

Long-Term Unemployment and the Great Recession: The Role of Composition, Duration Dependence, and Nonparticipation

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We explore the role of composition, duration dependence, and labor force nonparticipation in accounting for the sharp increase in the incidence of long-term unemployment (LTU) during the Great Recession. We show that compositional shifts account for very little of the observed increase in LTU. Using panel data from the Current Population Survey for 2002–7, we calibrate a matching model that allows for duration dependence in unemployment and transitions between employment, unemployment, and nonparticipation. The calibrated model accounts for almost all of the increase in LTU and much of the observed outward shift in the Beveridge curve between 2008 and 2013.

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I. Introduction

This paper investigates whether a search and matching model can explain important features of the US labor market in the Great Recession and its aftermath. In particular, we ask whether such a model can account for the rise in the unemployment rate and the increase in the incidence of long-term unemployment among the unemployed.¹

To motivate our analysis, we decompose the overall unemployment rate by unemployment duration. Figure 1 plots the unemployment rate for the short-term unemployed (< 15 weeks), the medium-term unemployed (15–26 weeks), and the long-term unemployed (> 26 weeks) from 1948 to 2013. The short-term unemployed typically represent the vast majority of the unemployed, with the short-term unemployment rate around 4% in normal times. The medium- and long-term unemployed account for much less of total unemployment, with rates typically near 1%. During the Great Recession, unemployment rates increased across all duration groups. However, the long-term unemployment rate reached record levels and remains historically high: unemployment rates for both the short-term and the long-term unemployed were around 3% in 2013. Although short-term and medium-term unemployment rates were roughly back to their normal pre-recession levels by 2012, long-term unemployment remains persistently high.

Another way to see this is in panel *A* of figure 2, which shows the share of unemployed workers who are long-term unemployed among prime-age workers (aged 25–55 years). This share increased from around 20% in 2008 to roughly 45% in 2013. Panel *B* of figure 2 shows that the Beveridge curve—the relationship between unemployment and job vacancies—shifted outward during the Great Recession. This paper attempts to account for these two facts—the rise in the long-term unemployment share and the shift in the Beveridge curve—by exploring the role of shifts in the composition of the unemployed, duration dependence in job finding rates for the unemployed, and transitions in and out of the labor force (between unemployment, employment, and nonparticipation). To preview our main result, we find that an enriched matching model—incorporating duration dependence and nonparticipation—can account for almost all of the increase in the incidence of long-term unemployment and most of the outward shift in the Beveridge curve during the Great Recession. By contrast, we do not find any evidence that compositional shifts play an important role.

for excellent research assistance. Contact the corresponding author, Matthew Notowidigdo, at noto@northwestern.edu. Information concerning access to the data used in this article is available as supplementary material online.

¹ By “incidence of long-term unemployment,” we mean the share of total unemployed individuals at a point in time who are currently experiencing long unemployment durations (typically defined as either above 26 weeks or 52 weeks).

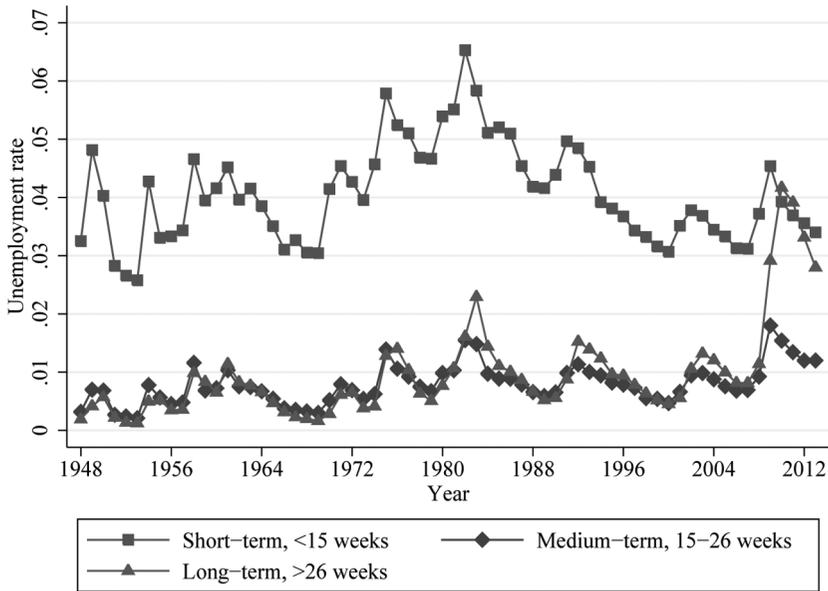


FIG. 1.—Short-term, medium-term, and long-term unemployment in the United States, 1948–2013. These figures use data from the Current Population Survey. See the legend to figure 2 for more information on the sample construction. A color version of this figure is available online.

We begin our analysis by showing that between 2008 and 2013, compositional shifts toward groups with traditionally longer unemployment durations account for very little of the overall rise in the incidence of long-term unemployment documented in figure 2. We show that long-term unemployment increased for virtually all groups and that compositional shifts do not go very far in accounting for the rise in long-term unemployment. For this exercise, compositional shifts refer to the changes in observed characteristics of unemployed workers—specifically, variables in the Current Population Survey (CPS) related to demographics, occupation, industry, region, and the reason for unemployment. We emphasize that this analysis cannot account for changes in the composition of the unemployed based on unobserved characteristics.

We next examine the extent to which a matching model along the lines of Mortensen and Pissarides (1994) and Shimer (2005) can account for the observed increase in long-term unemployment and the observed shift in the Beveridge curve. To do this, we enrich a standard matching model along three dimensions. First, we allow for duration dependence in the job finding rate of the unemployed. Second, we allow for flows between employment (E), unemployment (U), and nonparticipation (N), instead of focusing exclusively on flows between E and U, as in a standard match-

Panel A: Long-term Unemployment Share in the U.S., 2000-2013

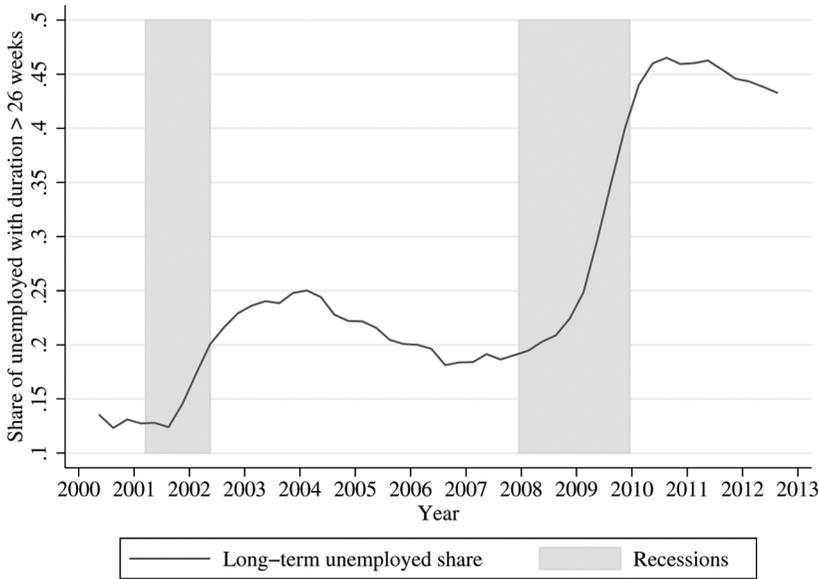


FIG. 2.—Long-term unemployment and the Beveridge Curve. This figure uses data from the Current Population Survey and the Job Openings and Labor Turnover Survey. Panel A shows the share of unemployed workers aged 25–55 who have unemployment durations of more than 26 weeks. The pooled, cross-sectional data come from monthly CPS surveys. In this panel and in figures 3–5, month fixed effects have been residualized out of the data to account for seasonality, and the data are smoothed by taking a 3-month average around each observation. Panel B shows the Beveridge curve, the relationship between unemployment and vacancies, with both series normalized by the total population (i.e., labor force plus non-participants). The arrow in panel B indicates the apparently outward movement of the Beveridge curve after 2008. A color version of this figure is available online.

ing model. Third, we allow flows from employment and nonparticipation into unemployment to occur not just into short durations but also into long unemployment durations, consistent with observed flows in the CPS.

Our rationale for exploring duration dependence in the unemployed job finding rate is based on several recent résumé audit studies that show that callbacks from employers to set up an interview decline with the current nonemployment duration on a job applicant’s résumé (Ghayad 2013; Kroft, Lange, and Notowidigdo 2013; Eriksson and Rooth 2014). This form of employer discrimination could arise from human capital depreciation or employer screening, whereby employers perceive the long-term unemployed to be less productive employees. Negative duration de-

Panel B: The Beveridge Curve in the U.S., 2000-2013

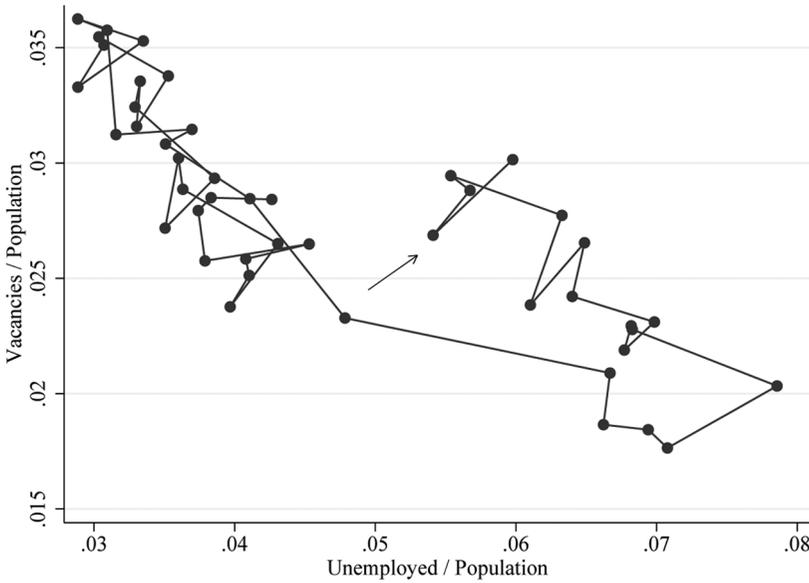


Fig. 2 (Continued)

pendence in the job finding rate could also be due to lower search effort among the unemployed at longer durations due to discouragement.

Negative duration dependence in the exit rate from unemployment can potentially “amplify” the effects of a downturn in the labor market and increase long-term unemployment. According to a recent report by the Congressional Budget Office, long-term unemployment may “produce a self-perpetuating cycle wherein protracted spells of unemployment heighten employers’ reluctance to hire those individuals, which in turn leads to even longer spells of joblessness” (Congressional Budget Office 2012). As a result, negative duration dependence in the job finding rate from unemployment would appear to be a promising candidate explanation for understanding the recent sharp rise increase in long-term unemployment. As more workers are pushed into longer unemployment spells, negative duration dependence lowers the average job finding rate and thus increases the overall unemployment rate. Therefore, duration dependence can potentially explain both the rise in long-term unemployment as well as the observed outward shift in the Beveridge curve during the Great Recession, as documented in Elsby, Hobijn, and Sahin (2010).

Our rationale for exploring the nonparticipation margin is motivated by previous work demonstrating the fluid boundary between nonparticipation and unemployment (Clark and Summers 1979; Flinn and Heckman 1983; Card and Riddell 1993; Jones and Riddell 1999; Elsby, Hobijn,

and Sahin 2015), as well as recent research on the effects of unemployment insurance (UI) benefit extensions on transitions between unemployment, employment, and nonparticipation (Rothstein 2011; Farber and Valetta 2013). The recent UI research finds significant effects of extended UI in reducing the exit rate from unemployment to nonparticipation. The substantial UI benefit extensions during the Great Recession may therefore have induced some jobless individuals to continue to report themselves as unemployed in the CPS, contributing to the observed rise in long-term unemployment. Beyond this specific mechanism, we also observe large changes in transition rates to and from nonparticipation since 2008.

We calibrate our enriched matching model using monthly data in the years before the Great Recession (2002–7) and study how well the calibrated model fits the data during the Great Recession, holding fixed the calibrated parameters.² In our analysis, we implement a two-step empirical approach. In the first step, we measure transition rates between the different labor market states (E, U, and N) over the entire 2002–13 period and estimate duration dependence using data from 2002 to 2007. In the second step, we calibrate the matching model parameters. By first measuring transition rates without imposing the structure of the matching model, we obtain measured hazard rates (between unemployment, employment, and nonparticipation) that are robust to model misspecification.³ An alternative to our two-step approach would be to estimate the hazard rates and the matching model parameters jointly in a single step. One advantage of our two-step approach is that it clarifies when failures to match the evolution of the job finding rates over this time period are due to shortcomings in the enriched matching model. Another advantage is that it is straightforward to impose alternative assumptions about the magnitude of “true” duration dependence to explore the sensitivity of the results (since the second step takes the duration dependence estimates from the first step as given, allowing alternative duration dependence estimates to be “plugged in” at the second stage).

In all of our analyses, we treat vacancies, transitions from employment to unemployment and nonparticipation, and transitions between nonparticipation and unemployment as the exogenous “forcing variables” of the model. By contrast, we allow the job finding rates (for both the unemployed and nonparticipants), the labor market states, and the distribution of unemployment durations to all evolve endogenously (holding constant the calibrated parameters from the 2002–7 period). Clearly, a

² The NBER’s Business Cycle Dating Committee dates the beginning of the Great Recession to be December 2007 and the end to be June 2009.

³ The assumptions required to estimate the transition rates are laid out in the data section and in appendix B.

more complete model of the economy would endogenize the forcing variables. However, we treat these variables as exogenous because endogenizing them would require a model of vacancy creation as well as a model of labor demand, which is beyond the scope of this paper. In our sensitivity analysis, we manipulate the vacancy rates that we use in our counterfactual experiments to examine how the model performs when the strength of labor demand changes.⁴

Summarizing our results, we find that our calibrated model does a very good job of accounting for the increase in the incidence of long-term unemployment and can also account for much of the observed outward shift in the Beveridge curve. These conclusions are fairly robust to a variety of alternative assumptions, such as allowing duration dependence to vary over the business cycle, as suggested by the experimental results in Kroft et al. (2013). On the other hand, our model has difficulty matching the observed relationship between vacancies and nonparticipation during the Great Recession. In particular, it predicts a job finding rate for non-participants that is too high after 2008. Why N-to-E transitions fell so much more than expected (and continue to remain so low through 2013) therefore remains an important open question for future work.

To understand the relative importance of duration dependence and changes in (N-to-U, U-to-N, and E-to-N) transition rates in the model's ability to account for the observed increase in long-term unemployment and the observed outward shift in the Beveridge curve, we simulate the calibrated model "shutting down" each of these features one by one. First, we shut down duration dependence by recalibrating the model under the assumption that the job finding rate is independent of unemployment duration. In this scenario, we find that the model accounts for much less of the rise in long-term unemployment and the observed outward shift in the Beveridge curve. We interpret this as evidence that duration dependence plays an important role in accounting for both of these phenomena.

Second, we shut down the exogenous nonparticipation flows by fixing these flows at the values observed at the end of 2007, and we find that the predicted long-term unemployment shares and unemployment rates both deviate substantially from our baseline calibrations. In particular, the counterfactual predictions show much less of an outward shift in the Beveridge curve. The E-to-N flows are not central to this result, but U-to-N flows and particularly N-to-U flows play an important role. This closely relates to results in Elsby et al. (2015), which find that the flows from unemployment to nonparticipation explain close to one-third of the cyclical variation in the unemployment rate. Overall, our analysis sug-

⁴ In other words, we can "force" different vacancy rates onto the model and evaluate how it performs quantitatively. This leads us to use the term "forcing variables" to describe the exogenous rates in our model.

gests that changes in the flows from nonparticipation to unemployment (specifically, flows into long-term unemployment) play an important role in the increase of long-term unemployment after 2008.

One explanation for this finding centers around the very large UI extensions that took place during the Great Recession. Our results indicate that flows from unemployment to nonparticipation declined from about 20% monthly in 2008 to about 14% monthly in 2009 and only slowly recovered after 2009. We conjecture that many unemployed individuals may have remained in unemployment longer and are now classified as long-term unemployed (rather than being classified as nonparticipants). We also speculate that UI extensions may have played a role in causing many UI recipients to continue to consider themselves as labor force participants, even after many weeks of joblessness. This is consistent with the empirical findings of Rothstein (2011) and Farber and Valletta (2013). Our counterfactual estimates suggest that a large amount of the increase in unemployment with durations longer than 52 weeks might be attributable to the decline in the rate at which the unemployed became nonparticipants.

While our calibrated model can account for much of the outward shift in the Beveridge curve, it does not provide a complete accounting of the shift. Davis, Faberman, and Haltiwanger (2013) offer a promising explanation for the residual shift in the Beveridge curve not accounted for by our matching model, which focuses on the vacancy rate rather than the unemployment rate in the Beveridge curve. They find a reduction in “recruiting intensity” and in “effective vacancies,” which may indicate continuing weak labor demand since the Great Recession. According to their research, employers are listing vacancies but are not recruiting workers as intensively to fill them (as in the recent past), implicitly waiting around for the “perfect” job candidates.

Our work closely relates to Elsby et al. (2011), which provides a thorough empirical exploration of long-term unemployment and nonparticipation in the Great Recession. An important difference is that our analysis is primarily based on a quantitative exploration of a calibrated matching model. One advantage of our model-based approach is that we can more readily conduct counterfactual scenarios to assess the relative importance of duration dependence and nonparticipation in accounting for the observed increase in long-term unemployment and the observed outward shift of the Beveridge curve. Our paper is also similar to subsequent research by Krueger, Cramer, and Cho (2014), who build on and extend our matching function to allow for differential effects by unemployment duration within the matching function and also allow for differential labor force withdrawal (i.e., U-to-N transitions) for the short-term and long-term unemployed. They also evaluate whether the long-term unemployed exert differential pressure on wage growth and inflation than the short-term unemployed.

Our work also relates to Barnichon and Figura (2015), which estimates a standard matching function over the period 1967–2012 and finds that the predicted job finding rate is much lower than the observed job finding rate during the Great Recession. Barnichon and Figura consider a generalized matching function incorporating worker heterogeneity (demographics, reason for unemployment, and duration of unemployment) and labor market segmentation (geography and occupation group) and find that it matches observed job finding rates during the Great Recession much more closely. While they consider a two-state model of the labor market and focus primarily on job finding rates, our paper considers a three-state model, adding nonparticipation, and also focuses more on the incidence of long-term unemployment.

Finally, our paper is broadly related to an active literature in macroeconomics on the relative contributions of inflows into and outflows from unemployment to unemployment dynamics (Hall 2005; Elsby, Michaels, and Solon 2009; Fujita and Ramey 2009; Barnichon 2012; Shimer 2012; Elsby et al. 2015). The emerging consensus from this literature is that the outflow contribution is at least 50%, but the literature is agnostic as to the factors behind falling outflows from unemployment. Our paper contributes to this literature by explicitly investigating two specific mechanisms behind the fall in the outflow rate: duration dependence and transitions in and out of the labor force.⁵

The remainder of the paper proceeds as follows. Section II describes the data. Section III investigates the role of composition. Section IV describes the matching function that we use to investigate the role of duration dependence and nonparticipation. Section V describes the methodology for the model calibration. Section VI presents the results of the model calibration. Section VII reports the counterfactual scenarios and discusses alternative explanations. Section VIII concludes.

II. Data

This section briefly describes our data sources. Appendix A provides more detail on the data used in our analysis.

⁵ A related paper that takes into account negative duration dependence in job finding rates is Hornstein (2012). Hornstein extends the framework in Shimer (2012) to allow for two types of unemployed workers: those with high exit rates from unemployment (the short-term unemployed) and those with low exit rates from unemployment (the long-term unemployed). The generalized framework is better able to account for long-term unemployment during recessions, whereas Shimer's framework with a homogeneous job finding rate significantly understates it. The extended framework also increases the inflow contribution to unemployment relative to Shimer's study.

A. Current Population Survey (CPS)

We use monthly CPS data between 2002 and 2013 (ending in April 2013), limiting the sample to individuals between the ages of 25 and 55. We focus on this prime-age sample to enable us to ignore issues of delayed labor force entry of younger workers and changes in retirement patterns of older workers. We use these CPS data in several ways. First, we use repeated cross-sectional data when investigating the role of composition, limiting the sample to unemployed workers. Second, we use both cross-sectional and panel data (merging individuals across months to build panel data) to investigate the role of duration dependence and nonparticipation. For this exercise, we use data on all employed, unemployed, and nonparticipants. In the cross section, we keep track of the total population of each category to estimate the “stocks.” To create panel data, we match observations across successive months, matching on household identifier, line number, age, gender, and race. We use the matched panel data in addition to the CPS cross-sectional estimates of the unemployed, the employed, and nonparticipants to estimate the transition rates between unemployment, employment, and nonparticipation in each month. We also compute overall (pre-2008) transition rates by unemployment duration (into both employment and nonparticipation). Finally, we compute transition rates from employment and nonparticipation into unemployment by unemployment duration.

B. Job Openings and Labor Turnover Survey (JOLTS)

We use monthly JOLTS data between 2002 and 2013 to compute the total number of vacancies. We use these vacancy data to calibrate the matching model below during the pre-2008 period. We then use the post-2008 vacancy data as one of the exogenous “forcing variables” for our counterfactual scenarios.

III. Long-Term Unemployment and the Great Recession: Assessing the Role of Composition

Figure 1 shows that the share of the labor force that is long-term unemployed substantially increased during the Great Recession and has remained elevated. We next examine the rise in the share of the currently unemployed with duration exceeding 26 weeks and investigate the role of composition in accounting for this observed increase.

Figure 2 (panel *A*) illustrates the dramatic increase in long-term unemployment as a share of overall unemployment. The long-term share increased from around 20% at the beginning of 2008 to roughly 45% in 2010. Most of the increase occurred in 2009, a year after the recession began. Moreover, the share remained elevated at around 45% well after the recession officially ended. By comparison, the recession that began

in 2001 saw this share increase from roughly 12% to 25%. Similar to the Great Recession, the share increased roughly a year after the recession began and remained elevated for several years after the recession officially ended. Nevertheless, the Great Recession was much deeper than the early 2000s downturn, and it had a substantially larger impact on the structure of unemployment durations.

In this section, we investigate the extent to which the increase in long-term unemployment during the Great Recession can be accounted for by shifting composition in observable characteristics of the unemployed. We do this by investigating the incidence of long-term unemployment over time for several demographic, industry, occupation, geographic, and reason-for-unemployment groups, along with each group's unemployment share.

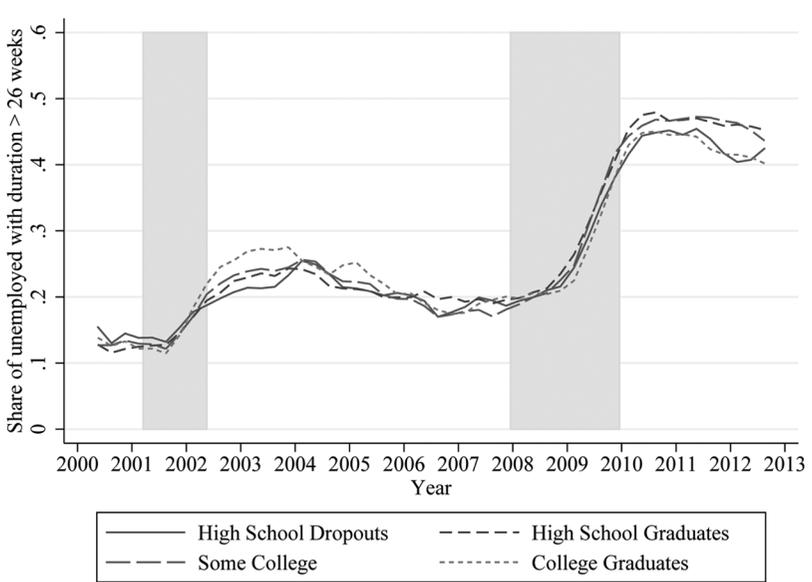
Panel *A* of figure 3 considers the education structure of the unemployed. It shows that the share of long-term unemployment in total unemployment is fairly similar across all education groups. During the recession, long-term unemployment uniformly increased across all education groups. Panel *B* of figure 3 shows that high school graduates are a larger share of the unemployed than college graduates. During the Great Recession, there is a small increase in the share of college graduates among the unemployed. Despite this, since the rate of long-term unemployment is fairly flat across all education groups, shifts in the education structure of the unemployed cannot account for the changing unemployment duration dynamic during the Great Recession.

Appendix figures C1–C7 (in appendix C, available online) consider different observable characteristics. The impact of the Great Recession was widespread, increasing the long-term unemployment share in all major demographic groups, industries, occupations, geographic regions, and reasons for unemployment. The long-term unemployment share also increased in groups by reason for unemployment (job losers, those on temporary layoff, job leavers, new entrants, and reentrants). To quantify how much compositional shifts overall could have explained the rise in long-term unemployment, we hold fixed the long-term unemployment rates for each group in the pre-2008 period and investigate how much observed shifts in group shares can explain the overall rise in long-term unemployment. The aggregated evidence presented in figure 4 shows that compositional changes in the unemployed account for virtually none of the observed rise in long-term unemployment. The rise in long-term unemployment is found for all major labor market groups and is not a demographically isolated phenomenon.

IV. Matching Framework

In this section, we outline our matching framework, which augments a standard matching model to allow for duration dependence in unemployment

Panel A: Long-term unemployment share



Panel B: Relative share of unemployed

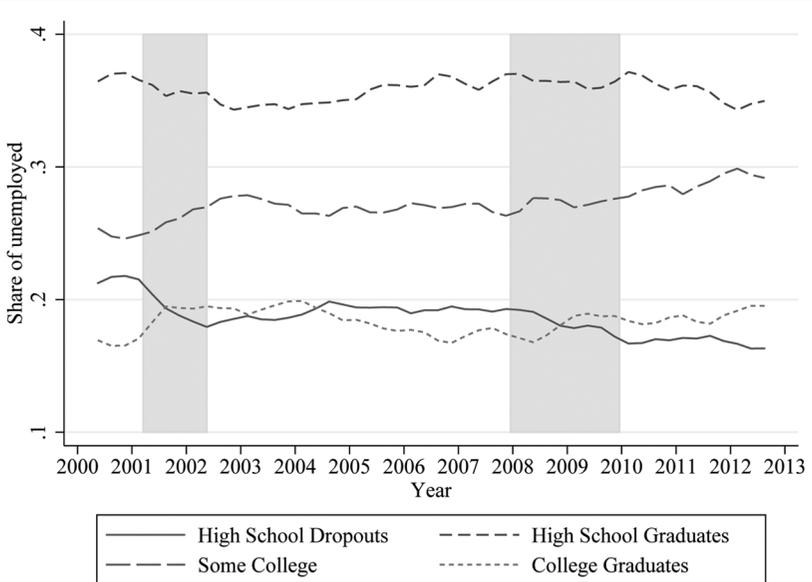


FIG. 3.—Long-term unemployment by education. These figures use data from the Current Population Survey. See the legend to figure 2 for more information. A color version of this figure is available online.

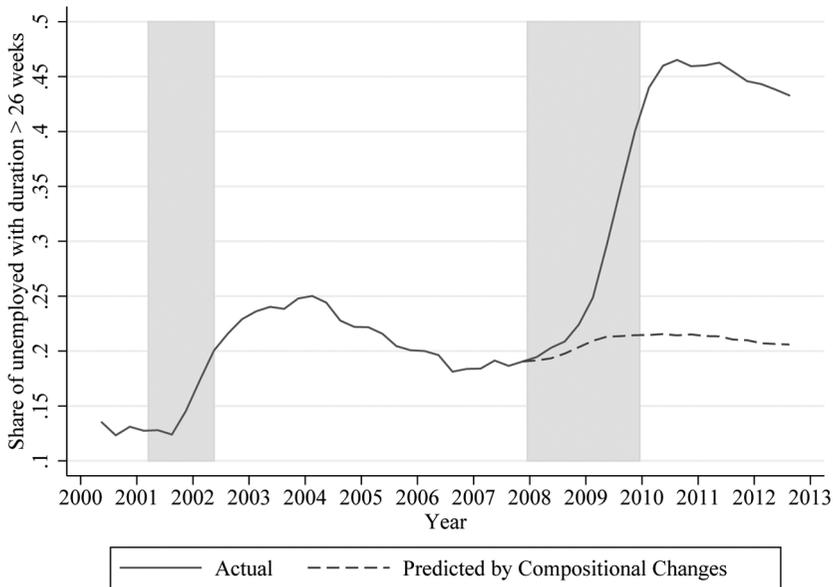


FIG. 4.—Accounting for long-term unemployment increase from observable compositional shifts. This figure uses data from the Current Population Survey that are summarized in figure 3 and appendix C, figures C1–C7, in order to estimate the role of composition. The *predicted* long-term unemployment share is calculated by multiplying the pre-2008 average long-term unemployment share by demographic group by the change in the share of unemployed with that characteristic. This procedure is repeated for each observable characteristic (e.g., education, age, gender, etc.) described in figures 3 and C1–C7 to construct the prediction shown in this figure. A color version of this figure is available online.

and flows to and from nonparticipation. We begin with a standard matching model of the labor market (Pissarides 1985; Mortensen and Pissarides 1994), which models fluctuations in the job finding probability through a reduced-form matching function. We enrich this standard matching model to allow for duration dependence in unemployment and we allow a full set of transitions between employment (E), unemployment (U), and nonparticipation (N).⁶

Our goal is to calibrate this model using data from before the Great Recession and assess how well it accounts for outflows from unemployment

⁶ Recent research by Elsyby et al. (2011) has highlighted the important role played by nonparticipants in understanding the dynamics of long-term unemployment during the Great Recession.

and nonparticipation into employment between 2008 and 2013. Throughout our analysis, we take the number of vacancies and inflows into unemployment and nonparticipation as given. These are the exogenous “forcing variables” of the model. The endogenous variables are the full distribution of unemployment durations, the population shares in each labor market state, and the job finding rates of the unemployed and nonparticipants.

To introduce the model, we begin with the following notation:

1. P_t = population size (t is monthly calendar time) and $\{E_t, U_t\}$ = number of employed and unemployed individuals with associated rates $\{e_t = E_t/P_t, u_t = U_t/P_t\}$. Note that the unemployment rate is defined relative to the total population (rather than the labor force), which imposes symmetry with the nonparticipation rate defined below.
2. $N_t = P_t - E_t - U_t$ = number of nonparticipants. Let the size of the labor force be denoted by $L_t = E_t + U_t$ and the nonparticipation rate by $n_t = N_t/P_t$.
3. V_t = total number of job vacancies. The number of job vacancies is an exogenous forcing variable during the period 2008–13 in the counterfactual scenarios we describe below.
4. Flows to unemployment: λ_t^{EU} (employment \rightarrow unemployment), λ_t^{NU} (nonparticipation \rightarrow unemployment). Both of these transition rates are forcing variables during the period 2008–13.
5. Flows to employment: λ_t^{UE} (unemployment \rightarrow employment), λ_t^{NE} (nonparticipation \rightarrow employment). These job finding rates are allowed to endogenously evolve during the period 2008–13.
6. Flows to nonparticipation: λ_t^{EN} (employment \rightarrow nonparticipation), λ_t^{UN} (unemployment \rightarrow nonparticipation). Both of these transition rates are forcing variables during the period 2008–13.

Appendix B provides more detail on how each of these transition rates are computed.

A. Labor Market Flows during the Great Recession

We begin by presenting descriptive evidence on labor market flows over time. Figure 5 plots the monthly transition rates to and from employment, unemployment, and nonparticipation. The measured transition rates are adjusted to be consistent with observed changes in stocks between months; appendix B provides the details of this procedure. We also account for seasonality by residualizing out month fixed effects, and we smooth the series by taking 3-month moving averages.

First, we see in panel A of figure 5 that the monthly transition rates from unemployment to employment and nonparticipation dropped sig-

nificantly during 2008. Starting in 2010, the flows from unemployment into nonparticipation began to recover and by the end of 2013 were close to their pre-recession levels. On the other hand, the job finding rates of the unemployed (flows from unemployment to employment) have remained low following the Great Recession.

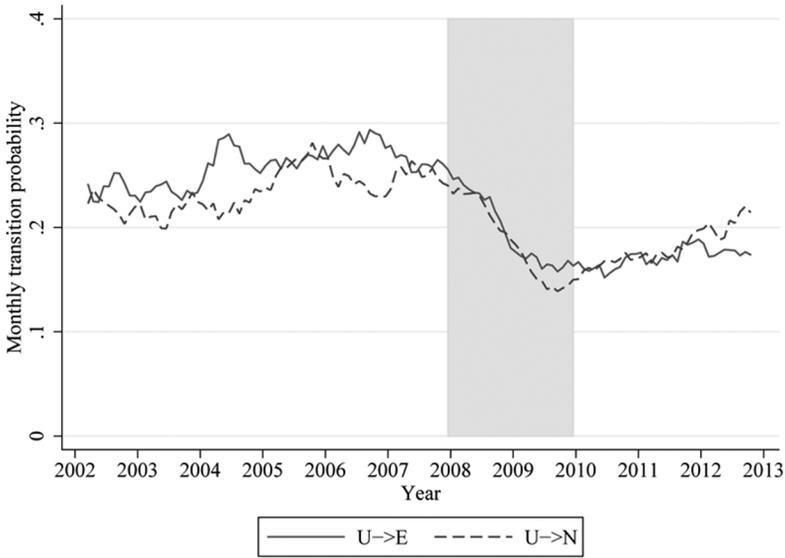
Second, panel *B* shows that flows from employment to nonparticipation remained relatively flat during the Great Recession. Job losses leading to unemployment (employment to unemployment flows) spiked up in the Great Recession in 2008–9 and have slowly come back down in the recovery.

Third, panel *C* shows that job finding rates of nonparticipants (flows from nonparticipation to employment) dropped in 2008 and remained low through the end of 2013. While the job finding rate for the unemployed declined sharply and bottomed out in 2009, the job finding rate for nonparticipants fell more smoothly and bottomed out in 2010. On the other hand, flows from nonparticipation to unemployment increased substantially in 2008 and remained high until the end of 2013. Interestingly, in the pre-Great Recession period, the outflow rate from nonparticipation to employment always exceeded the outflow rate to unemployment; however, during the Great Recession, and at least through 2013, the opposite was true. We show below that accounting for flows from nonparticipation to unemployment during the Great Recession is important for understanding the dynamics of the unemployment rate. In particular, we find that ignoring changes in the N-to-U and U-to-N transition rates after 2008 results in a much smaller outward shift in the Beveridge curve according to our calibrated model.⁷

Flows from unemployment to employment are in part affected by flows from unemployment to nonparticipation. For example, if more of the unemployed individuals were to withdraw from the labor force, these individuals do not go from unemployment to employment at the same rate. To explore this issue, we define labor market flows for “indomitable job seekers” (Clark and Summers 1979) to be the ratio of U-to-E flows to the sum of U-to-E and U-to-U flows. This conceptually corresponds to a hypothetical unemployed job seeker who is unable to exit the labor force (and thus can only either transition to employment or remain unemployed, perhaps indefinitely). This “rescaled” U-to-E transition rate is (mechanically) higher for indomitable job seekers, as illustrated in panel *D* of figure 5; however, we also see a similarly sharp drop in the job finding rate for this group during the Great Recession.

⁷ Additionally, we discuss below how many individuals flowing from nonparticipation to unemployment report longer unemployment durations after 2008.

Panel A: Transitions from Unemployment

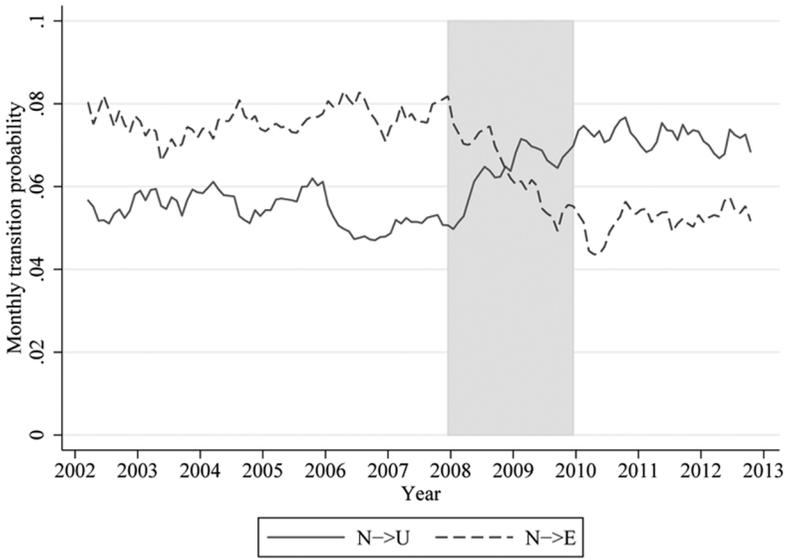


Panel B: Transitions from Employment



FIG. 5.—Transition rates between employment, unemployment, and nonparticipation. These figures use data from the Current Population Survey. See the legend to figure 2 for more information on the sample construction. A color version of this figure is available online.

Panel C: Transitions from Non-Participation



Panel D: Comparing $U \rightarrow E$ to “Indomitable Worker”



Fig. 5 (Continued)

B. Matching Function

We adapt the standard matching function to allow nonparticipants to find jobs. We assume that nonparticipants and unemployed individuals meet job openings according to the function $M(U + sN, V) = m_0(U + sN)^\alpha V^{1-\alpha}$.⁸ One may interpret s as the share of the nonparticipants who are “marginally attached,” or, alternatively, as the search efficiency of nonparticipants relative to the unemployed, following Jones and Riddell (1999, 2006). According to Jones and Riddell’s estimates, sN is about 25%–30% of the unemployed population, and these researchers also find that λ_t^{UE} is roughly twice as large as λ_t^{NE} .

We assume that the share of meetings with unemployed individuals is given by $U/(U + sN)$, while the remaining share is with nonparticipants. In addition, we assume (for the unemployed) that the probability that a meeting results in a hire depends on the duration of unemployment. In particular, $A(d)$ gives the relative hiring probability of an individual with unemployment duration d as compared to a newly unemployed individual (with duration $d = 0$). These assumptions imply that the job finding rates for the unemployed and nonparticipants are given, respectively, by the following expressions:

$$\lambda_t^{\text{UE}}(x_t; d) = A(d)m_0x_t^{1-\alpha}, \quad (1)$$

$$\lambda_t^{\text{NE}}(x_t) = sm_0x_t^{1-\alpha}, \quad (2)$$

where $x_t = V_t/(U_t + sN_t)$ is a measure of labor market tightness and d is the duration of unemployment. The parametric specification for $\lambda_t^{\text{UE}}(d)$ assumes that there is “true” duration dependence in job finding rates out of unemployment, that is, a genuine causal effect of longer unemployment durations on the hazard rate of exit out of unemployment (Heckman and Singer 1984).

We propose a parametric specification for $A(d)$ and estimate this function in the pre-Great Recession period, as we describe below. Let the probability density and distribution of ongoing unemployment durations be given by $\theta_t(d)$ and Θ_t , respectively. By integrating over the duration distribution, we get the average job finding rate for the unemployed:

$$\lambda_t^{\text{UE}}(x_t) = \int \lambda_t^{\text{UE}}(x_t; \tau)\theta_t(\tau)d\tau,$$

$$\lambda_t^{\text{UE}}(x_t) = m_0x_t^{1-\alpha} \int A(\tau)\theta_t(\tau)d\tau.$$

⁸ Note that this equation is to be interpreted as a *meeting* function, not a *matching* function. Job meetings are converted into job matches according to eqs. (1) and (2).

How does a recession affect the unemployment job finding rate? In a recession, x_t falls, lowering $\lambda_t^{UE}(x_t; \tau)$, and hence $\lambda_t^{UE}(x_t)$. The fall in $\lambda_t^{UE}(x_t)$ affects $\theta_t(\tau)$, which can feed back into a lower $\lambda_t^{UE}(x_t)$ through duration dependence and consequently a higher unemployment rate.

Note that

$$\frac{\lambda_t^{UE}}{\lambda_t^{NE}} = \frac{\bar{A}_t}{s},$$

where $\bar{A}_t = \int A(\tau)\theta_t(\tau)d\tau$. With empirical estimates for \bar{A}_t and the job finding rates, we can solve for $s = \bar{A}_t(\lambda_t^{NE}/\lambda_t^{UE})$. The right-hand side varies with t , but we assume that s is time invariant, so we can simply take the average of this expression in period 2002–7 to produce an estimate of s to use in our calibrations. Note that we also assume that both m_0 and $A(d)$ are time invariant: there are no cyclical changes in matching efficiency or cyclical variation in the magnitude of duration dependence. We explore alternative assumptions on how $A(d)$ varies over the business cycle in sensitivity analysis below, while cyclical variation in the matching efficiency parameter is studied in detail in Sahin et al. (2014).

C. Labor Market Dynamics

Given the transition rates between employment, unemployment, and nonparticipation, we can express the dynamics of each of these populations as follows:

$$\begin{aligned} N_{t+1} &= N_t(1 - \lambda_t^{NU} - \hat{\lambda}_t^{NE}) + E_t\lambda_t^{EN} + U_t\lambda_t^{UN}, \\ U_{t+1}(0) &= E_t\theta_t^{EU}(0)\lambda_t^{EU} + N_t\theta_t(0)\lambda_t^{NU}. \end{aligned} \tag{3}$$

$$\begin{aligned} U_{t+1}(d + 1) &= U_t(d)(1 - \hat{\lambda}_t^{UE}(d) - \lambda_t^{UN}) + E_t\theta_t^{EU}(d)\lambda_t^{EU} + N_t\theta_t^{NU}(d)\lambda_t^{NU}, \\ E_{t+1} &= P_t - U_{t+1} - N_{t+1}. \end{aligned} \tag{4}$$

In these dynamic equations, we have placed hats above $\hat{\lambda}_t^{NE}$ and $\hat{\lambda}_t^{UE}(d)$ to emphasize that these rates are endogenous in our counterfactual simulations. When we construct the counterfactual scenarios, we assume that if nonparticipants move to unemployment, they draw an unemployment duration from the (empirical) distribution of unemployment durations estimated from observed N-to-U transitions (where the empirical distribution is reestimated each quarter for three unemployment categories: [0–6) months, [6–12) months, and ≥ 12 months). Similarly, we also account for the fact that a share of entrants into unemployment from employment report unemployment durations of 6 months or longer, so

when employed workers move into unemployment, they draw an unemployment duration from the empirical distribution of unemployment durations (estimated analogously as for nonparticipants above). These two empirical distributions are $\theta_t^{\text{NU}}(d)$ and $\theta_t^{\text{EU}}(d)$, respectively. Since this share changes over time and increased during the Great Recession, we estimate these distributions in each year-quarter, and we use this time-varying distribution in our counterfactual simulations.

In the next section, we examine the incidence of long-term unemployment and the Beveridge curve. The share of unemployed individuals at calendar time t who have been out of work longer than τ weeks is given by

$$\text{LTU}_t^\tau = \frac{\sum_{d \geq \tau} U_t(d)}{U_t},$$

where $U_t(d)$ is defined by equations (3) and (4). We use this as our measure of the share of unemployed individuals who are long-term unemployed, and we focus on $\tau = 26$ weeks and $\tau = 52$ weeks. When we plot the Beveridge curve, we plot the the total unemployed individuals as predicted by our model against the total observed number of job vacancies, normalizing both measures by the total population (i.e., $U_t/(E_t + U_t + N_t)$ and $V_t/(E_t + U_t + N_t)$). Since our matching model focuses on capturing job finding rates of both unemployed and nonparticipants, we include the total population rather than the total labor force in the denominator.

D. Counterfactual Scenarios

The goal of our calibrations is to assess how far our enriched matching model can go in accounting for the rise in long-term unemployment and the outward shift in the Beveridge curve during the Great Recession. We also investigate the relationship between the nonparticipation rate and the vacancy rate. Our approach is to estimate the model fundamentals during the period 2002–7 on monthly CPS (panel and pooled cross-sectional) data and then assess the model by comparing our counterfactual predictions to observed labor market outcomes during the period 2008–13. We estimate duration dependence in the job finding rate from unemployment (how λ_t^{UE} varies with duration), the search effectiveness of the marginally attached (s), and the overall matching efficiency m_0 and matching technology parameter α . Our model uses as exogenous forcing variables shifts in labor demand—where labor demand is proxied for by $(V_t, \lambda_t^{\text{EU}}, \lambda_t^{\text{EN}})$ —and shifts between unemployment and nonparticipation versus unemployment, $(\lambda_t^{\text{UN}}, \lambda_t^{\text{NU}})$. Thus, we fix the pattern of duration dependence, as reflected in $A(d)$, and we allow the job finding rates $\lambda_t^{\text{UE}}(d)$ and λ_t^{NE} —and consequently the entire distribution of unemployment durations—to evolve endogenously during the Great Recession. Our methodology follows Shimer (2005) by treating the separation rates of em-

ployed workers from their jobs, λ_t^{EU} and λ_t^{EN} , as exogenous. Shimer also considers exogenous productivity shocks in his model, which affects the equilibrium level of vacancies. We do not explicitly model the determination of vacancies; rather, we take a more reduced-form approach and instead treat vacancies as exogenous. Finally, we view flows between non-participation and unemployment as being “outside the model” since they may reflect factors such as the extension of UI benefits.

In terms of predicting the incidence of long-term unemployment, we rely on the cross-sectional share of workers with ongoing unemployment spells exceeding 26 and 52 weeks, respectively. For predicting stocks of unemployment, employment, and nonparticipation over time, we use the dynamic equations above to simulate the model.

V. Calibration Methodology

We calibrate the model in the following steps.

1. We use data to estimate $\{\Theta_t, \{\lambda_t^{\text{UN}}, \lambda_t^{\text{UE}}(d), \lambda_t^{\text{EN}}, \lambda_t^{\text{EU}}, \lambda_t^{\text{NE}}, \lambda_t^{\text{NU}}\}, V_t, U_t, N_t\}$. Appendix B describes how we estimate the transition rates λ_t^{ij} from the monthly CPS cross-sections and the (matched) panel data component of the CPS.

2. An important issue is how we allocate flows from nonparticipation to unemployment of various durations. Elsby et al. (2011) show that roughly 60% of the inflows into unemployment at reported durations longer than 1 month originate from nonparticipation. It appears that there are marginally attached workers who alternate between unemployment and nonparticipation, and when these workers return to unemployment, they often report a duration that may include time since they separated from their last employer as opposed to duration of unemployment spell since last leaving nonparticipation. Panel A of figure 6 sheds light on this issue by plotting the share of flows from nonparticipation to unemployment of a particular duration. We see that in the pre-recession period, roughly half of the flows had durations less than or equal to 1 month; however, during the Great Recession, this share dropped substantially to around 30%. On the other hand, the share of flows with durations longer than 12 months increased from roughly 20% to over 30%. In light of this, we collapse the 2002–13 data quarterly, and each quarter we estimate the empirical distribution of unemployment durations that nonparticipants transition into. Therefore, for our post-2008 counterfactuals, we use this empirical distribution for each N-to-U transition implied by the dynamic equations of the model and the observed unemployment durations that the nonparticipants are transitioning into.

3. Another important issue is how we allocate flows from employment to unemployment of various durations. Panel B of figure 6 plots the share of E-to-U flows going to a given unemployment duration. In interpret-

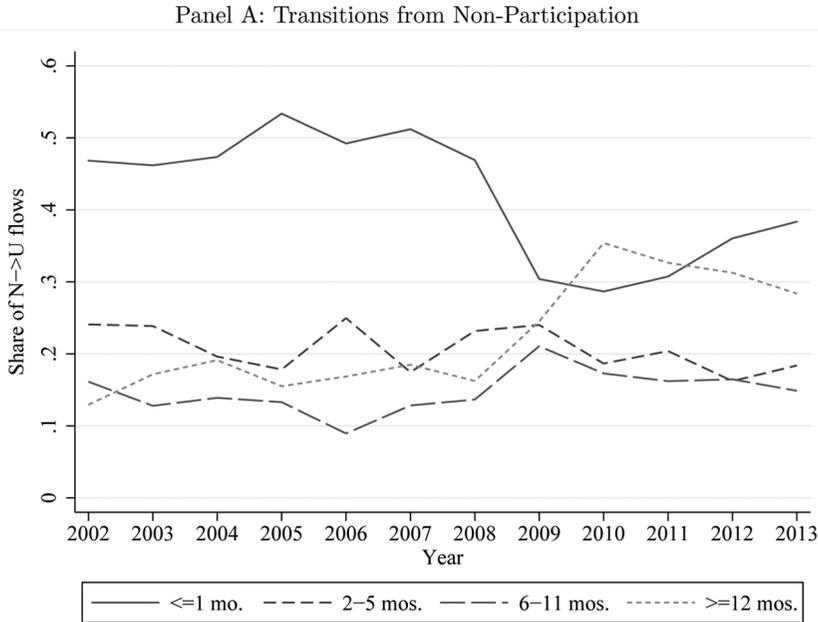


FIG. 6.—“Incoming” unemployment duration distributions. These figures report the share of individuals transitioning into unemployment from either non-participation (panel A) or employment (panel B). The figures show the share of workers transitioning into unemployment by unemployment duration. This reveals the extent to which unemployed individuals who did not report being unemployed in the previous month report unemployment durations that are inconsistent with being a newly unemployed worker. We report annual averages in this figure but use quarterly averages in the counterfactual simulations (and group [0, 6) months together). A color version of this figure is available online.

ing the shares in this figure, note that the scale of the left (right) axis is for durations less than or equal to (greater than) 1 month. We see that in the pre-recession period, roughly 80%–85% of the transitions from employment to unemployment report durations less than or equal to 1 month. However, this share falls to 70% during the Great Recession. We follow an analogous procedure as in the previous step, estimating the empirical distribution of unemployment durations that employed workers transition into (for each quarter), and we use this distribution in our counterfactual scenarios for each E-to-U transition.

4. We use the measured relative job finding rates at different durations ($\lambda_t^{\text{UE}}(d)$) to estimate $A(d)$. For the period 2002–7, we fit a curve through the empirical estimates of $\lambda_t^{\text{UE}}(d)$, normalized by $\lambda_t^{\text{UE}}(0)$, using the following functional form $A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$. See panel A of figure 7 for our preferred estimate of $\hat{A}(d)$. The estimates

Panel B: Transitions from Employment

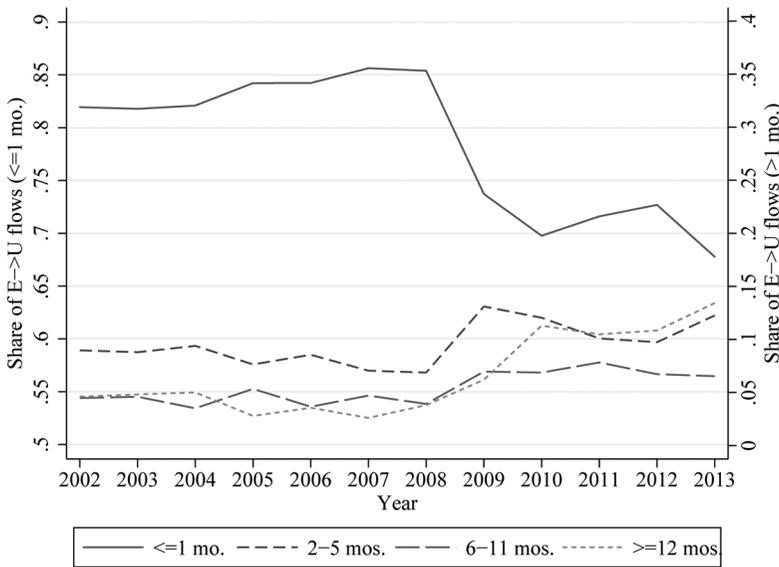


Fig. 6 (Continued)

reported in table 1 are $\hat{a}_1 = 0.314$, $\hat{a}_2 = 0.393$, $\hat{b}_1 = 1.085$, and $\hat{b}_2 = 0.055$. We find that the job finding rate declines sharply for the first 8–10 months of unemployment and then declines much less steeply after that. The declining job finding rate with duration of unemployment can reflect “true” negative duration dependence in which the longer any individual is unemployed, the lower becomes the job finding rate. Alternatively, it could reflect heterogeneity among the unemployed, with the remaining pool of the unemployed being more negatively selected at longer durations. To investigate this, we reestimate $A(d)$, controlling for a very rich set of observable characteristics available in the CPS: gender, fifth-degree polynomial in age, three race categories (white, black, other), five education groups (high school dropout, high school graduate, some college, college graduate, advanced degree), and gender interactions for all of the age, race, and education variables. When we control for these observable characteristics, we continue to find that the job finding rate (conditional on observables) declines sharply with unemployment duration; moreover, the estimated decline is very similar to the results from estimating $A(d)$ without controls, as can be seen by comparing the solid line (with controls) to the dashed line (without controls) in panel A of figure 7.

Of course, these results do not rule out the existence of unobserved heterogeneity—such as differences in recall rates to one’s previous job as

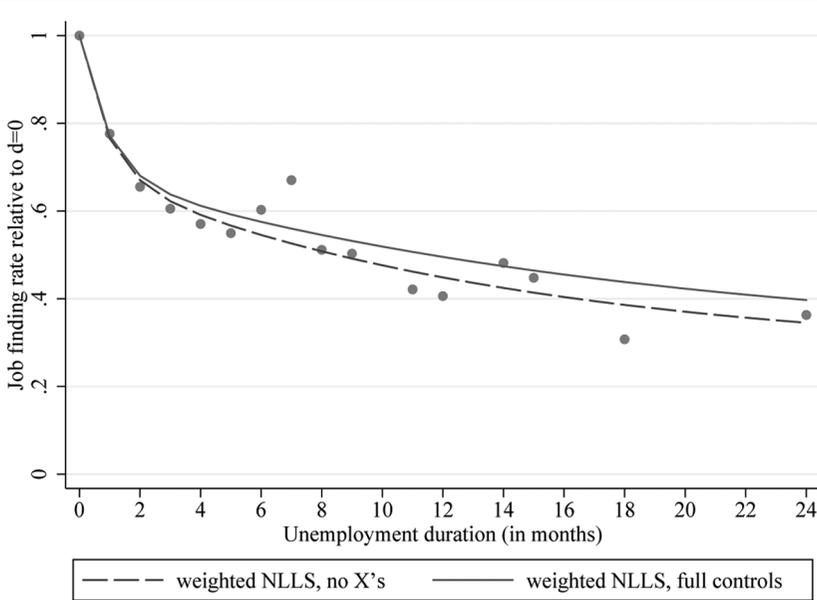
Panel A: Estimated Duration Dependence ($A(d)$ function)

FIG. 7.—Duration dependence and predicted unemployment job finding probability. In panel A, the figure uses data from the Current Population Survey and estimates (via nonlinear least squares) the negative exponential relationship between monthly job finding probability and unemployment duration. The NLLS uses CPS sample weights. The following functional form is used to estimate duration dependence: $A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$. The fitted values from the estimates with controls (solid line) are used to construct the counterfactuals shown in figures 7–10. The controls used are the following: gender, fifth-degree polynomial in age, three race dummies (white, black, other), five education category dummies (high school dropout, high school graduate, some college, college graduate, and other), and gender interactions for all of the age, race, and education variables. Only monthly cell means with at least 30 observations are shown. In panel B, the figure is generated by using estimates of how job finding probability varies with unemployment duration interacted with observed distribution of unemployment durations. Thus, the line in this figure shows the extent to which we would predict changes in job finding probability based solely on observed changes in distribution of unemployment duration. The y -axis scale is normalized so that a value of 1 indicates average job finding probability for a newly unemployed worker. A color version of this figure is available online.

documented by Katz (1986), Katz and Meyer (1990), and Fujita and Moscarini (2013), which could partially explain the apparent negative duration dependence after controlling for standard CPS observables. Additionally, declining employer perceptions of the quality of the unemployed at longer unemployment durations could also play an important role and would

Panel B: Predicted Job Finding Probability, \bar{A} , Based on Distribution of Unemployment Durations and $A(d)$

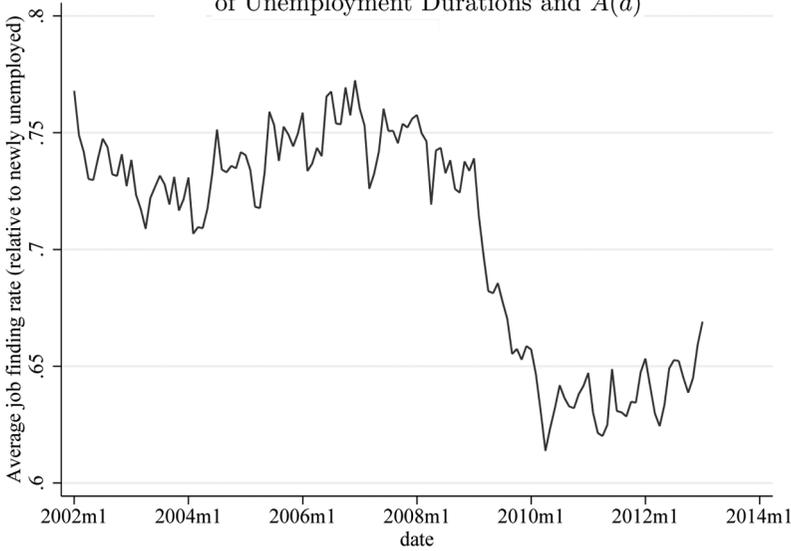


Fig. 7 (Continued)

be consistent with recent resume audit studies finding that job applications with longer employment gaps (longer duration of unemployment) get lower callback rates than those with implied shorter unemployment duration (Ghayad 2013; Kroft et al. 2013; Eriksson and Rooth 2014). We

Table 1
Model-Based Estimates

Parameter	Estimate
Duration dependence parameters:	
a_1 (intercept parameter 1)	.314
a_2 (intercept parameter 2)	.393
b_1 (slope parameter 1)	1.085
b_2 (slope parameter 2)	.055
$A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$	
Matching model parameters:	
α	.753
m_0 (scale parameter)	.435
s (relative search intensity of inactive)	.218
$M(U + sI, V) = m_0(U + sI)^\alpha V^{1-\alpha}$	

NOTE.—This table reports the model-based estimates using monthly CPS data and JOLTS data from 2002 to 2007. See the main text for more details. These parameter estimates are used to create the counterfactual predictions reported in the figures.

Table 2
Alternative Duration Dependence Estimates

Parameter	Estimate
(Baseline) duration dependence parameters [CPS data; full demographic controls]:	
a_1 (intercept parameter 1)	.314
a_2 (intercept parameter 2)	.393
b_1 (slope parameter 1)	1.085
b_2 (slope parameter 2)	.055
$A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$	
Alternative duration dependence parameters [CPS data; no controls]:	
a_1 (intercept parameter 1)	.307
a_2 (intercept parameter 2)	.424
b_1 (slope parameter 1)	1.104
b_2 (slope parameter 2)	.072
$A(d) = (1 - a_1 - a_2) + a_1 \exp(-b_1 \times d) + a_2 \exp(-b_2 \times d)$	
Alternative duration dependence parameters [Kroft et al. data; full sample]:	
a_1 (intercept parameter)	.425
b_1 (slope parameter)	.199
$A(d) = a_1 + (1 - a_1) \exp(-b_1 \times d)$	
Alternative duration dependence parameters [Kroft et al. data; high unemployment rate subsample]:	
a_1 (intercept parameter)	.631
b_1 (slope parameter)	.098
$A(d) = a_1 + (1 - a_1) \exp(-b_1 \times d)$	

NOTE.—This table reports the duration dependence estimates used in alternative scenarios reported in the main figures. In the first two panels, the data used to estimate the parametric function listed in the panel are monthly CPS data from 2002 to 2007. In the bottom panels, the data are from the résumé audit study by Kroft et al. (2013).

note that the pattern of negative duration dependence after controlling for the observables in the CPS in panel *A* of figure 7 is fairly similar to the results of declining employer callback rates with unemployment duration in the audit study of Kroft et al. (2013), which we also use in alternative counterfactual scenarios below. In our main results, we use the estimates of $A(d)$, which includes the large set of controls described above. The results of the alternative duration dependence estimates are reported in table 2. Given the concerns about $A(d)$ not representing the causal effect of longer unemployment durations, we also make adjustments to $A(d)$ assuming that, say, 50% of the observed duration dependence reflects a genuine causal effect.

5. Next, we estimate the parameters of the matching function by minimizing the distance between the observed job finding rates and the job finding rates implied by the matching functions using monthly CPS and JOLTS data for the period 2002–7. The implied job finding rates for a given parameter vector (s, m_0, α) , taking estimated parameters of $A(d)$ as given are the following:

$$\lambda_t^{UE}(s, m_0, \alpha) = m_0 \bar{A}_t \left(\frac{V_t}{U_t + sN_t} \right)^{1-\alpha} .$$

$$\lambda_t^{NE}(s, m_0, \alpha) = m_0 s \left(\frac{V_t}{U_t + sN_t} \right)^{1-\alpha} .$$

The minimum distance estimates are reported in table 1 and are as follows: $\hat{\alpha} = 0.753$, $\hat{m}_0 = 0.435$, and $\hat{s} = 0.218$.

6. Finally, we use $\{V_t, \lambda_t^{EU}, \lambda_t^{EN}, \lambda_t^{UN}, \lambda_t^{NU}\}_{t \geq 1/2008}$ as the exogenous forcing variables to form our counterfactual predictions below.

VI. Calibration Results

A. Predicted Job Finding Rates

During the Great Recession, average job finding rates declined in part because average unemployment durations increased. Panel *B* in figure 7 shows what happened to average job finding rates due to the increase in durations by plotting $\bar{A}_t = \int A(\tau)\theta_t(\tau)d\tau$ from 2002 to 2013. Here \bar{A}_t is a useful measure of the duration structure of unemployment since it summarizes how the duration structure affects the average job finding rate assuming that $A(d)$ describes the effect of unemployment duration on the job finding rate. We use the estimated $A(d)$, which controls for the rich set of observable characteristics available in the CPS (gender, age, race, and education). To the extent that the recession shifted the unemployment toward longer durations, this will lower \bar{A}_t since $A'(\tau) < 0$.⁹

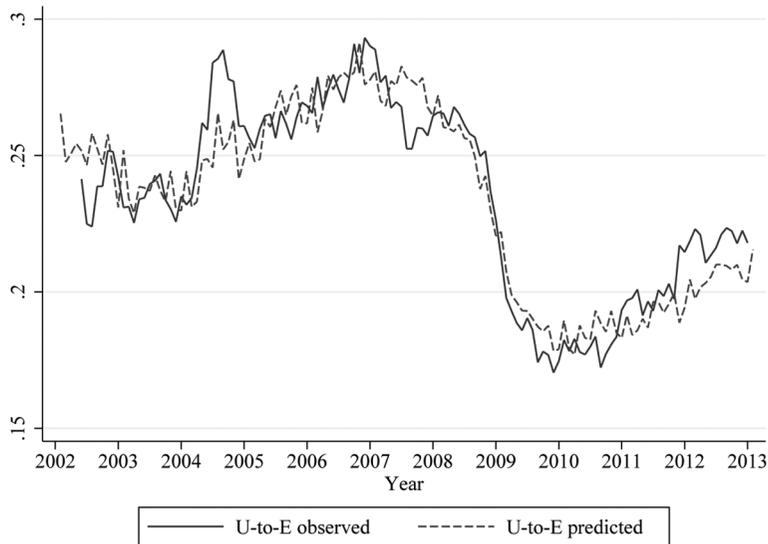
We see that, starting in 2008, there was a sharp drop in \bar{A}_t from around 0.75 to roughly 0.63 (where $A(0)$ is normalized to 1, so that $A(d)$ can be interpreted as the relative job finding rate for high durations compared to the newly unemployed). This figure therefore shows that the indirect effect of a drop in market tightness on the average job finding rate is quantitatively important, and it suggests the possibility of a prominent role for negative duration dependence in the job finding rate out of unemployment in accounting for changes in long-term unemployment share as well as an outward shift in the Beveridge curve.

In panels *A* and *B* of figure 8, we plot the predicted and observed job finding rates for the unemployed and nonparticipants, respectively.¹⁰ These transition rates are the two key endogenous variables of the model. By construction, the predicted rates match the observed rates in the pre-Great-

⁹ Note that this variable does not include the direct effect of market tightness on the average job finding rate through the matching function; rather, it only includes the mechanical effect of changes in duration distribution on average job finding rates.

¹⁰ We refer to the job finding rates estimated according to the method in appendix B as “observed job finding rates” throughout the text.

Panel A: Job Finding Rates for Unemployed



Panel B: Job Finding Rates for Non-Participants

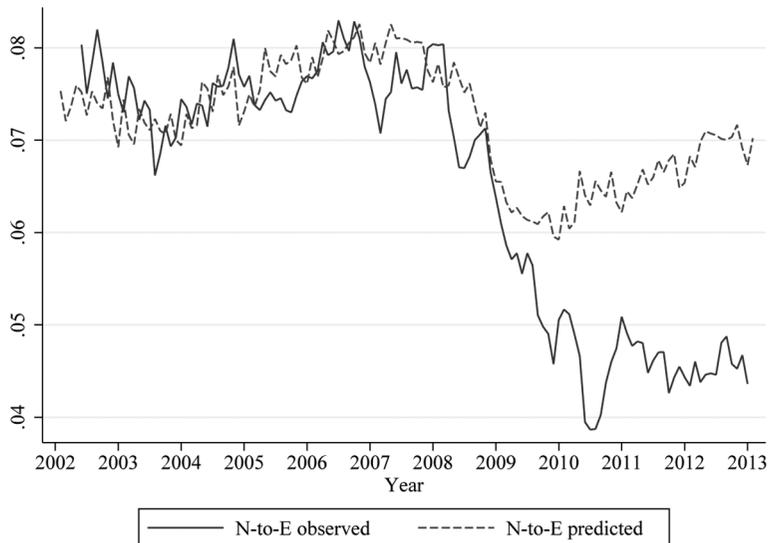


FIG. 8.—Model predictions for job finding rates for unemployed and non-participants. These figures report the model-generated predicted job finding rates for unemployed workers and nonparticipants, where the predictions are based on model estimates calibrated to match the 1/2002–12/2007 time period. See the main text for more details. A color version of this figure is available online.

Recession period. During the Great Recession, we see that the model does a reasonable job of predicting the job finding rate for the unemployed; however, nonparticipants were not filling jobs at the rate they were predicted to during this time period. This suggests that there was something fundamentally different about the Great Recession in terms of its impact on individuals out of the labor force that is at odds with the behavior of this group in the pre-recession period. We investigate this issue below.

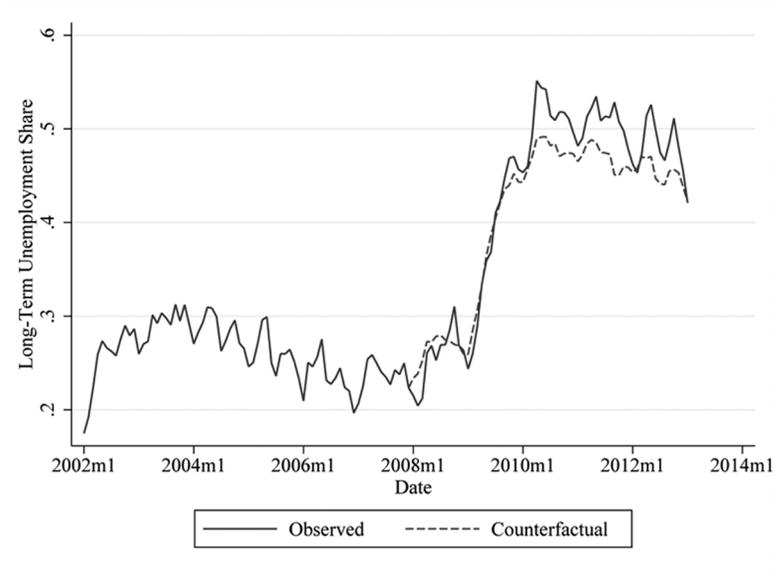
B. Long-Term Unemployment

Panel A in figure 9 investigates how well our calibrated model matches the observed increase in incidence of long-term unemployment. The calibrated model fits the data by construction up to the final quarter of 2007. From 2008 onward, we use the job finding rates for the unemployed and nonparticipants that are predicted by our model. We label the data generated by model as “Counterfactual.” Panel A of figure 9 shows that our model does very well in accounting for the observed increase in share of unemployed that are long-term unemployed when long-term unemployment is defined to be > 26 weeks. In panel B of figure 9, long-term unemployment is now defined to be > 52 weeks. In this case, our model does not do quite as well, although it still accounts for a large share of the actual increase in long-term unemployment. The relatively poorer fit for long-term unemployment > 52 weeks could be partly due to the fact that the estimated $A(d)$ —which controls how job finding probability falls with unemployment duration—declines sharply during the first several months and declines much less steeply after that.

C. Beveridge Curve

Panel C of figure 9 plots the Beveridge curve using unemployment and vacancy rates, where the denominator in each case is defined as total population between ages 25 and 55. We plot two curves in this figure. The solid curve, labeled “Observed,” plots the actual unemployment and vacancy rate in a given quarter. Next, the dotted curve, labeled “Counterfactual,” plots the predicted unemployment along with the observed vacancy rate for the quarters starting with 2008Q1. The figure shows a significant spike in unemployment during the first quarter of 2008. At this point, vacancies were very low compared to the 2002–7 period. However, even as vacancy rates recovered during 2010 and 2011, the number of unemployed declined only very slowly. It seems as if the Beveridge curve has shifted out. This is a manifestation of what has been dubbed the “jobless recovery.” Overall, we see that our model also predicts an outward shift in the Beveridge curve during the Great Recession, although by not as much as observed. This is because, while our model accounts

Panel A: Long-Term Unemployment (> 26 weeks)



Panel B: Long-Term Unemployment (> 52 weeks)

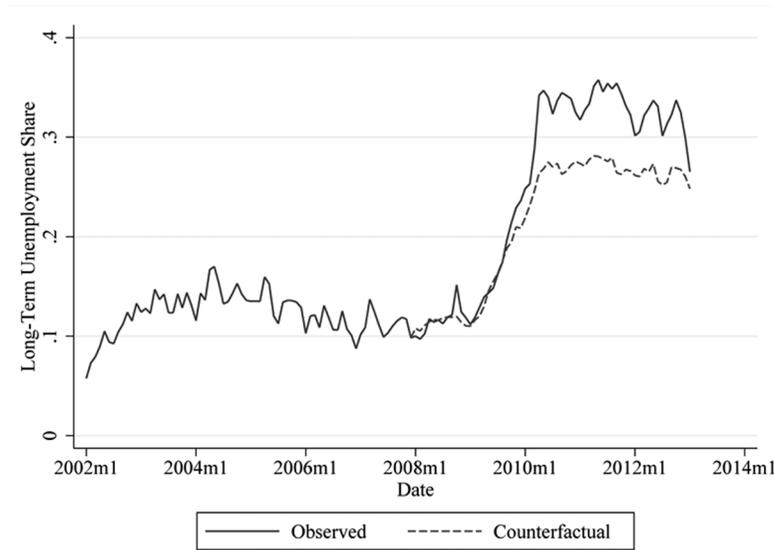
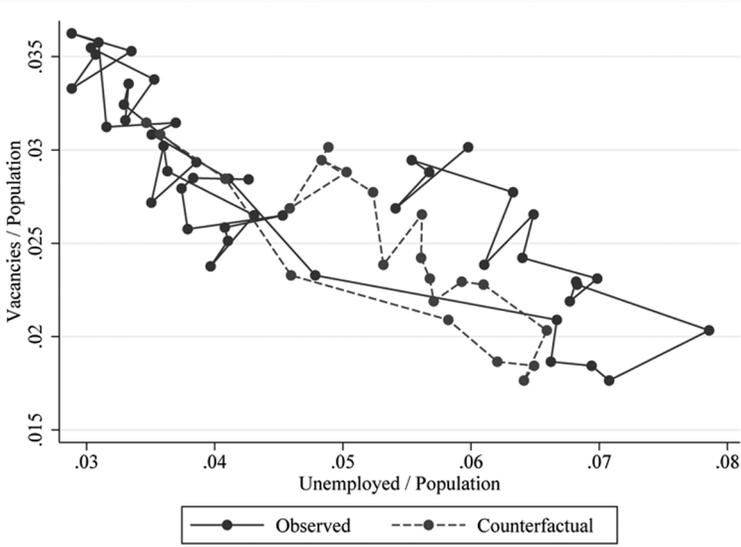


FIG. 9.—Model predictions for long-term unemployment and Beveridge Curve. These figures use data from the Current Population Survey and the Job Openings and Labor Turnover Survey. See the main text for more details on model calibration. A color version of this figure is available online.

Panel C: Beveridge Curve



Panel D: Model Predictions for $N - V$ Curve

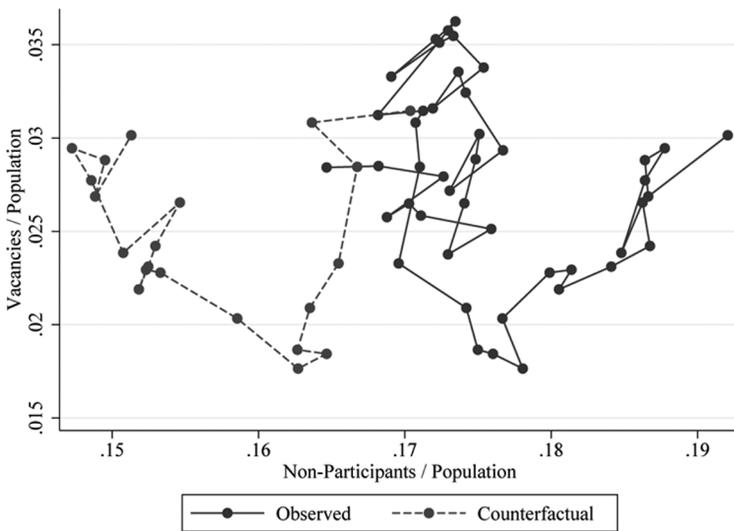


Fig. 9 (Continued)

for the rise in the long-term unemployed share of total unemployment, it somewhat underpredicts the overall unemployment rate.

D. Nonparticipation and Vacancies

We next investigate the relationship between nonparticipation and vacancy rates. Panel *D* of figure 9 is identical to panel *C* of figure 9, except that we consider rates of nonparticipation instead of unemployment rates (where again the total population $P = L + N = E + U + N$ is the denominator). Although our model does a reasonably good job of describing the relationship between unemployment and vacancies, it does a very poor job of fitting the relationship between nonparticipation rates and vacancies. In particular, the model substantially underpredicts nonparticipation rates during the Great Recession. This is primarily due to the fact that the predicted job finding rate for nonparticipants is too high.

E. Alternative Assumptions Regarding Duration Dependence

Our last sensitivity analysis examines whether our results are sensitive to using alternative estimates of duration dependence. These results are reported in figure 10, where we compare the predicted increase in long-term unemployment, defined as the share of the unemployed with ongoing durations exceeding 26 weeks, under several scenarios. In panel *A*, we report results that estimate $A(d)$ from the CPS controlling for a rich set of observables, as well as results that impose the $A(d)$ function that most closely matches the experimental estimates in Kroft et al. (2013). One of the scenarios uses the experimental estimates from the overall sample, while another scenario allows $A(d)$ to vary with the unemployment rate. In our baseline calibration, we assume that $A(d)$ is stable over the business cycle, while Kroft et al. (2013) present evidence that suggests that the magnitude of duration dependence is smaller when the unemployment rate is relatively high. We therefore allow $A(d)$ to vary with the unemployment based on experimental estimates and calibrate the model with this alternative assumption on duration dependence. Overall, we find that the predictions are fairly similar across these scenarios, reflecting the fact that the estimate of duration dependence in the CPS (with and without controls) is fairly similar to the experimental estimates in Kroft et al. (2013).

Next, in panel *B* of figure 10, we re-scale the CPS estimate of $A(d)$ by assuming that only a fixed percentage represents “true” duration dependence (i.e., a genuine causal effect of unemployment duration on job finding rate). When we assume that only 50% of observed duration dependence is causal, we still find that our calibrated model can account for a large share of the rise in long-term unemployment. This is because

even in this scenario the job finding rate still falls sharply over the first 6 months of unemployment.

VII. Counterfactual Scenarios

A. Ignoring Duration Dependence

We next demonstrate that accounting for duration dependence in job finding rates is crucial for this success in matching the data. To do this, we reestimate the matching model setting $A(d) = 1$. The results of this exercise are reported in figure 11, where panels *A* and *B* report long-term unemployment shares and panels *C* and *D* report the Beveridge curve and the curve relating nonparticipation rates to vacancy rates, respectively. Panels *A* and *B* show that the predicted long-term unemployment from model calibration ignoring duration dependence is much lower than the predicted long-term unemployment we get when accounting for negative duration dependence in the exit rate from unemployment. Thus, duration dependence in job finding rates is empirically important in understanding the historical increase in long-term unemployment during the Great Recession.

Turning to the Beveridge curve in panel *C*, we see that the model does worse when ignoring duration dependence in terms of predicting the observed unemployment rate during the Great Recession. This is clear visual evidence that a standard matching model—without negative duration dependence—underpredicts unemployment. On the other hand, panel *D* shows that the magnitude of duration dependence does not substantially affect predicted nonparticipation rates, although duration dependence does appear to begin to matter for calibrations during the last few quarters of the sample period.¹¹

B. Counterfactual Scenarios Ignoring Nonparticipation

Figure 12 considers a counterfactual that holds all flows to and from nonparticipation constant at their 2007 values (except for the N-to-E flow, which is determined endogenously by the matching function). It is evident from panels *A*–*C* that ignoring the nonparticipation margin leads one to substantially underpredict overall unemployment and the structure of unemployment during the Great Recession. We also see in panel *D* that

¹¹ We also explored a counterfactual scenario where the distribution of unemployment durations is fixed at the level prevailing in December 2007. That is, we do not allow individuals to be pushed into longer durations by the recession, which would lower the average job finding rate, since the long-term unemployed have lower job finding rates than the short-term unemployed. The results of this exercise are similar to those reported in fig. 11.

Panel A: Comparing to Kroft et al. (2013) experimental estimates

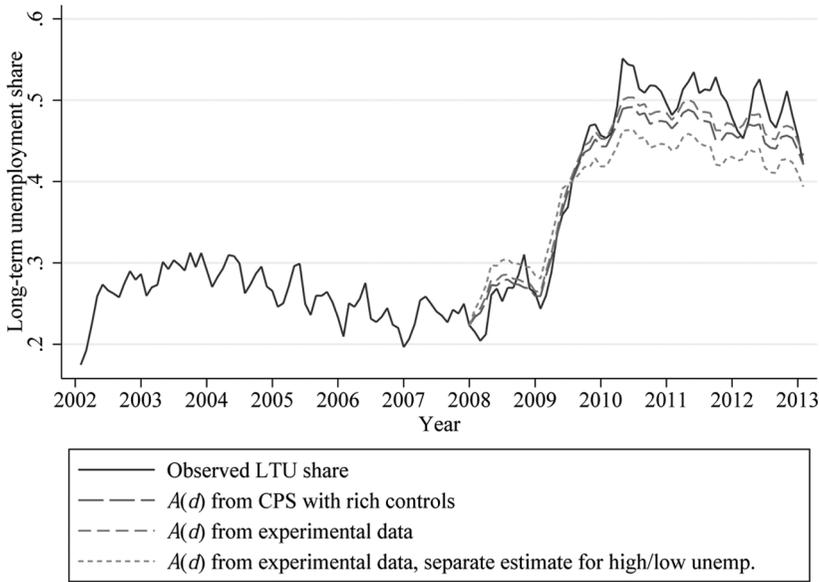


FIG. 10.—Model predictions using alternative estimates of duration dependence. In panel A, the figure shows robustness of the baseline calibration (long dashed line) to alternative assumptions about the magnitude of duration dependence. The medium dashed line shows calibration results based on estimated $A(d)$ function based on the full sample of experimental data from Kroft et al. (2013). The short dashed line allows $A(d)$ to vary with labor market conditions, as found in Kroft et al. (2013); specifically, $A(d)$ is flatter than average when the unemployment rate exceeds 8.8% (in April 2009) and steeper before that point. In panel B, the figure shows robustness to assuming that the estimated $A(d)$ function recovers a mixture of “true” duration dependence and unobserved heterogeneity. By making assumptions on the share of unobserved heterogeneity captured by the function, $A(d)$ can be rescaled to be a measure of “true” duration dependence. A color version of this figure is available online.

rather than underpredicting nonparticipation rates as in the baseline calibration, we now substantially overpredict these rates. Intuitively, by ignoring the increase in N-to-U flows and the decrease in U-to-N flows that occurred during the Great Recession, we instead predict nonparticipation rates that are much too high. Therefore, accounting for nonparticipation flows is crucial in understanding the dynamics of unemployment during the Great Recession. This is related to (and consistent with) the findings in Elsby et al. (2015), which reports that the participation margin accounts for one-third of the cyclical variation in the unemployment rate. We next consider ignoring flows to and from nonparticipation one by one.

Panel B: Alternative assumptions of “true” duration dependence

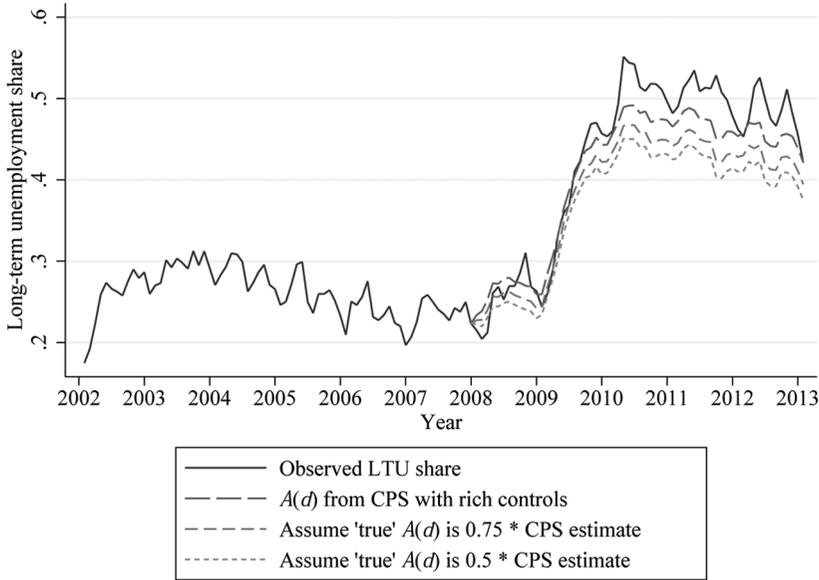


Fig. 10 (Continued)

1. Ignoring Changes in N-to-U

We saw in figure 5 that transitions from nonparticipation to unemployment rose significantly during the Great Recession. Moreover, we know from research by Elsbey et al. (2011) that some of the transitions from nonparticipation to unemployment go to long durations. We next examine the importance of these flows by holding N-to-U rates fixed at their values in December 2007. Panels A and B of figure C8 show that the predicted long-term shares fall somewhat relative to the counterfactual that does not fix these flows. Additionally, when the N-to-U flows are fixed at their 2007 values, the model is less able to match the outward shift in the Beveridge curve. Overall, these transitions appear to be somewhat important to understanding the rise in long-term and overall unemployment during the Great Recession.¹² Interestingly, the evidence in panel D suggests the alternative model is better able to explain the dynamics of nonparticipation.

¹² It is worth emphasizing, however, that if one were to form the counterfactuals by assuming that all transitions from nonparticipation to unemployment go to 0 months of duration, the prediction would be very poor.

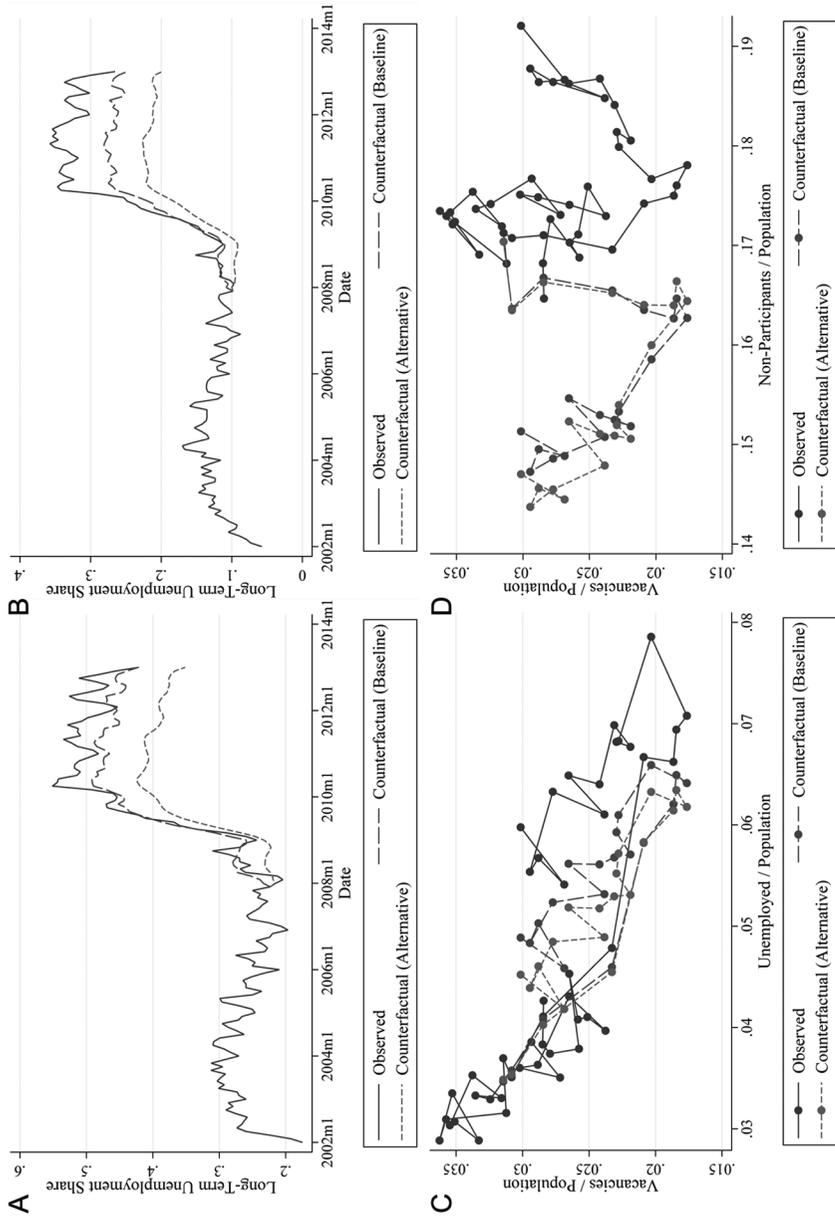


FIG. 11.—Model predictions ignoring duration dependence. These figures use data from the Current Population Survey and the Job Openings and Labor Turnover Survey. See the main text for more details on model calibration. A color version of this figure is available online.

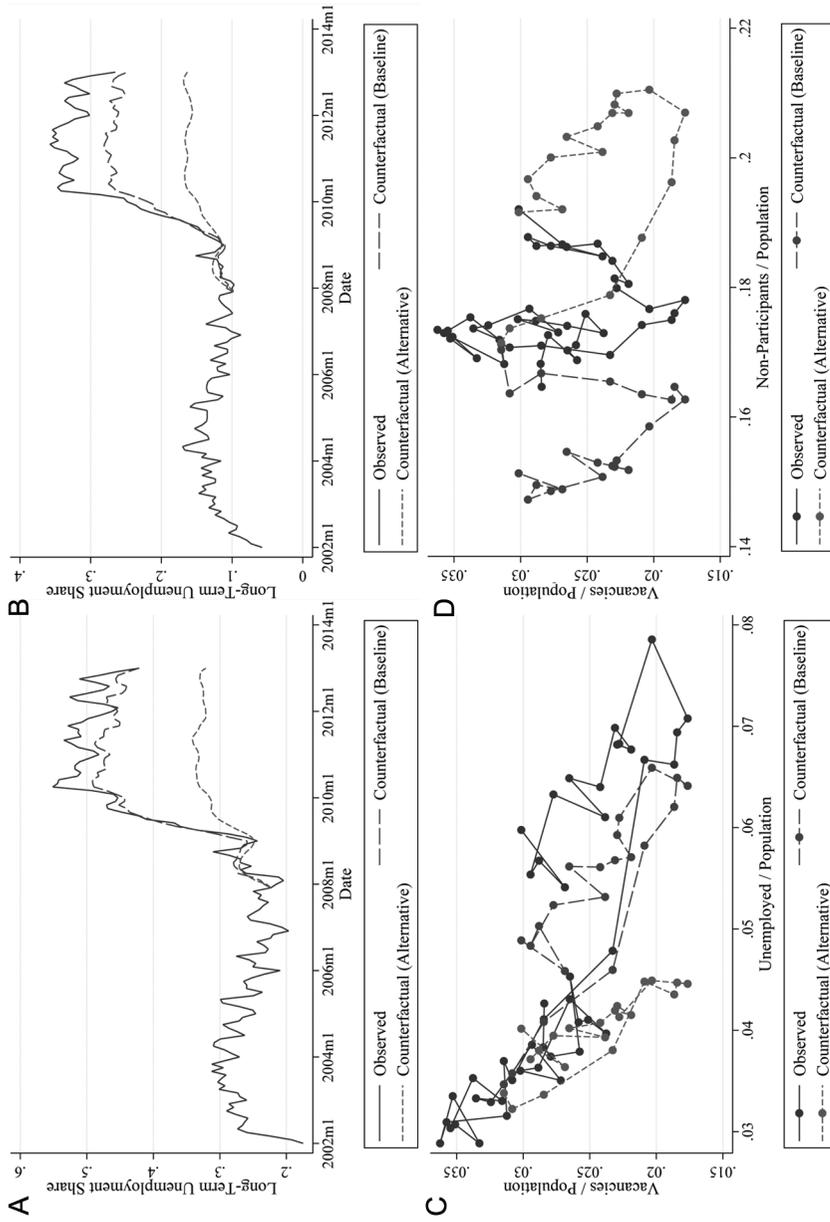


FIG. 12.—Model predictions ignoring changes in $N \rightarrow U$, $U \rightarrow N$, and $E \rightarrow N$. These figures use data from the the Current Population Survey and the Job Openings and Labor Turnover Survey. See the main text for more details on model calibration. A color version of this figure is available online.

2. Ignoring Changes in U-to-N

Another fact about the Great Recession is that flows from unemployment to nonparticipation significantly declined, at least from 2008 to 2010. Elsby et al. (2015) document the procyclicality of these flows during recessions since 1970. They argue that in recessions, the composition of the unemployed shifts to those who are more “attached” to the labor market and that this explains three-quarters of the drop in the flow rate from unemployment to nonparticipation.¹³ We examine the importance of this change during the Great Recession by holding U-to-N rates fixed at their values in December 2007. The results are reported in figure C9 and show that the model somewhat underpredicts long-term unemployment and also the overall level of unemployment, at least until the end of 2010. Why are these flows so important for understanding long-term unemployment and the movement of the Beveridge curve? Intuitively, if we assumed more transitions from unemployment to nonparticipation than was actually the case, this would lower the stock of the unemployed and lead to a lower unemployment rate.

3. Ignoring Changes in E-to-N

Finally, figure C10 investigates the flows from E-to-N, which were largely stable during the Great Recession, according to the results in figure 5. Therefore, it is not surprising to see that the model predictions do not substantively change when we “shut down” changes in E-to-N flows by holding them at their December 2007 values.

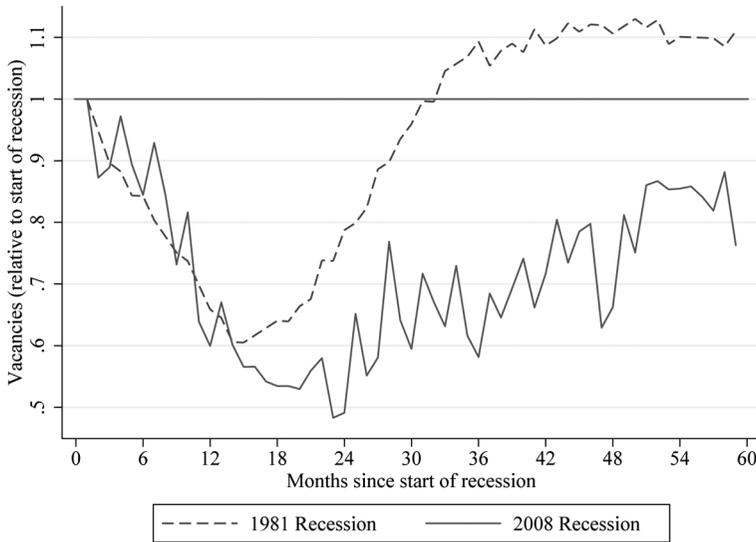
C. Comparison to the 1981 Recession

The 1981–82 recession generated double-digit unemployment similar to peak unemployment in the Great Recession, but long-term unemployment did not rise nearly as much in the early 1980s’ downturn. It is useful to consider what would have happened to long-term unemployment if vacancies had evolved as in the early 1980s recession as opposed to the way they evolved during the Great Recession.¹⁴ Panel A of figure 13 shows the (relative) differences in evolution of vacancies between the two recessions. The vacancy data for the 1981 recession are filtered data from Help Wanted Index from Elsby et al. (2011). Compared to vacancies during the Great Recession, in the early 1980s vacancies fell by roughly the same order of magnitude but rebounded much more quickly. Panel B in figure 13 displays the model predictions for long-term unemployment using vacancies in the 1981 recession as the forcing variable in the model (in place of

¹³ Their novel measure of labor market attachment is based on whether an individual was employed 1 year prior to the Current Population Survey.

¹⁴ We also ignore observed changes in N-to-U, U-to-N, and E-to-N flows in this counterfactual exercise (i.e., fixing values of the flows at their 2007 values).

Panel A: Dynamics of Vacancies in 1981 Recession and 2008 Recession



Panel B: Long-Term Unemployment (> 26 weeks)

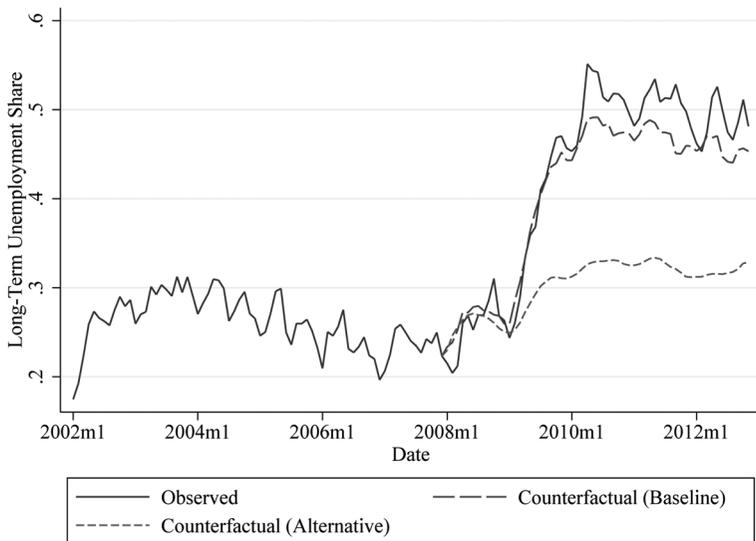


FIG. 13.—Model predictions using vacancy series during the 1981 recession (instead of the 2008 recession) and ignoring changes in $N \rightarrow U$, $U \rightarrow N$, and $E \rightarrow N$. In panel A, vacancy data for the 2008 recession come from Job Openings and Labor Turnover Survey, while vacancy data for the 1981 recession are filtered data from Help Wanted Index from Elsby et al. (2011). In panel B, figure uses data from the Current Population Survey. See the main text for more details on model calibration in these panels. A color version of this figure is available online.

the 2008 recession). We see that the predicted long-term unemployment share is much lower than the share predicted during the Great Recession. Thus, our model is able to provide an explanation for why long-term unemployment rose much more sharply in the Great Recession as compared to the 1981 recession, arising from a more sustained decline and much weaker recovery in labor demand (as reflected in the vacancy rate).

D. The Beveridge Curve and Long-Term Unemployment

Ghayad and Dickens (2012) consider the recent outward shift in the Beveridge curve and note that it occurred over a period of less than 1 year as compared to the roughly 8 years it took for the Beveridge curve to shift in the recession of the 1970s. They also note that if one constructs separate Beveridge curves for the short-term and long-term unemployed, all of the movement in the aggregate Beveridge curve is relative to the long-term unemployment rate. This is mechanically related to the duration-specific unemployment rates discussed in figure 1 above.

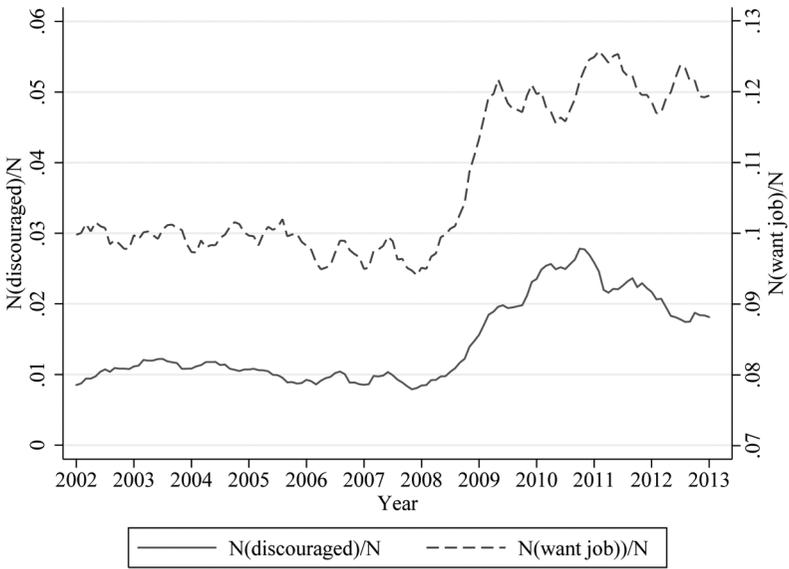
Our results can help account for these findings. First, we saw that long-term unemployment increased rapidly over a short period of time. This change, combined with negative duration dependence in job finding rates, helps explain the fast shift in the Beveridge curve. To shed light on the second finding, in figure C11, we plot two separate Beveridge curves, one for the short-term unemployed (panel *A*) and one for the long-term unemployed (panel *B*). Similar to Ghayad and Dickens (2012), we see that the shift in the overall Beveridge curve is due to the shift in the Beveridge curve for the long-term unemployed. We also see that our model is unable to completely account for these shifts in both curves. In particular, it tends to predict too large a drop in unemployment for the later years of the Great Recession for both curves. The next subsection provides some explanations for the difficulty of the model to fully explain some of the stylized facts of the Great Recession.

E. Alternative Explanations

Our results indicate that our model can account for unemployment dynamics reasonably well but has a harder time matching dynamics among nonparticipants. One possibility is that those who drop out of the labor force during the Great Recession may be less marginally attached (less likely to be interested in work) than those who drop out during normal times. In other words, it might be the case that s falls during the Great Recession in a way that we are not accounting for in the matching framework and this could explain some of the discrepancy.

We examine this possibility in panel *A* of figure 14, which plots the share of nonparticipants who are “discouraged” and the share of nonparticipants

Panel A: Share of Non-Participants Reporting “Discouraged” or “Want Job”



Panel B: Job Finding Rates for Non-Participants Reporting “Want Job”



FIG. 14.—Changing composition of labor force nonparticipants. These figures report statistics from the Current Population Survey on the share of nonparticipants who report either being “discouraged” or saying that they “want a job.” In panel *B*, the monthly job finding rates for unemployed, nonparticipants (overall), and nonparticipants (who are in “want a job” category) are displayed between 2002 and 2013. A color version of this figure is available online.

who report that they want a job. The figure shows that, starting in 2008, both increased sharply. This suggests that s actually increased during the Great Recession and that if we were to account for this change in our matching framework, then our model-based predictions would likely be even worse. Panel *B* of figure 14 plots the transition rates from non-participation to employment—for those who report that they want to work. We see that for this group, the job finding rate fell during the Great Recession. We are thus left with an incomplete understanding of why non-participants did not find jobs at the rate predicted by our calibrated model.

We conclude with several speculative thoughts regarding other possible explanations of the lower-than-expected job finding rate of non-participants. First, our model does not capture the possibility of negative duration dependence in job finding rates for nonparticipants; the model only allows for duration dependence in unemployment. Recent work by Autor et al. (2015) reports strong evidence that additional months out of the labor force has a negative causal effect on probability of employment.¹⁵ Unfortunately, we cannot readily estimate such duration dependence in the job finding rate of labor market nonparticipants since the CPS does not record time spent out of the labor force. Second, our model ignores factors such as the recent rise in Social Security Disability Insurance (SSDI) applications and SSDI enrollments in the Great Recession. Third, the dynamics of our calibrated matching model may possibly obscure other changing features of the labor market during times of weak aggregate demand. For example, models of “queuing” and “ranking” may feature discouraged and/or marginally attached workers ending up at the end of the queue, and this could lead to long-term joblessness (Okun 1973; Blanchard and Diamond 1994). Finally, some adult workers may be returning to school and/or job training and not looking for work (Barr and Turner 2013). This would represent a compositional change that would reduce the job finding rate for nonparticipants in a way that could potentially account for the residual decline not accounted for by our calibrated model.

VIII. Conclusion

Both short-term and long-term unemployment increased sharply in 2008–9 during the Great Recession. But while short-term unemployment returned to normal levels by 2013, long-term unemployment remains at historically high levels in the aftermath of the Great Recession. We showed that long-term unemployment increased for virtually all groups

¹⁵ While this surely can account for some of the discrepancy, we showed that ignoring duration dependence for the unemployed causes us to underpredict unemployment but that the gap between predicted and observed in this case is less than the gap between predicted and observed for nonparticipants.

and that shifts in observable characteristics of the unemployed do not go very far in accounting for the rise in long-term unemployment.

By contrast, an enriched matching model that allows for duration dependence in unemployment and transitions between employment (E), unemployment (U), and nonparticipation (N) can account for almost all of the increase in the incidence of long-term unemployment and much of the observed outward shift in the Beveridge curve between 2008 and 2013. We emphasize that duration dependence is not the primary force behind rising long-term unemployment in the Great Recession *per se*; rather, duration dependence serves to reinforce and amplify the initial labor demand shock that shifted the distribution of unemployment durations. Our results suggest that both negative duration dependence in the job finding rate out of unemployment and transitions to (and from) nonparticipation may play an important part in understanding both the rise in long-term unemployment and the observed outward shift in the Beveridge curve.

Much evidence suggests that there is sizable causal negative duration dependence in the escape rate from unemployment. The longer one has been unemployed, the less likely one is to get a callback from an employer, and job search effort also is likely to decline. A strong negative labor demand shock like from a major financial crisis and/or from consumer, firm, and lender behavior can build up the stock of the long-term unemployed. Negative duration dependence means that the long-term unemployed are less effective job seekers than the short-term unemployed. Thus, the rise in long-term unemployment itself can help explain much of the outward shift in the traditional Beveridge curve following the Great Recession. Essentially, the overall matching efficiency of the labor market is reduced when the incidence of long-term unemployment is high. This is not the whole story, however. Firms continue to worry about demand conditions and have lowered their recruiting intensity for posted vacancies (Davis et al. 2013), further contributing to the outward Beveridge curve shift and the persistence of the low flows from unemployment to employment in the aftermath of the Great Recession.

Appendix A

Data Sources

These are the data sources used for both calibration (which only uses pre-1/2008 data) and counterfactual estimation (which uses post-1/2008 data):

- Θ_t (duration distribution): CPS monthly data from the period 1/2002–1/2013. We estimate the unemployment duration distribution monthly for all unemployed adults aged 25–55. We group all unem-

- ployment durations greater than or equal to 24 months together in a single category, and the rest of the durations are grouped by month.
- V_t (vacancies): JOLTS monthly data between 1/2002 and 1/2013. We use the seasonally unadjusted data released by the BLS and residualize out month fixed effects to account for seasonality and then calculate three-month moving averages to smooth the series.
 - U_t, E_t, N_t (stocks of unemployed, employed, and nonparticipants): CPS monthly data between 1/2002 and 1/2013. We use CPS survey weights to estimate stocks in each month for each group for our base-line sample of adults aged 25–55.
 - $\{\lambda_t^{UE}, \lambda_t^{UN}, \lambda_t^{EU}, \lambda_t^{EN}, \lambda_t^{NE}, \lambda_t^{NU}\}$ (transition rates between E/U/N): CPS monthly data between 1/2002 and 1/2013. See appendix B for more details on construction of these panel transition rates, which are based on matching individuals across months as in Shimer (2012).
 - $A(d)$ (duration dependence function): We estimate $A(d)$ in several ways. For the main results, we use job finding rate for unemployed workers (by unemployment duration in months) pooling all monthly CPS data between 1/2002 and 12/2007. The job finding rate is defined as the monthly probability that a given unemployed job seeker reports employment in both of the following 2 months (the requirement of 2 months follows Rothstein 2011; see references therein for discussion and justification). For robustness, we also use estimates of $A(d)$ from the experimental data in Kroft et al. (2013); see the main text for more details.

Using the data sources above, we calibrate α, m_0, s (matching function parameters) using data from before 1/2008. See the main text for more details.

Appendix B

Identification of Transition Rates from CPS

In this section, we will describe how we identify the transition rates $\{\lambda_t^{UE}, \lambda_t^{UN}, \lambda_t^{EU}, \lambda_t^{EN}, \lambda_t^{NE}, \lambda_t^{NU}\}$. The straightforward approach is to recover them from the CPS panel. However, we found that these rates are not consistent with the levels of unemployment, employment, and nonparticipation in each period. Here we describe a procedure that ensures consistency by brute force. The only requirement is the assumption that the relative flow rates from the CPS panel are correct. The steps of this procedure are as follows:

1. Normalize the population so that $N_t + U_t + E_t = 1$ in each period.
2. Obtain the levels $\{N_t, U_t, E_t\}$ and net flows $\{\Delta N_t, \Delta U_t, \Delta E_t\}$ from the data. Note that $\Delta N_t + \Delta U_t + \Delta E_t = 0$ so without loss of generality, we will work with ΔN_t and ΔE_t .

3. Obtain $U_{t+1}(d = 0)$, the (normalized) number of newly unemployed, as well as $\theta_t(d = 0)$, from the data.

4. Let the transition rates $\{\lambda_t^{UE}, \lambda_t^{UN}, \lambda_t^{EU}, \lambda_t^{EN}, \lambda_t^{NE}, \lambda_t^{NU}\}$ be unknown parameters.

5. We have by definition:

$$\begin{aligned} \Delta N_t &= \lambda_t^{UN} U_t + \lambda_t^{EN} E_t - (\lambda_t^{NU} + \lambda_t^{NE}) N_t. \\ \Delta E_t &= \lambda_t^{UE} U_t + \lambda_t^{NE} N_t - (\lambda_t^{EU} + \lambda_t^{EN}) E_t. \\ U_{t+1}(d = 0) &= \lambda_t^{EU} \theta^{EU}(d = 0) E_t + \lambda_t^{NU} \theta_t(d = 0) N_t. \end{aligned}$$

6. This leaves us with six unknown parameters in three equations.

7. To identify the parameters, we will impose three additional restrictions that require that the relative transition rates between states are identified from the panel data. Let the observed relative transition rate for state X in time period t be denoted by ψ_t^X :

$$\begin{aligned} \psi_t^N &= \frac{\lambda_t^{NU}}{\lambda_t^{NE}}. \\ \psi_t^E &= \frac{\lambda_t^{EN}}{\lambda_t^{EU}}. \\ \psi_t^U &= \frac{\lambda_t^{UN}}{\lambda_t^{UE}}. \end{aligned}$$

This leaves us with the following system of equations:

$$\begin{pmatrix} E_t & 0 & U_t & 0 & -N_t & -N_t \\ -E_t & -E_t & 0 & U_t & 0 & N_t \\ 0 & \theta^{EU}(d = 0)E_t & 0 & 0 & \theta_t(d = 0)N_t & 0 \\ 0 & 0 & 0 & 0 & 1 & -\psi_t^N \\ 0 & 0 & 1 & -\psi_t^U & 0 & 0 \\ 1 & -\psi_t^E & 0 & 0 & 0 & 0 \end{pmatrix} \times \begin{pmatrix} \lambda_t^{EN} \\ \lambda_t^{EU} \\ \lambda_t^{UN} \\ \lambda_t^{UE} \\ \lambda_t^{NU} \\ \lambda_t^{NE} \end{pmatrix} = \begin{pmatrix} \Delta N_t \\ \Delta E_t \\ U_{t+1}(d = 0) \\ 0 \\ 0 \\ 0 \end{pmatrix}.$$

8. We recover $A(d)$ from the panel data job finding rates for the unemployed.

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