NBER WORKING PAPER SERIES

THE INEXORABLE RECOVERIES OF US UNEMPLOYMENT

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Working Paper 28111
http://www.nber.org/papers/w28111

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2020, Revised August 2021

Hall's research was supported by the Hoover Institution. The opinions expressed are those of the authors and do not reflect those of the Federal Reserve Bank of San Francisco, the Federal Reserve System, or the National Bureau of Economic Research. We thank Stephane Dupraz, Emi Nakamura, and Jón Steinsson for providing the code for their business-cycle chronology function and Marcelo Perlin for providing code for estimating hidden Markov models. We thank Markus Brunnermeier and Peter Diamond for comments. Backup data and code are available at Kudlyak's website.

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JEL No. E32,J64

ABSTRACT

Unemployment recoveries in the US have been inexorable. Between 1949 and 2019, the annual reduction in the unemployment rate during cyclical recoveries was tightly distributed around 0.1 log points per year. The economy seems to have an irresistible force toward restoring full employment. Unless another crisis intervenes, unemployment continues to glide down to a level of approximately 3.5 percentage points. Occasionally unemployment rises rapidly during an economic crisis, while most the time, unemployment declines slowly and smoothly at a near-constant proportional rate. We show that similar properties hold for other measures of the US unemployment rate and for the unemployment rates of six other advanced countries.

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We undertake a close examination of the behavior of unemployment during cyclical recoveries, over the period from 1948 to 2019, using data from the Current Population Survey (CPS). We find that during this period, unemployment has shot upward 10 times as the economy has experienced economic crises. Following a crisis, the unemployment rate glides downward on a predictable but slow recovery path. In some cases, the path ends with unemployment still above its minimal level, and in others, such as the longest recovery, from October 2009 to February 2020, unemployment reached 3.5 percent, which may be the current minimum feasible level. Unemployment reached its historical minimal level over the entire period in the early 1950s, at 2.5 percent.

This paper is empirical and limited to the period from the beginning of modern unemployment measurement, in January 1948, to the end of the recovery in February 2020. Further, we do not enter the thicket of general equilibrium models or Phillips curves. Rather, we study the behavior of unemployment in completed recoveries recorded in the CPS.

We find that the observed behavior of unemployment comprises (1) occasional sharp upward movements in times of economic crisis, and (2) an inexorable downward glide at a low but reliable proportional rate at all other times. The glide continues until unemployment reaches a low barrier of approximately 3.5 percent or until another economic crisis interrupts the glide.

We focus on recoveries. Our measurement starts in an economy that has been hit recently by an adverse shock that triggered a recession. These shocks have heterogeneous sources. The major recession that began in 1981 is generally viewed as the result of a sharp monetary contraction, while the major recession that began at the end of 2007 got much of its strength from the financial crisis of September 2008. This paper recognizes that the shocks that propel unemployment sharply upward are heterogeneous. The paper is about the homogeneity of historical recoveries.

Figure 1 shows our main evidence. It displays the log of the unemployment rate during the 10 completed recoveries since 1948, with the recession spells of sharply rising unemployment left blank. The key fact about recoveries is apparent in the figure: Unemployment declines smoothly but slowly throughout most recoveries most of the time, at close to the same proportional rate. In the log plot, the recoveries appear as impressively close to straight lines. In terms of levels rather than logs, this behavior implies that unemployment falls in a year by one tenth of its level at the beginning of the year. For example, in a year starting with 7 percent unemployment, the rate falls by 0.7 percentage points during the year. We document this regularity within the two main statistical approaches to business-cycle analysis and measurement: (1) construction of a chronology of turning points, and (2) estimation of a Markov regime-switching model. We also show that measures of US unemployment extended

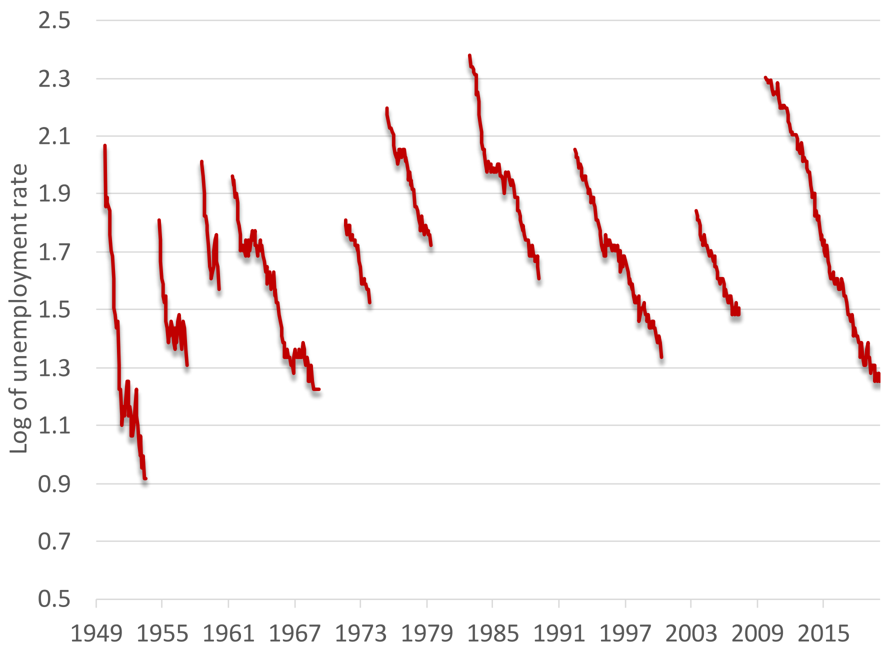


Figure 1: The Paths of Log-Unemployment During Recoveries

to include discouraged workers and others, not counted in the labor force, display the same consistent pattern as the standard unemployment rate. And we show that unemployment of other advanced countries behaves in much the same way as in the US.

We are not the first to study the time-series properties of US unemployment. The basic asymmetry between the sharp rise of unemployment in contractions and the slow pace of expansions is well known, and studied carefully with new results and a thorough discussion of the earlier literature in Dupraz, Nakamura and Steinsson (forthcoming). We note that a well-documented property of the unemployment rate—most recently confirmed by those authors—is that unemployment rises rapidly in response to a significant aggregate adverse shock and then gradually recovers to a level of 3 to 5 percent of the labor force. Like fuel prices, unemployment rises like a rocket and falls like a feather. Our contribution to this literature is our demonstration of the astonishing reliability of the recovery process. We measure the rate of recovery of unemployment from recession-highs and demonstrate how uniform the rate is.

In a companion paper (Hall and Kudlyak (forthcoming)), we consider resolutions of the puzzle of *slow decline* of unemployment in recoveries. Initially pointed out by Cole and Rogerson (1999), the puzzle is that unemployment declines much more slowly than the measured individual job finding rates would seem to indicate. In that paper, we discuss models in the Diamond-Mortensen-Pissarides tradition that can account for the puzzle.

In response to a lengthy period prior to 2021 of falling short of its target rate of inflation, the Federal Reserve Board announced that, in future expansions, policy would not lean against a glide path that brought unemployment below 4 percent until there were clear signs of rising inflation (Powell (2020)). The Fed's new policy of not resisting the downward glide in unemployment during periods of calm is consistent with our conclusions.

1 Business Cycle Measurement

1.1 Our measure of the business cycle

To study recoveries, we need a measure of the business cycle. Romer and Romer (2019) discuss cycle measures in detail. They conclude that the preferred defining characteristic of the measure is its ability to capture unused resources. In current business-cycle research, the primary alternative definition is based on extracting a higher-frequency component from real GDP or other output measure. That component is the higher-frequency series from the Hodrick-Prescott or other bandpass filter. We agree with the Romers that tying the business cycle to unused resources is conceptually superior to tying it to higher-frequency movements.

Our view further adopts the Romers' conclusion that the unemployment rate, or a measure derived from the unemployment data from the Current Population Survey, is the best available measure of the cycle. The unemployment rate appears to contain almost no movements associated with productivity or similar forces that would call for filtering out. A modest slow-moving demographic component of the unemployment rate is present—see Hornstein and Kudlyak (2019) and Crump, Eusepi, Giannoni and Sahin (2019).

1.2 Econometrics of business-cycle measurement

We model log-unemployment in recoveries as the sum of a latent declining path component and a latent stationary component capturing survey sampling errors and other deviations from the path. The path is modestly downward. Our objective is to measure the central tendency and dispersion of the rate of decline of the latent systematic component of the monthly change of log-unemployment rate during recoveries.

We formalize the model as

$$\log u_t = \alpha - \beta t + \epsilon_t, \tag{1}$$

where $\alpha - \beta_t$ is the systematic linear path component capturing the recovery phase of the business cycle, and ϵ_t is the random unsystematic component, taken to be uncorrelated with t. Toward the end of the paper, we test for curvature of the time path and find little evidence for it. In Figure 1, the linearity of the recovery paths of log unemployment is plainly visible.

In the specification with $\log u_t$ on the left-hand side, the slope $-\beta_t$ is measured in log points, that is, percent declines in unemployment per unit of t. Where possible, we avoid stating the results in the potentially confusing terms of percents of percents, but that is the actual implication of the specification. We use the term log points and state them as decimals. For example, a typical finding is that unemployment declines during a recovery by 0.1 log points per year, which is 0.7 percentage points if the unemployment rate starts at 7 percent of the labor force.

The literature has focused on two general classes of specifications for the systematic component. One is *chronology-based* and proceeds by assigning turning points—dates when recessions end and recoveries begin, and dates when recoveries end and recessions begin. Chronologies are available from published sources, notably the National Bureau of Economic Research, which identifies monthly dates of turning points in a latent measure called economic activity. Chronologies can be created for a particular time series, such as the unemployment rate, as an exercise in human pattern recognition. And chronologies can be created by algorithms, such as the one described in Dupraz et al. (forthcoming). Given a chronology, we estimate the systematic component $\alpha - \beta_t$ by standard econometric methods.

The other class of models focuses on *regime switching*, where the systematic component is modeled as a statistical time series that obeys one model in contractions and another in recessions. Hamilton (1989) launched the econometric literature on Markov-switching models in this class.

The key difference between these classes is that turning points are latent unobserved events in regime-switching models. These models yield a probability that a given month is a turning point, not an unambiguous turning-point date.

2 Estimation Methods

2.1 Estimation based on chronologies

We consider three monthly business-cycle chronologies:

1. NBER: The chronology maintained by the National Bureau of Economic Research identifying turning points in economic activity, as described in detail at NBER.org

2. DNS: The chronology produced by the DNS algorithm based on US unemployment from January 1948 through February 2020, with size parameter 1.5

3. HK: The chronology produced by the authors based on observed business cycle peaks and troughs

DNS developed an algorithm that maps a time series into another time series taking on three discrete values: trough, peak, and neither. For unemployment, most months are classified as neither a trough nor a peak, but rather a continuation of a previous path. The DNS algorithm is based on judgment about how to extract turning points from time-series data, but its application banishes human judgment from the actual determination. The algorithm is a filter that applies prior beliefs embodied in the algorithm to determine turning points. Because the algorithm makes it cheap to extract a chronology from hypothetical data, and because it is a function, producing a single chronology from any particular input, it is a suitable basis for experimenting with the use of a chronology in a situation where noise partly obscures an underlying true chronology. We have subjected the algorithm to thousands of experimental paths of unemployment in this endeavor.

Our procedure (HK) delivers turning points similar to the DNS algorithm. However, we pick the latest points for peaks and troughs, consistently with our definition of the recovery. The results based on the HK chronology are quite similar to those based on the DNS chronology.

Figure 2 shows the three chronologies. One disagreement is immediately apparent—the NBER chronology has a recovery beginning in July 1980 and ending 12 months later in July 1981. There is no comparable recovery in the other chronologies. In general, DNS and HK are similar to one another and differ from NBER. The reason is that DNS and HK are chronologies for unemployment alone, while NBER is a chronology for latent economic activity. For the dates in the table starting with January 1980, NBER.org has published explanations of the various indicators that form the basis for the determination of the dates. Although the NBER has determined that April 2020 was a turning point between recession and recovery, we do not include that recovery because it is incomplete as we write, and because of the explosion of temporary-layoff unemployment, discussed later in this paper..

Given a recovery running from an initial high point of unemployment, which we number as $t = 0$, to the following low point, which we number as T, our model for a single recovery is

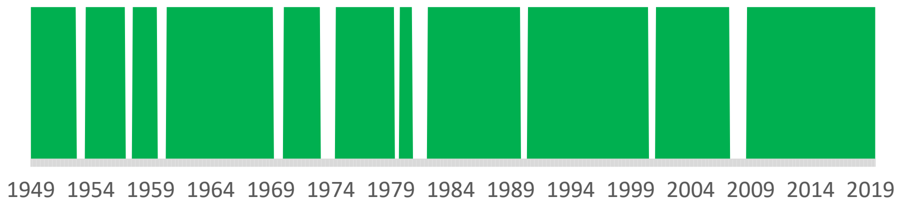
$$\log u_t = \alpha - \beta\, t + \epsilon_t. \tag{2}$$

The residual, ϵ_t, follows an AR(1) process,

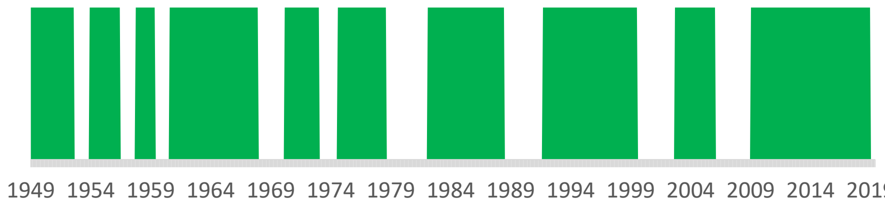
$$\epsilon_t = \rho \epsilon_{t-1} + \eta_t. \tag{3}$$

The innovation η_t is white noise. We apply an autoregressive transformation to obtain

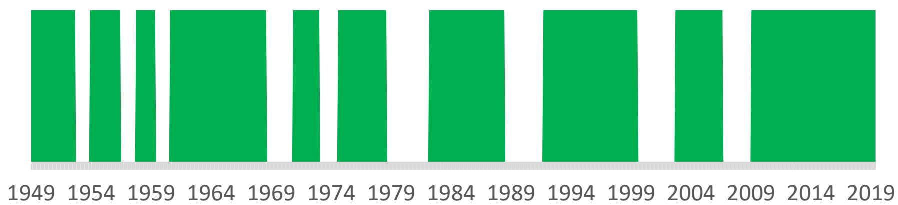
$$\log u_t = \rho \log u_{t-1} + (1 - \rho)\alpha - \beta[t - \rho \cdot (t - 1)] + \eta_t. \tag{4}$$



(a) NBER



(b) Dupraz, Nakamura and Steinsson



(c) Hall and Kudlyak

Figure 2: Three Chronologies for the US Unemployment Rate

We rewrite this equation in terms of two parameters, $\kappa = (1-\rho)\alpha - \rho\beta$ and $\gamma = (1-\rho)\beta$, so that the equation becomes

$$\log u_t = \rho \log u_{t-1} + \kappa - \gamma t + \eta_t. \tag{5}$$

We use a first-stage regression to estimate ρ and, incidentally, κ and γ. We could recover the implied values of α and β from the definitions above, but instead we run a second-stage regression with $\log u_t - \rho \log u_{t-1}$ as the left-hand variable, and right-hand variables comprising the constant, 1, and $(1-\rho)t$, using the first-stage estimate of ρ. The second-stage regression yields the same coefficients as the direct calculation, but also yields standard errors for the original parameters. We report the second-stage estimates of the recovery rate β and their standard errors from the second-stage regression.

The autoregressive parameter ρ indexes a range of estimators of the key parameter β, the recovery rate. If the random part of the unemployment path is serially uncorrelated, with $\rho = 0$, the second-stage equation is

$$\log u_t = \alpha - \beta t + \eta_t, \tag{6}$$

and the estimated recovery rate is the coefficient of $-t$ in a simple regression. If random part is a random walk, with $\rho = 1$, the second-stage equation is

$$\log u_t - \log u_{t-1} = -\beta + \eta_t, \tag{7}$$

and the estimated recovery rate is the mean decline in log unemployment over the recovery, which can also be estimated as $\beta = (\log u_0 - \log u_T)/T$.

We estimate β separately for each recovery. To characterize the recovery rate over multiple recoveries, we report the equally weighted mean of the recoveries, together with the implied standard error of the average recovery rate on the hypothesis that the estimates are uncorrelated across recoveries. This hypothesis is reasonable given our estimates of the serial correlation of the random factors and the lengths of the recessions separating the recoveries.

2.2 Estimation using the hidden Markov approach

Our second approach to modeling business cycles posits the same basic cyclical structure,

$$\log u_t = x_t + \epsilon_t, \tag{8}$$

where x_t is unobserved, but hypothesized to switch between positive and negatively sloped segments at random, according to a Markov process. Under the assumption that the disturbance is a random walk, $\Delta\epsilon_t = \eta_t$, with η_t being white noise, the model becomes

$$\Delta \log u_t = -\beta_i + \eta_t. \tag{9}$$

The monthly decrement, β_i, $i \in \{1, 2\}$, shifts back and forth between $i = 1$ for recessions and $i = 2$ for recoveries. We focus on β_2, the log-decline in unemployment during recoveries. James Hamilton pioneered the econometric analysis of this class of models. He derived the likelihood function in a computationally convenient form (Hamilton (1989)). Marcelo Perlin provided the Matlab package for estimating hidden Markov models that we used (Perlin (2015)).

We note that the assumption that ϵ is a random walk is essential to our application of the hidden Markov model. We need the assumption to justify taking first-differences, which has the effect of isolating β_i on the right-hand side of the equation. This step also puts the iid innovation η_t on the right-hand side, a property that is the starting point for the regime-change class of models. However, in the results for the chronology-based model, ϵ has an AR(1) parameter ρ around 0.7, not 1. Thus, first-differencing does not yield the true innovation η, but only something approximating to it.

	Chronology			*Hidden Markov*
	NBER	*Dupraz-Nakamura-Steinsson*	*Hall-Kudlyak*	
Annual recovery rate, log points	0.086	0.108	0.107	0.066
(Regression standard error)	(0.011)	(0.013)	(0.012)	
(Information matrix standard error)				(0.015)
Coefficient on quadratic term in recovery rate as a function of duration	-0.37	0.08	0.07	
(Regression standard error)	(0.07)	(0.29)	(0.29)	

Table 1: Statistical Results

2.3 Sampling distributions of the estimators of the recovery rate

For our chronology-based estimates, we report the conventional regression standard errors for the second-stage regression. These measures are conditional on the chronologies; that is, they presume exact knowledge of the turning-point dates when in fact the dates are subject to sampling error. They do reflect the contribution of the noise innovations η_t.

For the hidden Markov estimates, Hamilton's approach is an application of maximum likelihood, so the information matrix is the basis of an estimator of the covariance matrix of the estimated parameters. Despite the specification error discussed above, we believe that the reported standard errors are indicative of sampling variation that includes uncertainty about the dates of transitions.

3 Estimates of the Unemployment Recovery Rate

Table 1 shows our statistical results for both approaches. Here and in the rest of the paper, we report recoveries at annual rates, 12 times the monthly rates from the estimation. The upper panel shows the estimates of the key result in this study: the annual recovery rate in log points, β. The sample period is October 1949 through February 2020. The left three values are the estimated recovery rate β in log points per year using the chronology approach, together with their standard errors, for each of the three chronologies. The rightmost value is the recovery rate estimated by the hidden Markov approach, together with its standard error.

For the NBER chronology, the estimated average decline rate pooled across recoveries is 0.086. Recovery rates for the DNS and HK chronologies are similar to each other and are above the NBER level, at 0.108 and 0.107. The DNS and HK chronologies, constructed from unemployment alone, are more successful at capturing the movements of unemployment during recoveries, because they are better synchronized with the actual movements. Of course, DNS and HK would be correspondingly poorer at tracking economic activity, the concept behind the NBER chronology.

We illustrate the interpretation of the annual decline figures in the table with an example from the recovery rates based on the NBER chronology. Consider the situation just after a severe recession, with the unemployment rate starting at 10 percent. The expected unemployment rate a year later is $10 \exp(-0.086) = 9.0$ percent. With the recovery rate based on DNS, the rate a year later would be essentially the same as with the HK chronology. According to the DNS rate, starting from 6 percent, the unemployment rate a year later would be 5.4 percent. The standard errors of the three chronology-based estimates are around 0.012.

The right-hand result in Table 1 pertains to the hidden Markov model. The estimated annual recovery rate is 0.066, below the results for the chronology-based estimates, especially in the case of DNS and HK. We attribute the lower estimate to the uncertainty about the timing of the transitions. The standard error of the hidden-Markov result is higher than for the chronology-based results for the same reason.

One reason for the disagreement between the two estimators is that the theory of the application of the hidden-Markov setup to our problem requires the assumption that the disturbance is a random walk, whereas it is actually an AR(1) process with coefficient somewhat less than one.

The chronology-based estimator can be considered an application of Bayesian thinking, in that it imposes prior beliefs about the process. The posterior, so to speak, may involve a higher implied value of the recovery rate because the prior belief pushes the posterior in that direction, relative to the likelihood.

3.1 Estimates by recovery

Figure 3 shows the results for the 10 recoveries in the HK chronology separately. The estimates from 1961 to 2020 cluster close to 0.10 with tiny standard errors. Over that 60-year period, with 7 recessions and recoveries, some mild and two quite severe, the recovery rates are remarkably similar. Estimated rates for the first three recoveries are more variable and have much higher standard errors. These results nail down the primary thesis of our study—the uniformity of recovery rates over the past 60 years and their remarkably low levels.

Why is there a widespread impression that the recovery from the 2007 recession and financial crisis of 2008 was slower than previous recoveries? The answer is that recoveries

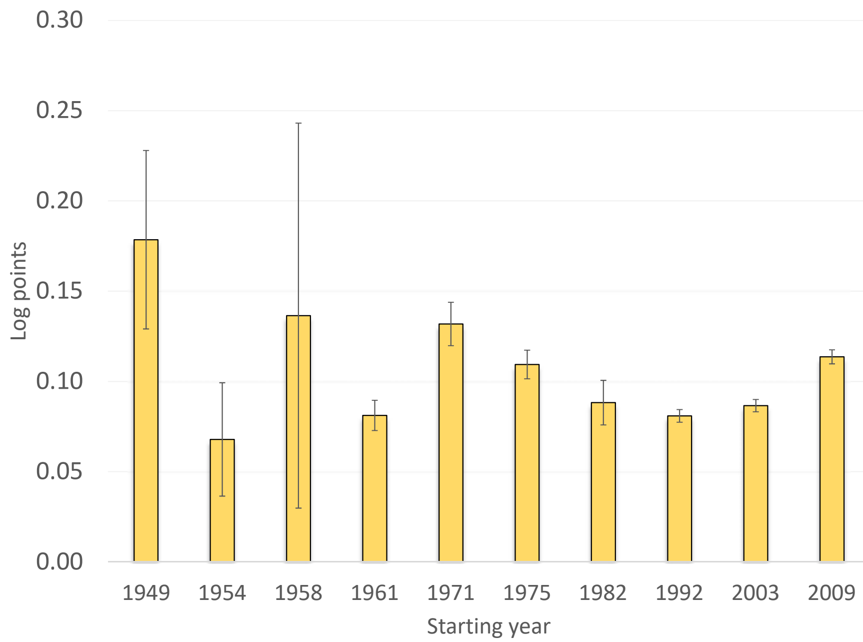


Figure 3: Estimated Recovery Rates by Recovery

tend to be judged in terms of output. Both actual growth of real GDP and growth of potential GDP were lower for a number of reasons, including especially the decline in the rate of productivity growth—see Fernald, Hall, Stock and Watson (2017). The facts are that output growth was substandard during the recovery but the decline in unemployment was at the normal rate for recoveries after 1960.

The serial correlation parameter ρ has a mean of 0.71 for the HK estimates, across recoveries, with a range from 0.37 to 0.88.

3.2 Evidence of departures from the log-linear specification

To study the possibility that the paths of log-unemployment are not straight lines, we add a curving quadratic term to the model, controlled by a parameter χ, so the model for a recovery becomes

$$\log u_t = \alpha - \beta\, t + \chi t \cdot (T - t) + \epsilon_t. \tag{10}$$

The curving add-on is normalized to have no contribution at the beginning of the recovery (t=0) and none at the end of the recovery (t=T). The $\alpha - \beta\, t$ component controls the total decline in unemployment over the recovery, while the new component, $\chi t \cdot (T - t)$, bends the path to make it convex or concave.

Results for this specification are summarized at the bottom of Table 1. These are averages across the regressions for individual recoveries. There is statistically unambiguous evidence of curvature for the NBER chronology, but not for the DNS or HK chronologies. This evidence confirms the visual impression in Figure 1 that unemployment in recoveries follows a reasonably strict log-linear path.

4 Temporary-Layoff Unemployment

As we write, the United States is recovering from a major pandemic and resulting deep slump. The recovery of the US unemployment rate has been vastly speedier so far than its low historical value, dropping from its maximum of 14.7 percent in April 2020 to 6.9 percent in October 2020. In a separate paper (Hall and Kudlyak (2020)), we discuss how a completely unprecedented volume of temporary layoffs accounts for the highly unusual rate of decline of unemployment, and why it is likely that the normal pattern of low but reliable decline of unemployment will resume once those individuals are back at work. A substantial fraction of workers on temporary layoff are recalled to their previous positions—in effect, these individuals are on leave from jobs that they continue to hold. See Fujita and Moscarini (2017) on recalls in general and Gregory, Menzio and Wiczer (2020) on the role of recalls in the recovery from the pandemic.

Since 1967, the CPS has included questions that identify workers on temporary layoff. In recessions in the 1970s and 1980s, temporary layoffs spiked to just over two percent of the labor force, but subsequently declined to under one percent in recent decades and around 0.5 percentage points during the long recovery after 2009. In our related research, we make the case that unemployment analysis should distinguish temporary-layoff unemployment from what we call lost-job unemployment—individuals who are searching actively and do not hold existing jobs. Accordingly, we have repeated our measurement of recovery rates using data starting in 1967 that excludes workers classified as temporarily laid off. We find almost no difference from the results studied in this paper. Only in the pandemic recession and recovery did temporary-layoff unemployment rise to a level visible in the recovery rate.

5 Results for Alternative US Measures and for Other Advanced Economies

In this section, we study data on unemployment rates apart from the standard US rate. We form chronologies using the DNS software and then estimate recovery rates as described earlier in this paper, using both the chronology and hidden Markov approaches.

For the US, the BLS publishes a number of alternative measures of unemployment, based on the CPS. The more interesting of these include more individuals than does the standard

	Chronology approach		*Hidden Markov*	
Alternative US unemployment rate	*Recovery rate, β*	*(standard error)*	*Recovery rate, β*	*(standard error)*
Standard unemployment plus discouraged workers	0.099	(0.002)	0.069	(0.017)
Above plus marginally attached to labor force	0.097	(0.002)	0.061	(0.015)
Above plus part time for economic reasons	0.096	(0.002)	0.054	(0.015)

Table 2: Results for Alternative US Unemployment Rates

	Chronology approach			*Hidden Markov*	
Country	*Number of recoveries*	*Recovery rate, β*	*(standard error)*	*Recovery rate, β*	*(standard error)*
Canada	9	0.135	(0.007)	0.047	(0.014)
France	3	0.083	(0.010)	0.037	(0.007)
Germany	2	0.087	(0.004)	0.096	(0.008)
Italy	3	0.084	(0.009)	0.044	(0.017)
Japan	2	0.105	(0.007)	0.068	(0.008)
United Kingdom	3	0.074	(0.004)	0.001	(0.010)

Table 3: Results for Six Advanced Countries

unemployment rate. Table 2 reports results in the framework of this paper for the three extended unemployment rates, called U-4, U-5, and U-6, over the period of publication, which began in 1994, after a comprehensive revision of the CPS. The results are quite similar to those in Figure 3. We believe that this evidence supports the hypothesis that our findings are robust across measures of unemployment and are not an artifact of the specific choices embodied in the standard unemployment rate.

The Organisation for Economic Co-operation and Development compiles harmonized unemployment data that are adjusted to US definitions, for many countries . Table 3 reports results for countries in the G-7. Only Canada has a record almost as long as the US, with 9 recoveries. The unemployment recovery rates for advanced economies cluster in the range of the US rates for more recent recoveries, around 0.1 log points per year. Slow but sure is not limited to the US. The findings of this paper are not strictly limited to the US.

6 Concluding Remarks

We have developed a parsimonious statistical model of the behavior of observed unemployment. In economies subject to occasional major negative shocks, it describes an inexorable downward glide at a low but reliable proportional rate of 0.1 log points during quiescent times. The glide continues until unemployment reaches approximately 3.5 percent or until another economic crisis interrupts the glide.

Our companion paper, Hall and Kudlyak (forthcoming), has the goal of explaining the mechanisms that underlie the movements we document in this paper. We show that the immediate victims of job loss in a crisis tend to have downstream unemployment lasting several years, but not long enough to account for more than a fraction of the persistence documented in this paper. And the evidence shows that the long bulge in unemployment following a crisis involves recruitment of additional victims who did not lose jobs in the crisis itself.

In view of these findings, we seek a mechanism that delivers consistent but slow recoveries of unemployment during the last seven decades, in the US and other advanced economies. We argue that such a mechanism generates self-recovery in the labor market. Self-recovery is present in the standard Diamond-Mortensen-Pissarides model of unemployment, but it is faster than in the data. We propose a mechanism whereby a negative feedback from high unemployment to job creation early in the recovery generates reliable but slow recoveries, as in the data. Models of congestion are a leading example of the mechanisms we discuss.

References

Cole, Harold L. and Richard Rogerson, “Can the Mortensen-Pissarides Matching Model Match the Business-Cycle Facts?,” *International Economic Review*, 1999, *40* (4), 933–959.

Crump, Richard K., Stefano Eusepi, Marc Giannoni, and Aysegul Sahin, “A Unified Approach to Measuring u,” *Brookings Papers on Economic Activity*, 2019, pp. 143–214.

Dupraz, Stephane, Emi Nakamura, and Jon Steinsson, “A Plucking Model of Business Cycles,” *Journal of Political Economy*, forthcoming.

Fernald, John., Robert E. Hall, James H. Stock, and Mark W. Watson, “The Disappointing Recovery of Output after 2009,” *Brookings Papers on Economic Activity*, 2017, *Spring.*

Fujita, Shigeru and Giuseppe Moscarini, “Recall and Unemployment,” *American Economic Review*, 2017, *107* (12), 3875–3916.

Gregory, Victoria, Guido Menzio, and David Wiczer, “Pandemic Recession: L or V-Shaped?,” *Quarterly Review*, 2020, (4011). Federal Reserve Bank of Minneapolis, May 27.

Hall, Robert E. and Marianna Kudlyak, “The Unemployed With Jobs and Without Jobs,” Working Paper No. 27886, National Bureau of Economic Research 2020.

____ and ____ , “Why Has the US Economy Recovered So Consistently from Every Recession in the Past 70 Years?,” *NBER Macro Annual*, forthcoming.

Hamilton, James D., “A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle,” *Econometrica*, 1989, *57*, 357–384.

Hornstein, Andreas and Marianna Kudlyak, “Aggregate Labor Force Participation and Unemployment and Demographic Trends,” 2019. Federal Reserve Bank of San Francisco, Working Paper No. 2019-07.

Perlin, Marcelo, “MS Regress - The MATLAB Package for Markov Regime Switching Models,” 2015. Available at SSRN.

Powell, Jerome H., “New Economic Challenges and the Fed’s Monetary Policy Review,” Technical Report, Remarks by Chair Board of Governors of the Federal Reserve System at “Navigating the Decade Ahead: Implications for Monetary Policy,” an economic policy symposium sponsored by the Federal Reserve Bank of Kansas City Jackson Hole, Wyoming August 2020.

Romer, Christina D. and David H. Romer, "NBER Business Cycle Dating: History and Prospect," December 2019. University of California, Berkeley.