The Cyclicality of Job-to-Job Transitions and Its Implications for Aggregate Productivity

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Abstract

This paper analyzes the job-to-job transitions of workers in the United States. I propose a new method of correcting the time-aggregation bias. The bias correction does not significantly alter the cyclical properties of the job-to-job transition rates. The bias-corrected series from 1996 to 2011 reveals a procyclical pattern of job-to-job transitions and a large decline since the beginning of the 2000s. I construct a model of on-the-job search and explore the implications of this phenomenon. The calibrated model quantifies the effect of the decline in the reallocation of workers through job-to-job transitions on total factor productivity (TFP). From 2009 to 2011, the model accounts for about 0.4% to 0.5% annual decline in TFP.

Keywords: job-to-job transition, time-aggregation bias, on-the-job search
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1 Introduction

From a macroeconomic perspective, job-to-job transitions are an important part of the reallocation of productive resources. Job-to-job transitions, defined as workers moving across jobs without experiencing nonemployment, are common in the U.S. economy—occurring on a magnitude comparable to the movement of workers from employment to unemployment. Job-to-job transitions contribute to an improvement in resource allocation because workers tend to be better suited to the new job when they move; in support of this view, microeconomic studies have documented substantial wage gains at the time of job switch. Whereas early literature on frictional unemployment argues that unemployment contributes to such reallocation by providing opportunities to find new jobs, Tobin (1972) has criticized this view, pointing out that many job switches occur without any intervening unemployment period and that the majority of these switches end up being an improvement.

Despite their significance, the macroeconomic implications of job-to-job transitions are much less studied than the flows across labor market states (employed, unemployed, and not in the labor force). One of the reasons for this discrepancy is the measurement challenge: the study of job-to-job transition requires panel data recording the identity of a worker's employer, and in the past, no such data, both nationally representative and of sufficiently high frequency, were available. However, significant data development has occurred in recent years, and this paper uses the information from one of these datasets. Job-to-job transition is the only component of the total hires and separations that does not involve a switch across labor market states, and understanding its behavior enhances our knowledge of the worker reallocation process.

In addition to its quantitative significance, job-to-job transition is conceptually interesting. A job-to-job transition can be viewed as a part of "separations" by the employer that is losing the worker, but from the viewpoint of the new employer, the transition is a part of "new hires." These dual views of a job-to-job transition pose a challenge for how to model it appropriately.

Earlier studies observed that job-to-job transition rates in the United States are procyclical. Barlevy (2002) argues that recessions can reduce aggregate productivity through the lack of reallocation that results from this procyclicality. He names this effect the "sullying effect of recessions" and contrasts it with commonly argued efficiency gains in recessions coming from increased destruction of unproductive job-worker matches (often called the "cleansing effect of recessions").

The aim of this paper is to quantify the effect of job-to-job transitions on aggregate productivity using recent US data and a simple model of on-the-job search. One advantage of this paper over Barlevy's study is that I use higher-frequency data based on the monthly Current Population Survey (CPS) from the Bureau of Labor Statistics (BLS), whereas Barlevy relied on annual data mainly from the Panel Study of Income Dynamics. It turns out that the job-to-job transition rate has dramatically declined since the beginning of the 2000s, and because of this large decline, the use of recent data further clarifies the effect of job-to-job transitions on productivity. Also, my model is substantially simpler than Barlevy's, and thus the role of each assumption is more transparent.

This paper makes two contributions. The first is a methodological contribution to the measurement of the job-to-job transition rate. This paper uses the monthly observation of job switching in the CPS, tabulated by Fallick and Fleischman (2004) in their innovative work on measuring the job-to-job flow. One problem with using monthly observations is that they give no information on workers' behavior between two data points. For example, a worker who reports being employed in two consecutive months for different employers may have experienced brief unemployment in between. Because such short-term unemployment is cyclical, ignoring that possibility may bias the measured cyclicality of the true job-to-job transitions. This bias, called a "time-aggregation bias," is discussed extensively in the context of measuring the true transitions between employment and unemployment (and other labor market states). Shimer (2012, footnote 3), for example, lists papers that discussed the importance of time-aggregation bias dating back to the 1970s. In a recent study, Elsby et al.

(2009) finds a result consistent with “the notion that correcting for aggregation bias limits the capacity for inflows to explain cyclical unemployment” (p.98). Although Fallick and Fleischman (2004) argue that “at the monthly frequency of the CPS we do not regard this problem as serious,” how the time-aggregation correction alters the cyclical properties of the job-to-job transition rate is not obvious.

Nagypál (2008) attempted to address this issue in an earlier study. Her approach was to use another dataset, the Survey of Income and Program Participation (SIPP), which contains weekly information on labor market status. By contrast, my method is analogous to the ones developed for the analysis of transitions across labor market states, such as the one employed in Shimer (2012). Two main advantages of my approach are that it is a continuous-time adjustment and that it can be implemented easily without relying on other data sources. An additional advantage is that the underlying assumptions on the stochastic process are similar to the commonly employed methods for the transitions across different labor market states.

I find that the time-aggregation correction does not significantly alter the cyclical properties of the job-to-job transition rate. Least squares regressions reveal that the (log of) corrected series and the (log of) uncorrected series move almost parallel to each other. Both corrected and uncorrected series exhibit procyclical patterns, and the job-to-job transition rate has declined substantially since the beginning of the 2000s.

To see how the procyclical job-to-job transition rates in recent years compare to the past, I follow Blanchard and Diamond (1990) and Shimer (2005a) and measure the job-to-job transition rate in the past using the March CPS data. This analysis reveals that the job-to-job transition rate has been procyclical at least since the late 1970s.

My second and the main contribution is to use the time-aggregation-adjusted data to examine the implications for aggregate productivity. To this end, I extend the model developed by Shimer (2005a). It is a simple model that keeps track of the movement of (ex-post) heterogeneous workers. The model can provide rich predictions on how job-to-job transition rates evolve in the economy based only on a few assumptions about worker behavior. In the calibrated version of the model, I find that productivity loss from the recent decline in job-to-job transitions can account for a large part of the recent decline in total factor productivity (TFP). The basic model accounts for about a 0.5% annual decline of TFP over 2009–2011. In the model with the cleansing effect of recessions, that is, a relatively larger destruction of bad job-worker matches during recessions, the annual decline of model TFP over the same period is about 0.4%.

Lazear and Spletzer (2012) use the Job Openings and Labor Turnover Survey and document that replacement hires (they use the term "churn") are procyclical. Churn and job-to-job transitions are both part of the gross worker flow, but they are conceptually distinct. An economy can have a large amount of churn without any job-to-job transitions, and an economy can have many job-to-job transitions with no churn. (They are not unrelated—in an economy without any job flows, a job-to-job transition necessarily creates churn.) In their Figure 1, churn is procyclical but does not have a declining trend from the early 2000s, unlike the job-to-job transition rate. In measuring "the cost of reduced churn" in recent years, they use the wage gain from job-to-job transitions measured in Fallick et al. (2012), which does not necessarily correspond to the gain from churn. (To measure the gain from churn, they would need a productivity gain from replacing a worker in a given position.) The analysis of this paper has a more direct link between the model and the data.

Several recent papers have studied the time-series patterns of the job-to-job transition rate. In addition to the papers mentioned above, Bjelland et al. (2011) utilize the Longitudinal Employer Household Dynamics (LEHD) dataset and study the job-to-job transitions from 1991 to 2003 in Wisconsin, North Carolina, and Oregon. Hyatt and McEntarfer (2012) also use the LEHD dataset and study a more recent period (1998-2010). Both papers find that job-to-job transition rates are procyclical. Hyatt and Spletzer (2013) compare job and worker flows from four different data sources. They find that hires, separations, job creation and destruction, and job-to-job flows all declined from the late 1990s to 2010. They find that the composition shifts of individual and business characteristics do not explain a large part of the decline.

The paper is organized as follows. Section 2 describes the time-aggregation adjustment. Section 3 looks further into the past by using information from another dataset. Section 4 analyzes a model of on-the-job search and quantitatively examines the implications of job-to-job transitions on aggregate productivity. Section 5 extends the model to incorporate the cleansing effect of recessions. Section 6 concludes.

2 Data and time-aggregation adjustment

The data I use come from Fallick and Fleischman (2004), who use the "dependent interviewing" feature of the CPS since its 1994 redesign.[1] The CPS has some panel aspects (BLS interviews the same household for 4 months and then, after an interval of 8 months, interviews them for 4 more months), and since the redesign, the interviewers have asked some questions that refer back to previous months' answers (this process is called "dependent interviewing"). In particular, if a person is employed in one month and also employed in the previous month, the interviewer asks whether the person still works for the same employer as reported in the previous month. Fallick and Fleischman construct series of the number (and the rate) of workers who work for the same employer, as well as the flows across different labor market states. I use their tabulation for all flow rates in 1996–2011. Because their tabulated numbers are not seasonally adjusted, I first use the X12-ARIMA procedure to perform seasonal adjustment for all flow rates (both job change and labor market state change). The fraction of the workers who stayed at the same labor market status are calculated as one minus the sum of the fractions of workers who changed their labor market status.

Before performing the time-aggregation adjustment on the job-to-job transition data, I make the time-aggregation adjustment for the flows across the labor market states. I assume the switch from labor market state i to j follows a Poisson process within a month, with the Poisson probability λ_t^{ij} between times t and $t+1$. Note that t takes an integer and it

[1] They update their tabulation at http://www.federalreserve.gov/econresdata/researchdata/feds200434.html.

represents a “period” (1 month). Later (in Section 4), I introduce another time notation s, which takes a real value on a continuous line. Here, i and j are each one of three labor market states: (i) employment E, (ii) unemployment U, and (iii) not in the labor force N. The aim of the adjustment is to recover λ_t^{ij} from the observed flow (the fraction of workers who are in state j at time $t+1$ among the ones who are in state i at time t), p_t^{ij}. This part of the adjustment is identical to Shimer (2012), and I do not repeat it here. For completeness, I describe the details of this procedure in Appendix A. This adjustment is independent of job-to-job switching behavior of workers, and thus I can make this adjustment first and use the results as inputs of the analysis below.

My time-aggregation adjustment of job-to-job transition data is based on a similar assumption. I assume that the direct job-to-job switch follows a Poisson process with probability λ_t^{JS} (JS represents “job switch”). The goal is to recover λ_t^{JS} from the information of the observed job-switching flow (the ratio of workers who are working for a different employer at time $t+1$ among the ones who were working at time t), denoted by p_t^{JS}, as well as the above information (λ_t^{ij} and p_t^{ij} for $i, j = E, U, N$).

The details of the method is described in Appendix B.[2] One important factor that influences this adjustment is the frequency of “recalls”—the many instances in which workers who separate from an employer come back to the original employer after working for another employer or experiencing a spell of nonemployment. The degree (and the direction) of time-aggregation adjustment depends on how frequently a recall occurs. Here, I consider two extreme cases—one is the case with no recall and the other is the case in which all workers who can be back at the original employer on the next survey date are actually back (I call it “perfect recall”). Appendix C considers an in-between case, based on Fujita and Moscarini's (2013) measurement.

The probability of receiving a job-switching shock at least once during one period is

[2]The Matlab programs for the time-aggregation adjustment are available at https://sites.google.com/site/toshimukoyama/timeaggregation.zip.

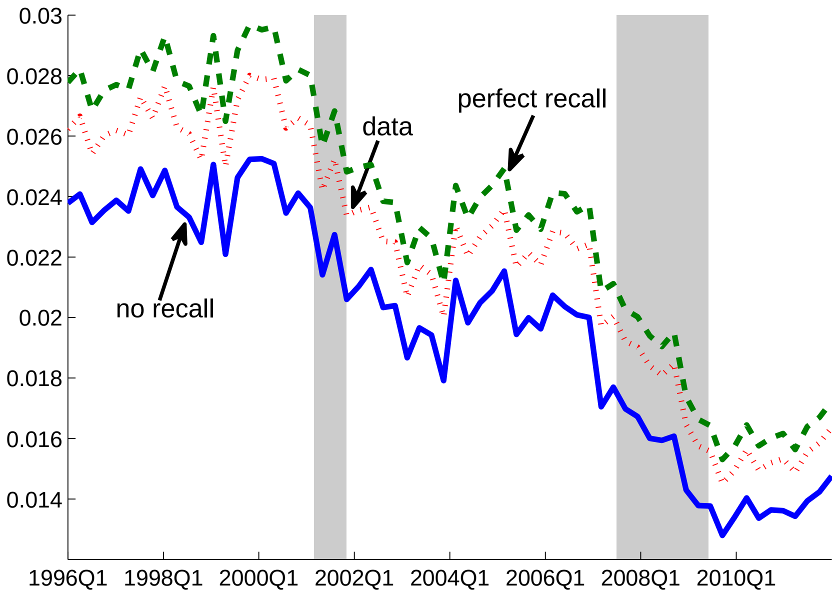

Figure 1: The probability of job-to-job transition with time-aggregation adjustment: p_t^{JS} (labeled as "data") and $\tilde{p}_t^{JS}$ with different recall assumptions (labeled as "no recall" and "perfect recall")

computed as

$$\tilde{p}_t^{JS} = 1 - \exp(-\lambda_t^{JS}).$$

Figure 1 plots p_t^{JS} (labeled as "data") and $\tilde{p}_t^{JS}$ with the no-recall assumption (labeled as "no recall") and the perfect-recall assumption (labeled as "perfect recall"). The monthly p_t and $\tilde{p}_t$ are somewhat noisy, and here I plot the quarterly average of the monthly results. All time series exhibit a procyclical pattern of job-switching behavior and a declining trend after the early 2000s. The decline in recent years is particularly dramatic: the job-switching probability in 2010–2011 is almost half of the probability in the late 1990s.

Regarding the time-aggregation adjustment, one can see that $\tilde{p}_t^{JS}$ is smaller than p_t^{JS} in the no-recall case, because the main correction the adjustment accomplishes is the elimination of instances of within-period short-term unemployment that are contained in p_t^{JS}. Note that $\tilde{p}_t^{JS}$ in the perfect recall case is larger than p_t^{JS}, because now all short-term unemployed are counted as "working for the same employer" in the data. Some workers experience the job-switching shock multiple times (or one job-switching shock and multiple labor market status-changing shocks) and end up at the original job by the assumption of perfect recall. These people are not counted in p_t^{JS} in the data but do experience job-switching shocks; thus the actual probability is adjusted upward. In both cases, the time-aggregation adjustment is quantitatively small and does not significantly alter the cyclical properties of the job-switching shock. Least squares regressions of $\log(\tilde{p}_t^{JS})$ on the $\log(p_t^{JS})$ (both quarterly averages, with a constant) reveal coefficients of 1.03 for the no-recall case and 1.01 for the perfect-recall case—both very close to 1. In both cases, the R-squares are over 0.99. In other words, $\log(\tilde{p}_t^{JS})$ and $\log(p_t^{JS})$ move almost parallel to each other.

Note that the assumption on recalls does not have a significant effect on the cyclical properties. The band between the no-recall case and the perfect-recall case is narrow, and the recent decline of $\tilde{p}_t^{JS}$ is apparent regardless of how r_t changed over time.

How should the recent dramatic decline be interpreted? A job-to-job transition has two "faces": it is a job finding (or a hiring from an employer's viewpoint) at the same time it is a separation. Should it be interpreted as a job finding or a separation? Figure 2 plots the time series of $\tilde{p}_t^{UE}$ and $\tilde{p}_t^{EU}$, where, similar to $\tilde{p}_t^{JS}$, $\tilde{p}_t^{ij}$ is calculated as $1-\exp(-\lambda_t^{ij})$ $(i, j = E, U, N)$. Clearly, the time series of $\tilde{p}_t^{JS}$ looks more similar to $\tilde{p}_t^{UE}$. Thus, associating the job-switching behavior with the job-finding behavior seems more reasonable. This observation is important in making the modeling choice later on.

To see the similarities and discrepancies between job switching and job finding, I plot $\tilde{p}_t^{JS}/\tilde{p}_t^{UE}$ in Figure 3. The first observation is that this ratio looks stationary: aside from cyclical movements, this ratio does not have an apparent trend. This finding is a stark contrast to Figure 1, which exhibits a clear downward trend. For example, at the recovery phase of the 2007–2009 recession, the level of $\tilde{p}_t^{JS}$ is much lower compared to the previous recovery, but the level of $\tilde{p}_t^{JS}/\tilde{p}_t^{UE}$ is almost the same as in the previous recovery. This finding indicates that common factors are influencing $\tilde{p}_t^{UE}$ and $\tilde{p}_t^{JS}$ with respect to the low

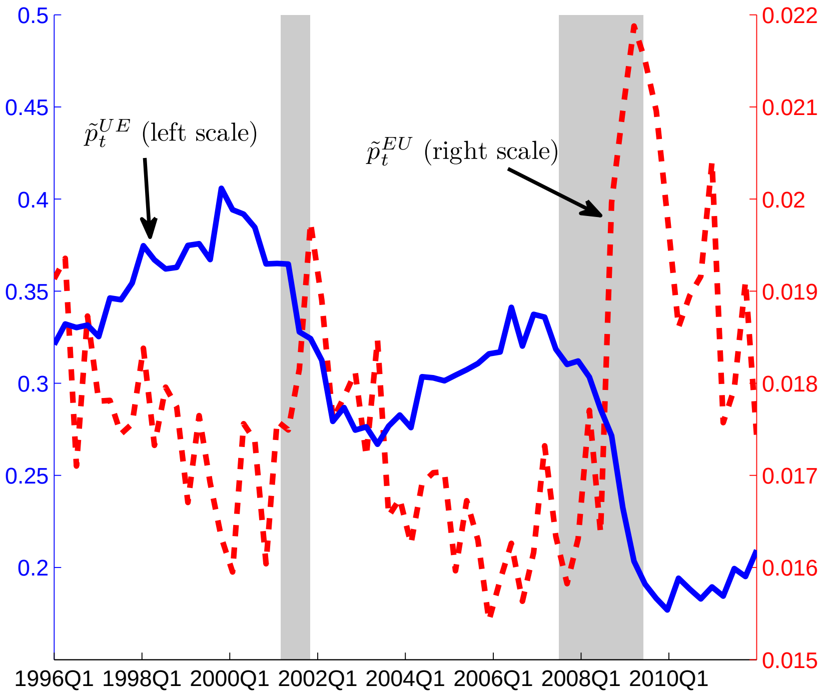

Figure 2: Unemployment-to-employment transition probability and employment-to-unemployment probability

level of both variables in recent years. Thus, if the low job-finding probability of unemployed workers in recent years is the result of weak labor demand, the same can likely be said of the job-to-job transitions.

The second observation about Figure 3 is that $\tilde{p}_t^{JS}/\tilde{p}_t^{UE}$ has some cyclicality. It will be show later that the model can qualitatively replicate this pattern through the change in the composition of employed workers.

3 Looking further into the past

The main findings in Section 2 are that (i) the job-to-job transition rate is procyclical and (ii) the job-to-job transition rate has declined significantly since the beginning of the 2000s.

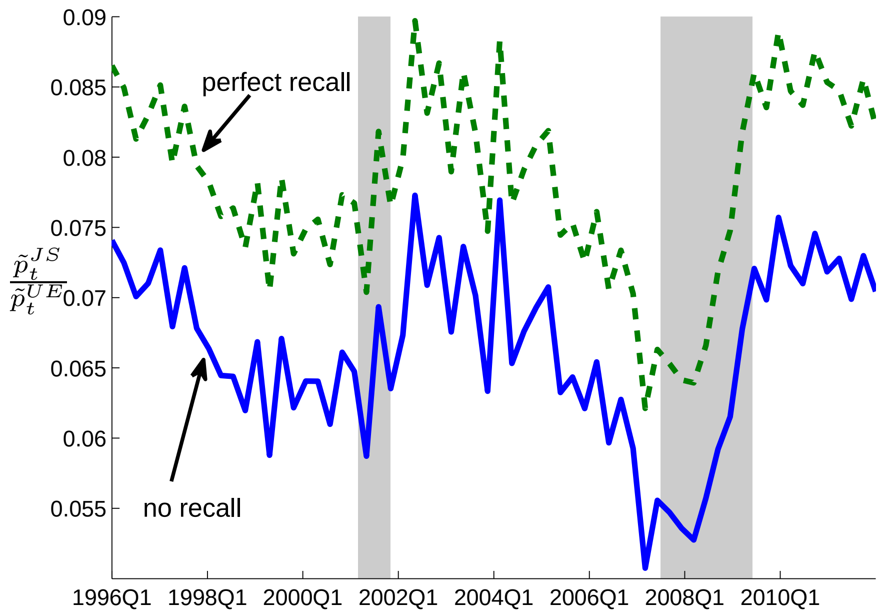

Figure 3: The probability of job-to-job transition divided by the unemployment-to-employment transition probability

A natural question is how these facts compare to the behavior of the job-to-job transition rate in the past. The data in Section 2 only go back to mid-1990s, but this section uses another dataset to make this comparison.

Earlier studies, such as Blanchard and Diamond (1990) and Shimer (2005a), use the March supplement to the CPS to measure the annual job-to-job transition rate. Since 1976, the March CPS has asked workers the number of employers they worked for during the previous year. The workers are also asked the number of spells of job search. Using this information, Blanchard and Diamond (1990) construct three measures of the job-to-job finding rate, and Shimer (2005a) constructs three additional measures. Here I extend their analyses through 2011.

The information obtained from the March CPS is less ideal than the monthly information in Section 2 for the following three reasons: First, the survey is annual and thus less frequent than the typical frequency used in business-cycle analysis. Second, a problem of "recall bias" arises because the survey relies on workers remembering their employment history over the previous year. Third, as is explained below, some of the answers are "capped" by an upper bound. An obvious advantage of the March CPS is that it goes back to 1975 (the information from 1975 is in the 1976 survey), and the purpose of this section is to compare the information obtained from the March CPS to the results in Section 2 in order to obtain a historical perspective on the results obtained above.

I focus on Shimer's measures in this section, and I discuss Blanchard and Diamond's measures in Appendix D. Shimer first computes $\Theta_1 \equiv \sum_{i=1}^{3} n_i(i-1)$, where n_i is the number of workers who experienced i number of employers. He considers Θ_1 the "upper bound" of the total job-to-job transitions in the economy in the previous year, because the worker with i number of employers experienced the job-to-job transitions $i-1$ times at most. The value of i is capped at 3 in the interview, and thus even this "upper bound" might understate the total number of job-to-job transitions. To translate Θ_1 into the transition rate, it has to be divided by the number of employed workers in each year. Shimer approximates this figure by the total number of workers times the average fraction of weeks worked, which is equivalent to (total number of weeks worked)/52. He calls the result the "upper measure."

Shimer's second measure (the "lower measure") computes the same object as Θ_1 above, but only for the workers who reported working for 52 weeks. He considers this figure the "lower bound" of the total job-to-job transitions, because even the workers who did not work some part of the year may experience job-to-job transitions. Again, he divides this figure by (total number of weeks worked)/52 to obtain the transition rate.

His third measure (the "intermediate measure") uses an additional piece of information, which is the number of job-search spells. He first computes $\Theta_2 \equiv \sum_{i=1}^{3} \sum_{j=0}^{3} n_{ij} \max\{i-j-1, 0\}$ instead of Θ_1. Here, i is the number of employers, j is the number of job-search spells (which is also capped at 3), and n_{ij} is the number of workers who report i employers and j spells. Again, he divides Θ_2 by (total number of weeks worked)/52 to obtain the transition

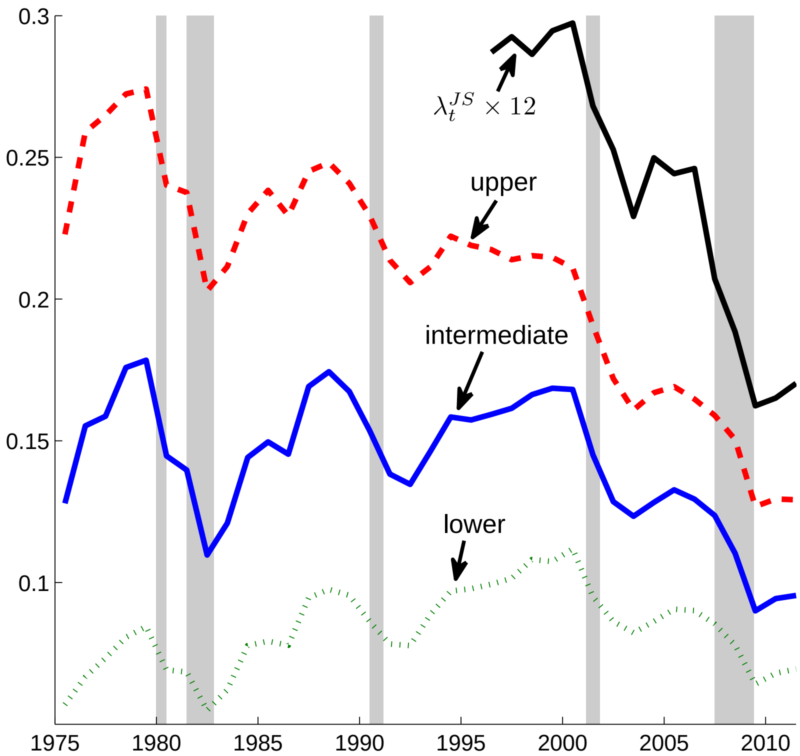

Figure 4: Annual job-to-job transition probabilities

rate.

Figure 4 plots these three measures. Note that these measures are already "rates," so time-aggregation corrections are not necessary. For comparison, Figure 4 also plots the time series of λ_t^{JS} that is computed in Section 2 (with no recall, annual average), multiplied by 12 so that it is adjusted from a monthly rate to an annual rate.

From 1996 to 2011, Shimer's measures from the March CPS are all lower than the frequency-adjusted version of λ_t^{JS} from Section 2. This difference is partly due to the caps in the March CPS measurement mentioned above. An additional issue is that of reporting error (recall bias). If the Poisson assumption does not hold in annual frequency, adjusting the frequency by multiplying by 12 may not be appropriate.

Despite the differences in level, however, the overall movement of the job-to-job transition rates over 1996–2011 is consistent across different measures. In particular, each series shows that the job-to-job transition rate is procyclical and that it exhibits a large decline from the beginning of the 2000s.

Looking back in time, the job-to-job transition rates were also procyclical in the 1980s and 1990s. Although different measures disagree in terms of levels, they all indicate a large decline occurred in the job-to-job transition rate in the early 1980s. They also provide some insight into the recent decline—the declines in each of the recent recessions (2001 and 2007–2009) were comparable to the past recessions, but the combined decline became unusually large because the recovery in the mid-2000s was small.

One important conclusion from Figure 4 is that the amount of the total decline in job-to-job transition rates since the early 2000s is unusual, even compared to the historical standards from the 1970s. The next section analyzes how this decline has affected the macroeconomic performance of the US economy.

4 Model

How does the procyclical job-to-job transitions matter for macroeconomic performance? How did the persistent decline in the job-to-job transition rate in recent years affect the aggregate economy? To assess the implications of the change in job-to-job transitions for aggregate productivity, I build a simple model and quantitatively evaluate it. The basic model is identical to the one used by Shimer (2005a), who analyzes an on-the-job search model in the tradition of Burdett (1978). (This type of model is often called a "job ladder model.") It is a quantitative dynamic model of unemployment and job-to-job transition with only a few assumptions. This model focuses on the behavior of workers (employed workers in particular) and remains agnostic about employers' behavior. This agnosticism is an advantage rather than a shortcoming of the model, because I can directly use the measured probabilities that are calculated in the previous section, without taking a stand on why these probabilities behave as observed. Because this model employs only a few assumptions, it is consistent with many models that have more structure.

4.1 Model setup

I make two background assumptions throughout the following analysis. First, I consider only transitions between unemployment and employment, ignoring the "not in the labor force" status. This choice is mainly motivated by the simplicity of the analysis, but it is also based on the fact that my focus is the effect of labor market frictions (which are associated with unemployment) on resource allocation. To the extent that the job-to-job transition is about the match between a job and a worker, rather than the general (ex-ante) productivity of workers, this omission should not have a large influence on my results.

The second background assumption is that the economy is in a steady state in the beginning of 1996 (with the parameter values that are measured in January 1996). I make this assumption because of the lack of information for earlier years, and I believe it is reasonable, but we have to keep in mind that this assumption somewhat influences the behavior of the model economy in the late 1990s.

The model is in continuous time. At time $s \in \mathbb{R}_+$, an unemployed worker finds a job with a Poisson rate f_s. Each job-worker match is characterized by "match quality," ε. The value of ε stays constant over the lifetime of a particular match. I call a job with a higher value of ε a "better job." When I calculate the aggregate productivity in Section 4.4, I will be more specific about how I link the match quality to wage and productivity. Here, the only assumption I need is that the wage is increasing in ε so that a worker prefers a job with higher ε. On meeting, a new match draws a new ε from a time-invariant distribution. As will be seen below (and also discussed in Shimer (2005a)), the behavior of the labor market in this model is independent of the distributional assumptions on ε, because only the relative ranking of the jobs matter for the individual behavior. Here, I denote the percentile of ε by z and describe the behavior of the economy by z instead of ε. By definition, z follows a uniform distribution on $[0, 1]$. I assume that an employed worker with match-quality percentile z loses a job and moves to unemployment at rate $\ell_s(z)$. On-the-job search also occurs: employed workers find an alternative job at rate f_s^e.

The behavioral assumptions of the unemployed and the employed workers are the following:

1. An employed worker accepts a job that is better than the current one.

2. An unemployed worker accepts any job offer.

The first assumption is relatively uncontroversial and holds in most of the existing models with on-the-job search. The idea here is that a job with a high match quality provides a better wage. (Later I will assume that a better job is also associated with higher productivity.) One implicit assumption here is that the mobility cost does not exist. If the mobility cost is substantial, the worker might decide not to move even if the newly offered job provides a better wage. However, this assumption is unlikely to be very important in our measurement—one can interpret the match quality of the new job as the "net benefit" after taking the mobility cost into account, or interpret f_s^e as the Poisson rate of receiving job offers that do not involve a very high mobility cost. The second assumption can be somewhat more controversial, given that unemployed workers' reservation wage may change over the business cycle. From the viewpoint of measuring the impact of procyclical job-to-job transitions on productivity, a procyclical reservation wage would worsen the productivity distribution during the recession, thus deepening the deterioration of productivity in recessions.

In the basic model, an additional assumption is that all separations are exogenous with constant probability across matches, that is, $\ell_s(z)$ is independent of z. This assumption rules out the cleansing effect, and it is not necessarily suited for our purpose of contrasting the productivity loss from fewer job-to-job transitions in recessions with the productivity gain from the cleansing effect in recessions. Later I extend the model to make $\ell_s(z)$ dependent on z in order to see the extent in which incorporating the cleansing effect would change our conclusion.

Let E_s be the number (share in the total population) of employed workers and U_s be the number of unemployed workers, where $E_s + U_s = 1$. Under the assumptions above, E_s satisfies the following differential equation:

$$\frac{dE_s}{ds} = f_s U_s - \ell_s E_s. \tag{1}$$

The quality distribution of active jobs is characterized by the density function $g_s(z)$. That is, $G_s(z) \equiv \int_0^z g_s(z')dz'$ is the number of employed workers with match quality percentile below z at time s. Note that $g_s(z)$ satisfies the differential equation

$$\frac{d(g_s(z)E_s)}{ds} = f_s U_s - \ell_s g_s(z) E_s - f_s^e(1-z) g_s(z) E_s + f_s^e G_s(z) E_s. \tag{2}$$

The left-hand side is the change in the mass of employed workers who are employed at match quality (percentile) z. The first term in the right-hand side is the entry of workers with match quality z from unemployment. The second term is the exit by separation. The third term is the outflow from quality z due to job-to-job transitions ($f_s^e(1-z)$ is the probability that they receive a job offer better than z). The last term is the inflow from lower qualities into quality z due to job-to-job transitions.

4.2 Calibration and computation

I solve the model numerically, with the assumption that in the beginning of 1996, the economy is in the steady state of (1) and (2); that is, $dE_s/ds = 0$ and $dg_s(z)/ds = 0$ for all z. The inputs required are f_s, f_s^e, and ℓ_s. I assume $f_{t+\tau} = \lambda_t^{UE}$ and $\ell_{t+\tau} = \lambda_t^{EU}$, where $t = 0, 1, ...$ (each month in the data) and $\tau \in [0, 1)$. Shimer (2005a) assumes that f_s^e is proportional to f_s, and this assumption seems reasonable given that we observed that the job-to-job transition rate looks similar to the job-finding rate of unemployed workers. Thus $f_s^e = af_s$, where a constant a is set so that the steady-state job-to-job transition rate in the model (with the initial January 1996 values of λ_t^{EU} and λ_t^{UE}) is identical to the January 1996 value of λ_t^{JS}. This procedure leads us to set a equal to 0.247. Which value of a is a reasonable one is not necessarily clear ex ante—for example, Tobin (1972) criticizes the "frictional unemployment"

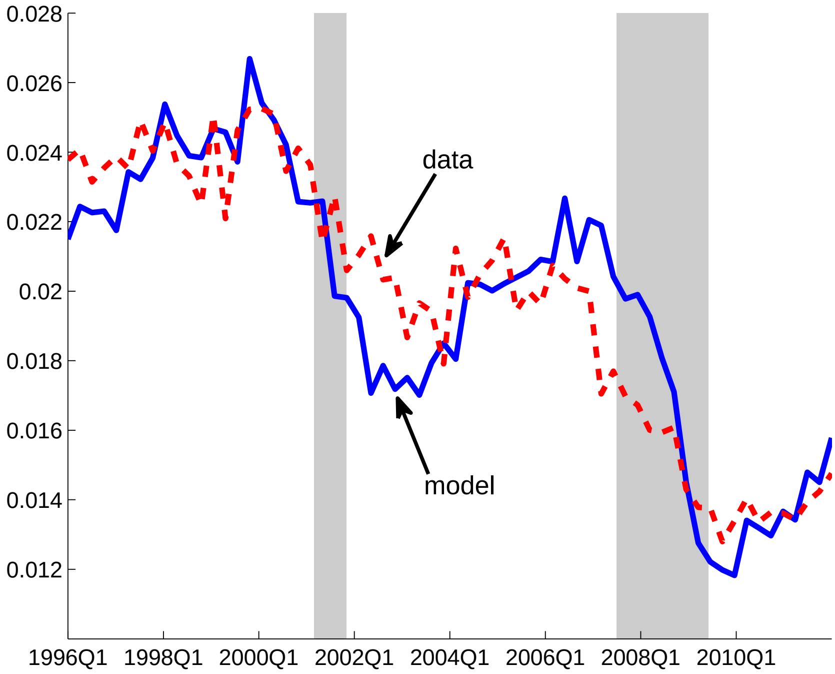

Figure 5: Job-to-job transition probability per month, model and data

models that do not include on-the-job search and argues that we do not have much reason to rule out that $a = 1$. I will return to this point later.

The computation of the model is based on discretization. I put 1000 grids on z and 10 grids on s (i.e., one period is divided into 10 subperiods).

4.3 Results

Note that I have used only the initial value of λ_t^{JS} as the calibration target. Thus one way of assessing whether the model reflects reality well is to compare the model-generated job-to-job transition rate with the job-to-job transition patterns in the data. In the model, the instantaneous job-switching probability can be computed as

$$\bar{\lambda}_s^{JS} = \int_0^1 f_s^e(1 - z)g_s(z)dz, \tag{3}$$

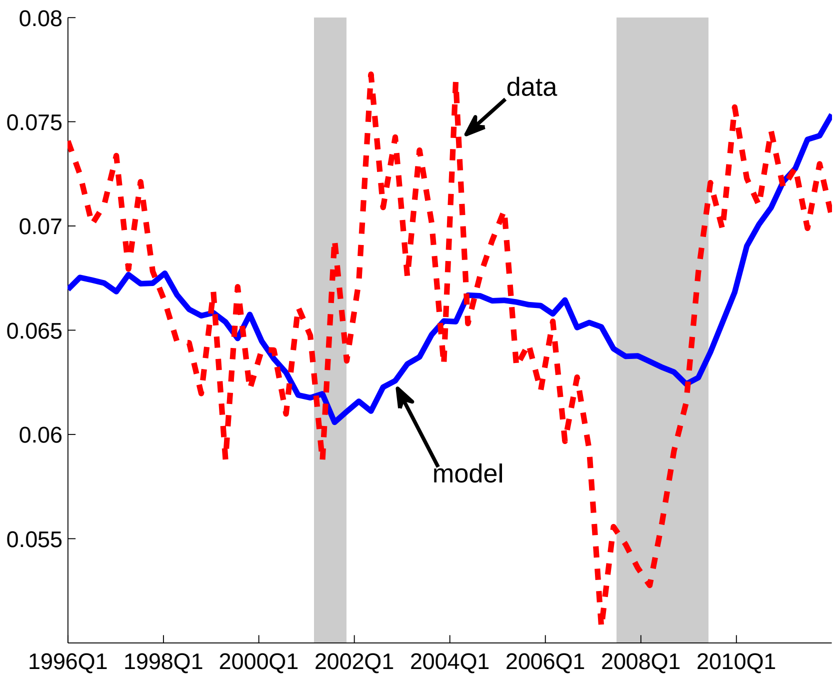

Figure 6: The probability of job-to-job transition divided by the unemployment-to-employment transition probability, model and data

and the monthly job-to-job transition probability can be calculated as $\bar{p}_t^{JS} = 1 - \exp(-\int_0^1 \bar{\lambda}_{t+\tau}^{JS} d\tau)$. Equation (3) shows that two elements affect the job-to-job transition rate. The first is the Poisson rate of an employed worker receiving a job offer, f_s^e. The second is the distribution of match quality, $g_s(z)$. The first moves together with f_s by assumption, and the second evolves endogenously over time.

Figure 5 compares the job-to-job transition probability per month (average for each quarter) generated from the model with $\tilde{p}_t^{JS}$ calculated from the data in the previous section (under the no-recall assumption—see Figure 1). The two time series match well. To examine the difference between the data and model more closely, Figure 6 plots the same probability ratio as Figure 3 for model and data (the data series is the no-recall case). The two series move in the same direction *qualitatively*. In particular, the model captures the property of the data that this ratio goes up in the beginning of the recovery and falls later. The movement of the distribution of match quality over time drives this behavior. Because f_s^e falls during the recession, the distribution of match quality worsens during the recession (more and more workers are "mismatch employed"). When the recovery starts and f_s^e starts to go up, the job-to-job transition rate goes up faster than f_s^e (and therefore faster than f_s) because workers with a bad match are more willing to move, and at that point, more of them exist than at the average time. As the recovery continues, these workers with bad matches are "cleared up," and the distribution of the match quality improves. This improvement slows down the job-to-job transition rate. The job-to-job transition rate is high relative to the job-finding probability of unemployed workers in 2011, because the 2008–2009 recession was long and significantly deteriorated the distribution of match quality. Quantitatively, the mechanism of this basic model does not generate as much swing in this ratio as the data series.

4.4 Implications for aggregate productivity

Next, I analyze the implications of the movement of the job-to-job transition probability on aggregate productivity. Note, once again, that the results so far do not depend on any distributional assumption on the match quality ε—so far I have worked out everything with the match-quality percentile z. In other words, the above results hold for any distribution of ε. However, to analyze the aggregate productivity, I now need to specify the distributional form of ε. I also need to explicitly link the wage and the productivity to ε. Denote the wage of worker i working at employer j as w_{ij}, and the worker's productivity as y_{ij}. I assume that both consist of two parts: the worker-specific factor and the match-specific factor. Let

$$\log(w_{ij}) = \alpha_i + \varepsilon_{ij}, \tag{4}$$

where α_i is the worker-specific factor and ε_{ij} is the match-specific factor (corresponding to the "match quality" above), and

$$\log(y_{ij}) = \gamma_i + \eta\varepsilon_{ij},$$

where γ_i is the worker-specific factor and $\eta > 0$ is the inverse of the elasticity of wage with respect to productivity. When the match-specific productivity increases by 1%, the wage increases by $1/\eta$%. From the balanced-growth perspective, $\eta = 1$ is the most reasonable value in the long run. As Shimer (2005b) and Hornstein et al. (2005) argue, in a typical Diamond-Mortensen-Pissarides model, $1/\eta$ is close to 1. Wage rigidity makes the value of η larger. Below, I consider the case with $\eta = 1$.

I assume that α_i and ε_{ij} are independent, and also that γ_i and ε_{ij} are independent. (I allow α_i and γ_i to be correlated—I do not need to make any further assumption about these two in the current context.) With these independence assumptions, given that different workers do not interact with each other (and f_s, f_s^e, and ℓ_s are independent of α_i and γ_i), I will be able to omit α_i and γ_i from the model and focus on ε_{ij}. In particular, when I calculate the change of aggregate productivity over time (i.e., relative to time s_0 productivity), I can compute

$$\bar{y}_s = \int \exp(\varepsilon) dH_s(\varepsilon)$$

and use $\bar{y}_s/\bar{y}_{s_0}$ instead of the ratio of the actual aggregate productivity, where $H_s(\varepsilon)$ is the distribution of ε among the employed workers at time s. Appendix E shows this equivalence formally.

I choose the distribution of ε in offered wages so that the steady-state distribution of $H_s(\varepsilon)$ at $s = s_0$ (with all parameter values at s_0) follows a normal distribution with mean 0 and variance σ^2. (Thus the wage conditional on α_i follows a lognormal distribution.) The size of σ plays an important role in determining the size of the productivity effect. In general, a large σ means the wage-offer distribution is more dispersed, which implies the gains from job-to-job transitions are large. Thus a large σ tends to imply a large productivity effect.

My calibration strategy is to set the value of σ by targeting the average wage gain from switching a job (in the initial steady state). Appendix E shows that this procedure is valid even in the presence of α_i and γ_i. Several empirical studies provide estimates of the wage gains from switching a job. Topel and Ward (1992), using the quarterly Social Security earnings records (Longitudinal Employer-Employee Data), find that a typical job change is accompanied by about 12% wage growth. Subtracting the typical quarterly wage increase within a job, the average gain from changing a job is about 10%. In Topel and Ward (1992), the average samples are young men below 34 years old, and younger workers tend to experience larger wage gains, so the wage gains for an average worker would likely be somewhat smaller. Fallick et al.'s (2012) samples include 25- to 55-year-old male and female workers, and they find that the median earnings increase for a worker who switched jobs within a quarter is about 10%, whereas a job stayer's increase is about 2% (their Table 4a). Hyatt and McEntarfer's (2012) Figure 5 reports that median earnings changes ranged from a 6% to 11% increase over different years. Note that all the above numbers are based on the quarterly measurement, and they may miss some of the actual job-to-job transitions. Some authors point out that negative wage changes are often observed at the time of a job-to-job transition (e.g., Postel-Vinay and Robin (2002) and Nunn (2012)), whereas the job-ladder model cannot generate a negative wage change. Explicitly dealing with these cases by incorporating other elements such as measurement errors, wage growth, and non-wage job characteristics is beyond the scope of this paper. The current calibration strategy implies that an omission of negative wage changes is always accompanied by an omission of above-average positive wage changes, because the mean wage change has to match the data. To the extent that these two offset each other, taking the negative wage changes into account will not significantly affect the main results below.

Considering the above empirical estimates, I target the average wage gain of 8% upon job switch. In the current model, this calibration implies the median wage gain is about 6%. Taking the wage growth of job stayers into account, this calibration implies an actual median wage increase that is in the lower to mid range of Hyatt and McEnterfer's (2012) estimates.[3] The resulting value of σ is 0.087. The corresponding standard deviation of the (log) wage-offer distribution is 0.081. Hall and Müller (2012) estimate this value to be

[3]In an earlier version of the paper (Mukoyama (2013)), I targeted the average wage gain of 12% (the corresponding median wage gain is 9%), which resulted in a larger productivity effect.

0.075. Their estimate is based on Krueger and Mueller's (2011) survey data of unemployed workers' reservation wages and the assumption that the reservation wage is proportional to the worker's productivity. My model's steady-state variance of the log match quality, $0.087^2 = 0.008$, is somewhat lower than Hagedorn and Manovskii's (2010) estimate of the variance of the log match quality, 0.016. My calibration implies that the wage ratio of the 90th percentile to the 50th percentile (and also of the 50th percentile to the 10th percentile) is 1.12, which is much smaller than the measured wage dispersion. Autor et al.'s (2008) measure of the "residual wage inequality" (the wage inequality after controlling for observable worker characteristics) gives this ratio at about 1.5 to 1.8 (from their Figure 8). Lemieux's (2006) result is somewhat smaller, but it implies a log standard deviation of the residual wage of 0.41 to 0.44 (from his Figure 1). Not all residual wage inequality is the result of the heterogeneity in match quality (e.g. measurement errors and unobservable heterogeneity of workers), and therefore it is reasonable that my σ is smaller than the estimates from the residual wage inequality. If I assume a higher value of σ, the effect of the change in the job-to-job transition rate on aggregate productivity would be stronger.

Figure 7 presents the results. The solid line plots $\bar{y}_s/\bar{y}_{s_0}$. The dotted line is the de-trended utilization-adjusted TFP level (normalizing the 1996:Q1 level as 1) calculated from Fernald's (2012) dataset.[4] The trend is assumed as a constant 0.25% quarterly growth. We can see that reallocations due to job-to-job transitions do not contribute much to the increase in TFP in the early 2000s, whereas they account for a significant part of the TFP decline in the past few years. From the start of 2009, the model accounts for about a 0.5% annual decline in TFP. (The de-trended TFP in Figure 7 declined about 1.0% annually during the same period.)

Note that the reallocation through job-to-job transitions does not explain all of the movements in TFP. For example, the model is silent about the large productivity increase that occurred in mid 2000s. This productivity increase can be attributed to various other fac-

[4]The data are downloadable from http://www.frbsf.org/csip/tfp.php.

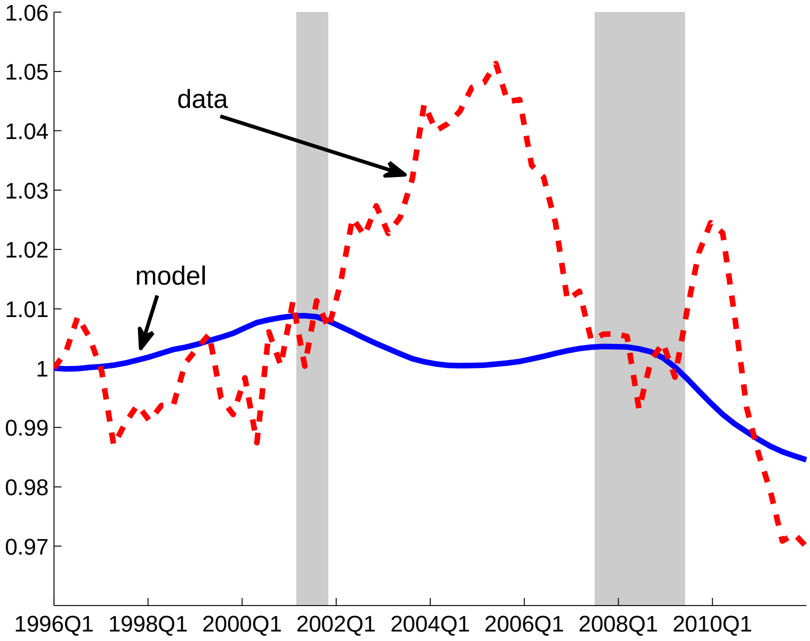

Figure 7: Average match quality from the model (relative to 1996:Q1 level) and the utilization-adjusted TFP (deviation from the trend) in the data

tors. For example, Jorgenson et al. (2007) show that much of the TFP growth from 2000 to mid-2000s originated in the industries that are the most intensive users of information technology (IT). We can reasonably imagine that productivity gain from the use of IT would tend to realize in the form of each worker's productivity enhancement, rather than realloca-tion. Cyclical factors also exist—demand booms may influence the measured productivity through various channels. Holman et al. (2008) argue that industries involved in producing and distributing construction materials benefited from the housing boom in the mid-2000s.

5 The role of the cleansing effect

This section extends the model to incorporate the idea of the cleansing effect of recessions. The basic structure of the model remains the same, but here I make the separation rate ℓ_s

dependent on the match-quality percentile z (and denote it as $\ell_s(z)$). In particular, I assume that $\ell_s(z)$ is decreasing in z—a job with low match quality is destroyed more frequently. Below I consider specifications where in recessions, $\ell_s(z)$ increases more for a low z than for a high z, in accordance with the "cleansing" idea. In the following, I consider two different specifications of $\ell_s(z)$.

5.1 Weak cleansing

The first specification is

$$\ell_s(z) = \ell_s(1)[1 + (\zeta - 1)(1 - z)],$$

where $\zeta \geq 1$ is a parameter. This equation implies that $\ell_s(0) = \zeta\ell_s(1)$ for all s. The value of $\ell_{t+\tau}(1)$ at each $t = 0, 1, ...$ and $\tau \in [0, 1)$ is set so that the separation rate at each instant is consistent with the data:

$$\int_0^1 \ell_{t+\tau}(z) g_{t+\tau}(z) dz = \lambda_t^{EU}. \tag{5}$$

The special case with $\zeta = 1$ is the model in Section 4. The case with $\zeta > 1$ exhibits a cleansing effect in the sense that when λ_t^{EU} increases, $s_{t+\tau}(z)$ increases for all z but increases more for a smaller z. That is, for a different time $t + \tau$ and $t' + \tau'$ ($t, t' = 0, 1, ...$ and $\tau, \tau' \in [0, 1)$),

$$\ell_{t'+\tau'}(z) - \ell_{t+\tau}(z) = (\ell_{t'+\tau'}(1) - \ell_{t+\tau}(1))[1 + \zeta(1 - z)].$$

Thus when $\ell_{t'+\tau'}(1) > \ell_{t+\tau}(1)$, $\ell_{t'+\tau'}(z) - \ell_{t+\tau}(z)$ is decreasing in z. I call this specification "weak cleansing." It is called "weak" because the *ratio* of separation rates $\ell_{t'+\tau'}(z)/\ell_{t+\tau}(z)$ is independent of z.

I continue to assume $\eta = 1$. Note that the other parameters have to be adjusted with the change of $\ell_s(z)$. The dispersion of the log-wage offer distribution, σ, has to be adjusted so that the average wage gain from job change is still 8%. The relative efficiency of on-the-job search compared with off-the-job search, a, has to adjust so that the job-to-job transition rate at the initial time (January 1996) is consistent between the data and the steady state of the model. In general, both σ and a have to increase with ζ. These adjustments have to

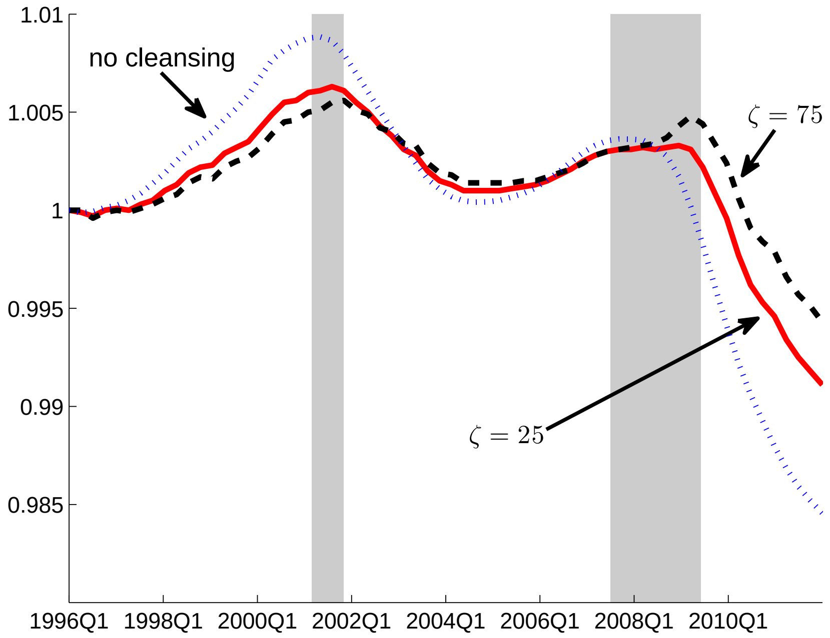

Figure 8: Average match quality from the model (relative to 1996:Q1 level) without cleansing effect ($\zeta = 1$), with $\zeta = 25$, and $\zeta = 75$.

be made because more cleansing implies that the steady-state distribution of match quality is better for a given set of parameter values, and therefore less room for improvement exists for an already employed worker.

Because a good estimate of ζ is not available, I compare several cases with different values of ζ, ranging from $\zeta = 1$ (no cleansing effect) to an extremely large value of ζ. Figure 8 compares three cases: $\zeta = 1$, $\zeta = 25$, and $\zeta = 75$. The $\zeta = 1$ case is analyzed in the previous section. The case with $\zeta = 25$ is already quite extreme—it implies that $\ell_s(0)$ is 25 times larger than $\ell_s(1)$. In this case, σ is adjusted to 0.113 (the median wage gain from job change is 5.7%) and a is adjusted to 0.623. The case with $\zeta = 75$ requires that $\sigma = 0.126$ (the median wage gain on job change is 5.6%) and $a = 0.998$. The value of $a = 0.998$ means that an employed worker receives job offers with almost the same frequency as an unemployed worker. Tobin (1972) argues that no evidence exists that an employed worker is less efficient in job finding than an unemployed worker; thus a being close to one is a useful benchmark from this perspective.

Comparing different time paths of the average match quality in Figure 8, we can see that the existence of the cleansing effect dampens its fluctuations. Because of the cleansing effect, the average match quality *increases* over a large part of the 2007–2008 recession in the cases of $\zeta = 25$ and $\zeta = 75$. The drop in average match quality from the peak in recent years (2008:Q4 for $\zeta = 25$ and 2009:Q1 for $\zeta = 75$) to the end of 2011 is still sizable in both cases: 1.2% for $\zeta = 25$ and 1.1% for $\zeta = 75$. The existence of the cleansing effect does not overturn the detrimental effect of reduced reallocation. In particular, even with these extreme specifications, the model accounts for about a 0.4% annual decline in TFP.

5.2 Strong cleansing

The second formulation I consider is

$$\ell_s(z) = \ell_{s_0}(1)[1 + (\tilde{\zeta}_s - 1)(1 - z)], \tag{6}$$

where s_0 is the initial time (January 1996). When $s = s_0$, $\tilde{\zeta}_s$ is set equal to the value of a parameter ξ. Equation (6) means that $\ell_s(1)$ is always constant at the value of $\ell_{s_0}(1)$ and that $\ell_s(0) = \tilde{\zeta}_s \ell_s(1)$ for all s. When $s = s_0$, the value of $\ell_{s_0}(1)$ is set so that (5) is satisfied at the steady state of the model with $t = s_0$ (i.e., January 1996) parameters. When $s \neq s_0$, $\tilde{\zeta}_s$ is adjusted so that (5) is satisfied for each particular s (with $s = t + \tau$). Therefore, other things equal, $\tilde{\zeta}_{t+\tau}$ is high when λ_t^{EU} is high for $t = 0, 1, ...$ and $\tau \in [0, 1)$. I call this case "strong cleansing" because not only is the *difference* between the separation rates $\ell_{t'+\tau'}(z) - \ell_{t+\tau}(z) = \ell_{s_0}(1)(\tilde{\zeta}_{t'+\tau'} - \tilde{\zeta}_{t+\tau})(1 - z)$ decreasing in z when $\lambda_{t'}^{EU} > \lambda_t^{EU}$, but the *ratio* $\ell_{t'+\tau'}(z)/\ell_{t+\tau}(z) = [1 + (\tilde{\zeta}_{t'+\tau'} - 1)(1 - z)]/[1 + (\tilde{\zeta}_{t+\tau} - 1)(1 - z)]$ is also decreasing in z (where $t, t' = 0, 1, ...$ and $\tau, \tau' \in [0, 1)$).

Figure 9 compares the no-cleansing case with the case with $\xi = 75$. In the initial steady state, the $\xi = 75$ case is identical to the $\zeta = 75$ case in the previous section, so the parameters of $\sigma = 0.126$ and $a = 0.998$ are the same as in that case. We can see that, similar to the

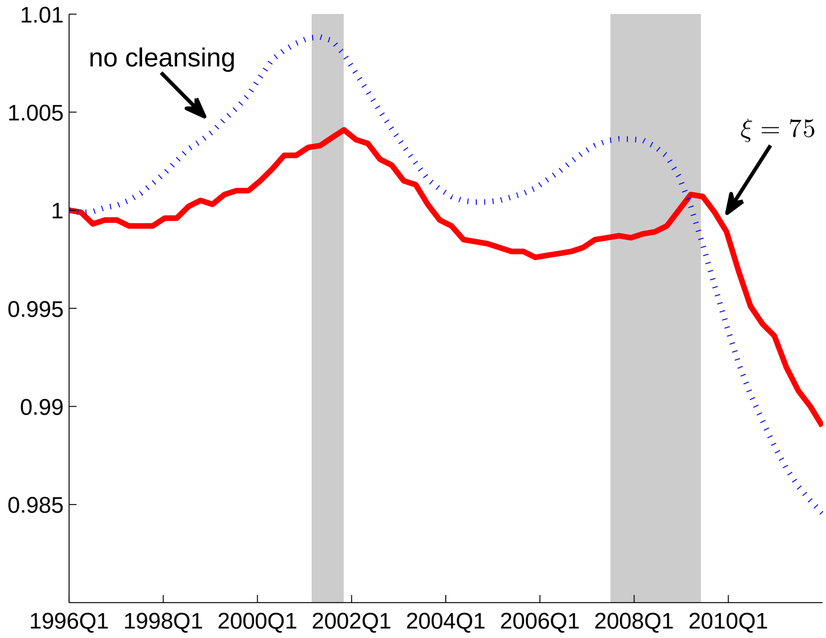

Figure 9: Average match quality from the model (relative to 1996:Q1 level) without cleansing effect and $\xi = 75$.

previous section, the existence of the cleansing effect dampens the fluctuations of the average match quality and also tends to raise the match quality during the recessions. In the $\xi = 75$ case, the drop from the recent peak (2009:Q1) to the end of 2011 is 1.2%—still a sizable amount. Similar to the previous section, the model accounts for about a 0.4% annual decline of TFP. The main takeaway from this section is that the main conclusion of Section 4, that the decline in the job-to-job transitions accounts for a sizable decline of TFP in recent years, is robust to the inclusion of an extreme amount of the cleansing effect.

6 Conclusion

This paper analyzes the job-to-job transition behavior of workers. The paper has two contributions. First, it develops a simple method of time-aggregation correction for the data.

Second, using a simple model, it evaluates the effect of the recent movement of job-to-job transition rates on aggregate productivity.

My time-aggregation adjustment method is simple and uses a set of assumptions similar to the existing adjustment methods for other labor market flows. The adjusted time series reveals that the behavior of the job-to-job transitions is procyclical and has been declining since the early 2000s. My method can accommodate recalls—the existence of recalls alters the outcome of the adjustment, but it does not overturn the cyclicality and the recent declining trend. An examination of the March CPS data, going back to 1970s, reveals that this recent decline is an unusual episode.

The model is based on a few simple assumptions about worker behavior. The decline of job-to-job transitions reduces the reallocation of workers to better matches and therefore is detrimental to aggregate productivity. The calibrated version of the model reveals that the change in job-to-job transition rates significantly affects aggregate productivity. From 2009 to 2011, the model TFP declined about 0.5% annually.

My model can accommodate the cleansing effect of recessions. I find that even under extreme assumptions about the cleansing effect, the model still accounts for a large decline in productivity in recent years—from 2009 to 2011, the model TFP declined about 0.4% annually.

This paper focuses on the *consequences* rather than the *causes* of the change in job-to-job transition rates. A natural question is why the job-to-job transition rate behaves in the observed manner. To answer this question, one has to analyze the incentives of the employers in hiring workers from the employment pool as well as from the nonemployment pool. This analysis is beyond the scope of this paper, but it is an important topic for future research.

Appendix

A Three-state time-aggregation adjustment

The following method is identical to the one developed by Shimer (2012). Let $\lambda_t^{ij} \geq 0$ denote the Poisson arrival probability of a shock that moves a worker from state i to state j ($i \neq j$), where $i, j \in \{E, U, N\}$, which applies during the time interval $[t, t+1)$. For example, denoting the number of workers in state i at time $t + \tau \in [t, t + 1)$ as $\chi^i(t + \tau)$,

$$\frac{d\chi^E(t+\tau)}{d\tau} = -(\lambda_t^{EU} + \lambda_t^{EN})\chi^E(t+\tau) + \lambda_t^{UE}\chi^U(t+\tau) + \lambda_t^{NE}\chi^N(t+\tau).$$

Let $\lambda_t^{ii} \equiv -\sum_{i \neq j} \lambda_t^{ij}$. Then, the above equation becomes

$$\frac{d\chi^E(t+\tau)}{d\tau} = \lambda_t^{EE}\chi^E(t+\tau) + \lambda_t^{UE}\chi^U(t+\tau) + \lambda_t^{NE}\chi^N(t+\tau).$$

With a discrete-time approximation, denoting Δ as a small time interval,

$$\lim_{\Delta \to 0} \frac{\chi^E(t+\tau+\Delta) - \chi^E(t+\tau)}{\Delta} = \lambda_t^{EE}\chi^E(t+\tau) + \lambda_t^{UE}\chi^U(t+\tau) + \lambda_t^{NE}\chi^N(t+\tau).$$

Let

$$\chi(t+\tau) \equiv \begin{pmatrix} \chi^E(t+\tau) \\ \chi^U(t+\tau) \\ \chi^N(t+\tau) \end{pmatrix}$$

and

$$\Lambda_t \equiv \begin{pmatrix} \lambda_t^{EE} & \lambda_t^{UE} & \lambda_t^{NE} \\ \lambda_t^{EU} & \lambda_t^{UU} & \lambda_t^{NU} \\ \lambda_t^{EN} & \lambda_t^{UN} & \lambda_t^{NN} \end{pmatrix}.$$

Note that each column sums to 0. The transition equation can be written in matrix form:

$$\lim_{\Delta \to 0} \frac{\chi(t+\tau+\Delta) - \chi(t+\tau)}{\Delta} = \Lambda_t \chi(t+\tau). \tag{7}$$

Because λ's are not directly observed, Λ is recovered from the observed Markov transitions in discrete time. Let p_t^{ij} be the probability of a worker moving from state i to j (where $i, j \in \{E, U, N\}$) between periods t and $t + 1$. In matrix form,

$$P_t \equiv \begin{pmatrix} p_t^{EE} & p_t^{UE} & p_t^{NE} \\ p_t^{EU} & p_t^{UU} & p_t^{NU} \\ p_t^{EN} & p_t^{UN} & p_t^{NN} \end{pmatrix}.$$

Note that each column sums to 1. The matrix P_t can be recovered from the CPS data (with the assumption that all workers are subject to the same shock probabilities). In terms of the populations,

$$\chi(t+1) = P_t \chi(t)$$

holds.

If we divide one period into a sequence of ($1/\Delta$ numbers of) subperiods whose length is Δ each, the transition probability during each subperiod can be defined as $P_{t,\Delta}$, which satisfies

$$P_t = {P_{t,\Delta}}^{1/\Delta}. \tag{8}$$

Also, for $\tau = 0, \Delta, 2\Delta, ...,$

$$\chi(t+\tau+\Delta) = P_{t,\Delta} \chi(t+\tau)$$

holds. Thus, once a $P_{t,\Delta}$ that satisfies (8) is found,

$$\frac{\chi(t+\tau+\Delta) - \chi(t+\tau)}{\Delta} = \frac{1}{\Delta}(P_{t,\Delta} - I)\chi(t+\tau)$$

(where I is the identity matrix) can be calculated, and from (7), Λ_t can be recovered by

$$\Lambda_t = \lim_{\Delta \to 0} \frac{1}{\Delta}(P_{t,\Delta} - I).$$

To calculate the right-hand side of the equation, suppose first that P_t can be diagonalized as

$$P_t = V_t D_t {V_t}^{-1},$$

where D_t is the diagonal matrix (and suppose that all elements of D_t are real and distinct) of P_t's eigenvalues and V_t consists of corresponding eigenvectors. Then the matrix $P_{t,\Delta}$, calculated by

$$P_{t,\Delta} = V_t D_t^{\Delta} {V_t}^{-1},$$

(where D_t^{Δ} is a diagonal matrix whose elements are the corresponding elements of D_t raised to the Δth power) satisfies (8). Therefore (since $I = V_t I {V_t}^{-1}$ for any V_t),

$$\Lambda_t = \lim_{\Delta \to 0} \frac{1}{\Delta} V_t (D_t^{\Delta} - I) {V_t}^{-1}.$$

And since $\lim_{\Delta \to 0}(d^{\Delta} - 1)/\Delta = \log d$,

$$\Lambda_t = V_t \tilde{D}_t V_t^{-1},$$

where $\tilde{D}_t$ is a diagonal matrix whose diagonal elements are the natural log of corresponding elements of D_t.

B Time-aggregation adjustment method

My method proceeds with three steps. First, consider the fraction (among the workers employed at time t) of workers who have never experienced the job-switching shock or the labor market state-changing shock between t and $t+\tau$, where $\tau \in [0,1)$. Call it $\chi_0^E(t, t+\tau)$. It satisfies the following differential equation:

$$\frac{d\chi_0^E(t, t+\tau)}{d\tau} = -(\lambda_t^{JS} + \lambda_t^{EU} + \lambda_t^{EN})\chi_0^E(t, t+\tau).$$

With the boundary condition $\chi_0^E(t,t) = 1$, this equation can be solved as

$$\chi_0^E(t, t+\tau) = \exp(-(\lambda_t^{JS} + \lambda_t^{EU} + \lambda_t^{EN})\tau). \tag{9}$$

Second, consider the fraction (again, among the workers employed at time t) of workers who (i) experienced a job-switching shock exactly once and (ii) have never changed their labor market state between time t and $t+\tau$ to be $\chi_1^E(t, t+\tau)$, where $\tau \in [0,1)$. Call it $\chi_1^E(t, t+\tau)$. It satisfies the following differential equation:

$$\frac{d\chi_1^E(t, t+\tau)}{d\tau} = \lambda_t^{JS}\chi_0^E(t, t+\tau) - (\lambda_t^{JS} + \lambda_t^{EU} + \lambda_t^{EN})\chi_1^E(t, t+\tau).$$

From the above solution for $\chi_0^E(t, t+\tau)$ and the boundary condition $\chi_1^E(t,t) = 0$, the solution is

$$\chi_1^E(t, t+\tau) = \tau\lambda_t^{JS} \exp(-(\lambda_t^{JS} + \lambda_t^{EU} + \lambda_t^{EN})\tau). \tag{10}$$

Third, I make an assumption about recalls and use the above formulas to obtain the equation whose solution is λ_t^{JS}. It is clear that, regardless of the existence of recalls, the workers who are in $\chi_0^E(t, t+1)$ are not observed in p_t^{JS} (but are observed in p_t^{EE}). It is also clear that, again regardless of the existence of recalls, the workers in $\chi_1^E(t, t+1)$ are observed in p_t^{JS} (and also in p_t^{EE}). The rest of the workers who are employed in both period t and $t+1$, the workers in $p_t^{EE} - \chi_0^E(t, t+1) - \chi_1^E(t, t+1)$, are in the "gray area." These workers include the ones who are hit by the job-switching shock more than twice within a month and the workers who are hit by the labor market state switching shock more than twice (and come back to employment) within a month. If there are no recalls, they would be working for a different employer at time $t+1$ and therefore would be included in p_t^{JS}. If there are recalls, some of them may be back at the original employer and, in that case, are not in p_t^{JS}.

In general, therefore, the formula for the time-aggregation adjustment is the solution λ_t^{JS} to the equation

$$p_t^{JS} = \chi_1^E(t, t+1) + (1 - r_t)(p_t^{EE} - \chi_0^E(t, t+1) - \chi_1^E(t, t+1)), \tag{11}$$

where $\chi_0^E(t, t+1)$ and $\chi_1^E(t, t+1)$ can be derived from (9) and (10). Note that $r_t \in [0, 1]$ is the ratio of recalled workers within "gray area" workers and that (for a given r_t) all variables in equation (11) are observable (or obtained earlier), except for λ_t^{JS}.

In the main text, I implement this time-aggregation adjustment method for two extreme cases.[5] One is the case where there are no recalls: $r_t = 0$. The other is $r_t = 1$. The latter is the case where all workers who can possibly go back to the original employer at the end of the month actually go back. I call it the "perfect recall" case.

In the case of no recall, using (9) and (10) with $\tau = 1$, (11) can be rewritten as

$$\lambda_t^{JS} = -\log(p_t^{EE} - p_t^{JS}) - \lambda_t^{EU} - \lambda_t^{EN}.$$

With the assumption of perfect recall, (11) boils down to $\chi_1^E(t, t+1) = p_t^{JS}$. Thus, using

[5]It is clear from the above argument that once can recursively compute the fraction of workers who were hit by the job switching shocks i times and the labor market switching shocks j times between time t and $t+\tau$, where $i, j = 0, 1, ...$; $t = 0, 1, ...$; and $\tau \in [0, 1)$. This computation would allow a more elaborate adjustment if necessary. Indeed, this type of logic can be used for time-aggregation adjustments for other types of shocks, as long as the underlying process can reasonably be assumed as Poisson.

(10) with $\tau = 1$, λ_t^{JS} is equal to the solution of

$$\lambda_t^{JS} - \log(\lambda_t^{JS}) = -\log(p_t^{JS}) - \lambda_t^{EU} - \lambda_t^{EN}.$$

C An alternative value of r_t in time-aggregation adjustment

In a recent paper, Fujita and Moscarini (2013) measure the frequency of recalls using the SIPP data. The average value of the recall probability in their data is about 37% (the average value of their Table 3, third row). Here, I use $r_t = 0.37$ in equation (11), although r_t here does not exactly correspond to what Fujita and Moscarini (2013) measure. In particular, I solve the equation (11) using (9) and (10) for λ_t^{JS} under the assumption of $r_t = 0.37$. The values of p_t^{JS} and p_t^{EE} directly come from the data, and λ_t^{EU} and λ_t^{EN} are calculated using the method of Appendix A.

Figure 10 corresponds to Figure 1 in the main text. The time-aggregation adjustment moves the job-switching probability down, but the magnitude of adjustment is small and the cyclicality of the adjusted series is very similar to that of the original data.

D Job-to-job transition rates following Blanchard and Diamond (1990)

Blanchard and Diamond (1990) construct the time series of job-to-job transition rates using the information from the March CPS. They characterize individuals with three numbers: x, y, and z. They set x equal to 1 if the individual was not in the labor force at any point during the year, and 0 otherwise. Their y runs from 0 to 3 and stands for the number of employers (here, 3 is actually 3 or more since the number is capped). Their z also runs from 0 to 3, and it stands for stretches of unemployment (again, it is capped at 3; also note that z is unknown for a worker who did not work during the year and was not in the labor force at least once). Let X_{xyz} be the fraction of individuals in each category.

Blanchard and Diamond then calculate the "upper bound" measure, the intermediate

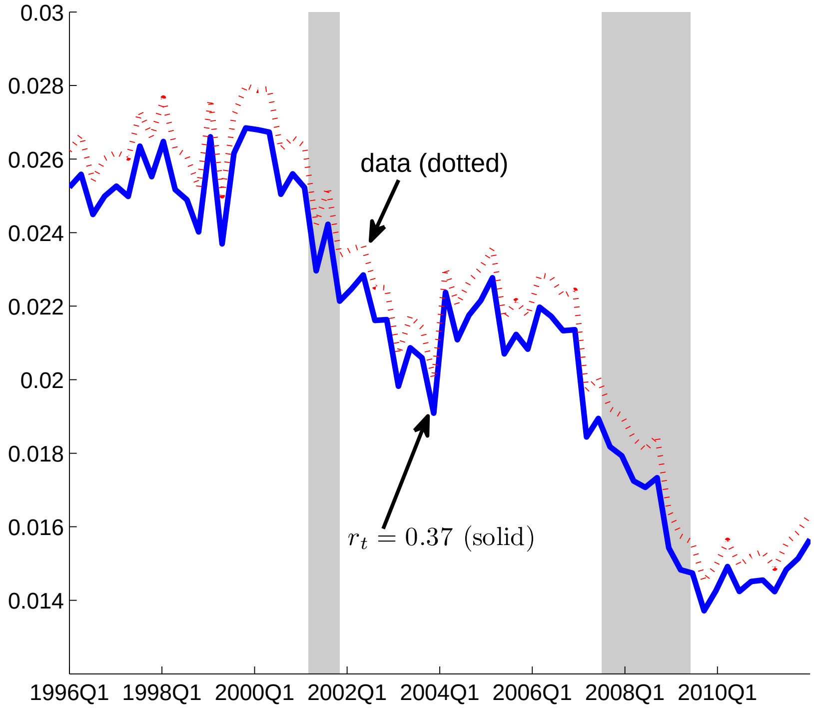

Figure 10: The probability of job-to-job transition with time-aggregation adjustment: p_t^{JS} (labeled as "data") and $\tilde{p}_t^{JS}$ with $r_t = 0.37$

("best guess") measure, and the "lower bound" measure by

$$\text{upper} = \sum_{z=0}^{3} X_{02z} + 2\sum_{z=0}^{3} X_{03z} + \sum_{z=0}^{3} X_{12z} + 2\sum_{z=0}^{3} X_{13z},$$

$$\text{intermediate} = X_{020} + 0.5X_{021} + 2X_{030} + 1.5X_{031} + 0.5X_{120} + 1.5X_{130} + X_{131},$$

and

$$\text{lower} = X_{020} + 2X_{030} + X_{031} + X_{130}.$$

Figure 11 plots these three series, along with $\lambda_t^{JS} \times 12$ from Section 2 (with no recall, annual average). The overall properties are similar to Shimer's (1995a) measures, and the discussions in Section 3 also apply here.

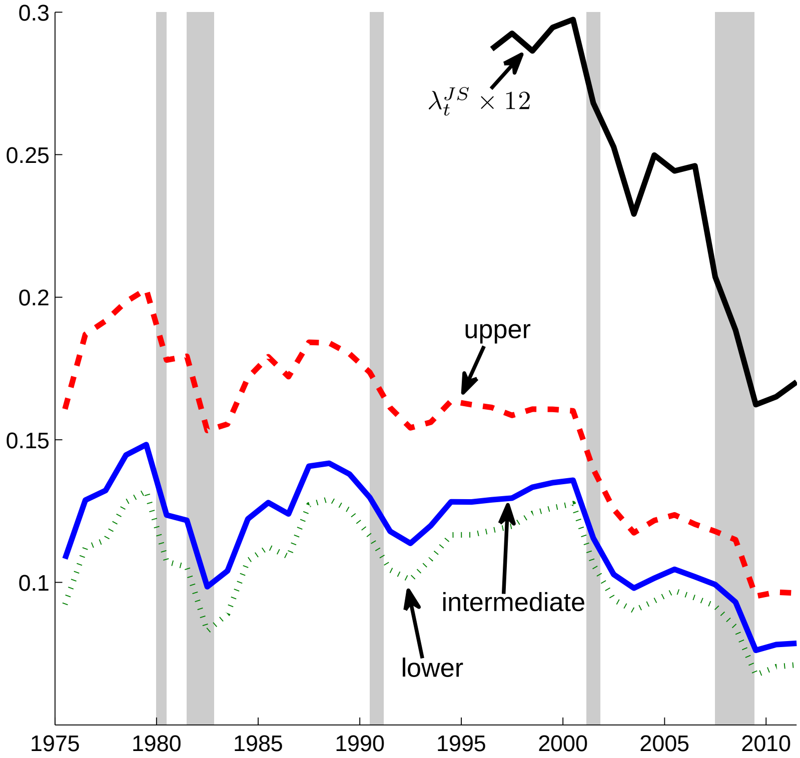

Figure 11: Annual job-to-job transition probabilities

E Why α_i and γ_i can be dropped in calculating aggregate productivity

This Appendix shows why α_i and γ_i can be dropped in calculating aggregate productivity in Section 4.4. First, note that since α_i does not change for a given worker, the worker's decision to switch jobs only depends on ε_{ij}. Second, γ_i is irrelevant for the worker's decision. Thus, an economy where $\log(w_{ij})$ is determined by (4) and an economy where $\log(w_{ij}) = \varepsilon_{ij}$ (or its monotonic transformation) would behave identically in terms of worker behavior. The log change of the wage from job j to job j' is $\log(w_{ij}) - \log(w_{ij'}) = \varepsilon_{ij} - \varepsilon_{ij'}$, and it is also independent of α_i.

The actual aggregate productivity is measured as

$$\bar{Y}_s = \int \exp(\gamma + \eta\varepsilon) dK_s(\gamma) dH_s(\varepsilon),$$

where $K_s(\gamma)$ is the distribution function of γ and $H_s(\varepsilon)$ is the distribution function of ε. From the independence assumption (and the fact that the behavior of a worker is independent of γ), the distributions of γ and ε are independent across employed workers. Thus when the average productivity is compared to its initial time s_0 (i.e., January 1996) level,

$$\frac{\bar{Y}_s}{\bar{Y}_{s_0}} = \frac{\int \exp(\gamma + \eta\varepsilon) dK_s(\gamma) dH_s(\varepsilon)}{\int \exp(\gamma + \eta\varepsilon) dK_{s_0}(\gamma) dH_{s_0}(\varepsilon)} = \frac{\int \exp(\gamma) dK_s(\gamma) \int \exp(\eta\varepsilon) dH_s(\varepsilon)}{\int \exp(\gamma) dK_{s_0}(\gamma) \int \exp(\eta\varepsilon) dH_{s_0}(\varepsilon)} = \frac{\int \exp(\eta\varepsilon) dH_s(\varepsilon)}{\int \exp(\eta\varepsilon) dH_{s_0}(\varepsilon)}$$

holds—this corresponds to $\bar{y}_s/\bar{y}_{s_0}$ in the main text (with the assumption of $\eta = 1$). This ratio is independent of α and γ. The second equality is from the independence of γ and ε. The third equality holds because the *distribution* of γ among employed workers is identical over time because of the independence assumption and the fact that the behavior of a worker is independent of γ.

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