housing boom, among other factors, before the Great Recession caused workers to sort themselves across states in ways that might call this assumption into question. Our attempts to account for migration do not address this possibility.

[22]Here we use the matched version of the CPS data available from IPUMS. We have verified that our baseline results are the same using these data.

[23]It is also true that some persons in (not in) the prime age group the previous year will not (will) be in the prime age group in the current year. Restricting the sample to these matched observations also addresses, to a large extent, this concern.

Table 8: Spatial Models

	(1) Baseline	(2) SAR Contiguity	(3) SDM Contiguity	(4) SAR Migration	(5) SDM Migration
$(e/p)_{s,t-1}$	0.55***	0.55***	0.55***	0.55***	0.55***
	(0.023)	(0.016)	(0.016)	(0.014)	(0.016)
U_{st}	-1.97***	-2.14***	-2.09***	-2.16***	-2.08***
	(0.13)	(0.14)	(0.13)	(0.14)	(0.13)
$U_{s,t-1}$	1.39***	1.56***	1.52***	1.56***	1.53***
	(0.11)	(0.14)	(0.14)	(0.14)	(0.13)
TU_{st}	0.27	0.41***	0.38***	0.42***	0.38***
	(0.18)	(0.14)	(0.14)	(0.14)	(0.14)
$TU_{s,t-1}$	-0.16	-0.29*	-0.27	-0.30***	-0.27*
	(0.18)	(0.17)	(0.17)	(0.16)	(0.16)
Spatial ρ	–	0.072*	0.054	0.070	0.023
	–	(0.038)	(0.037)	(0.051)	(0.048)
Observations	1,900	1,776	1,776	1,776	1,776
R-squared	0.818	0.676	0.646	0.677	0.6012

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

MIS 5-8, since only individuals in their second year of the CPS are potentially in the CPS one year earlier. We indicated in section 3.7 that this restriction to MIS 5-8 affects the estimates. To gauge the role of this rotation-group restriction as opposed to the smaller sample size in the nonmigrant sample, we drew several three-fourth random samples of the individuals who satisfied the MIS 5-8 restriction, which gives us a sample of MIS 5-8 observations that is the same size as the nonmigrant sample. This yielded a coefficient on lagged e/p of around 0.27. Thus, the MIS 5-8 restriction can account for about one-half of the difference between the nonmigrant and baseline estimates. In sum, these two factors of sample size and rotation group can account for almost all of the difference between the nonmigrant and baseline estimates, leaving little (0.05) to be accounted for by migration itself. Therefore, migration itself does not appear to have much effect on our baseline estimates.

3.9 Duration

Persistence in the e/p may depend upon the duration of high or low employment. A labor market that is tight only briefly may not draw in members of disadvantaged groups who have remained out of the labor force for many years. Or brief periods of employment may be insufficient to instill the human or network capital or match quality that would have lasting effects on attachment to employment, and brief periods of nonemployment may be insufficient to remove these advantages.

To examine this possibility, in column 2 of Table 9 we add second lags of the RHS variables to the model. None of the coefficients on second lags are statistically significant.

However, the second lag alone may not truly address questions of duration, where the effect of, say, a higher e/p in $t-1$ on current e/p depends on whether the e/p was also high in $t-2$. To address this possibility, column 3 adds interactions between $(e/p)_{s,t-1}$ and $(e/p)_{s,t-2}$, between $U_{s,t-1}$ and $U_{s,t-2}$, and between $TU_{s,t-1}$ and $TU_{s,t-2}$. The coefficient on the interaction in e/p is positive, but small and not statistically significant. It makes little difference to the excess persistence illustrated in the bottom of the table.

4 Simulations

4.1 Historical simulations

In order to provide a better idea of the implications of our estimated degree of hysteresis, we generate a "historical" simulation in which we allow the actual unemployment rate in each state to evolve as it did over a period of years and trace out the implied e/p of the disadvantaged group for our estimated level of excess persistence versus no excess persistence. We set the detrended e/p of the disadvantaged group to zero in the year (1986) before the simulation commences.[24] We show simulations only for prime-age men with no more than a high school diploma, since the other groups in Table 5 exhibit less hysteresis, and only the baseline specification and the specification with quadratic asymmetry. The simulations are performed at the state level and aggregated to the national level.

Figure 3 shows the two simulated e/p series, along with the actual e/p for the period 1997 to 2016, the first being a year in which the gap between the national unemployment rate and the Congressional Budget Office's (CBO) estimate of the natural rate of unemployment was small (-0.2 percentage point). Notice that the simulated e/p and the actual e/p follow similar trajectories over this period, suggesting that our dynamic panel model accounts well for the variations in actual e/p.

Also notice that the simulated e/p ratios from the baseline and quadratic asymmetry models are similar, indicating that the estimated asymmetry was not sufficiently large to

[24]The outcomes are not sensitive to this choice. Nor are they sensitive to the choice of starting year.

Table 9: Duration

	(1) Baseline	(2) 2nd lags	(3) Interactions
$(e/p)_{s,t-1}$	0.55***	0.52***	0.52***
	(0.024)	(0.032)	(0.034)
$(e/p)_{s,t-2}$		0.027	0.030
		(0.038)	(0.037)
(e/p) *interaction*			0.0012
			(0.0040)
$U_{s,t}$	-1.97***	-2.06***	-2.09***
	(0.13)	(0.15)	(0.14)
$U_{s,t-1}$	1.39***	1.60***	1.76***
	(0.11)	(0.19)	(0.19)
$U_{s,t-2}$		-0.16	-0.0021
		(0.13)	(0.14)
U *interaction*			-0.020***
			(0.0070)
$TU_{s,t}$	0.27	0.37	0.47*
	(0.18)	(0.22)	(0.24)
$TU_{s,t-1}$	-0.16	-0.40	-1.03***
	(0.18)	(0.37)	(0.37)
$TU_{s,t-2}$		0.16	-0.28
		(0.21)	(0.27)
TU *interaction*			0.070***
			(0.020)
Observations	1,900	1,850	1,850
R-squared	0.818	0.806	0.806
	Illustration of "shock" to e/p equivalent to 1 pp decrease in U_{st}		
Impact	1.97	2.06	2.09
Impact+1	1.08	1.08	1.10
Impact+2	0.59	0.62	0.64
Impact+3	0.32	0.36	0.37

Driscoll-Kraay standard errors
***p<0.01, **p<0.05, *p<0.1

Note: The disadvantaged group is prime-age men with no more than a high school education. The unemployment rate of prime-age men with more than high school but less than a bachelor's degree serves as an instrument for the overall unemployment rate. Weighted by number of observations of the disadvantaged group.

make a notable difference even in the tight labor market at the end of the 1990s expansion or the severity of the 2008-09 recession. Given this, we will concentrate on the baseline specification.

Figure 4 illustrates the influence of hysteresis (that is, excess persistence) on the e/p in these simulations. The black line shows the difference between the simulated e/p of the disadvantaged group using all of the baseline estimated coefficients from equation (1) (Table 1, column 3), and a simulation with the coefficient β on lagged e/p set to zero while holding

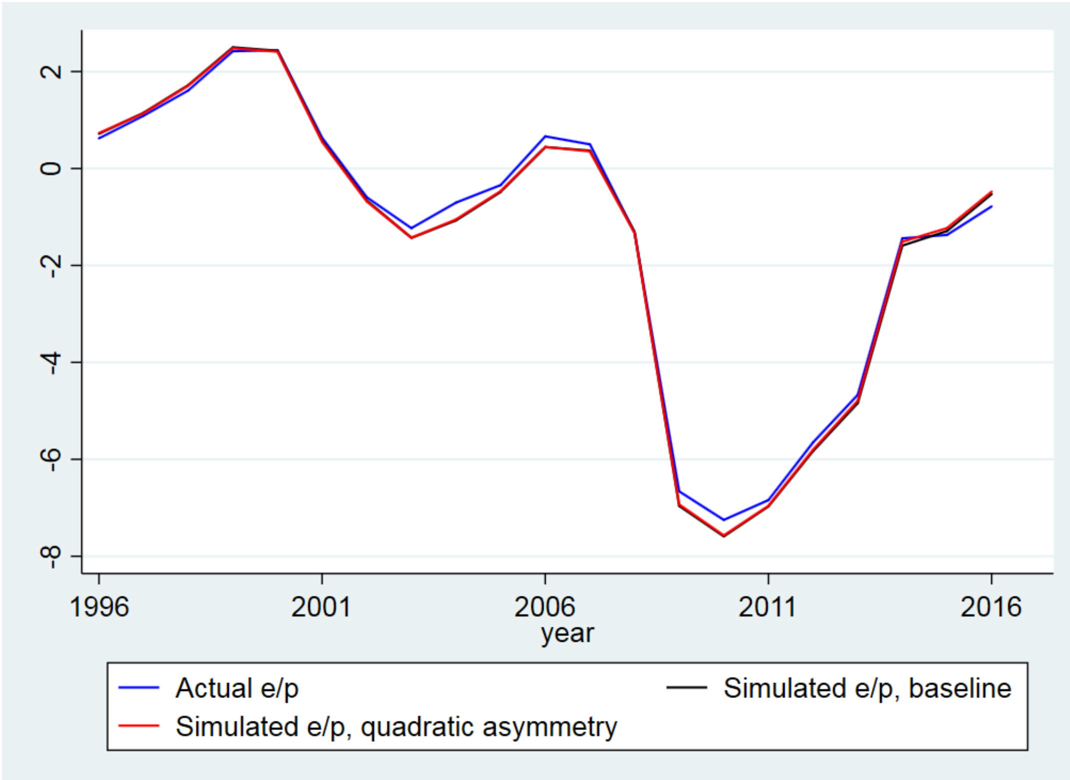

Figure 3: Actual and Simulated e/p of Disadvantaged Group

the coefficients on the actual and trend unemployment rates at their estimated levels.[25] The difference between the two represents the influence of hysteresis. The blue line shows the (aggregated) unemployment rate for reference.

During the tight labor market toward the end of the 1990s expansion and through the 2001 recession, hysteresis served to buoy the e/p of the disadvantaged group by up to 1 percentage point. Following the recession, however, hysteresis pulled in the opposite direction, weighing on the e/p of this group by up to 3/4 percentage point. Cumulatively, the former benefit outweighed the latter cost somewhat.

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 hysteresis raised the e/p ratio by little. The severity of the 2008-09 recession, however, meant that hysteresis weighed on the e/p of the disadvantaged group by as much as 4 percentage points in 2011, and even in 2016, when the national unemployment rate was only 0.1 percentage point above the CBO's natural rate of 5.7 percent, hysteresis held the

[25] As opposed to re-estimating the equation constraining β to be zero.

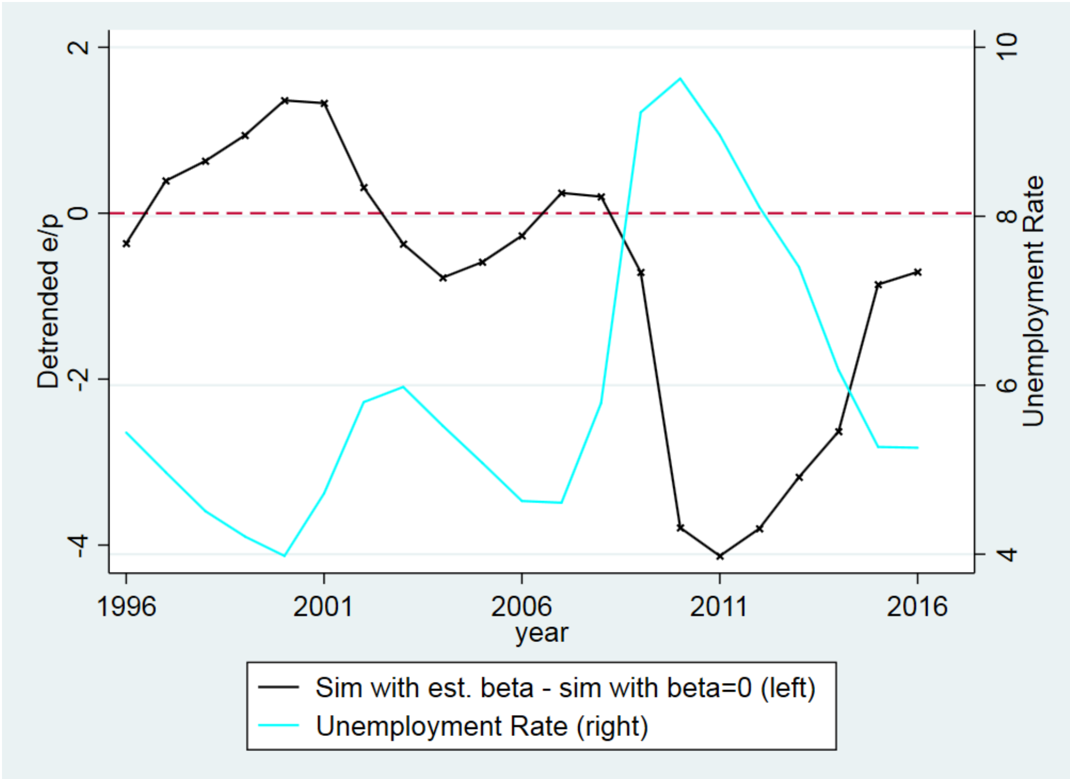

Figure 4: Simulated e/p of Disadvantaged Group and Unemployment Rate

e/p down by 3/4 percentage point.

4.2 Policy simulations

Because substantial increases in the unemployment rate in the United States have occurred only during recessions in the post-war period, historical simulations like those above cannot represent the sort of situation possibly envisioned by Yellen (2016), in which a "high-pressure" labor market is followed by a gradual rise in the unemployment rate that comes to rest at a more sustainable level. In this section we simulate such a "soft-landing" scenario and assess the gain from hysteresis. We do this by comparing the simulated e/p to that from a "recession" scenario.

As with the historical simulations in section 4.1, we show simulations for prime-age men with no more than a high school diploma and the baseline specification.

We simulate these scenarios directly at the national level, in contrast to the historical simulations we performed at the state level before aggregating to the national level.

The simulations for both scenarios begin in 1987. In both cases, we set the detrended e/p of the disadvantaged group to zero in the year before the simulation commences. In order to abstract from changes over time that are not due to the assumed paths for the unemployment rate, we set the trend unemployment rate in every year 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.

In both the soft-landing and the recession scenarios, we set the unemployment rate at the actual unemployment rate through 2000 (in which year the national unemployment rate was as far below the CBO's estimate of its natural rate as occurred during the span of our data). In both cases, from 2005 on we set the unemployment rate in 2005 (in which year the national unemployment rate was quite close to the CBO's estimate of the natural rate) to trend. What differs between the two scenarios is the path by which the unemployment rate reaches that 2005 level.

We show the two paths for the unemployment rate in the upper panel of Figure 5. For the recession scenario, we set the unemployment rate at its actual value from 2001 (the year the actual recession commenced) through 2003 (the year in which the unemployment rate 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 unemployment rate to rise at a constant rate from its low in 2000 to trend in 2005.

For ease of exposition, we show the simulated e/p from the soft-landing and recession scenarios as the deviations from the "steady-state" e/p implied by our baseline coefficients.[26] The lower panel of Figure 5 shows this deviated 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 tight labor market of 2000. In the soft landing scenario, the e/p then falls toward the steady state as the unemployment rate reverts to trend. There is some small overshooting attributable to the difference in coefficients on the contemporaneous and lagged unemployment rates, as discussed in section 3.1, which fades away by 2007.

The e/p in the recession scenario, of course, falls relative to the soft-landing scenario during 2001 to 2003. By 2006, when both current and lagged unemployment rates are equal in the two scenarios, the 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

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

weak years of recession and "jobless recovery," once the unemployment rate stabilizes there is little difference between the e/p in the two scenarios. The period of high pressure has no lasting effect on the e/p of the disadvantaged group.

5 Conclusion

In this paper, we estimated a dynamic model on a panel of state-level data to estimate the persistence of employment-to-population ratios of disadvantaged workers beyond that implied by the persistence of aggregate labor market conditions (hysteresis). We find that the employment-to-population ratio of less-educated prime-age males exhibits insufficient hysteresis to continue to make a substantial difference a few years after a "shock" to the employment-to-population ratio. 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 hysteresis 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 of temporarily running a "high-pressure" economy are small.

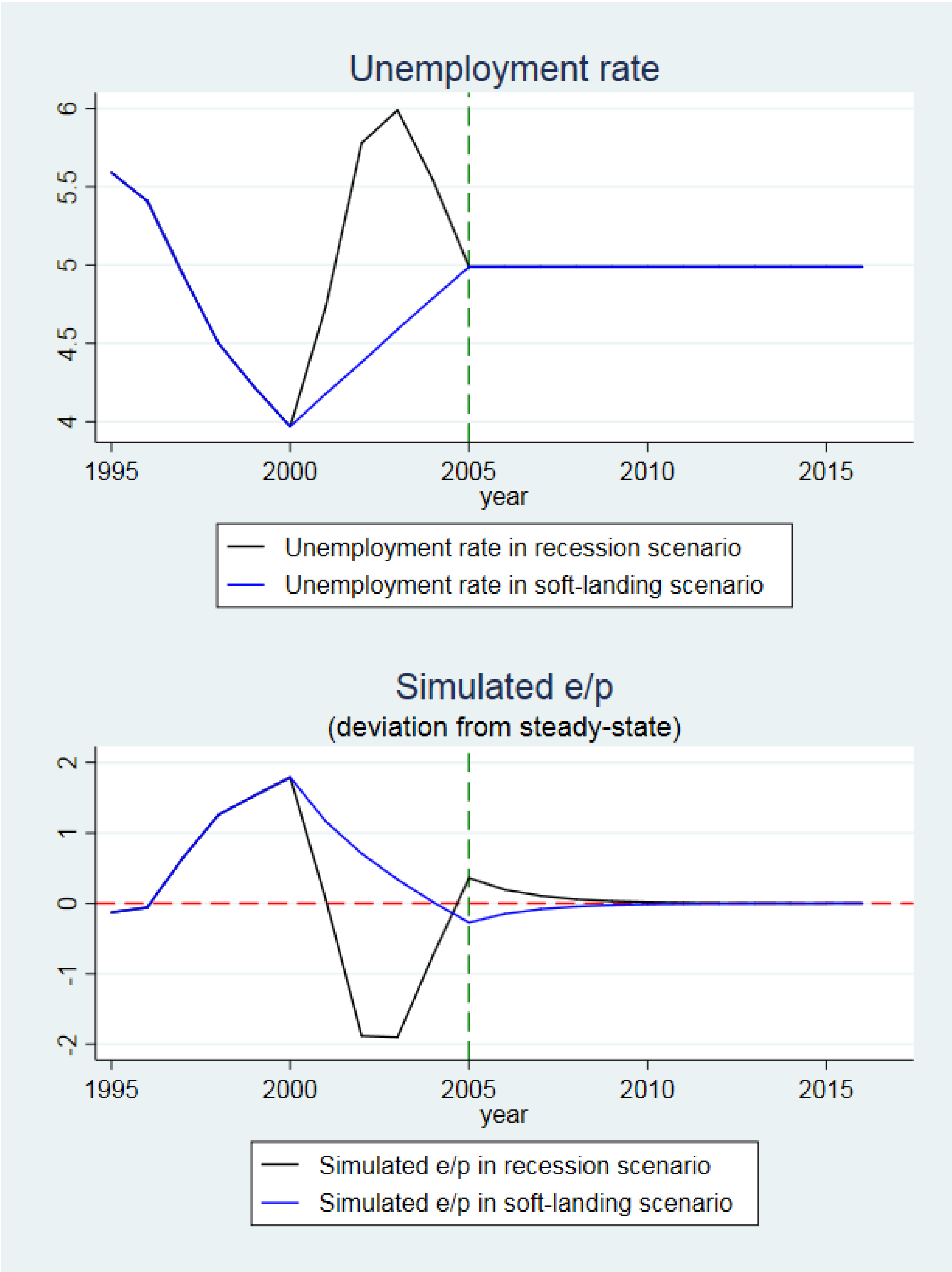

Figure 5: Soft-Landing and Recession Scenarios

References

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.

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

Arellano, Manuel and Stephen Bond (1991). "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations." *The Review of Economic Studies*, 58(2), pp. 277–297. doi:10.2307/2297968.

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." URL `https://www.cbpp.org/sites/default/files/atoms/files/3_30_15fe_ball.pdf`, Center on Budget and Policy Priorities, March 30.

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.

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.

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.

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.

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. URL `https://www.govinfo.gov/content/pkg/ERP-2017/pdf/ERP-2017.pdf`, Washington: Government Printing Office, January 2017.

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

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.

Elhorst, J. Paul (2014). *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Berlin, Heidelberg: Springer. doi:10.1007/978-3-642-40340-8.

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.

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

Foote, Andrew, Michel Grosz, and Ann Huff Stevens (2015). "Locate Your Nearest Exit: Mass Layoffs and Local Labor Market Response." doi:10.3386/w21618.

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.

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

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. (2017). "Why You Should Never Use the Hodrick-Prescott Filter." doi:10.3386/w23429. Manuscript, UC San Diego, May.

Hines, James, Hilary Hoynes, and Alan Krueger (2001). "Another Look at Whether a Rising Tide Lifts All Boats." In Alan B. Krueger and Robert M. Solow, editors, *The Roaring Nineties: Can Full Employment Be Sustained?*, chapter 10, pp. 493–537. Russell Sage Foundation.

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 (2000). "The Employment, Earnings and Income of Less Skilled Workers over the Business Cycle." In David E. Card and Rebecca M. Blank, editors, *Finding Jobs: Work and Welfare Reform*, chapter 1, pp. 23–71. Russell Sage Foundation.

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.

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.

Kiviet, Jan F. (1995). "On Bias, Inconsistency, and Efficiency of Various Estimators in Dynamic Panel Data Models." *Journal of Econometrics*, 68(1), pp. 53–78. doi:10.1016/0304-4076(94)01643-E.

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.

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.

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.

Notowidigdo, Matthew J. (2011). "The Incidence of Local Labor Demand Shocks." doi:10.3386/w17167.

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.

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.

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.

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).

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.

Tasci, Murat (2011). "The Ins and Outs of Unemployment in the Long Run: A New Estimate for the Natural Rate?" doi:10.26509/frbc-wp-201017r. Federal Reserve Bank of Cleveland, Working Paper 1017.

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).