Brookings Papers
ON ECONOMIC ACTIVITY

BPEA Conference Drafts, March 19, 2020

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# How Tight is the U.S. Labor Market?*

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March 17, 2020

*We are grateful to Daniel Aaronson, Steven Davis, Jason Faberman, Robert Hall, Chris Nekarda, Aysegul Sahin, Sam Schulhofer-Wohl, Jim Stock, Robert Valletta, and Justin Wolfers for helpful conversations and comments on an earlier draft, to colleagues at the University of Maryland for comments during a brown bag seminar that helped to sharpen our thinking about these issues and to participants in the Federal Reserve System's June 2019 Conference on Monetary Policy Strategy, Tools and Communication Practices at which an earlier version of this paper was presented.

Researchers and policymakers alike have been confounded in recent years regarding how to interpret what available data are saying about the tightness of the labor market. Unemployment is as low as it has been since the 1960s. The ratio of job vacancies to unemployment, a measure of labor market tightness shown in Figure 1 for the period from 1994 to the present, is far above its level at the end of the 1990s expansion.[1] Yet, both wages and prices have been surprisingly stable. There are a number of possible explanations for why wages and prices are not growing more rapidly, including better anchoring of inflation expectations (Ball and Mazumder 2014, Blanchard 2018, Crump et al. 2019), increasing globalization (Bean 2006; Auer, Borio and Filardo 2017; Jasova, Moessner and Takats 2018); and declining worker bargaining power (Krueger 2018). Another potential contributing factor, and the focus of our paper, is that existing measures may be overstating the true tightness of the labor market.

For a simple summary of labor market conditions, observers and analysts long have turned to the unemployment rate. Unemployment exhibits clearly cyclical behavior, rising during downturns and falling during recoveries. It is tempting to view the unemployment rate as a sufficient statistic for understanding the state of the labor market, but there are good reasons to think this may not be the case. For one thing, different groups among the unemployed may be more or less attached to the labor market and more or less likely to move into employment. In a seminal paper published in the third issue of the *Brookings Papers on Economic Activity*, Perry (1970) noted that women's rising labor force participation and the entry of the Baby Boom generation into the labor force could have raised measured unemployment independently of underlying labor market conditions. In recent years, researchers have argued that the higher-than-usual share of long-term unemployment among the unemployed following the Great Recession

[1] The vacancy series for 2000:12 forward is from the Job Openings and Labor Turnover Survey (JOLTS). The construction of the series for 1994-2000:11 is discussed later in the paper.

implied effective unemployment lower than suggested by the unemployment rate (see, e.g., Krueger, Cramer and Cho 2014). Further, as emphasized in a number of recent empirical studies, most new hires originate from out of the labor force or from another job (job-to-job flows) rather than from unemployment. Data showing that an unusually large number of those out of the labor force say they would like to work or an unusually large share of workers are part time but would have preferred full-time work, for example, may lead analysts to suspect that effective unemployment is higher than suggested by the unemployment rate (see, e.g., Yellen 2014).

Search and matching models of the labor market (see, e.g., Diamond 1982, Blanchard and Diamond 1992, Mortensen and Pissarides 1994, Pissarides 2000) imply that unemployment (or more generally job searchers) must be considered together with job openings in assessing labor market tightness. In these models, a higher ratio of vacancies to unemployment—a larger number of jobs that employers would like to fill relative to the number of unemployed people available to fill them—makes filling jobs more difficult and thus indicate that the labor market is tighter. Again, however, standard statistics—in this case, the ratio of vacancies to unemployment—may not tell the whole story. In addition to the fact that many of those searching for jobs are out of the labor force or employed, meaning that unemployment is an incomplete measure of effective job searchers, existing evidence implies that the intensity with which firms recruit to fill their vacancies varies over time. This variation in recruiting intensity also helps to account for observed variation in both job-filling and job-finding rates (Davis, Faberman and Haltiwanger 2013) (DFH 2013).

Building on the search and matching literature and previous research by Hall and Schulhofer-Wohl (2018), we propose a generalized measure of labor market tightness that addresses the limitations of the standard measures. The framework we employ accounts both for variation in the number of effective job searchers, drawn not only from the unemployed but also from those currently out of the labor force or already working, and for variation in the intensity with which employers seek to fill their jobs. Our generalized measure of labor market tightness is equal to the ratio of effective vacancies (recruiting intensity times measured vacancies) to effective searchers (a weighted sum of the different groups within the working age population with weights based on relative job-finding rates as a proxy for relative job search intensities).

One of the puzzles of recent labor market history has been the pronounced and persistent outward shift in the Beveridge curve relating job vacancies and unemployment following the Great Recession. Over the period from 1994 through 2019, the Beveridge curve constructed using effective vacancies and effective searchers is much more stable than that constructed using just vacancies and unemployment. Further, our generalized measure of labor market tightness outperforms the ratio of vacancies to unemployment as a predictor of both the job-filling rate (hires per vacancy) and the job-finding rate among the unemployed (hires from unemployment as a ratio to the stock of unemployment). Over the 1994-2019 period, the job-filling rate predicted using our generalized index has a root mean squared error that is just 38 percent as large as that based on the standard measure. For the job-finding rate among the unemployed, the predicted series using our generalized index has a root mean squared error that is just 29 percent as large as that based on the standard measure.

The paper proceeds as follows. Section I develops the organizing framework that guides our analysis. In Section II, we review the recent theoretical and empirical literature motivating our approach. Section III presents our generalized labor market tightness measure and Section IV discusses the relationship between effective searchers and effective vacancies over time. Section V investigates the properties of our generalized measure of labor market tightness relative to those of the standard measure. Section VI offers some concluding remarks and a discussion of possible future extensions.

## I. An Organizing Framework

The perspective on the labor market that motivates our analysis focuses on labor market flows and the drivers of those flows. In the canonical search-and-matching model (Diamond 1982, Blanchard and Diamond 1992, Mortensen and Pissarides 1994, Pissarides 2000), employers create job openings they would like to fill (V) and unemployed individuals (U) search among these job openings for employment. The process of matching unemployed workers to vacant jobs is represented by a production function, often assumed to be Cobb-Douglas in form, with vacancies and unemployment as the inputs and matches (hires) as the output:

$$H_t = m(V_t, U_t) = \mu V_t^{1-\alpha} U_t^{\alpha} \tag{1}$$

where H is hires, V is the number of job openings, U is the number of unemployed people, $t$ is the time period, $\mu$ is a potentially time varying matching efficiency parameter and $\alpha$ is a key elasticity of the matching function. In this framework, labor market tightness ($\theta$) typically is expressed as:

$$\theta_t = \frac{V_t}{U_t} \tag{2}$$

This relationship may be viewed through the lens of the job-finding rate, expressed as hires relative to the number of unemployed workers:

$$\frac{H_t}{U_t} = \mu \left( \frac{V_t}{U_t} \right)^{1-\alpha} = \mu (\theta_t)^{1-\alpha} \tag{3}$$

An alternative but equivalent approach is to view it through the lens of the job-filling rate, expressed as hires relative to the number of vacant jobs:

$$\frac{H_t}{V_t}=\mu\left(\frac{U_t}{V_t}\right)^{\alpha}=\mu\left(\frac{1}{\theta_t}\right)^{\alpha} \tag{4}$$

When the labor market is tighter ($\theta$ is larger), unemployed individuals have a greater chance of finding employment. Conversely, in a tighter labor market, employers have a smaller chance of recruiting an unemployed person to fill their vacant job.

In the case of a matching function with constant returns to scale, we can rewrite equation (1) as a relationship among the hiring rate $h$, vacancy rate $v$ and unemployment rate $u$:

$$h_t = m(v_t, u_t) = \mu v_t^{1-\alpha} u_t^{\alpha} \tag{5}$$

where $h$=H/E, $v$=V/E and $u$=U/E. An additional constraint is that, in steady state, the number of separations (inflows to unemployment) must equal the number of hires (outflows from unemployment). This steady state relationship can be expressed:

$$\delta_t = h_t = m(v_t, u_t) = \mu v_t^{1-\alpha} u_t^{\alpha} \tag{6}$$

where δ is the separation rate (in this case separations from employment into unemployment and the rate expressed as a fraction of employment) and the other terms are as previously defined.[2] The downward sloping relationship between the unemployment rate and the vacancy rate implied by equation (6) commonly is termed the Beveridge curve. Over the course of a business cycle, unemployment and vacancies will move inversely along the Beveridge curve. Shifts in $\delta$ or shifts in the matching function (i.e., shifts in $\mu$ ) will shift the position of the Beveridge curve. Improvements in the matching function (an increase in $\mu$ ), for example, will shift the Beveridge

[2] Nothing fundamental is changed if this expression is modified to allow for steady state growth at rate $g$ in desired employment, in which case the left hand side becomes $\delta+g$. Although the standard Beveridge curve specification writes both vacancies and unemployment relative to employment, as shown in equation (6), for comparison with the generalized Beveridge curve examined later, our empirical implementation works with vacancies and unemployment as a share of the population.

curve inwards (lowering unemployment for given vacancies), while deterioration in the matching function will shift the Beveridge curve outwards (raising unemployment for given vacancies).

The job creation curve (JCC) discussed in Daly et. al. (2012) pins down the economy's position along the Beveridge curve. The JCC is a core feature of the standard Diamond-Mortensen-Pissarides search and matching framework. The JCC reflects the equilibrium vacancy-to-unemployment ratio consistent with profit maximization by firms and utility maximization by workers taking into account search and matching frictions including the cost of posting vacancies. The JCC depends on aggregate demand, so that the vacancy-to-unemployment ratio rises in response to increases in aggregate demand, but also depends on the wage determination process.[3] Wages must be consistent both with firms achieving normal profits (i.e., zero economic profits) and with the outcome of bargaining between firms and workers taking into account workers' outside options. As articulated by Blanchard (2009), wage setting in this framework can be represented as:

$$\overline{w} = w(\frac{v_t}{u_t}, z) = w(\theta_t, z) \tag{7}$$

where $\overline{w}$ is the wage that is consistent with normal profits, $z$ is a vector representing the other factors that may affect the wage bargaining process, and other terms are as previously defined. Changes in labor market tightness $\theta$ will be associated with changes in workers' bargaining power—when $v_t/u_t$ is larger, employers will find it more difficult to fill their vacancies and, all else the same, the wage will be higher. The vector $z$ can be thought of as including anything else that affects workers' bargaining power, such as unionization, minimum wages, unemployment insurance benefits, and globalization, among other factors. Allowing prices to be sticky

[3] The JCC also depends on aggregate productivity.

introduces dynamic implications so that equation (7) can be recast as a Phillips-curve type equation. In this framework, $u$, $v$ and $w$ depend on $\delta$, $\mu$, $z$ and shifters of the JCC curve such as aggregate demand and productivity. We don't pursue the implications for wage and price dynamics of our generalization of the matching function here, but this would be an interesting area for future research.

While the search and matching framework has proven to be of enormous value for thinking about the labor market, the simple model just outlined omits many significant features of the real-world labor market. Our focus in this paper will be on rethinking the measurement of labor market tightness that underlies the simple model. As described in the model as just sketched out, $\theta_t = \frac{V_t}{U_t}$, but unemployment and vacancies are imperfect proxies for the measures of effective searchers and effective vacancies that we will argue should be the objects of interest. The simple model ignores heterogeneity among the unemployed; does not allow for job search among those who are out of the labor force or employed; and does not incorporate the possibility of temporal variation in either search intensity (on the part of those seeking work) or recruiting intensity (on the part of employers seeking to fill jobs). If the number of effective job seekers of each of the different types rose and fell in the same proportions over time, it would not be important to account for them separately, as in this case, any single measure such as the aggregate unemployment rate would capture the mirroring movements in all of the relevant series. As we will show, however, this is not the case, implying that the unemployment rate will give a biased picture of movements in the number of effective job seekers over time (Broersma and van Ours 1999, Sedlacek 2016).

We can elaborate the simple model to account for these complexities in real-world labor markets. Building on the standard hiring function, we can write:[4]

$$H_t = m(\rho_t^v V_t, \sum_i \rho_t^{s_i} S_{it}) = \mu\left(\rho_t^v V_t\right)^{1-\alpha}\left(\sum_i \rho_t^{s_i} S_{it}\right)^{\alpha} \tag{8}$$

where V again represents the number of job openings, $S_i$ represents the number of job searchers of type *i*, $\rho_t^v$ represents the intensity of employer recruiting effort at time *t*, and $\rho_t^{s_i}$ represents the intensity of job search on the part of searchers of type *i* at time *t*. In this expanded framework, labor market tightness can be written as:

$$\tilde{\theta}_t = \frac{\rho_t^v V_t}{\sum_i \rho_t^{s_i} S_{it}} \tag{9}$$

We will refer to the numerator of this expression as effective vacancies and the denominator as effective searchers.[5] This generalized measure of labor market tightness can be substituted into the equation for the job-filling rate (to produce a generalized version of equation (4)). The latter is given by:

$$\frac{H_t}{V_t} = \mu\left(\frac{1}{\tilde{\theta}_t}\right)^{\alpha} \rho_t^v \tag{10}$$

For the generalized model, the ratio between hires and unemployment is less naturally interpretable as a job-finding rate since not all hires come from among the unemployed. Formally, this ratio in the generalized model is given by:

$$H_t / U_t = \mu\left(\rho_t^v V_t\right)^{1-\alpha}\left(\sum_i \rho_t^{s_i} S_{it}\right)^{\alpha} / U_t = [\mu\left(V_t / U_t\right)^{1-\alpha}][(\rho_t^v)^{1-\alpha}(\left(\sum_i \rho_t^{s_i} S_{it}\right) / U_t)^{\alpha}] \tag{11}$$

[4] This formulation builds on specifications of generalized matching functions in Davis (2011) and DFH (2013).
[5] An even more general formulation would allow search intensity to vary by type of employer, as suggested by Gavazza, Mongey and Violante (2018), but we do not pursue that line of inquiry here.

The expression after the second equal sign in equation (11) highlights that, in the generalized model, the ratio of hires to unemployment depends not only on the ratio of vacancies to unemployment but also on time variation in recruiting intensity and on the evolution in the size of the pool of effective searchers relative to the number of unemployed people. While equation (11) can be used to characterize the ratio of hires to unemployed, what is of greater interest is the job-finding rate among the unemployed, i.e., the ratio of hires from among the unemployed to the starting stock of unemployment. We develop the implications of the generalized model for the job-finding rates of specific groups, such as the unemployed, in more detail below.

The steady state equilibrium of hires equal to separations is now given by:

$$\delta_t = h_t = m(\rho_t^v v_t, \sum_i \rho_t^{s_i} s_{it}) = \mu\left(\rho_t^v v_t\right)^{1-\alpha}\left(\sum_i \rho_t^{s_i} s_{it}\right)^{\alpha} \tag{12}$$

where separations are now all separations from employment and variables are rates expressed as fractions of the population. Over the course of a business cycle, absent changes in matching efficiency or other factors that shift the position of the generalized Beveridge curve, effective searchers and effective vacancies will move inversely as implied by equation (12).[6] In our empirical work, we exploit the differences between (4) and (10), between (3) and (11) and between (6) and (12). We also explore the implications of the standard versus the generalized model for the job-finding rate among the unemployed.

[6] Something we have not considered explicitly is the possibility of mismatch between vacant jobs and effective job seekers. Although commonly cited by business leader and policy officials as an important contributor to unemployment, especially during periods when the labor market is weak (Abraham 2015), available evidence suggests that mismatch plays at most a modest role in explaining aggregate unemployment fluctuations (Sahin et al. 2014, Crump et al. 2019). In our framework, we will think of mismatch as captured by $\mu$ and, in models that allow for time-varying relative search intensities, perhaps in the measured $\rho_t^{s_i}$.

## II. A Broader Perspective on Labor Market Tightness

A first step towards a more comprehensive treatment of effective searchers is to consider the potential role of heterogeneity among the unemployed. Further, a broader perspective should recognize effective searchers who are out of the labor force or already hold a job. Constructing an aggregate measure of effective searchers also requires a way to measure the search intensity of those in the effective searcher pool. In addition, we would like to allow for the possibility of temporal variation in the intensity of employers' recruiting efforts.

### *A. The Pool of Effective Searchers*

There is a lengthy literature that has examined how changes in the composition of the unemployed may affect the interpretation of the official unemployment rate. One strand of the literature, launched by the seminal work of Perry (1970) and further developed by Shimer (2001), Aaronson et al. (2015), and Barnichon and Mesters (2018), among others, focuses on the demographic composition of the unemployed. Another strand focuses on the relative numbers of long-term and short-term unemployed. It is well known that the long-term unemployed have lower job-finding rates than the short-term unemployed (see, e.g., Kaitz 1970, Krueger, Cramer and Cho 2014). Whether this is because of lower search intensity, loss of human capital, or employer unwillingness to hire the long-term unemployed (see e.g. Abraham et al. 2019), the long-term unemployed may contribute proportionately less than the short-term unemployed to the pool of effective searchers.

The route by which a person entered unemployment also may be important. As an example, the job-finding pattern among those laid off from a job differs considerably from the pattern for other groups among the unemployed (Katz 1986, Katz and Meyer 1990, Fujita and

Moscarini 2017). Relatedly, an unemployed individual's recent labor market history may help to predict how likely it is that she will find a job (Kudlyak and Lange (2018)).

A comprehensive measure of effective job searchers also needs to account for the potential labor supply of people who are outside of the labor force. The job-finding rate of those out of the labor force is much lower than that among the unemployed. Because there are so many of them, however, even a modest job-finding rate translates into a large number of job fillers. In a typical month, in fact, the number of people who enter employment directly from out of the labor force is much larger than the number entering directly from unemployment (see, e.g., Hornstein, Kudlyak and Lange 2014).

Similar to the unemployed, there is considerable heterogeneity among the out-of-the-labor-force population. While less likely than the unemployed to be employed the following month, people who are out of the labor force but say they want a job are much more likely to enter employment than the rest of the out-of-the-labor-force population (Jones and Riddell 1999, Hall and Schulhofer-Wohl 2018). The Richmond Fed Non-Employment Index counts as effective searchers not only two groups of unemployed job seekers, but also seven groups of people who are out of the labor force, three among those saying they want a job and four among those saying they do not want a job (Hornstein, Kudlyak and Lange 2014, Kudlyak 2017).

A final group to consider are employed searchers (Sedlacek 2016, Hall and Schulhofer-Wohl 2018). In the canonical search-and-matching model, vacancies include the job openings created by departing employees. Symmetrically, the measurement of effective searchers should take into account the on-the-job searchers who may fill those jobs. Available survey data suggest that on-the-job search is prevalent (see, e.g., Black 1980, Blau and Robins 1990 and Faberman et al. 2017). Consistent with the survey evidence, administrative data show that a large share of hires are people moving from one job to another (Haltiwanger, Hyatt and McEntarfer 2018, Haltiwanger et al. 2018).

B. *Job Search Intensity*

In addition to properly identifying those in the effective searcher population, measuring the volume of effective search activity also requires a measure of search intensity. Measures that do not allow for varying search intensity, such as the unemployment rate or the Bureau of Labor Statistics U6 measure, which adds the marginally attached and involuntary part-timers to the unemployed, implicit treat search intensity as constant across the included population and over time. Approaches used in the literature to account for job search intensity include directly measuring search activities, making use of information on the gap between individuals' desired and actual hours, and inferring relative search intensity from relative job-finding rates.

In an early example of the first approach, Shimer (2004) uses information from the CPS on the number of different search methods reported by the unemployed to proxy for their job search intensity. Deloach and Kurt (2013) and Gomme and Lkhagvasuren (2015) measure search intensity among the unemployed using American Time Use Survey (ATUS) data on time devoted to job search. ATUS data are available only beginning in 2003. Mukoyama, Patterson and Sahin (2018) use ATUS data together with information from the Current Population Survey (CPS) to construct a longer search intensity series for the unemployed. They model the relationship of search time to the search methods reported by the unemployed, then use that estimated relationship to construct a search intensity series using CPS data for the post-1993 period on the search methods of the unemployed. These studies using ATUS data reach conflicting conclusions about whether search intensity among the unemployed is procyclical or countercyclical. Ahn and Shao (2017) use ATUS data to study the cyclicality of job search among the employed. Because the ATUS does not ask what respondents are doing while they are at work, ATUS measures of job search among the employed seem especially likely to miss at least some job search activity. Faberman and Kudlyak (2016) use information on the job application behavior of the users of Snag-A-Job, an online job site. Applications on Snag-A-Job represent only one among many possible search channels, however, making it hard to know how to interpret these results.

Rather than measuring search activity directly, Faberman et al. (2019) use information on the gap between desired and actual hours to assess fluctuations in job search intensity. Data on the hours gap come from a module added to the 2013, 2014 and 2015 Survey of Consumer Expectations. The authors show that the gap between desired and actual hours reported by survey respondents is correlated with a measure of search intensity also collected in the module. Module data are used to calculate the average difference between desired and actual hours for each of 39 groups defined based on labor force status and demographic characteristics. Treating the gap in hours within each of the 39 groups as constant over time, the authors use this information to produce a measure of aggregate slack defined as the total gap between desired and actual hours divided by total desired hours.

Finally, job-finding rates have been used to proxy for job search intensity. The simplest version of this approach uses group-specific job-finding rates in some base period to weight the people in each group to produce an aggregate measure of effective searchers. The Richmond Fed's Nonemployment Index uses long-run average job-finding rates based on CPS data beginning in 1994 to aggregate its nine groups of effective searchers among the unemployed and those out of the labor force (Hornstein, Kudlyak and Lange 2014, Kudlyak 2017).

Seeking to capture variation in within-group search intensities over time, several studies have modeled the changes in relative job-finding rates for different groups of searchers. Veracierto (2011) develops a model in this vein with both the unemployed and nonparticipants as effective searchers. Hornstein and Kudlyak (2016) fit a similar model that considers three alternative characterizations of the job searcher pool, two consisting of different breakouts of the unemployed (by duration and by reason) and the third consisting of all nonemployed persons broken out into four groups (unemployed or out of the labor force by gender). Sedlacek (2016) considers three groups—unemployed, out of the labor force and employed—as sources of potential hires. Hall and Schulhofer-Wohl (2018) offer the most disaggregated characterization of the job searcher pool among these previous studies, considering sixteen groups of job seekers—thirteen groups among the unemployed and two among those out of the labor force plus the employed.

The basic strategy in all of these studies is, in effect, to infer what is happening to group-specific search intensities based on how having more or fewer people in any given group affects the number of matches. If adding people to a group makes a larger-than-expected contribution to the number of matches realized when the labor market is tight, for example, procyclicality in search intensity is a plausible explanation.[7] A limitation of this strategy is that cyclical variation in search intensity that is common across groups cannot be distinguished empirically from the elasticity of matching with respect to the (properly measured) ratio of vacancies to searchers in the standard matching function or the possible effects of common changes in matching efficiency. A modeler can hope to quantify changes in aggregate search intensity that result from

[7] Alternatively, the cross-group differences that are the basis for the suggested inference about job search intensity could be attributable to differences in the pattern of the shocks experienced by different groups of searchers. This is a less parsimonious explanation and it is not entirely apparent what the source of such shocks might be, though it cannot be ruled out.

changes in the relative sizes of groups with relatively procyclical or relatively countercyclical job finding rates. Changes in search intensity that are common across groups, however, may be more important than these relative changes and cannot be quantified using this approach.

### C. *Time-varying Employer Recruiting Intensity*

A final factor missing from the standard search-and-matching model is employer recruiting intensity. Empirical implementations of the standard model use data on the number of jobs that employers say they would like to fill. The intensity with which employers recruit to fill their vacant jobs can vary considerably, however, depending both on the company's own circumstances and on aggregate labor market conditions.

Recruiting intensity can take a number of different forms. The most literal interpretation of recruiting intensity is the time and effort devoted to advertising the firm's job openings, processing applications and so on, but other aspects of firms' recruiting behavior may be even more important. When the labor market tightens, employers may choose to consider job candidates with criminal records who previously would have been disqualified (see, e.g., Casselman 2018, Smialek 2019) or lower the levels of education and experience they require of job candidates. Other steps might include offering better working conditions or raising wages. We view all of these as changes in recruiting intensity, in the sense that employers who take such steps are trying harder to fill their vacant jobs.

Evidence on employer recruiting behavior and its temporal variation is in relatively short supply. Modestino, Shoag and Balance (2019) show that, controlling for occupation, the shares of online job advertisements stating a requirement for a college degree or for four-plus years of experience rose during the Great Recession. These changes were larger in states and occupations that experienced a larger increase in the supply of workers. In an analysis of establishment-level JOLTS data, DFH (2013) show that employers with a larger number of vacancies to fill experience considerably larger hiring rates than employers with fewer openings, holding constant the state of the aggregate labor market. They interpret this finding through the lens of recruiting intensity—that is, they infer that recruiting intensity is positively associated with the gross hiring rate. Later in the paper, we make use of the index of employer recruiting intensity constructed by applying the relationship between these two variables in the cross sectional data documented by DFH (2013) to changes in gross hiring over time.

## III. Creating a Measure of Labor Market Tightness Based on Effective Searchers and Effective Vacancies

Measures of effective searchers and effective vacancies are needed to produce a generalized measure of labor market tightness. In the framework we have adopted, a generalized measure constructed as the ratio of effective vacancies to effective searchers should do a better job of capturing the state of the labor market than the unadjusted ratio of vacancies to unemployment. Our objective, then, is to implement equation (9), the generalized measure of labor market tightness discussed earlier in the paper, and then to assess its performance as compared to the standard measure. As a part of this process, we examine the properties of the standard versus the generalized Beveridge curve. We use as our metrics for evaluating the performance of the generalized versus the standard measure of labor market tightness the success of each in explaining changes in the overall job-filling rate and changes in the job-finding rate among the unemployed over time.

To carry out this plan of work, we must first define a set of job searcher categories that do a good job of capturing the heterogeneity in search behavior across the population. Then, we need to construct measures of search intensity for each of these groups, allowing both for differences in the base level of search intensity across groups and ideally also for possible heterogeneity across groups in how search intensity evolves time. Finally, we need to construct a measure of employer recruiting intensity for translating the number of job vacancies into effective vacancies.

Our measures of effective searchers build on the analysis of Hall and Schulhofer-Wohl (2018) (HSW). Using CPS microdata to track flows across labor market states and from job to job, we quantify systematic variation in job-finding rates across 22 groups, including 13 groups among the unemployed, seven groups among those who are out of the labor force, and two groups among the employed. Among the unemployed, as in HSW, those out of work less than 5 weeks and those out of work 5-26 weeks are disaggregated by reason for unemployment (job leaver, permanent layoff, temporary layoff, temporary job ended, entrant, or re-entrant). Those reporting unemployment already having lasted 27 or more weeks constitute a thirteenth category. Among those who are out of the labor force but say they want a job, we distinguish among discouraged workers, others who have looked for work within the last 12 months but give a reason other than discouragement for not having searched recently, and anyone else who wants a job but has not searched within the last 12 months. Among those out of the labor force who say they do not want a job, we distinguish among those in school, the retired, the disabled and others. Finally, we disaggregate the employed into those working part time involuntarily and other employed persons.[8] As described below, we estimate job-finding rates for each of the 22 groups.

[8] Our 22 categories elaborate on the 16 used by HSW by disaggregating both the want-a-job and don't-want-a-job groups among those out of the labor force (adding five categories) and by distinguishing the involuntary part time

We interpret the cross-group variation in job-finding rates as variation in search intensity and use these estimates to measure the $\rho_t^{S_i}$ in equation (9).

We use a two-step procedure to construct the $\rho_t^{S_i}$. First, we generate estimates of job-finding rates for the 22 groups that control for changing demographics. Second, we use the resulting job-finding rate series to construct measures of relative job search intensities. Following HSW, we begin by estimating a logit using the CPS microdata motivated by the following specification:

$$f_{i,t,x} = \frac{\exp(\kappa_{i,t} + x'\beta_i)}{1 + \exp(\kappa_{i,t} + x'\beta_i)} \tag{13}$$

where $f_{i,t,x}$ is the job-finding rate in period $t$ for an individual in initial status $i$ with the characteristic bundle $x$. The $\kappa_{i,t}$ are group-specific time effects. The characteristics controlled for in $x$ are age (six age groups), gender, marital status and education (four education groups).[9] We estimate this relationship separately for each of the 22 groups using monthly CPS microdata for the period from 1994:1 through 2019:12. All of the estimates of job-finding rates we use in subsequent analysis hold demographic composition effects constant based on 2005-2007 population characteristics. Table 1 shows estimates of the predicted job-finding rates for 2006 and 2010 based on equation (13).[10] Average predicted job-finding rates differ substantially

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from other employed people (adding another category). The seven groups we define for people out of the labor force are the same as in the Richmond Fed's Nonemployment Index, but we allow for 13 groups among the unemployed rather than just two. The headline Richmond Fed Index also does not consider search among the employed. There are sizable differences in job-finding rates across the more detailed categories we use compared to those used in earlier studies.

[9] Following HSW we also include five more detailed duration group controls for all of the unemployed groups with 5-26 weeks of unemployment.

[10] To calculate the rates shown in Table 1, we use our estimates of equation (13) which yield predicted monthly values for each cell defined by $x$, $i$, and $t$. We aggregate these estimates using the 2005-07 base period demographic shares of $x$ to produce monthly values of job-finding rates for each searcher group $i$ in period $t$. Time variation in these job-finding rates is driven by the $\kappa_{i,t}$ estimates from the estimation of (13). For Table 1, we average those monthly values across the 12 months of the year to produce the estimates reported in the table for 2006 and 2010. For the 2010 estimates, after calculating the monthly values, we make a further adjustment before taking the annual

across the 22 groups, with those on temporary layoff having the highest rate and employed people other than the involuntary part-time the lowest rate. Involuntary part-time workers have a job-finding rate that is twice that of other employed people, though still relatively low compared to most of the other identified groups. Not surprisingly, average job-finding rates fell between 2006 and 2010 as the economy worsened following the onset of the Great Recession. Our primary interest, however, lies with the relative job-finding rates across the different groups. These are much more stable—the correlation in relative job-finding rates between 2006 and 2010 is 0.98.

Table 1 also reports relative job-finding rates for 2006 and 2010 calculated directly from the CPS microdata not controlling for changing demographics, shown in the column denoted "Rel. JFR (raw)." Although there is a conceptual basis for wanting to control for demographics, doing so in fact has very little effect on the estimated relative job-finding rates. Our main analysis uses the estimates derived from equation (13), but as discussed below, our results are robust to using the raw 2006 average relative job-finding rates instead. HSW note that controlling for demographics is not particularly important over their sample period and this carries over to our extended sample period. Two factors likely have contributed to the limited role we find for demographics. First, changes in demographics are less dramatic in our sample period than in some earlier periods. Second, differentiating among 22 groups means that we have implicitly controlled for considerable heterogeneity across the job searcher population, meaning that there is less left over for demographics to explain than otherwise would be the case.

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averages. Specifically, we adjust the job-finding rates for employed persons to correct for a problem identified by Fujita, Moscarini, and Postel-Vinay (2019) (FMPV). As they discuss, beginning in 2007:1, CPS interviewers stopped asking some proxy respondents whether currently employed household members for whom they were reporting were still working for the same employer as in the previous month. As FMPV show, this change in procedures created a downward bias in the estimated job-finding rates for the employed. FMPV provide monthly adjustment factors to correct for this bias and we incorporate their adjustment factors throughout our analysis for all months subsequent to 2007:1.

Intuitively, we build our measure of effective searchers by weighting each of the 22 groups by its relative job-finding rate. Our baseline estimates use the time-invariant 2006 relative job-finding rates shown in the third column of Table 1 to weight the number of people in the different groups. This approach has both advantages and disadvantages, and we also consider effective searcher estimates that incorporate changes search intensities over time. As already discussed, an issue with the latter is that we cannot distinguish variation in job-finding rates due to variation in search intensity that is common across groups from the effects of the inherent procyclicality in the matching function or changes in matching efficiency that also may be common across groups. For this reason, the estimation underlying our fully generalized effective search measure with time-varying search intensity captures only the *relative* variation in search intensity across groups. We return to this point below.

To produce the time-vary search intensity measure, we consider cross-group differences in the elasticity of job-finding rates with respect to vacancy duration, where longer vacancy duration is an indicator of tighter labor market conditions common to all groups. To be more specific, following HSW, we assume that, after adjusting for search intensity, all groups have a common job-finding rate that varies with vacancy duration:

$$\frac{H_t}{ES_t} = \frac{H_{it}}{ES_{it}} = \frac{H_{it}}{\rho_t^{S_i} S_{it}} = \tilde{f}_t = \tilde{f}_{it} = A_t T_t^{\eta} \tag{14}$$

where $T_t = \frac{V_t}{H_t}$ is average vacancy duration and the $A_t$ are any common time effects on job-finding rates not captured by vacancy duration.

It is important to emphasize that we are not imposing the same job-finding rate on all groups. Rather, the heterogeneity in job-finding rates is captured by the relative job search intensity measures $\rho_t^{S_i}$, with expected hires per group member lower for groups with lower $\rho_t^{S_i}$ values. To see this, define $A_t = \tilde{A}_t^{1+\eta}(\rho_t^v)^\eta$. Then with appropriate substitution we have:

$$H_t = \tilde{A}_t(\rho_t^v V_t)^{\eta/(1+\eta)}(\sum_i \rho_t^{S_i} S_i^t)^{1/(1+\eta)} \tag{15}$$

where $\alpha = 1/(1+\eta)$. Returning to the job-finding rate for group *i*, we can write:

$$\frac{H_{it}}{S_{it}} = f_{it} = \rho_t^{S_i} A_t T_t^\eta \tag{16}$$

In the empirical analysis below, we exploit equation (16) to consider the implications of the generalized versus the standard model for particular groups of interest, such as the unemployed.

Writing $\rho_t^{S_i} = \gamma_i T_t^{\eta_i}$ along with (16) implies a relationship between the job-finding rate and vacancy duration for each group *i*:

$$f_{it} = \gamma_i A_t (T_t)^{\eta+\eta_i} \tag{17}$$

Taking natural logs of (17) (and adding a group-specific time trend similar to HSW), we estimate the following relationship:

$$\log(f_{it}) = \log(\gamma_i) + \tilde{\eta}_i \log(T_t) + \tilde{\lambda}_i t + \varepsilon_{it} \tag{18}$$

where the dependent variable is the predicted average job-finding rate across individuals for initial status *i* in month *t* based on equation (13) and the right hand variables are vacancy duration and a time trend.[11] The dependent variable for equation (18) is available for the full sample period 1994:1 through 2019:12, but the Job Openings and Labor Turnover Survey

[11] This estimating equation is essentially the same as HSW equation (7), but without the second post-2008 trend they include. HSW consider estimation of job finding rates for different horizons, whereas we focus on job finding rates from one month to the next, which simplifies the analysis on a number of dimensions. When estimated using their sample period and 16 groups, our one-month-horizon job findings rates closely approximate the short span estimates in Table 6 of HSW. The estimates for our 22 groups and longer sample period differ from the HSW estimates, but we have found in unreported results that our main findings are robust to constructing the effective searchers measures using 16 groups along with the HSW short-span weights.

(JOLTS) data needed to construct $T_t$ are available only beginning in 2000:12. As such, we estimate equation (18) using the "gold standard" JOLTS data for the 2000:12 through 2019:12 period.[12]

Table 2 presents the estimates of $\tilde{\eta}_i$ and $\tilde{\lambda}_i$ based on equation (18). The estimated elasticity of the job-finding rate with respect to vacancy duration is positive for all groups, but there is considerable cross-group variation. Groups with especially procyclical job-finding rates include unemployed new entrants, the long-term unemployed, and individuals out of the labor force who want a job and searched within the last 12 months. Involuntary part-time workers also have job-finding rates that are more procyclical than average. All groups exhibit a declining trend in job-finding rates, but again there is considerable cross-group variation.

We use the estimates in Table 2 in two ways. First, even in our baseline approach using time-invariant relative search intensities, we need the estimated values of $\tilde{\eta}_i$ to construct an estimate of the elasticity of the matching function that we can use to test the performance of our generalized measure as compared to the standard measure for predicting job-filling and job-finding rates. Second, the estimates of $\tilde{\eta}_i$ and $\tilde{\lambda}_i$ are what we use to construct time-varying relative search intensities. We use the notation $\tilde{\eta}_i = \eta + \eta_i$ and $\tilde{\lambda}_i = \lambda + \lambda_i$ to distinguish between common and idiosyncratic components of the elasticity of job-finding rates with respect to vacancy duration and the time trend effect. As noted above, the common component of the

[12] In what follows, we will use the back-cast hires and vacancies series created by Davis, Faberman and Haltiwanger (2012) (DFH 2012) for the period from 1994:1 through 2000:11 to extend the period covered by our analysis of effective searchers and effective vacancies. In establishment-level data from the BLS Business Employment Dynamics (BED) program and the JOLTS, DFH (2012) found close relationships among job creation and job destruction in the BED and hires, separation and vacancies in the JOLTS. Based on these relationships, they produced back-cast estimates of the main JOLTS series. We use those back-cast estimates series to measure vacancy duration (V/H) in our analysis, splicing those estimates to estimates from the JOLTS starting in 2001, and to construct our measures of labor market tightness.

elasticity with respect to vacancy duration ( $\eta$ ) and the common component of the time trend ( $\lambda$ ) can be expected to capture factors in addition to variation in search intensities. The time-varying versions of the $\rho_t^{S_i}$ 's that we estimate incorporate only the idiosyncratic components of these effects (the $\eta_i$ and the $\lambda_i$). These are assumed to have mean zero on a base-period-population-weighted basis. Our most general estimate of job search intensity for the members of group *i* is thus $\rho_t^{S_i} = \gamma_i T_t^{\eta_i} e^{\lambda_i t}$.

We implement the time-varying measure of search intensity as follows. First, we use the estimates of average 2006 job-finding rates reported in Table 1 to generate our measures of $\gamma_i$. We normalize the reported job-finding rates so that, for the recently laid off unemployed, $\gamma_i = 1$ on average over the 12 months of 2006. The values of $\gamma_i$ for all of the other groups then are defined based on the ratio of their 2006 average job-finding rate to that for the recently laid off unemployed. We use the estimated elasticities with respect to vacancy duration shown in Table 2 to construct our measure of $\eta_i$. The elasticities reported in Table 2 are estimates of $\tilde{\eta}_i$; based on those values, we compute $\eta_i = \tilde{\eta}_i - \eta$ where $\eta$ is the (base period) population weighted average of the estimates from Table 2.[13] Similar remarks apply to the measurement of the idiosyncratic trend component $\lambda_i$. For the time-varying search intensity measures, all of the $T_t^{\eta_i}$ and $e^{\lambda_i t}$ are normalized to equal 1.0 on average over the 12 months of 2006.[14]

[13] The base period estimate of $\eta$ is 0.75, implying an elasticity of the generalized matching function of 0.57.
[14] As just laid out, our estimates with time-varying relative search intensities allow both for cyclical variation and for trend variation. In unreported results, we also consider the intermediate case with only cyclical variation in relative search intensities. These results are broadly similar to the two cases we report.

Figure 2 shows the standard measure of searchers (the unemployed) together with the two versions of our generalized searcher measure—one constructed using fixed relative search intensities and the second constructing using time-varying relative search intensities as just described. All three measures shown in the figure are ratios of searchers to the population age 16 and older normalized to equal 1.0 in 2006. The standard measure is much more cyclical than either generalized measure.[15]

One important reason for the greater cyclicality of the standard measure compared to the baseline generalized measure (the version with fixed relative job search intensities) is that the generalized measure counts more people as effective searchers. In the standard measure, any proportional increase in the number of unemployed people is *de facto* a proportional increase in the number of effective searchers. In the baseline version of the generalized measure, in contrast, the unemployed are only a fraction of all effective searchers and increases in unemployment thus mechanically have a smaller proportional effect on the aggregate number of effective searchers. In addition, in the baseline version of the generalized measure, even though the employed have lower relative search intensities than the unemployed, their search intensities are positive. This means that, during a downturn, reductions in the number of employed effective searchers partially offset increases in the number of effective searchers associated with rising unemployment.

The generalized measure that allows for time-varying relative search intensities is slightly less countercyclical than the baseline measure. In part, this reflects the fact that, in contractions, the unemployed are a rising share of effective searchers, but the relative search intensity of key groups, such as the long-term unemployed, is declining. Given that the behavior of the two

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[15] Figures A.1-A.3 show the shares of effective searchers for the generalized approach using the time invariant relative job search intensities.

effective search measures is so similar, however, in the interest of keeping the discussion to a manageable length, we focus on the effective searcher measures using constant relative job search intensities. Results for the time-varying relative search intensity case are reported in the appendix.

Focusing on the measures based on time-invariant relative job search intensities also has other advantages. One is that the time-invariant relative job search intensities are transparent and readily interpretable. Further, using the time invariant relative search intensities avoids the risk of unfairly advantaging the generalized matching function relative to the standard matching function for tracking time series variation in actual job filling and job-finding rates. The fact that even the measure based on time-varying job search intensities as proxied by time variation in job-finding rates used only the idiosyncratic portion of that variation should largely obviate such concerns in any case. Still, using the measure that assumes fixed relative search intensities avoids it altogether. In addition, the time invariant approach makes it more straightforward to construct alternative effective searcher measures that are more restrictive in the groups they incorporate than the fully generalized measure. Comparing these alternative measures to the fully generalized measure and assessing the alternative measures' relative performance provides useful insights into the importance of the various subgroups of effective searchers. A limitation of the time invariant approach is that there may be important variation in relative search intensities that we miss. Figure 2 suggests, however, that the amount of identifiable variation in relative job search intensities missed is not great, though as already discussed there may be common variation in job search intensities our approach simply cannot capture.

To provide further perspective, Figure 3 displays the standard measure of searchers (unemployment) along with several others that move in the direction of our fully generalized measure. The first of these alternative measures considers only the unemployed as effective searchers, but allows for changes in the composition of the unemployed across the 13 groups among the unemployed we have specified. The important difference between this measure and the standard measure is that the alternative measure assigns different weights to the different groups among the unemployed, whereas the standard measure weights all of them equally. The second alternative measure incorporates the three groups we specify among the people who are out of the labor force but say they want a job, for a total of 16 groups, and third adds the four groups specified among the remainder of those out of the labor force, for a total of 20 groups. Again, each group receives a weight in the construction of the corresponding effective searcher aggregate that reflects its relative 2006 job-finding rate. The fourth and final alternative effective searcher measure is our fully generalized measure that adds the two groups of employed people, thus allowing for a total of 22 effective searcher groups.

The alternative series shown in Figure 3 are highly correlated, but are distinctly different in their volatility. Allowing for heterogeneity among the unemployed yields a measure that is less cyclically volatile than the standard unemployment measure. Including, in turn, those who are out of the labor force but want a job, others who are out of the labor force, and finally the employed yields progressively less volatile measures. The standard deviations over the 1994-2019 period of the normalized series plotted in Figure 3 are reported in the first column of Table 3. Whereas unemployment as a share of the population, normalized to equal 1.0 in 2006, has a standard deviation of 0.34 over the 26-year period, the standard deviations of the alternative measures, also expressed as a share of the population and normalized to equal 1.0 in 2006, are progressively lower. The standard deviation of our fully generalized measure, calculated on a basis comparable to that of the unemployment measure, is just 0.06.

Another way to look at the alternative measures is to ask how the current level of effective searchers as a share of the population compares to the level at points of time in the past. Similar to the year 2019, the year 1999 came at the end of an extended expansion and thus offers one interesting point of comparison. The standard measure based on the count of unemployed people implies that the level of effective searchers as of December 2019 was substantially lower than at any other point in our sample including December 1999. In contrast, the December 2019 level of the fully generalized measure of effective searchers relative to the population was only slightly below its December 1999 level. Another interesting point of comparison is with the values for June 2009, the trough of the Great Recession. Whereas the standard measure shows effective searchers to have fallen by 65 percent between June 2009 and December 2019, the fully generalized series fell by just 23 percent.

Figure 4 compares our generalized measure of effective searchers with alternatives that have been proposed in the literature. The first is an index based on the Bureau of Labor Statistics' U6 measure of slackness. The BLS U6 measure counts the marginally attached and involuntary part-timers along with the unemployed, but weights all of them equally. The Richmond Fed Non-Employment index incorporates both the unemployed and those who are out of the labor force, weighting different groups within each category based on persistent differences in their average relative job-finding rates. The Richmond Fed index is constructed using the same out-of-the-labor force groups as our generalized measure, but distinguishes only between the short-term and long-term unemployed as opposed to the 13 groups used for our generalized measures and does not incorporate search among the employed.[16] For consistency

[16] There is a version of the Richmond Fed index that allows for search among people working part-time for economic reasons but not among the remainder of the employed.

with our effective searcher measure, both the U6 index and the Richmond Fed index are normalized by the population age 16 years and older.

Figure 4 shows that the U6-based index has about the same volatility as the standard measure. The cyclical variation in the Richmond Fed index is proportionally less than that of the standard measure but greater than that of our generalized index of effective searchers. Table 3 reports summary statistics for both the U6 index and the Richmond Fed index. Consistent with the visual impression conveyed by Figure 4, over the 1994-2019 period as a whole, the U6 index has roughly the same volatility as the standard unemployment index. The volatility of the Richmond Fed index lies between that of the standard measure and our generalized measure.

As already mentioned, in constructing our generalized measures of effective searchers, we have used estimated job-finding rates based on equation (13) holding demographics constant. We also have constructed similar measures using the simple average 2006 job-finding rates for the 22 groups. Comparing these measures, shown in Figure A.6, to those in Figure 3 suggests that controlling for demographics is relatively unimportant, though this is not something that necessarily would have been obvious in advance. As noted above, in addition to demographic changes having been less dramatic over our period than in prior decades, distinguishing among 22 different groups itself controls for a substantial amount of worker heterogeneity. As a further sensitivity analysis, we also have asked how much we buy ourselves by breaking the unemployed into 13 different groups, as opposed to distinguishing just between the short-term and the long-term unemployed. Measures constructed using the latter approach are shown in Appendix Figure A.8. They look broadly similar to the results based on the more disaggregated approach shown in Figure 3. Later in the paper, we consider the performance of the job searcher measures based on each of these alternative approaches in explaining job-filling and job-finding rates.

We now turn to our generalized measure of effective vacancies, which rests on the analysis of DFH(2013). As described previously, the DFH (2013) measure of recruiting intensity makes use of the strong relationship between the number of vacancies firms are seeking to fill and the gross hiring rate, holding aggregate labor market conditions constant. Figure 5 depicts the DFH (2013) index of recruiting intensity, which like the various measures of search intensity used to construct our alternative measures of effective searchers has been normalized to 1.0 in 2006.[17] This measure is highly procyclical. Figure 6 shows how accounting for recruiting intensity affects the measure of effective vacancies. Actual vacancies are procyclical, but because effective vacancies also incorporate the effects of procyclical recruiting intensity, they decline more than actual vacancies in the Great Recession and increase more than actual vacancies in the recovery. Reflecting the positive relationship between recruiting intensity and hiring rates, effective vacancies are higher than actual vacancies in the robust labor market of the 1990s, though we caveat this finding with the caution that it rests on back-cast series for the pre-2001 period. In appendix Figure A.4, we show that actual and effective vacancies for the pre-2001 period are quite similar if we use the Barnichon (2010) estimated vacancy series based on help-wanted advertising instead of the backcast DFH (2012) vacancy series.

We are now ready to put the pieces together and look at how our generalized measures of labor market tightness compare to the standard vacancy-to-unemployment ratio. Figure 7 plots several generalized measures and the standard measure. The numerator for all of the generalized

[17] The series in Figures 6 and 7 use back-casted JOLTS hires and vacancies from DFH (2012) for 1994:1 to 2000:11 spliced with the actual JOLTS hires and vacancy data to compute the recruiting intensity index, effective vacancies and actual vacancies.

measures is effective vacancies, i.e., vacancies adjusted based on our measure of recruiting intensity. The denominators of the various measures incorporate successively more encompassing pools of effective searchers, in each case with the subgroups we have defined weighted in accord with their relative search intensities. The first generalized labor market tightness measure shown in Figure 7 considers only the unemployed as effective searchers, while allowing for changes in the composition of the unemployed. The second generalized tightness measure incorporates people who are out of the labor force but say they want a job and the third adds the remainder of those out of the labor force. The final fully generalized tightness measure also treats the employed as effective searchers. Once again, for ease of comparison, all of the measures in Figure 7 have been normalized to equal 1.0 on average in 2006.

All of the generalized tightness measures displayed in Figure 7 are less cyclical than the standard tightness measure—they fell less steeply during the Great Recession and subsequently have risen less. The December 2019 value of the generalized measure incorporating only unemployed searchers is not very different from the value of the standard measure, but each of the other measures is lower, implying that the labor market was not as tight at that point as implied by the standard measure. To put this into context, the December 2019 value of the standard labor market tightness measure is almost 30 percent higher than in December 1999. In contrast, the fully generalized measure is about the same in December 2019 and December 1999 (the latter is 1 percent higher). In short, our generalized measures suggest a significantly different evolution of labor market tightness than the standard measure. [18]

[18] In unreported results, we find that the patterns for the generalized measures of tightness are robust to using the relative search intensities constructed directly from (raw) relative job finding rates, to collapsing the unemployed into two groups (short-term and long-term) rather than 13 groups, and to using the Barnichon (2010) vacancies before 2001.

## IV. Beveridge Curve

A closely related but distinct way to look at the properties of the effective versus standard measures of searchers and job openings is through the lens of the Beveridge curve. Figure 8 displays the standard Beveridge curve using monthly data on vacancies and unemployment from 1994:1 to 2019:12. For this purpose, we use the normalized unemployment series from Figure 2 and the normalized job vacancy series from Figure 6. Note that the values of these series are defined relative to their 2006 average values. Plotting these series against one another makes clear their inverse relationship. In addition to the familiar downward sloping relationship between vacancies and unemployment, the figure also shows the substantial outward shift in that relationship during the long, slow recovery from the Great Recession. As an illustration, consider November 2004, the month three years after the trough of the 2001 recession, as compared to June 2012, the month three years after the trough of the Great Recession. Job openings are slightly higher in June 2012 than in November 2004 (by about 7 percent) but unemployment is much higher (by about 46 percent). The marked increase in unemployment compared to that associated in the past with a similar level of vacancies led many to speculate that, following the Great Recession, there had been an increase in mismatch or decline in matching efficiency in the labor market.

Figure 9 depicts the generalized Beveridge curve using effective vacancies and effective searchers, based on the constant job-finding rate version of the latter, again using the series from Figures 2 and 6 that have been normalized so the values plotted all are relative to their 2006 averages. There are some notable differences between the generalized curve shown in Figure 9 and the standard Beveridge curve shown in Figure 8. First, the generalized Beveridge curve is much steeper than the standard version. As noted previously in the context of discussing Figures

2 and 3, the proportional variation in effective searchers over time is much smaller than the proportional variation in unemployment. This translates into a normalized Beveridge curve that spans a much shorter distance along the normalized effective searcher axis than does the standard Beveridge curve. The generalized Beveridge curve also is much more stable than the standard curve during the period following the Great Recession. Consider again the comparison between November 2004 and June 2012. Effective vacancies are slightly lower in June 2012 compared to November 2004 (about 6 percent lower) and effective searchers are only slightly higher (about 10 percent higher).

Table 4 presents estimates of the intercept and the slope of the Beveridge curve obtained from a descriptive regression of vacancies on unemployment using the data plotted in Figure 8 (shown in the top row) and from a descriptive regression of effective vacancies on effective searchers using the data plotted in Figure 9 (shown in the fifth row). In addition to the estimates using the fully generalized measures of effective searchers, Table 4 also reports the results of several intermediate generalized Beveridge curve equations, all using effective vacancies but varying the construction of effective searchers. The effective searcher measure used in the first of these intermediate equations differs from the standard equation only in allowing for heterogeneity among the unemployed; the next adds those out of the labor force who want a job; and the third adds the remaining people who are out of the labor force. Consistent with Figure 8, the slope of the standard Beveridge curve is well below one in absolute value, reflecting the much greater proportional variation in unemployment than in job openings. In contrast, consistent with Figure 9, the slope of the descriptive regression using the fully generalized measure is much larger than one in absolute value, reflecting the much greater proportional variation in effective vacancies than in effective searchers. Not surprisingly, the slope coefficients estimated using the intermediate versions of effective searchers lie between these two extremes.

Also included in Table 4 are estimates for Beveridge curve using alternative measures such as the those underlying U6 and the Richmond Fed index as effective searchers. For the latter two measures, the standard measure of vacancies is used. The slope of the Beveridge curve using the U6 measure is similar to that for the standard unemployment measure. The slope using the Richmond Fed index lies between that for the standard and the fully generalized measures, similar that for our measures with intermediate versions of effective searchers.

## V. Implications of Generalized Labor Market Tightness Measure

We have argued that the generalized measure of labor market tightness should be preferred conceptually to the standard measure, but would like to have evidence that it actually does a better job of explaining labor market outcomes. To evaluate the alternative measures, we return to the standard matching function of equation (1) and the generalized matching function of equation (8), and ask how well each performs in tracking actual job-filling and job-finding rates. As discussed above, the details of the implications of the two matching functions for job-filling and job-finding rates are somewhat different and we analyze each in turn. Examining both job-filling and job-finding rates yields independent insights about the relative performance of the generalized versus the standard approach.

## A. *Actual versus Model-based Patterns in the Job-filling Rate*

Both the standard and the generalized matching function have predictions about the evolution of the job-filling rate (H/V) as illustrated in equations (4) and (10).[19] Because the left hand sides of equations (4) and (10) are the same and are based on data that are readily available, we can compare the performance of the predictions for the job-filling rate obtained using the standard and the generalized matching functions, respectively.

In addition to the vacancy (effective vacancy) and unemployment (effective searcher) measures appearing in equations (4) and (10), the predicted job-filling rate also depends on the elasticity of the matching function. For the prediction of the job-filling rate based on the general model, we use our empirical estimate of $\eta$ of 0.75 and note that $\alpha = 1/(1+\eta)$, which gives us an estimated $\alpha$ equal to 0.57. For the standard model, we estimate equation (18) for the pooled unemployed and obtain an estimate for $\eta$ of 1.04, implying a value for $\alpha$ of 0.49. For the U6 measure, we estimate equation (18) for the pooled U6 group and obtain $\alpha = 0.48$ ($\eta = 1.1$).[20] The Richmond Fed Non-Employment Index is constructed similarly to our measure of effective searchers, but as explained earlier using nine rather than 22 groups. We estimate equation (18) for each of the groups used in constructing the Richmond Fed index and obtain a population-weighted estimated based on those nine groups of $\alpha = 0.60$, slightly higher than the $\alpha$=0.57 for

[19] In recognition of some time-aggregation issues related to the flow of hires over the month relative to initial vacancies, DFH (2013) refer to the ratio H/V as the vacancy yield rather than the job-filling rate. They provide a method for adjusting the H/V measure so that it is a true job-filling rate. The exercise DFH (2013) conduct to evaluate their recruiting intensity measure as an input into the measurement of labor market tightness is similar in spirit to the exercises we report below for evaluating our more fully generalized labor market tightness measures. The two approaches are closely aligned in that both examine the relationship between H/V and predicted H/V.

[20] We generate the elasticity estimates for the pooled unemployed and pooled U6 in the same way as the estimate of the elasticity for any given group of searchers in the generalized approach. That is, we control for demographics by first estimating equation (13) for each of these pooled groups, respectively. This yields estimates of the job finding rates for each of the groups that abstract from changes in demographic composition. These are used to estimate equation (18). The standard error of $\eta$ is 0.05 for both estimates.

our estimate based on 22 groups. The fact that it is slightly higher is not surprising. The Richmond Fed index excludes the employed and, as can be seen in Table 2, they have an above-average η, which translates into a lower value for the 22-group α. All of these estimates are reasonably similar and well within the middle of the range of estimates in the matching function literature (Petrongolo and Pissarides 2001). We show below that all of our main results are broadly unchanged if we apply a common value of the matching function elasticity within the range of the separate estimates to calculate predicted job-filling rates.[21]

Figure 10 presents the actual and predicted job-filling rates from (4) and (10) using the standard measure, our generalized measure, the U6 measure and the Richmond Fed measure. Once again, all series have been normalized to average 1.0 in 2006.[22] The predicted job-filling rate based on equation (10) and our generalized measure tracks the actual job-filling rate much more closely than the predicted job-filling rate based on equation (4) and the standard measure. The U6 index performs no better than the standard labor market tightness measure. The Richmond Fed Non-Employment Index performs substantially better than the standard measure, but not nearly so well as our generalized measure.

To quantify the improvements in performance, panel A of Table 5 reports the root mean-squared error (RMSE) of the predicted job-filling rates as compared to the actual rates based on the different labor market tightness measures. The generalized measure produces a RMSE that is only about 38 percent as large as the RMSE produced using the standard measure. For comparison purposes, we also show the RMSEs for the U6 and the Richmond Fed indexes. The

[21] Davis (2011) and DFH (2013) use $\alpha = 0.5$ evaluating job-filling and job-finding rates using alternative measures of searchers and vacancies.

[22] The model specific normalization for the predicted job filling rates implies that we are permitting the mean matching efficiency for each model to be different. Moreover, the mean is permitted to vary in such a way that the predicted job-filling rate is equal to the actual job-filling rate on average in 2006.

RMSE for the U6 index is identical to that for the standard measure; the RMSE for the Richmond Fed index is intermediate between those for the standard and the generalized model.

To help with understanding the factors underlying the improvement in performance of the generalized tightness measure compared to the standard tightness measure, Figures 11 and 12 present predicted job-filling rates using different versions of the generalized measure that incorporate the differences between it and the standard measure in stages. For these figures and the associated analysis, we use the same matching function elasticity of $\alpha = 0.57$ for all of the counterfactual measures and for the standard measure. This allows us to quantify the relative gains associated with each of the ways in which our generalized measure differs from the standard measure. In essence, we are exploring how the variation in Figures 3 and 6 translates into variation in predicted job-filling rates for a given elasticity of the matching function. Panel B of Table 5 reports the RMSE's in the predicted job-filling rate using each of the different versions of the generalized tightness measure. We find that each step taken in moving from the standard measure to the fully generalized tightness measure contributes to the improvement in performance. Accounting for variation in recruiting intensity, which directly affects the vacancy yield, reduces the RMSE in the predicted job-filling rate by about 20 percent.[23] Without making any recruiting intensity adjustment, allowing for heterogeneity among the unemployed also reduces the RMSE by about 20 percent. Making both changes together reduces the RMSE by almost 40 percent. We gain another 5 percent by including in the pool of effective searchers those out of the labor force who want a job, another 20 percent by including the remaining

[23] DFH (2013) report that they account for about 30 percent of the gap between the standard and actual job filling rate that opens up between 2007 and 2009 using a generalized matching approach that incorporates variation in recruiting intensity. They use a matching elasticity of 0.5 and the unemployed as the measure of searchers for both their standard and generalized approach. In unreported results, we have found that we can replicate the findings they report in their Figure 1 for the 2001-2011 period with our data.

people who are out of the labor force, and another 8 percent by including the employed. Appropriate caution should be used in interpreting these figures, as the numbers we have reported are not an exact decomposition, but they do provide useful guidance with respect to which features of our generalized measure account for its better performance.

We have also explored a number of additional sensitivity checks that we summarize briefly here; details are shown in the appendix. First, we replicate the analysis of job-filling rates using simple averages of the direct (raw) relative job-finding rates from Table 1 rather than the relative job-finding rates based on equation (18) that abstract from demographics. We also replicate the findings with a generalized measure that breaks the unemployed into just two groups, the short-term and the long-term unemployed, rather than 13 more disaggregated groups. In both cases, the results are very similar to those we have just reported (see Figure A.7 and Figure A.9).

In addition, we have replicated the job-filling-rate analysis using the Barnichon (2010) vacancy estimates based on help-wanted advertising for the 1994:1-2000:12 period in place of the series based on the methodology described by DFH (2012). Again, the results are broadly similar (see Figure A.5), though over the 1994:1-2000:12 period for which we are forced to use projected vacancies, the generalized measure using the DFH(2012) methodology performs better in predicting the job-filling rate than the Barnichon (2010) series. Over that period, the RMSE using the DFH series is 40 percent of the standard while the RMSE using the Barnichon series is 79 percent of the standard.

*B. Actual versus Model Based Patterns in the Job-finding rate*

We now turn to investigating the performance of the generalized versus standard matching function for tracking job-finding rates. As discussed in section I, H/U is the conceptual job-finding rate in the standard approach but not in the general approach given that hires may be drawn from groups outside of the unemployed. While equation (11) shows that the general matching function has predictions for H/U, it is not clear this is an especially interesting moment to target.[24] Instead, in this section we use the BLS Gross Flows data, which allows us to measure the flow of individuals each month from unemployment (U) into employment (E), to construct a measure of the job-finding rate for the unemployed. More specifically, we measure the job-finding rate of the unemployed as the month-over-month UE flow from the Gross Flows data divided by the stock of the unemployed in the initial month. Then we examine how well the different approaches perform in predicting that job-finding rate.

Equation (16) can be used to quantify the predicted job-finding rate for the unemployed using the generalized model. Using the 13 unemployment groups and equation (16), we have:

$$\frac{H_{ut}}{U_t} = \frac{H_{ut}}{S_{ut}} = \tilde{A}_t^{1+\eta} (\rho_t^v)^\eta (V_t / H_t)^\eta \sum_{i \in u} (S_{it} / S_{ut}) \rho_t^{S_i} \tag{19}$$

The left-hand side of equation (19) is the ratio of hires from the unemployed to unemployment—that is, the empirical job-finding rate for the unemployed. The right-hand side of (19) is the model-based prediction for this job-finding rate from the generalized model. The standard model is just a special case of (19) with recruiting intensity equal to 1.0 and all of the relative job search intensities for the unemployed also equal to 1.0 (and the relative search intensities for those not unemployed equal to zero). In other words, the standard model implies:

[24] While H/U (inclusive of all hires in JOLTS) is less easy to interpret in the general model than in the standard model, we show in Figure A.10 of the appendix that the general model tracks it more closely.

$$\frac{H_{ut}}{S_{ut}} = \tilde{A}_t^{1+\eta}(V_t / H_t)^{\eta} \tag{20}$$

Figure 13 shows the actual and predicted job-finding rates for the unemployed for the generalized and standard matching functions based on using equations (19) and (20), respectively. As with our analysis of job-filling rates, we normalize both the actual and the predicted series to be equal to 1.0 in 2006.[25] The actual job-finding rate is highly procyclical and falls especially sharply in the Great Recession. Both the generalized and the standard matching function track the job-finding rate among the unemployed reasonably well during the period prior to the Great Recession, though the generalized matching function performs somewhat better over that period. The generalized matching function tracks the sharp decline in the job-finding rate among the unemployed during the Great Recession quite closely, while the standard model yields a much more modest predicted decline.

Panel C quantifies the improvement in performance in the prediction of the job-finding rate for the unemployed from using the generalized rather than the standard matching function. The RMSE of the generalized prediction of the job-finding rate from unemployment is 54 percent of the RMSE for the standard prediction. Using $\alpha = 0.57$ (the elasticity for the generalized matching function), Panel C shows that the RMSE of the standard prediction is only 85 percent of the RMSE when using $\alpha = 0.49$. There is an important implication here about the relative performance of the standard model and its sensitivity to the matching function elasticity. Comparing Figure 10 to Figure 13, the standard model yields too much volatility in the job-filling rate relative to the actual and too little volatility in the job-finding rate of the unemployed

[25] As before, this implies that we are permitting the mean matching efficiency to differ across the standard and generalized models in such a way that both yield values in 2006 with mean equal to 1.0. The prediction error can be interpreted as specification error and/or unmeasured variation in matching efficiency.

relative to the actual. Increasing $\alpha$ from 0.49 to 0.57 worsens the relative performance of the standard model for predicting the job-filling rate (compare results in panels A and B of Table 5) but improves its relative importance for predicting the job-finding rate among the unemployed. Conversely, decreasing $\alpha$ from 0.57 to 0.49 yields an improvement in the performance of the standard model for predicting the job-filling rate but a worsening of the performance of the standard model for predicting the job-finding rate among the unemployed. The implication is the relatively poor performance of the standard model cannot be rescued with an alternative estimate of the matching function elasticity.

As we have already noted by comparing Figure 3 and Figure A.8, the time series patterns for effective searchers are quite similar whether we use 13 unemployed groups or collapse to two groups for the unemployed. Figure 14 repeats the same exercise as in Figure 13 but using just two unemployment groups for effective searchers—short-term unemployed and long term unemployed but keeping the 9 groups for those not unemployed. The patterns in Figure 14 closely mimic those in Figure 13. There is only a modest reduction in performance of the generalized model using this approach. The RMSE for the generalized model with only two unemployment groups is about 55 percent of the RMSE for the standard model, as compared to 54 percent for the fully general model.

While the generalized matching function strongly outperforms the standard matching function, there is a widening gap between the actual and predicted job-finding rate for the unemployed using the generalized matching function in the recovery from the Great Recession. Although there is an even larger widening gap for the standard model, it nonetheless would appear that something outside the scope of the generalized model has contributed to the job-finding rate of the unemployed recovering more sluggishly than would have been anticipated in the post-Great Recession period. We did not observe this widening gap for the job-filling rate but this is an apples-to-oranges comparison. The job-filling rate reflects hires from all groups relative to vacancies. In contrast, the job-finding rate for the unemployed we are targeting reflects hires only from the unemployed relative to the overall unemployed.

## VI. Conclusions and Next Steps

The generalized measure of labor market tightness we have constructed based on the ratio of effective vacancies to effective searchers suggests that the U.S. labor market was considerably less tight at the end of 2019 than implied by the standard ratio of vacancies to unemployment. The differing behavior of the two measures reflects the fact that the standard tightness measure does not account for important variation in search behavior on the part of both firms and workers. The best available evidence suggests that employer recruiting intensity was considerably lower at the end of 2019 than it had been in the late 1990s and early 2000s, implying a relatively lower level of labor market tightness during the later period than would have been estimated without making that adjustment. Job searchers include not only the unemployed but also those who are out of the labor force and the employed. In downturns, a more general index of effective searchers rises proportionally less than unemployment. The unemployed are only about 30 percent of all effective searchers, so that, all else the same, any percentage increase in unemployment has a proportionally smaller effect on the overall number of effective searchers. In addition, when the number of unemployed searchers rises, there is a partially offsetting decline in effective search among the employed as their numbers fall. Likewise, in booms the more general index of effective searchers does not decline as much as implied by the decline in unemployment. Even among the unemployed, there are differences in job search intensities across groups defined by duration and, to some extent, reason for unemployment, implying that just counting up their numbers will not adequately capture effective search among the unemployed. The Beveridge curve constructed using effective vacancies and effective searchers is much more stable than the standard Beveridge curve.

The generalized measure of labor market tightness we have constructed dramatically outperforms the standard measure via the lens of the matching function for hires. Specifically, the predicted job-filling rate (hires per vacancy) using the generalized measure tracks the actual job-filling rate much more closely than the job-filling rate predicted using the standard measure of labor market tightness. In addition, the generalized measure also outperforms the standard measure in predicting the job-finding rate among the unemployed.

The prototype measure we construct in this paper builds on a number of recent papers that have advocated for broader measures of labor utilization and labor market tightness. The closest antecedent to the measure of effective searchers we have constructed is the Non-Employment Index produced by the Richmond Federal Reserve Bank. The most significant difference between the two measures is that our effective searcher measure takes into account search and job-finding activity among the employed, whereas the headline Richmond Fed index makes use of information only for the non-employed. An important reason vacancies rise in booms is that job-to-job flows create more job openings. To understand what is happening to labor market tightness, the job search behavior of potential job changers also needs to be considered.

The measure of labor market tightness we have constructed undoubtedly could be improved and built upon. Its strong performance relative to the alternatives argues for its further development. We have several thoughts about next steps for this research agenda. One practical step that we suggest be taken sooner rather than later is to begin regular production of an index of effective searchers that incorporates fixed weighting factors constructed to capture differences in search intensity across groups. This index ideally would capture not only unemployed searchers and searchers who are out of the labor force, but also employed searchers. If a consensus can be reached about how to do this, producing such a measure on a regular basis should be relatively straightforward. It would require only weighting factors constructed using base period job-finding rates, which can be estimated using linked CPS microdata, and estimates of the number of people in each of the groups from the monthly CPS.

A generalized index of labor market tightness constructed assuming constant within-group relative search intensity likely will miss some important variation in effective search activity but is a conservative and transparent improvement over using either the standard measure of tightness based on unemployment or a measure such as the U6 index described earlier in the paper. Our finding that temporal variation in relative job search intensities contributes only modestly to the performance of the prototype generalized tightness measure leads us to believe that the first step we are suggesting would be not only practical but also informative.

That said, we readily acknowledge that, beyond agreeing on the best disaggregation of job searchers to use for the construction of a generalized measure of labor market tightness, considerable further research and development still is needed. First, the indirect approach used in our prototype uses observed job-finding rates to develop weighting factors for the different groups of searchers. As discussed in section II, there is a growing literature on the measurement and analysis of direct measures of job search behavior. Reconciling the indirect and direct approaches to the measurement of search intensity should be an active area of research. The same comment applies to the measurement of employer recruiting intensity. Second, the measure we have developed abstracts from the impact of changing demographics on labor market tightness. More fully exploring how changing demographics affect effective search and thus the type of generalized measure we advocate is another area for future research.

We do not in any way mean to suggest that the Bureau of Labor Statistics should stop producing statistics on unemployment. Unemployment can be devastating for those who experience it and that in itself is an important reason to monitor the unemployed population. Moreover, even purely from the perspective of assessing the tightness of the labor market, the unemployed are quite different in their search behavior from the employed and those out of the labor force. To implement our generalized approach, information will be needed not only on the size of the total pool of unemployment but also on unemployment decomposed by duration, reason for unemployment and perhaps other factors as well. Similar to other papers in the recent literature, however, we are arguing that the unemployment rate and the unemployment gap are not sufficient statistics for assessing the state of the labor market.

Another potentially important extension is to consider heterogeneity in recruiting intensity across employers. We have focused on heterogeneity for searchers but evidence from DFH (2013), Gavazza, Mongey and Violante (2018), and Mongey and Violante (2019) suggest that there would be value in accounting for heterogeneity in recruiting intensity technologies by sector and other firm characteristics. The Mongey and Violante (2019) analysis also suggests an alternative way to extract information from the data about time series variation in aggregate recruiting intensity. Our results suggest a larger contribution of taking effective searchers into account relative to incorporating effective vacancies in the generalized matching function, but this may be at least in part a reflection of reflect our more limited analysis of the variation in search intensity of employers.

A related area of inquiry is to consider the implications of generalized labor market tightness for wage and price pressures. It would be interesting to explore the estimation of Phillips-curve-type relationships using labor market tightness rather than the unemployment rate gap as the central explanatory variable. Even if it is true that labor market tightness is a better predictor of wage and price changes than the unemployment rate, however, there are other sources of instability in the Phillips curve relationship that seem likely to pose problems for the estimation of such relationships. Still, given that estimating and interpreting Phillips curves is an active area of research and relevant for policymakers, exploring the role of generalized labor market tightness measures in this context is of considerable interest.

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Table 1: Estimated Relative Job Finding Rate

| | Share | JFR | Rel. JFR | Rel. JFR (Raw) |
|---|---|---|---|---|
| | | **2006** | | |
| Unemployed: Recently Left Job | 0.16 | 39.46 | 0.71 | 0.61 |
| Unemployed: Recently Permanently Laid Off | 0.21 | 32.80 | 0.59 | 0.52 |
| Unemployed: Recently Temporarily Laid Off | 0.23 | 55.22 | 1.00 | 1.00 |
| Unemployed: Temp. Job Recently Ended | 0.12 | 38.63 | 0.70 | 0.60 |
| Unemployed: Recently Newly Entered | 0.11 | 21.26 | 0.38 | 0.33 |
| Unemployed: Recently Re-Entered | 0.34 | 29.89 | 0.54 | 0.46 |
| Unemployed: Left Job Months Ago | 0.15 | 27.86 | 0.50 | 0.43 |
| Unemployed: Permanently Laid Off Months Ago | 0.36 | 21.19 | 0.38 | 0.33 |
| Unemployed: Temporarily Laid Off for Months | 0.16 | 44.28 | 0.80 | 0.69 |
| Unemployed: Temp. Job Ended Months Ago | 0.13 | 26.03 | 0.47 | 0.40 |
| Unemployed: Newly Entered Months Ago | 0.12 | 14.75 | 0.27 | 0.23 |
| Unemployed: Re-Entered Months Ago | 0.45 | 23.44 | 0.42 | 0.37 |
| Unemployed: Long-Term Unemployed | 0.43 | 17.41 | 0.32 | 0.27 |
| Want Job: Discouraged | 0.15 | 14.74 | 0.27 | 0.23 |
| Want Job: Looked Last 12 Months | 0.43 | 14.24 | 0.26 | 0.22 |
| Want Job: Other | 1.24 | 15.26 | 0.28 | 0.24 |
| Not in Labor Force: In School | 4.34 | 9.41 | 0.17 | 0.15 |
| Not in Labor Force: Retired | 15.51 | 1.56 | 0.03 | 0.02 |
| Not in Labor Force: Disabled | 4.67 | 1.96 | 0.04 | 0.03 |
| Not in Labor Force: Other | 7.44 | 8.87 | 0.16 | 0.14 |
| Employed: Involuntary Part-Time | 1.79 | 5.12 | 0.09 | 0.08 |
| Employed: Not Involuntary Part-Time | 61.44 | 2.22 | 0.04 | 0.03 |
| | | **2010** | | |
| Unemployed: Recently Left Job | 0.09 | 27.81 | 0.54 | 0.48 |
| Unemployed: Recently Permanently Laid Off | 0.29 | 23.12 | 0.45 | 0.38 |
| Unemployed: Recently Temporarily Laid Off | 0.28 | 51.80 | 1.00 | 1.00 |
| Unemployed: Temp. Job Recently Ended | 0.13 | 32.88 | 0.63 | 0.56 |
| Unemployed: Recently Newly Entered | 0.12 | 12.65 | 0.24 | 0.22 |
| Unemployed: Recently Re-Entered | 0.27 | 21.30 | 0.41 | 0.37 |
| Unemployed: Left Job Months Ago | 0.16 | 19.29 | 0.37 | 0.32 |
| Unemployed: Permanently Laid Off Months Ago | 0.90 | 14.41 | 0.28 | 0.24 |
| Unemployed: Temporarily Laid Off for Months | 0.26 | 36.15 | 0.70 | 0.60 |
| Unemployed: Temp. Job Ended Months Ago | 0.24 | 20.06 | 0.39 | 0.33 |
| Unemployed: Newly Entered Months Ago | 0.24 | 9.41 | 0.18 | 0.16 |
| Unemployed: Re-Entered Months Ago | 0.57 | 16.45 | 0.32 | 0.28 |
| Unemployed: Long-Term Unemployed | 2.14 | 10.92 | 0.21 | 0.18 |
| Want Job: Discouraged | 0.47 | 11.33 | 0.22 | 0.19 |
| Want Job: Looked Last 12 Months | 0.52 | 9.76 | 0.19 | 0.17 |
| Want Job: Other | 1.27 | 12.30 | 0.24 | 0.21 |
| Not in Labor Force: In School | 5.07 | 6.28 | 0.12 | 0.11 |
| Not in Labor Force: Retired | 15.56 | 1.41 | 0.03 | 0.02 |
| Not in Labor Force: Disabled | 5.17 | 1.42 | 0.03 | 0.02 |
| Not in Labor Force: Other | 7.26 | 6.76 | 0.13 | 0.12 |
| Employed: Involuntary Part-Time | 3.73 | 3.63 | 0.07 | 0.06 |
| Employed: Not Involuntary Part-Time | 55.27 | 1.77 | 0.03 | 0.03 |

*Notes:* The job finding rates are estimated using CPS survey data linking households month-to-month. The relative job finding rate is calculated by dividing all the job finding rates by the job finding rate for the unemployed recently laid off. The recently unemployed groups refer to those who have been unemployed for 0-4 weeks. Unemployed Months Ago refers to those who have been unemployed for 5-26 weeks. Long-Term Unemployed refers to those who have been unemployed for 27 weeks or more.

Table 2: Cyclical And Trend Variation in the Job Finding Rate

| | Elasticity with Respect To Vacancy Dur | Trend in Efficiency |
|---|---|---|
| Unemployed: Recently Left Job | 0.96 | -0.27 |
| Unemployed: Recently Permanently Laid Off | 1.13 | -0.24 |
| Unemployed: Recently Temporarily Laid Off | 0.23 | -0.02 |
| Unemployed: Temp. Job Recently Ended | 0.51 | -0.16 |
| Unemployed: Recently Newly Entered | 1.98 | -0.53 |
| Unemployed: Recently Re-Entered | 1.15 | -0.29 |
| Unemployed: Left Job Months Ago | 0.92 | -0.27 |
| Unemployed: Permanently Laid Off Months Ago | 1.26 | -0.27 |
| Unemployed: Temporarily Laid Off for Months | 0.52 | -0.09 |
| Unemployed: Temp. Job Ended Months Ago | 0.94 | -0.20 |
| Unemployed: Newly Entered Months Ago | 1.76 | -0.47 |
| Unemployed: Re-Entered Months Ago | 1.22 | -0.31 |
| Unemployed: Long-Term Unemployed | 1.55 | -0.39 |
| Want Job: Discouraged | 1.11 | -0.25 |
| Want Job: Looked Last 12 Months | 1.37 | -0.32 |
| Want Job: Other | 0.74 | -0.21 |
| Not in Labor Force: In School | 1.11 | -0.42 |
| Not in Labor Force: Retired | 0.29 | -0.07 |
| Not in Labor Force: Disabled | 0.91 | -0.25 |
| Not in Labor Force: Other | 0.82 | -0.26 |
| Employed: Involuntary Part-Time | 1.20 | -0.37 |
| Employed: Not Involuntary Part-Time | 0.78 | -0.20 |

*Notes:* The recently unemployed groups refer to those who have been unemployed for 0-4 weeks. Unemployed Months Ago refers to those who have been unemployed for 5-26 weeks. Long-Term Unemployed refers to those who have been unemployed for 27 weeks or more, Trend coefficients are multiplied by 100. $p<0.01$ for all reported coefficients (except for trend coefficient on recently temporary layoffs which is not statistically significant from zero).

Table 3: Cyclical Volatility of Alternative Searchers Measures

| | Standard Deviation | Dec 1999 | June 2009 | Dec 2019 |
|---|---|---|---|---|
| Standard Measure | 0.34 | 0.87 | 2.06 | 0.73 |
| General Measure, Unemployed Only | 0.26 | 0.92 | 1.86 | 0.72 |
| General Measure, Unemployed+Want Job | 0.22 | 0.94 | 1.71 | 0.76 |
| General Measure, Unemployed+OLF | 0.10 | 0.95 | 1.32 | 0.90 |
| General Measure, All | 0.06 | 0.97 | 1.19 | 0.92 |
| U6 | 0.35 | 0.86 | 2.00 | 0.81 |
| Richmond Fed Index | 0.13 | 0.93 | 1.42 | 0.89 |

*Notes:* Standard=Unemployed; General Measure, All=All effective searchers; General Measure, Unemployed+OLF=Effective searchers excluding employed; General Measure, Unemployed+Want Job=Effective searchers with unemployed + want a job; General Measure, Unemployed=Effective searchers with unemployed only. All measures normalized to one in 2006.

Table 4: Slopes and Intercepts for Alternative Beveridge Curves

| | Intercept | Slope |
|---|---|---|
| Standard Measure | 1.06 (0.02) | -0.56 (0.02) |
| General Measure, Unemployed Only | 1.97 (0.03) | -0.88 (0.03) |
| General Measure, Unemployed+Want Job | 2.10 (0.04) | -1.00 (0.03) |
| General Measure, Unemployed + OLF | 3.29 (0.07) | -2.18 (0.07) |
| General Measure, All | 4.67 (0.12) | -3.57 (0.11) |
| U6 | 1.61 (0.03) | -0.50 (0.02) |
| Richmond Fed Index | 2.82 (0.06) | -1.72 (0.06) |

*Notes:* Standard=Unemployed; General Measure, All=All effective searchers; General Measure,Unemployed+OLF=Effective searchers excluding employed; General Measure, Unemployed+Want Job=Effective searchers with unemployed + want a job; General Measure, Unemployed=Effective searchers with unemployed only. All measures normalized to one in 2006. Reported are intercept and slope of regression of vacancy measure on searcher measure. Standard errors in parentheses.

Table 5: Relative Performance for Job Filling and Job Finding Rates

**A. Job Filling Rate**

| | RMSE | Ratio to Standard |
|---|---|---|
| Standard Measure | 0.25 | 1.00 |
| General Measure, All | 0.09 | 0.38 |
| U6 | 0.25 | 1.00 |
| Richmond Fed Index | 0.18 | 0.71 |

**B. Job Filling Rate using $\alpha = 0.57$ for all measures**

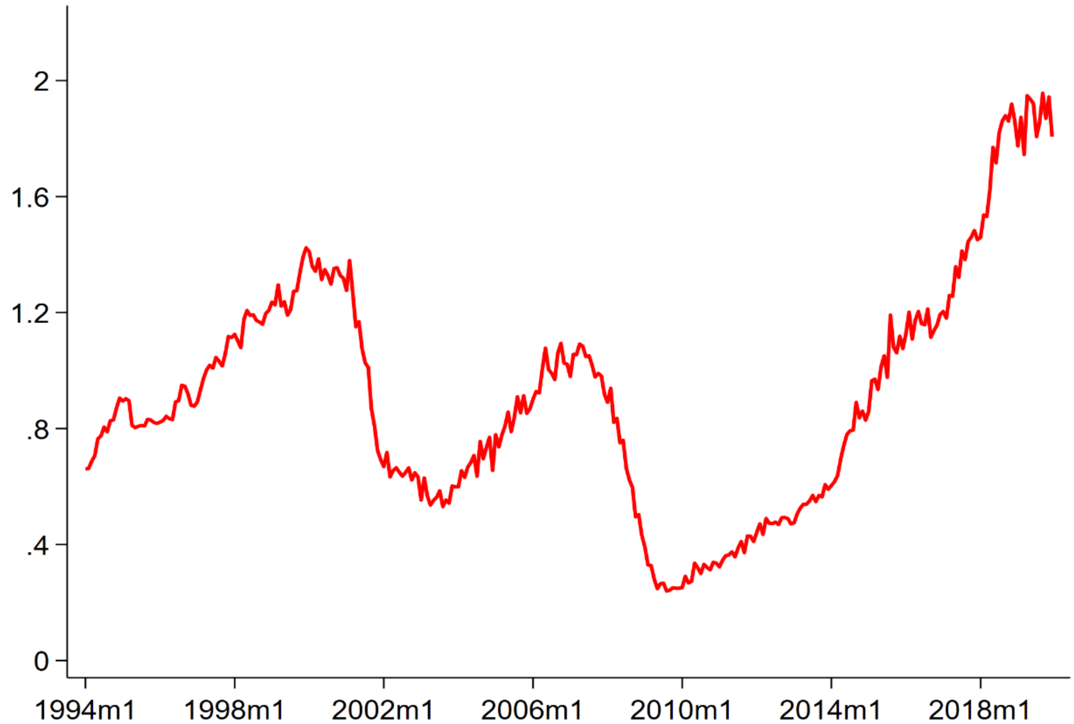
| | RMSE | Ratio to Standard |
|---|---|---|
| Standard Measure | 0.31 | 1.00 |
| General Measure, RI only | 0.25 | 0.81 |
| General Measure, U only (No RI) | 0.25 | 0.81 |
| General Measure, U only | 0.20 | 0.63 |
| General Measure, U+Want | 0.18 | 0.58 |
| General Measure, U+OLF | 0.12 | 0.38 |
| General Measure, All | 0.09 | 0.30 |

**C. Job Finding Rate for the Unemployed**

| | RMSE | Ratio to Standard |
|---|---|---|
| Standard Measure ($\alpha = 0.49$) | 0.26 | 1.00 |
| Standard Measure ($\alpha = 0.57$) | 0.22 | 0.85 |
| General Measure, All | 0.14 | 0.54 |

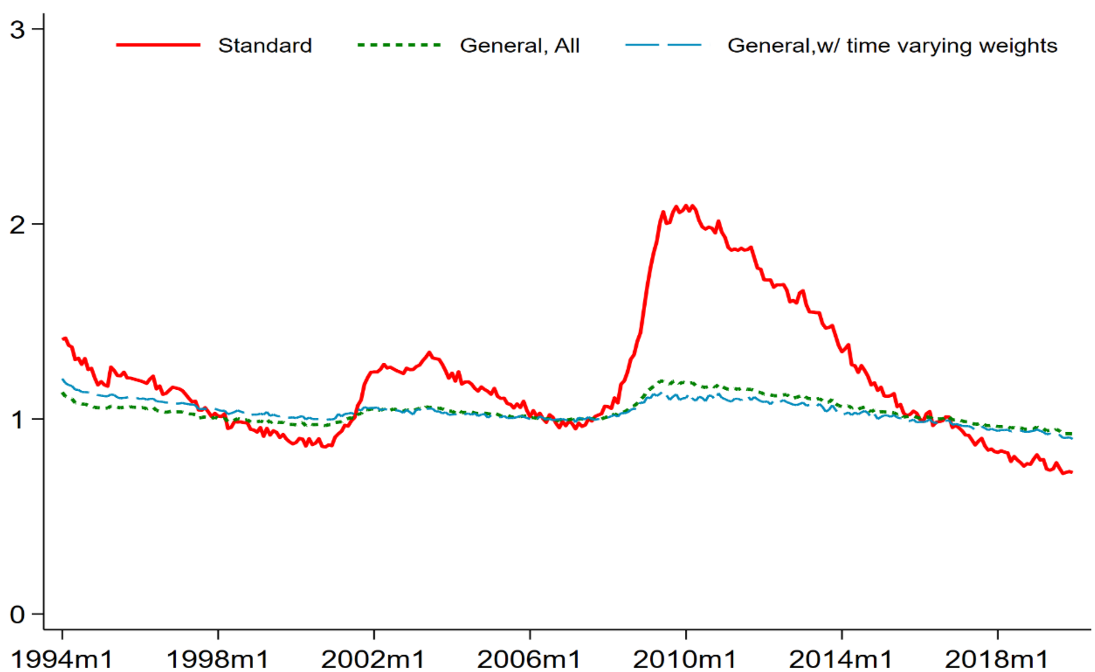
*Notes:* Panel A shows statistics for RMSE of actual minus predicted job filling rate using matching function elasticities specific to each measure. Panel B shows statistics for using same matching function elasticity for all measures. Panel C shows statistics for RMSE of actual minus predicted job finding rate for the unemployed.

**Figure 1. Standard Measure of Labor Market Tightness (V/U)**



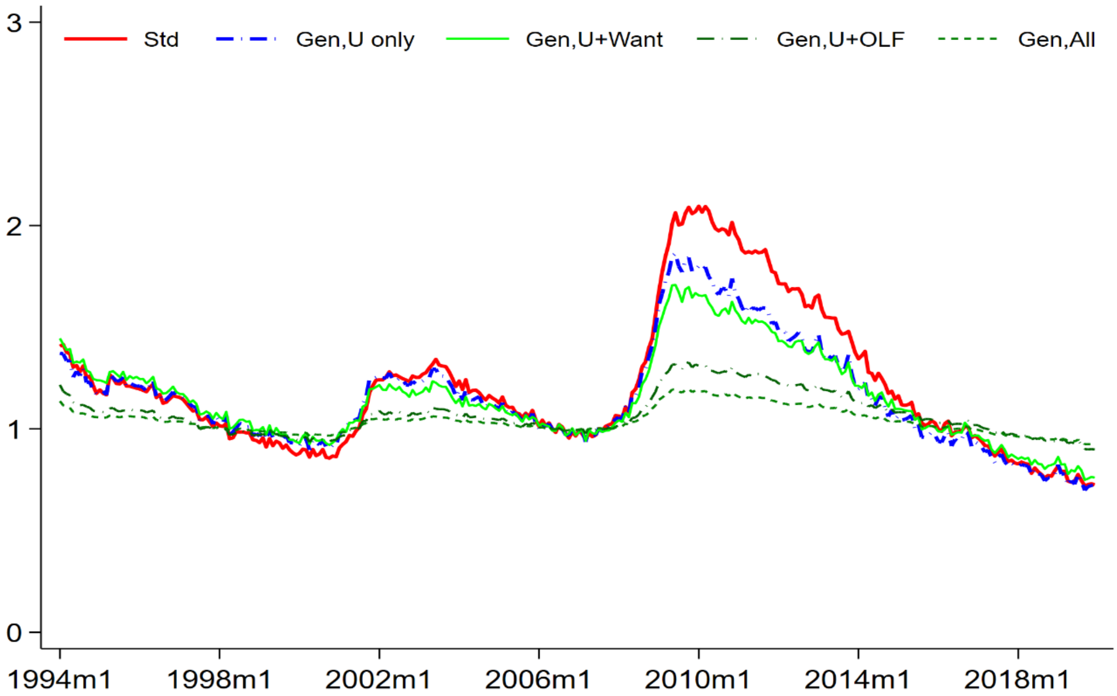

NOTE: V/U calculated using vacancies from JOLTS for 2000:12 to 2019:12 and back-cast vacancies from DFH (2012) for 1994:1 to 2000:11.Normalized to 1.0 in 2006

**Figure 2. Standard vs. Generalized Measures of Searchers**



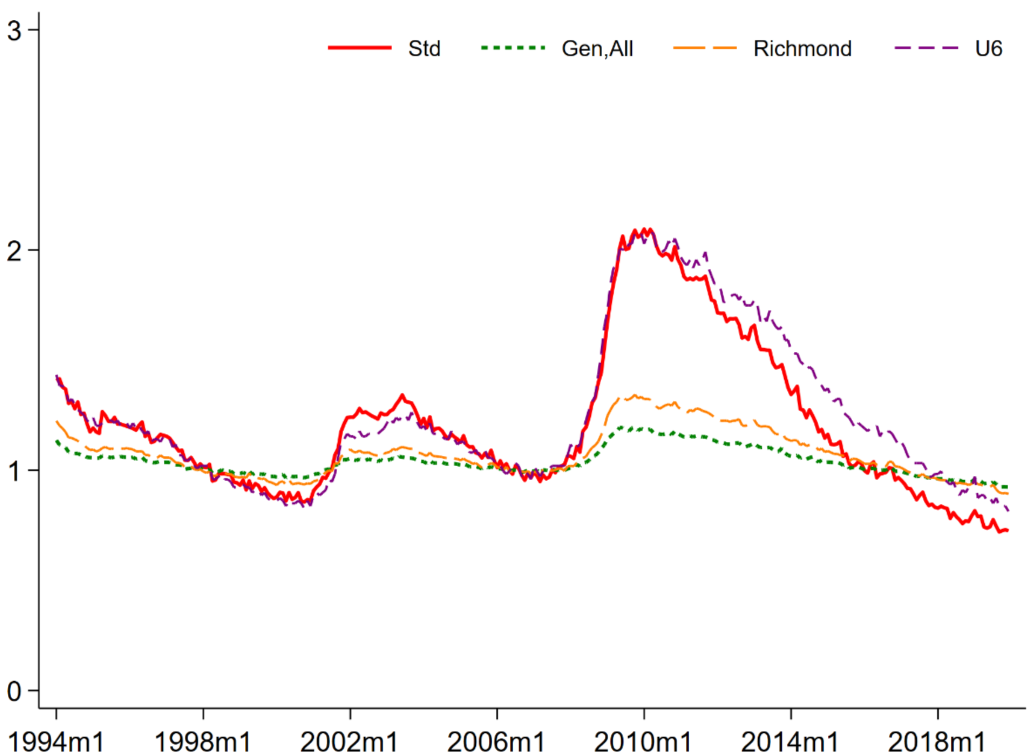

NOTE: All measures ratios to population age 16 plus and then normalized to 1.0 in 2006. Std=Unemployed, General, All=Generalized measure using all 22 groups with constant relative job search intensities; General, w/time varying weights=Generalized measure using all 22 groups with time varying relative job search intensities.

**Figure 3. Standard vs. Generalized Measures of Searchers**



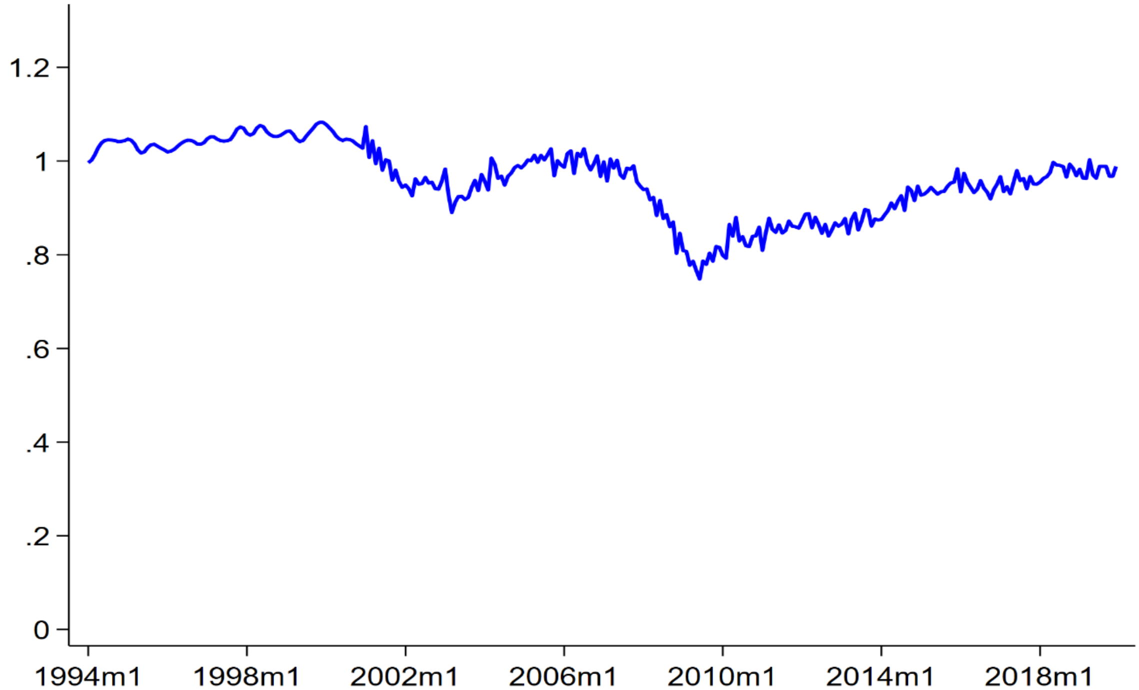

NOTE: All measures ratios to population age 16 plus and then normalized to 1.0 in 2006. Std=Unemployed, Gen, All=Generalized measure using all 22 groups with constant relative job search intensities; Gen,U+OLF=General, Excludes Employed; Gen,U+Want=General, Unemployed and Want a Job; Gen, U only=General, Unemployed only.

**Figure 4. Standard, U6, Richmond Fed, and Generalized Effective Searcher Measures**



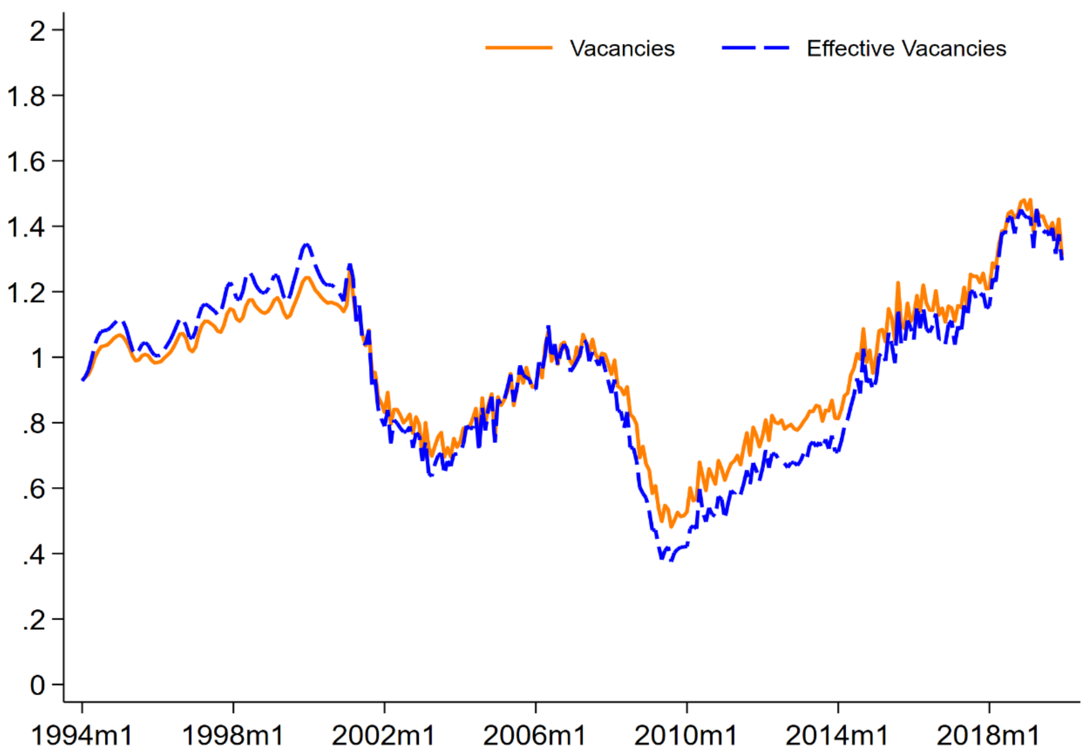

NOTE: See notes to Figure 2. Richmond=Richmond Fed Index; U6=U6 measure of unemployment.

**Figure 5. Index of Recruiting Intensity Per Vacancy**



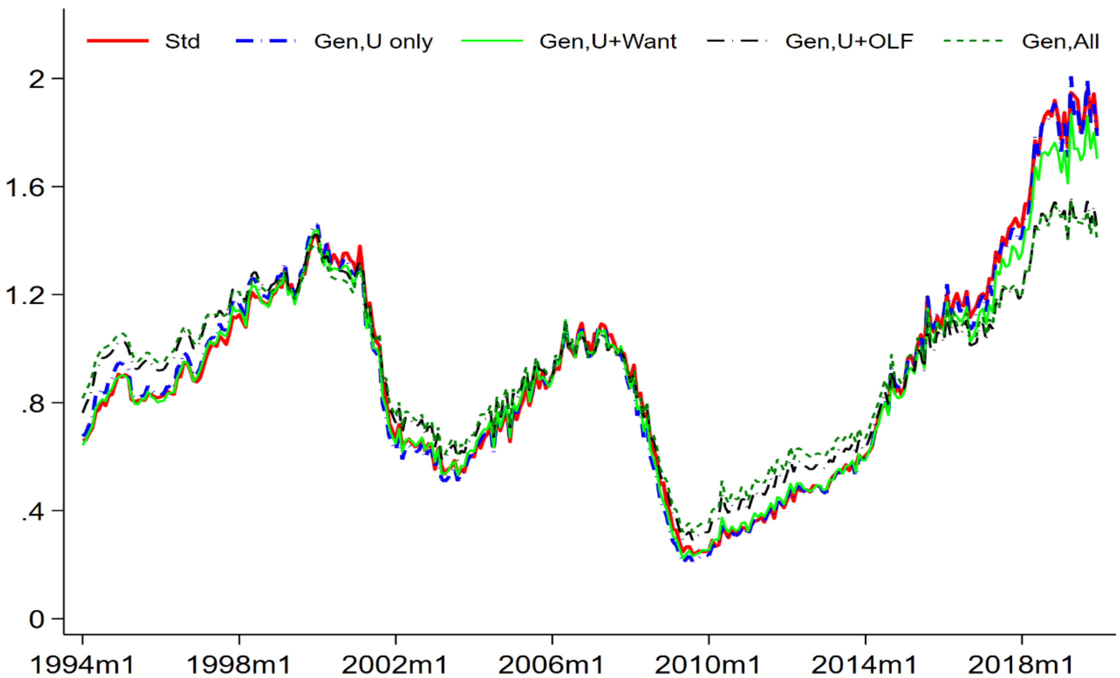

NOTE: Index of recruiting intensity from DFH (2013). Normalized to 1.0 in 2006.

**Figure 6. Vacancies vs. Effective Vacancies**



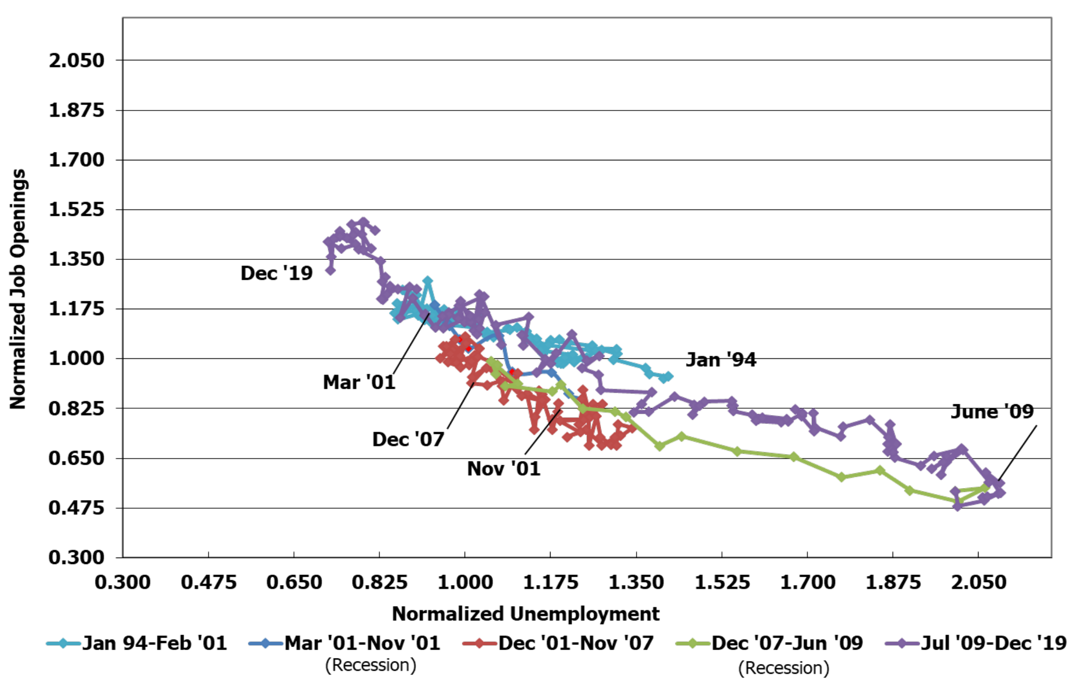

NOTE: Unadj Vacancies=vacancies from JOLTS for 2000:12 to 2019:12, back-casted series from DFH (2012) for 1994:1 to 2000:11. Adj Vacancies=same series multiplied by recruiting intensity from DFH (2013). Rates are ratio of vacancies to 16+ population and normalized to 1 in 2006.

## Figure 7. Standard vs. Generalized Measures of Labor Market Tightness



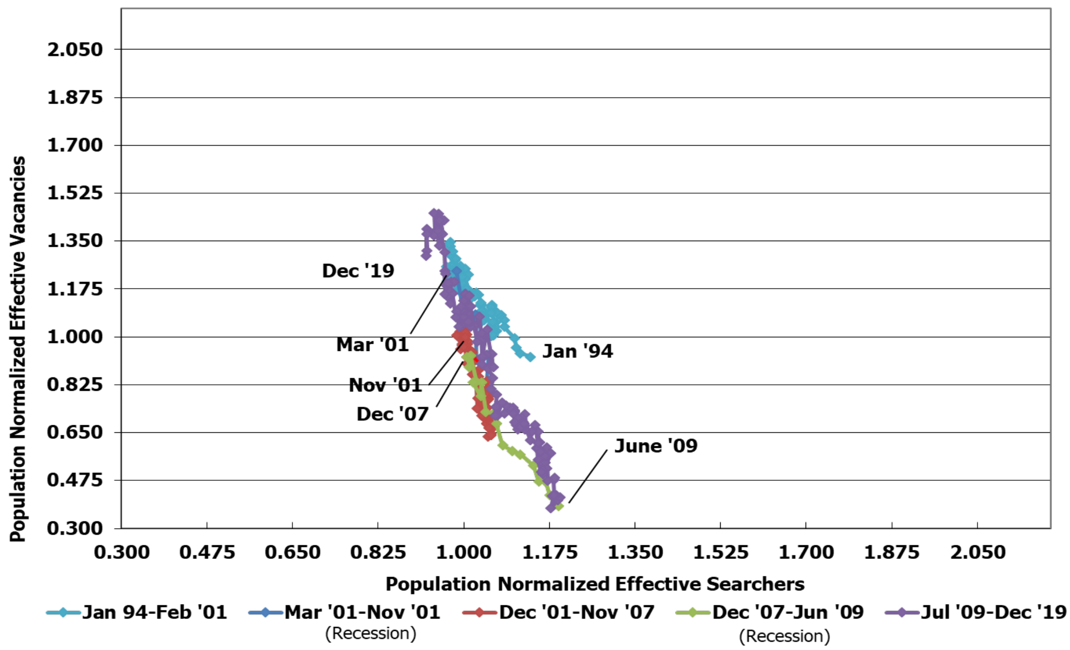

NOTE: Standard is V/U, with vacancies from JOLTS for 2000:12 to 2019:12 and back-cast vacancies from DFH (2012) for 1994:1 to 2000:11. Gen, All=EV/ES (All); Gen, U+OLF=EV/ES(excluding Employed); Gen, U+Want=EV/ES(Unemployed+Want a Job); Gen, U only=EV/ES(Unemployed only). All normalized to 1.0 in 2006.

## Figure 8. Standard Beveridge Curve



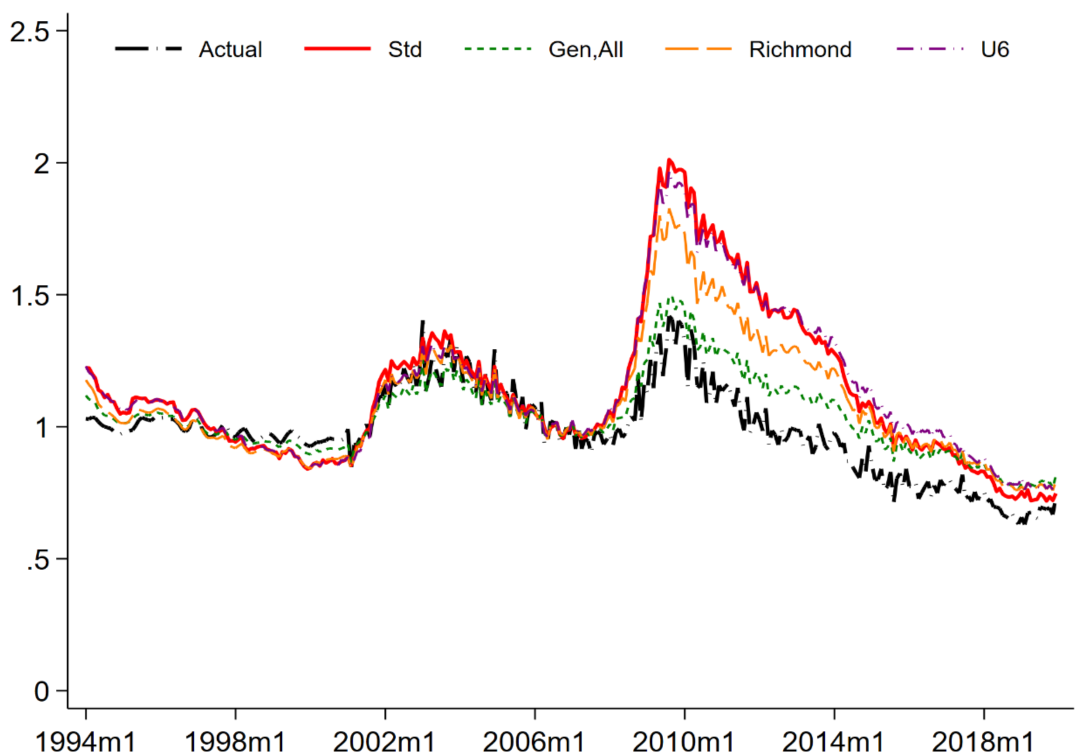

NOTE: Job Openings (vacancies) from JOLTS for 2000:12 to 2019:12 and back-cast vacancies from DFH (2012) for 1994:1 to 2000:11. Unemployed from CPS. Both series as rates relative to 16+ population and then normalized to 1.0 in 2006.

**Figure 9. Beveridge Curve Using Effective Vacancies and Effective Searchers**



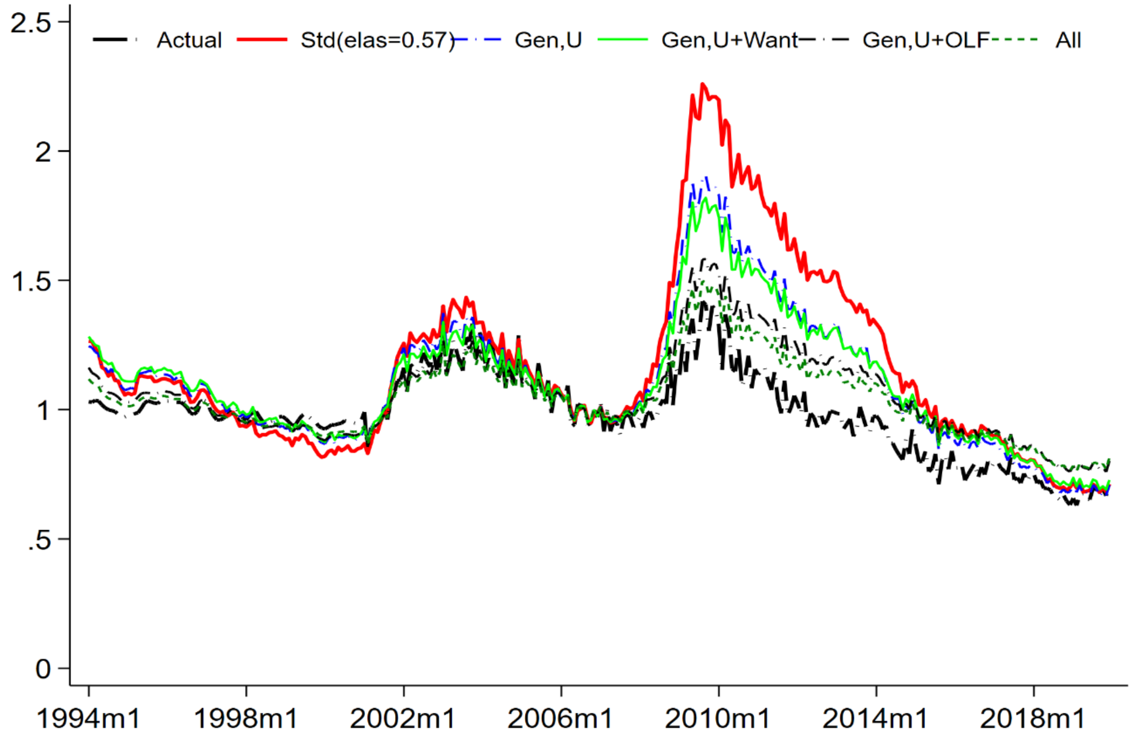

NOTE: Effective vacancies and effective searchers as described in the text. Both series as rates relative to 16+ population and then normalized to 1.0 in 2006.

**Figure 10. Actual vs. Predicted Job Filling Rates from Matching Function**



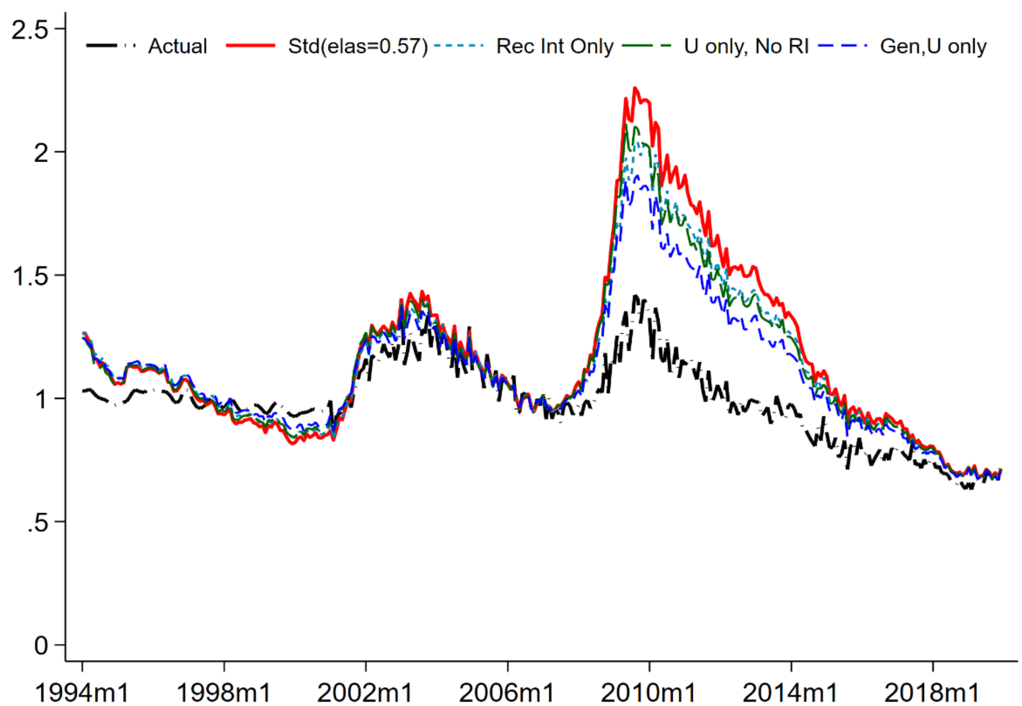

NOTE: Actual=job filling rate (H/V). Standard=predicted using V/U. Gen, All= predicted using generalized measure with all effective searchers; Richmond=predicted using (V/Richmond Fed Index); U6= predicted using (V/U6).All normalized to 1.0 in 2006.

**Figure 11. Actual vs. Predicted Job Filling Rates, Components, Using $\alpha = 0.57$ for all measures**



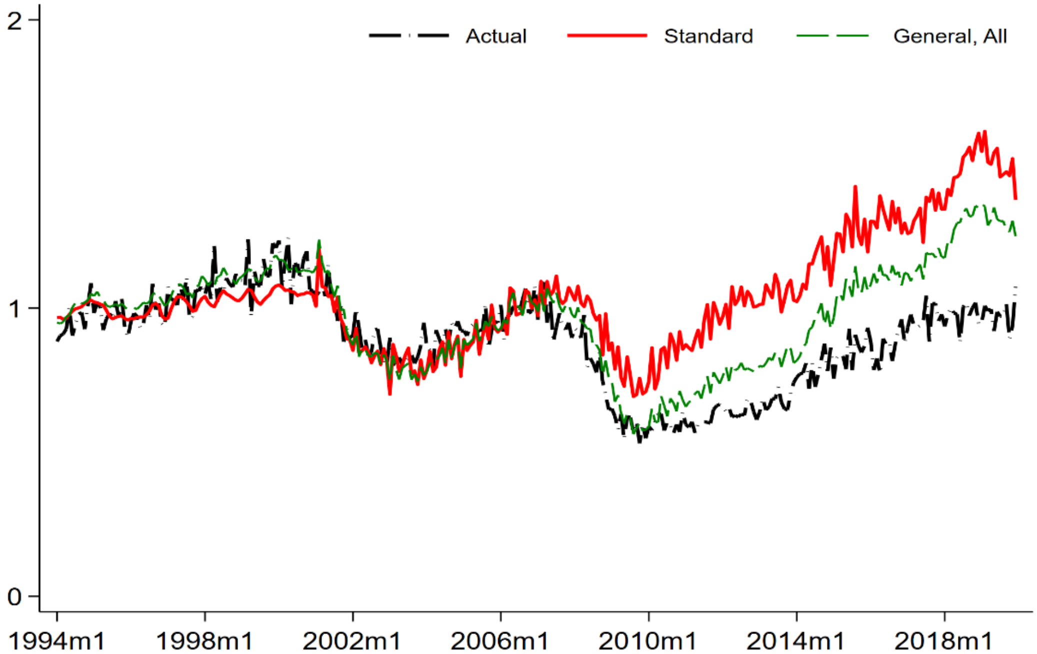

NOTE: See notes to Figure 9. Gen, No Emp= predicted using generalized measure excluding employed from searchers; Gen,U+Want=predicted using generalized measure with unemployed and want a job as searchers; Gen,U only= predicted using generalized measure with unemployed only as searchers.

**Figure 12. Actual vs. Predicted Job Filling Rates, Recruiting Intensity vs. U only, using $\alpha = 0.57$ for all measures**



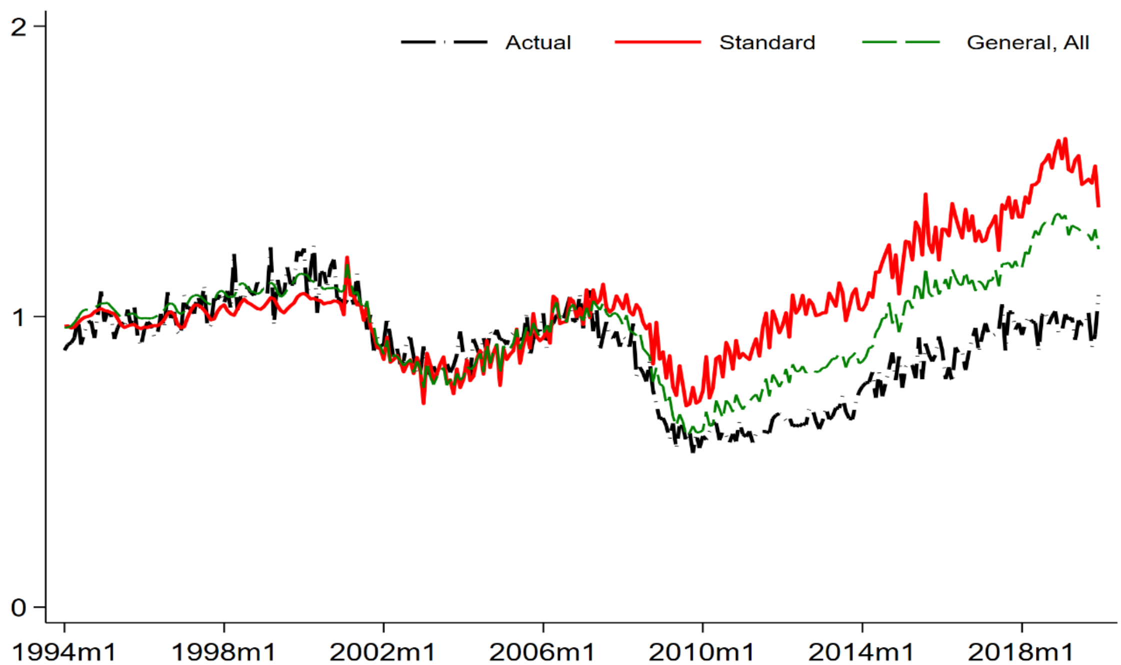

NOTE: See notes to Figure 9. Rec Int Only=predicted using (EV/U); U only, No RI=predicted using (V/ES U only)

**Figure 13. Actual vs. Predicted Job Finding Rates for the Unemployed**




NOTE: Actual=job finding rate for unemployed from published BLS Gross Flows UE/U. Std=predicted job finding rate for the unemployed using standard model (with α=0.49 (η=1.04)). General, All=predicted job finding rate for the unemployed using the general model. All normalized to 1.0 in 2006.

**Figure 14. Actual vs. Predicted Job Finding Rates for the Unemployed (using two unemployed groups, short term and long term unemployed)**

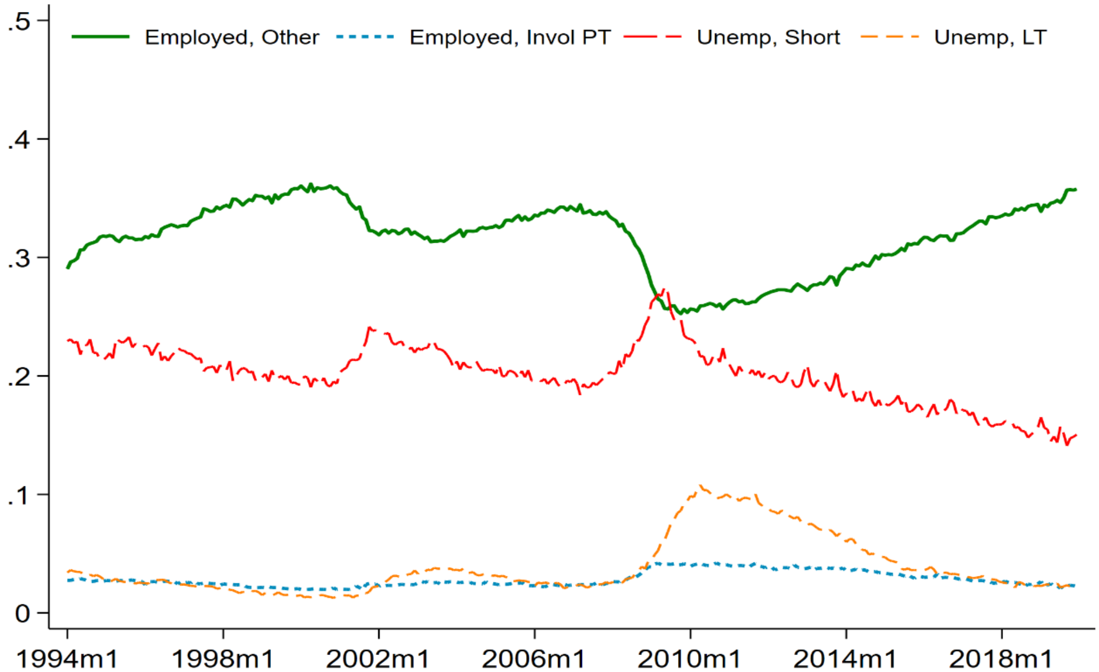



NOTE: Actual=job finding rate for unemployed from published BLS Gross Flows UE/U. Std=predicted job finding rate for the unemployed using standard model with α=0.49 (η=1.04). General, All=predicted job finding rate for the unemployed using the general model. All normalized to 1.0 in 2006.

## Appendix

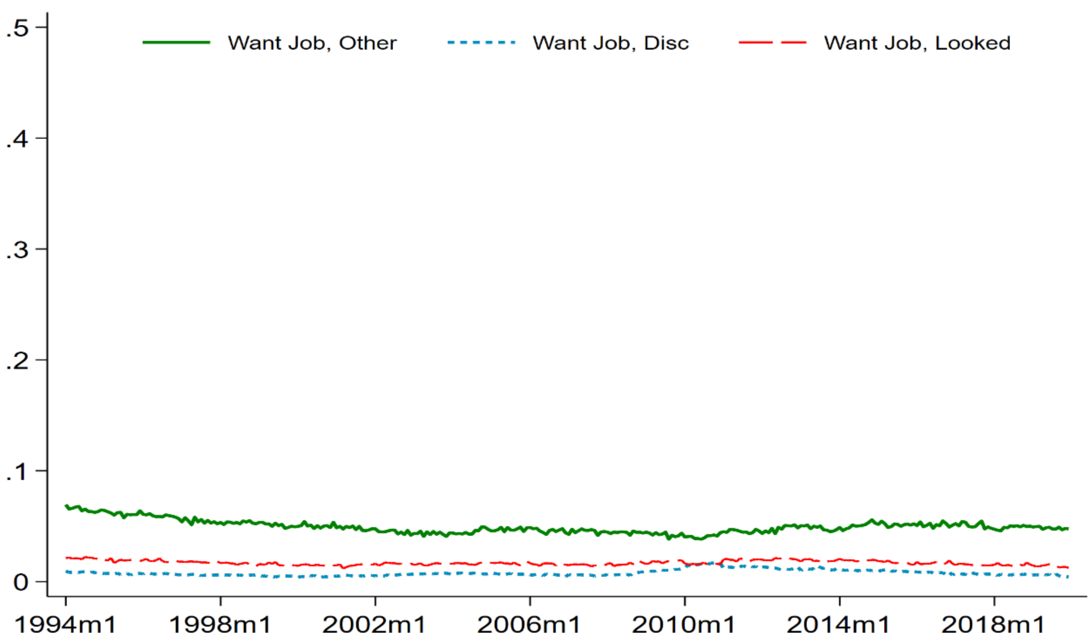
## Figure A.1. Shares of Effective Searchers

### A. Employed and Unemployed



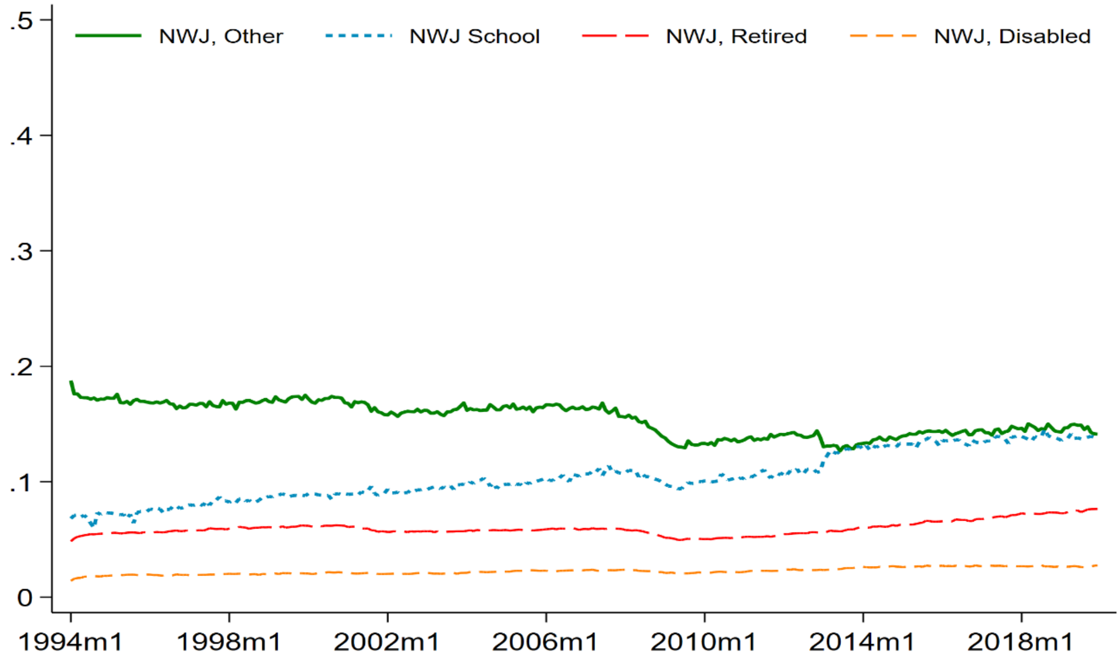

NOTE: Effective searchers in a group are number of people age 16 plus in group times group's 2006 relative search intensity. Shares across all groups sum to 1.0. Employed, Invol PT=employed who are involuntary part time. Employed, Other=employed who are not involuntary part time. Unemp, Short=aggregate of all groups of unemployed with unemployment duration less than 27 weeks. Unemp, LT=unemployed 27 or more weeks.

### B. Not in Labor Force, Want Job



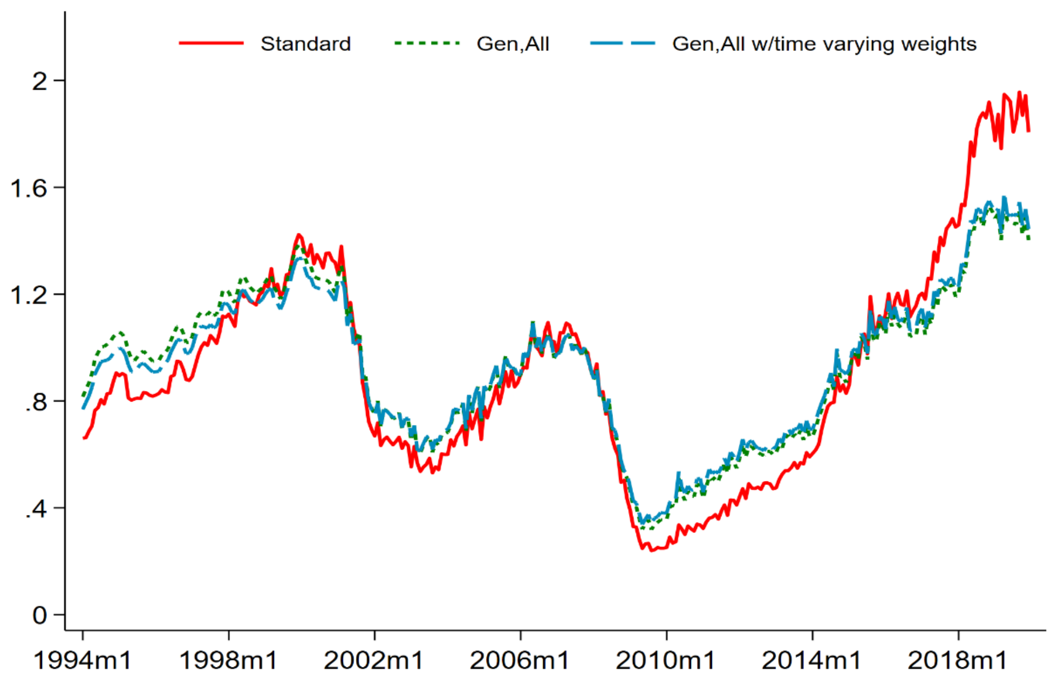

NOTE: Effective searchers in a group are number of people age 16 plus in group times group's 2006 relative search intensity. Shares across all groups sum to 1.0. Want Job, Disc=discouraged workers. Want Job, Looked=marginally attached but not discouraged workers. Want Job, Other=want a job but have not looked in last 12 months.

## C. Not in Labor Force, Not Want Job



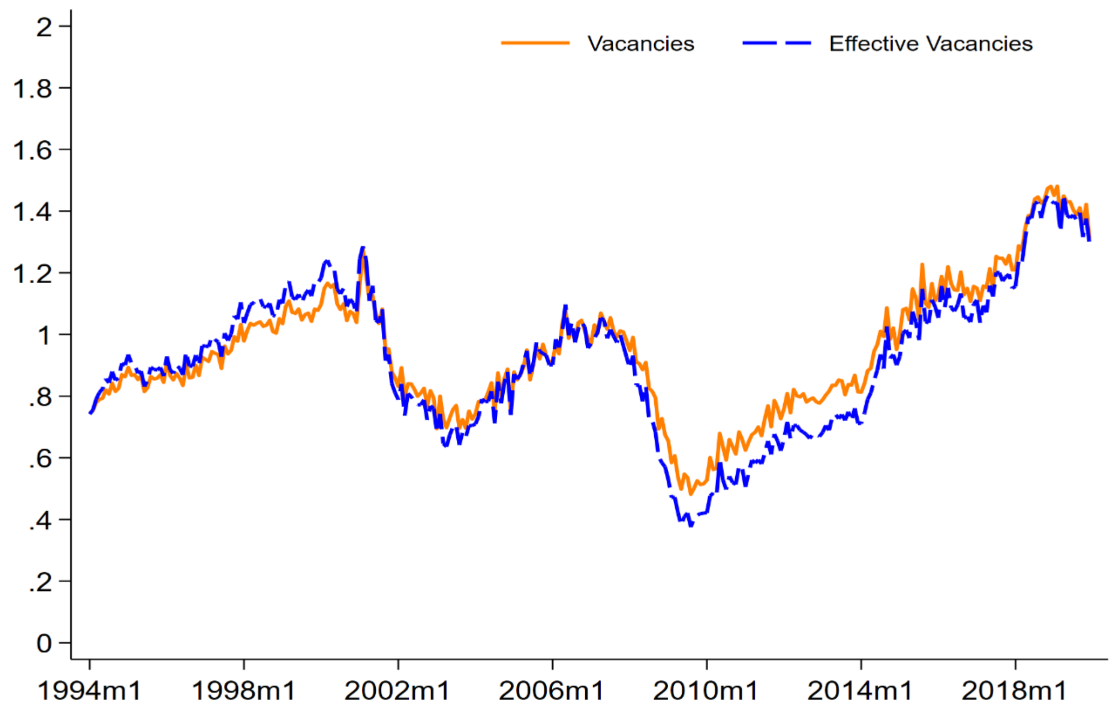

NOTE: Effective searchers in a group are number of people age 16 plus in group times group's 2006 relative search intensity. Shares across all groups sum to 1.0. Not Want Job, School=do not want a job and in school. Not Want Job, Retired=do not want a job and retired. Not want Job, Other=do not want a job and neither retired nor in school.

## Figure A.2 Generalized Measures Using Time Varying Weights



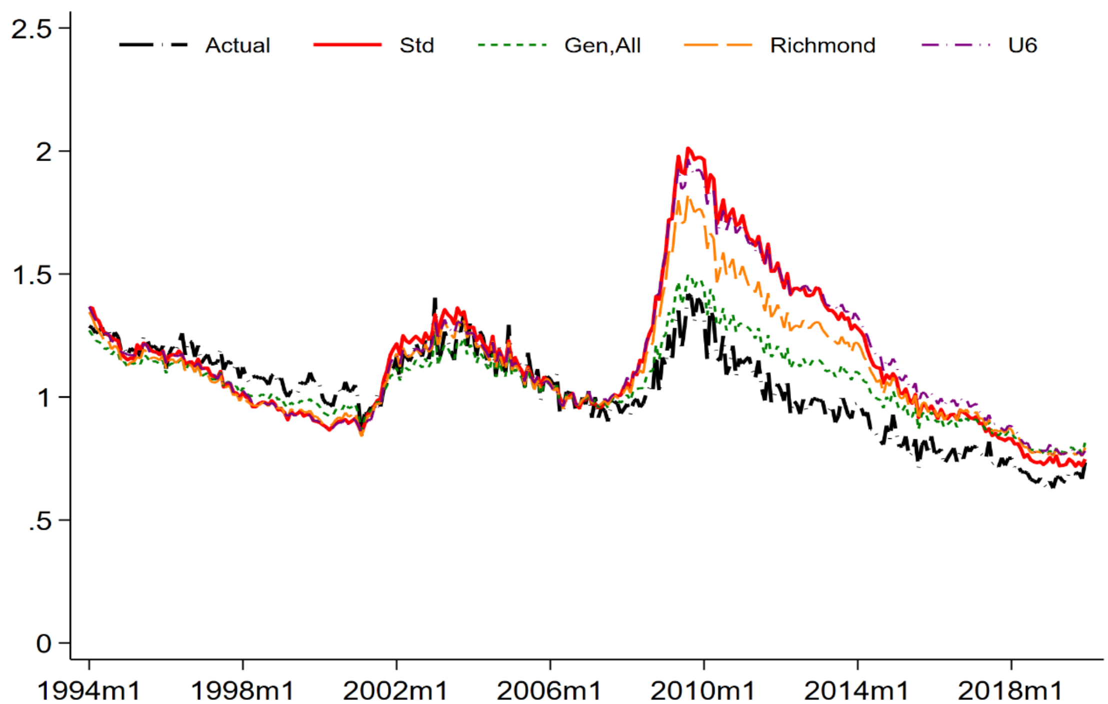

NOTE: See notes to Figure 6 in the main text. Gen, w/time varying weights=generalize measure using time-varying relative search intensities based on the method described in section 3. All normalized to 1.0 in 2006.

**Figure A.4 Actual and Effective Vacancies Using the Barnichon (2010) vacancies**



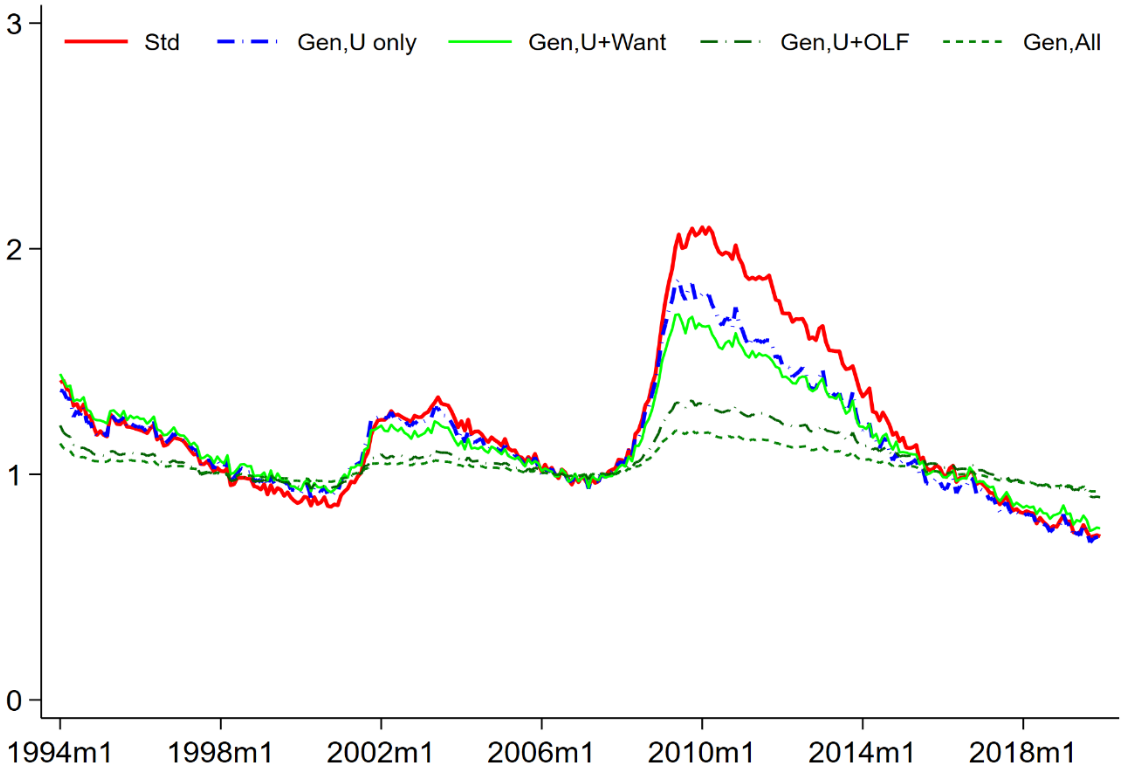

NOTE: Unadj Vacancies=vacancies from JOLTS for 2001:1 to 2019:12, and Barnichon (2010) series for 1994:1 to 2000:12. Adj Vacancies=same series multiplied by recruiting intensity from DFH (QJE, 2013). Rates are ratio of vacancies to 16+ population and normalized to 1 in 2006.

**Figure A.5 Actual vs. Predicted Job Filling Rates from Matching Function with Barnichon (2010) vacancies**



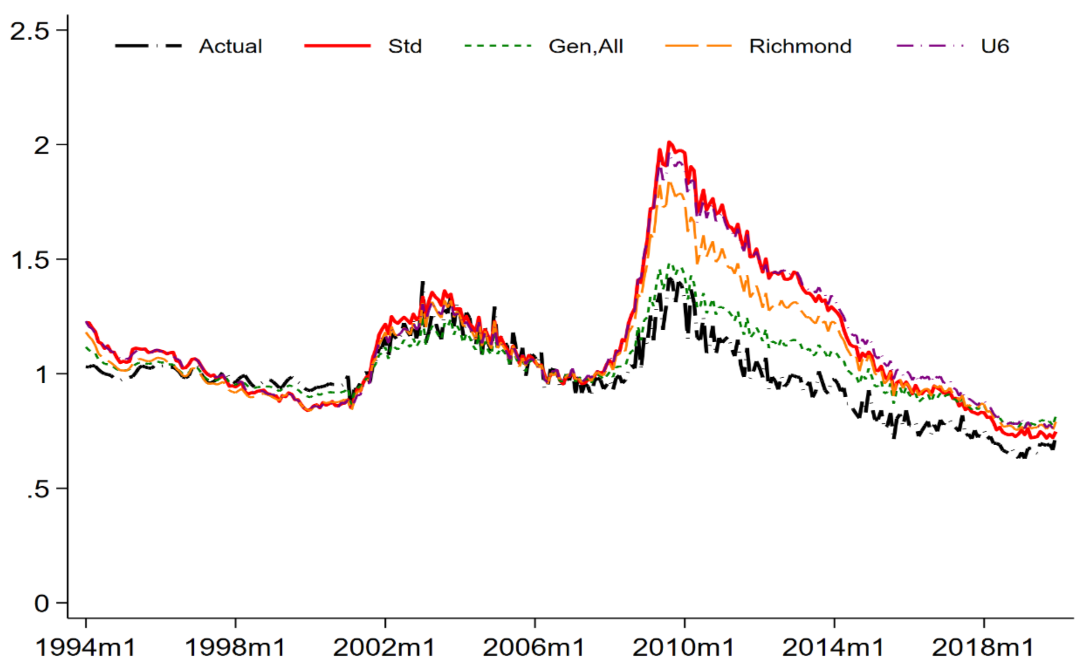

NOTE: See notes to Figure 10 in the main text.

**Figure A.6. Standard vs. Generalized Measures of Searchers (using direct (raw) measures of relative job finding rates to construct relative search intensities)**



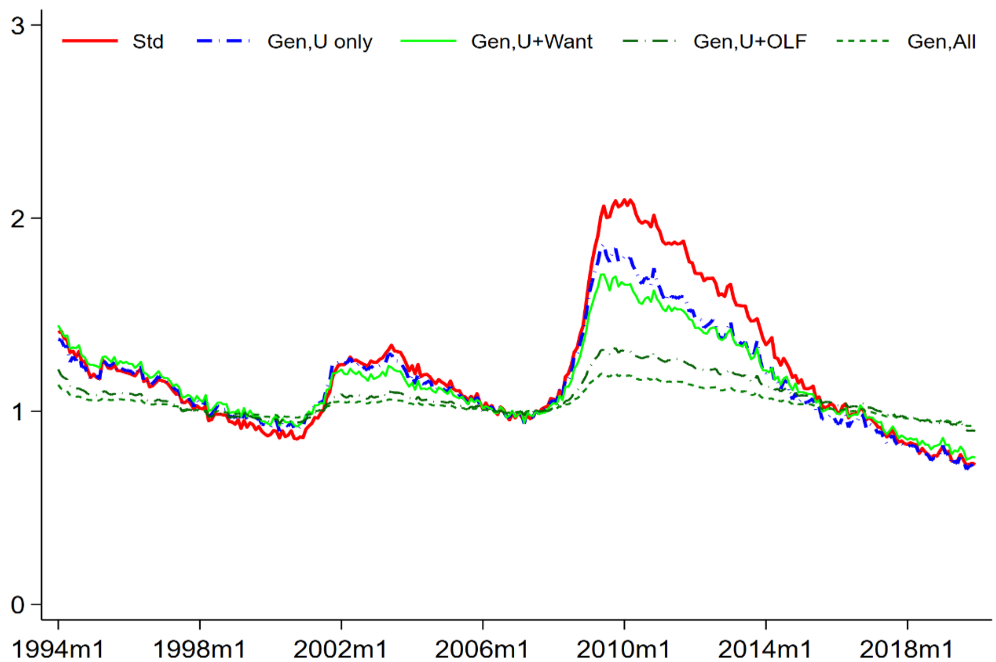

NOTE: See notes to Figure 3 in the main text.

**Figure A.7. Actual vs. Predicted Job Filling Rates from Matching Function (using direct (raw) measures of job finding rates to construct relative search intensities)**



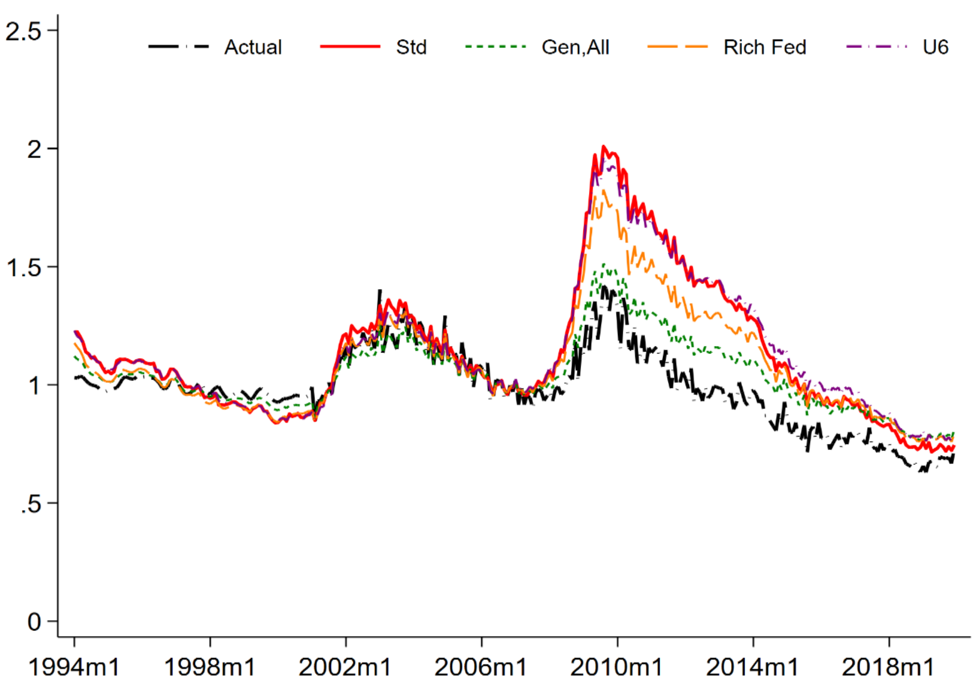

Note: See notes to Figure 10 in the main text.

**Figure A.8. Standard vs. Generalized Measures of Searchers (using two groups for unemployed – short term and long term unemployed)**



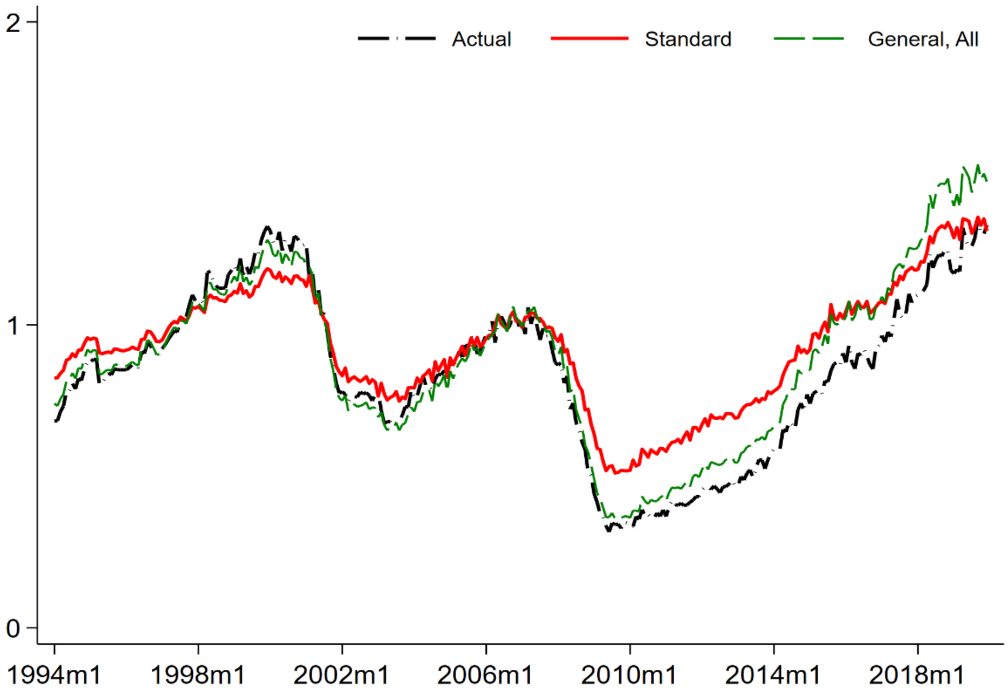

Note: See notes to Figure 3. These results use 11 groups of effective searchers for all (2 for unemployed and 9 groups for the employed and out of labor force)

**Figure A.9. Actual vs. Predicted Job Filling Rates from Matching Function (using two groups for unemployed – short term and long term unemployed)**




Note: See notes to Figure 11 in the main text and Figure A.8.

**Figure A.10. Actual vs. Predicted H/U**




NOTE: Actual=H/U using JOLTS for hires and CPS for unemployed. Std=predicted H/U using equation (4) from main text. General, All=predicted H/U using equation (12) from main text.. All normalized to 1.0 in 2006.