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Gross Worker Flows over the Business Cycle†

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We build a hybrid model of the aggregate labor market that features both standard labor supply forces and frictions in order to study the cyclical properties of gross worker flows across the three labor market states: employment, unemployment, and nonparticipation. Our parsimonious model is able to capture the key features of the cyclical movements in gross worker flows. Despite the fact that the wage per efficiency unit is constant over time, intertemporal substitution plays an important role in shaping fluctuations in the participation rate. (*JEL* E24, E32, J22, J31, J64, J65)

Modern research on aggregate labor market dynamics stresses the importance of microfounded models of labor market flows as a way to connect micro and macro data. In this paper we build a parsimonious model of individual labor supply in the presence of labor market frictions and assess its ability to account for gross worker flows between employment, unemployment, and nonparticipation over the business cycle.

Our model represents a hybrid of the two classes of benchmark models that dominate the literature: heterogeneous agent models in the spirit of Lucas and Rapping (1969), and reflected in Chang and Kim (2006), and search models in the spirit of

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Mortensen and Pissarides (1994). In the former, workers flow between employment and nonemployment and these flows represent optimal labor supply responses to changes in prices. In the latter, workers are passive, always wanting to work but subject to frictions that sometimes prevent them from working, thus generating flows between unemployment and employment. Reality seems to reflect elements of both benchmarks, and to the extent that participation reflects the desire to work and unemployment reflects frictions that create a wedge between desired and actual labor supply, we think the natural starting point for assessing a hybrid model of labor supply is to confront it with data on the gross worker flows.

Our analysis begins by documenting the cyclical properties of gross flows. We stress two key patterns. First, although the participation rate is much less volatile over the business cycle than either the unemployment or employment rate, the volatilities of flows into and out of the labor force are of roughly the same magnitude as are the much studied flows between employment and unemployment. Second, the cyclical properties of some of these flows seem counterintuitive; for example, the transition rate from unemployment to nonparticipation is procyclical despite the fact that the participation rate is procyclical.

We then build a model in which households are subject to idiosyncratic shocks in the presence of incomplete credit and insurance markets and labor market frictions, i.e., job-loss and job-finding rates. Our specification allows for endogenous search effort while non-employed, on-the-job search, heterogeneous match quality, and an unemployment insurance (UI) system that reflects key features of the US system. Aggregating across heterogeneous households yields a model of aggregate labor supply in the presence of frictions. The steady state of the model features flows across labor market states from one period to the next. An important part of our work is to show that it is possible to calibrate the model to yield a close match between the average flows in the US data and those in the model, something which previous models have been unable to do.

We then subject our model to aggregate shocks to the extent of labor market frictions, i.e., job-finding rates and job-loss rates, and examine the implications for the cyclical patterns in gross worker flows. We find that our benchmark model with shocks to frictions does a good job of accounting for the key features of fluctuations in gross worker flows between the three labor market states. In particular, it accounts for the fact that the participation rate fluctuates much less than the unemployment and employment rates and is less highly correlated with output, as well as generating large fluctuations in the flows into and out of the labor force that have the same pattern of cyclical correlations as found in the data.[1]

The weak procyclical nature of the participation rate reflects two forces that are close to offsetting in our analysis: a wealth effect that decreases the desire to participate in good times, and an intertemporal substitution effect that creates an incentive for additional search during good times. Although our model features a constant wage per efficiency unit of labor, a standard intertemporal labor supply channel nonetheless emerges due to the fact that higher job-to-job flows during good times

[1] As Shimer (2013) demonstrates, a model that provides a good match with the data in the cyclical behavior of the flows between unemployment and employment does not necessarily fit the cyclical pattern of labor force participation once it is extended to incorporate the participation margin.

imply that wages for individual workers increase more rapidly during good times. In our model, flows between participation and nonparticipation account for almost one third of fluctuations in the unemployment rate, consistent with the empirical findings in Elsby, Hobijn, and Şahin (2015).

Changes in the composition of individuals in the unemployment pool play a key role in explaining how our model accounts for the patterns of correlations for the flows into and out of the labor force. In particular, during good times the unemployment pool is more heavily populated by individuals who are closer to being indifferent between participating and not-participating, and as a result there is an increase in the rate at which workers transition from unemployment to nonparticipation.

Our paper is related to several strands in the literature. One of these is the literature on gross flows.[2] Another is the literature on individual labor supply in the presence of frictions. Ham (1982) was an early effort to rigorously study unemployment in a labor supply setting, showing that unemployment spells could not be interpreted as optimal labor supply responses. Consistent with his findings, our model features both an operative labor supply margin and unemployment, and unemployment is a departure from desired labor supply. More recently, Low, Meghir, and Pistaferri (2010) study life-cycle labor supply in the presence of frictions. Our study is very much in the spirit of theirs, though because our focus is on aggregate effects over the business cycle, our individuals are described in a more stylized manner (without regard to age, etc.). Our own earlier work, e.g., Krusell et al. (2010), is even more stylized and only looks at mechanisms in steady states, whereas the present paper is focused entirely on aggregate fluctuations.[3]

A third strand is a recent literature that extends general equilibrium business cycle models of employment and unemployment to allow for a participation decision.[4] The key feature that distinguishes our paper from these is our focus on gross worker flows—these papers only consider labor market stocks. In addition, our model improves upon labor supply models with household heterogeneity—such as in Chang and Kim (2006)—by introducing a labor market with realistic features.

An outline of the paper follows. In the next section we document the key business cycle facts for gross worker flows among the three labor market states for the United States over the period 1978–2012. Section II describes our theoretical framework and explains how we calibrate it. Section III examines the cyclical performance of the model. Section IV concludes.

[2] This includes, for example, Abowd and Zellner (1985); Poterba and Summers (1986); Blanchard and Diamond (1990); Davis and Haltiwanger (1992); Fujita and Ramey (2009); Shimer (2012); and Elsby, Hobijn, and Şahin (2015).

[3] Our earlier work is significantly less detailed: it does not have UI, costly search, match quality, nor on-the-job search. Our modeling of search costs here, moreover, allows us to fit the steady state flows significantly better. Finally, note that due to the nonlinearity of our model, with wealth effects, cutoff decision rules, etc., it is not sufficient to make steady state comparisons as a way to understand how cyclical movements are generated.

[4] These include Tripier (2004); Veracierto (2008); Christiano, Trabandt, and Walentin (2010); Galí, Smets, and Wouters (2011); Ebell (2011); Haefke and Reiter (2011); and Shimer (2013).

Table 1—Cyclical Properties of Stocks, 1978:I–2012:III

	u	$lfpr$	E
std(x)	0.1170	0.0026	0.0099
corr(x, Y)	−0.84	0.21	0.83
corr(x, x_{-1})	0.93	0.69	0.92

I. Worker Flows over the Business Cycle

In this section, we document the business cycle facts for gross worker flows using data from the Current Population Survey (CPS) for the period 1978:I–2012:III.[5] The flow rates are calculated for all respondents and are not only restricted to household heads. Further details regarding the data sources and the construction of labor market flows are provided in online Appendix A.1.

A model that successfully accounts for the behavior of gross worker flows will necessarily account for the behavior of net flows and hence the three labor market stocks—E (employment), U (unemployment), and N (not in the labor force)—though not vice versa. It follows that matching the behavior of the three labor market stocks is a less stringent test of a model. Because it is much simpler to describe the behavior of the stocks and they are subject to less measurement error, we think it is useful to examine the properties of both the stocks and the flows in the models that we consider.

To begin our analysis, Table 1 presents summary statistics from the data for the business cycle properties for the stocks.[6] We use u to denote the unemployment rate, $U/(E+U)$, *lfpr* to denote the labor force participation rate, $(E+U)/(E+U+N)$, and Y for GDP.

The resulting patterns are relatively well known: employment is strongly procyclical, and the unemployment rate is strongly countercyclical. Although the labor force participation rate is procyclical, it is not as strongly cyclical as the other two series. The unemployment rate is the most volatile of the three series, and the labor force participation rate is the least volatile. All three series are highly autocorrelated. The fact that the participation rate fluctuates relatively little compared to either the employment rate or the unemployment rate might lead one to conclude that movements into and out of the labor force are not of first-order importance in understanding fluctuations in the unemployment rate. However, this conclusion confuses the role of net flows with the role of gross flows. We now turn to look at the behavior of gross flows, and will see that the small fluctuations in net flows into and out of the labor force mask large fluctuations in the gross flows into and out of the labor force.

We estimate gross flows using matched CPS data for the period 1978:I–2012:III following an algorithm similar to that used elsewhere.[7] While some of the patterns

[5] We restrict attention to 1978:I–2012:III since this is the period for which we have consistent data on adjusted gross flows.

[6] The cyclical components in Table 1 and Table 3 are isolated using an HP-filter with a smoothing parameter of 1,600 applied to the log of quarterly averages of monthly data.

[7] In particular, see Blanchard and Diamond (1990); Fujita and Ramey (2009); Shimer (2012); and Elsby, Hobijn, and Şahin (2015).

Table 2—Gross Worker Flows, 1978:I–2012:III

Unadjusted data				Abowd-Zellner correction				De*NUN*ified data			
From	To			From	To			From	To		
	E	*U*	*N*		*E*	*U*	*N*		*E*	*U*	*N*
E	0.957	0.015	0.028	*E*	0.972	0.014	0.014	*E*	0.957	0.015	0.028
U	0.254	0.535	0.211	*U*	0.228	0.637	0.135	*U*	0.263	0.592	0.146
N	0.047	0.028	0.925	*N*	0.022	0.021	0.957	*N*	0.048	0.019	0.933

that we highlight have been documented in previous work (see, e.g., Blanchard and Diamond 1990 and Shimer 2012), some details vary across studies and it is important that we have a consistent set of statistics for the exercises we carry out later.[8]

An important concern when analyzing gross flows data is the possibility of classification error. Earlier research has found these errors to be substantial, especially for transitions between unemployment and nonparticipation.[9] We implement a correction following Blanchard and Diamond (1990) and Elsby, Hobijn, and Şahin (2015) to address this issue. In particular, we adjust the gross flows data using Abowd and Zellner's (1985) estimates of misclassification probabilities based on resolved labor force status in CPS reinterview surveys. Table 2 shows the average values of quarterly transition rates for the 1978:I–2012:III period with and without the Abowd-Zellner correction; in the table, f_{ij} denotes the fraction of workers that move from state i in the previous period to state j in the current period.[10]

Table 2 reveals that the adjusted flows using Abowd and Zellner's estimates of misclassification probabilities are systematically below their unadjusted counterparts. Put differently, all three labor market states are more persistent than predicted by unadjusted flow rates. As noted in the prior literature, flows that involve nonparticipation are affected much more than other flows. Transition rates between employment and nonparticipation are approximately halved, while those between unemployment and nonparticipation are adjusted down by around one third.

An alternative adjustment, suggested by Elsby, Hobijn, and Şahin (2015), involves recoding sequences of recorded labor market states to eliminate high-frequency reversals of transitions between unemployment and nonparticipation. This procedure identifies individuals whose measured labor market state cycles back and forth between unemployment and nonparticipation from month to month and omits

[8] Differences include the method used to identify cyclical components, the time period and whether to report statistics for flows of workers as opposed to transition rates. For example, Blanchard and Diamond (1990) focus on the component of the time series that is accounted for by what they call "aggregate demand shocks," whereas we focus on the cyclical component as identified using the HP filter. They consider the time period 1968–1986, whereas we consider 1978:I–2012:III, and we characterize transition rates, whereas they characterize the level of flows. This last feature can make some properties appear different. For example, whereas the transition rate from U to E (which we denote as f_{UE}) is strongly procyclical, the fact that the size of the unemployment pool is also countercyclical implies that the level of the U to E flow is actually countercyclical.

[9] See, for example, Abowd and Zellner (1985); Poterba and Summers (1986); Chua and Fuller (1987); and Elsby, Hobijn, and Şahin (2015).

[10] We do not make any correction for time aggregation when reporting statistics for the flows. Our model will explicitly allow for some time aggregation, so the statistics in Table 2 will be the appropriate ones for comparing with the values generated by our model. We note, however, that with time aggregation corrections, none of the qualitative patterns that we comment on below change. Shimer (2013) examines these flows using data that are corrected for time aggregation but finds the same cyclical properties as we do.

Table 3—Cyclical Properties of Gross Worker Flows

	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
Panel A. Unadjusted data						
std(x)	0.075	0.033	0.077	0.053	0.041	0.064
corr(x, Y)	−0.70	0.35	0.79	0.66	0.61	−0.70
corr(x, x_{-1})	0.69	0.22	0.82	0.71	0.52	0.78
Panel B. Abowd-Zellner (AZ) correction						
std(x)	0.089	0.083	0.088	0.106	0.103	0.072
corr(x, Y)	−0.63	0.43	0.76	0.61	0.52	−0.23
corr(x, x_{-1})	0.59	0.29	0.75	0.62	0.38	0.30
Panel C. DeNUNified data						
std(x)	0.069	0.036	0.076	0.066	0.041	0.063
corr(x, Y)	−0.66	0.29	0.81	0.55	0.57	−0.56
corr(x, x_{-1})	0.70	0.22	0.85	0.58	0.48	0.57

such transitions ("de*NUN*ification"). For example, a respondent who reported a sequence of labor market states of *NUN* is recoded as being a nonparticipant *NNN*. Elsby, Hobijn, and Şahin (2015) show that this correction results in transition rates between unemployment and nonparticipation that are quite similar to the adjusted rates based on the Abowd and Zellner (1985) estimates. The average values of the f_{UN} and f_{NU} transition rates with the adjusted data using de*NUN*ification were 0.146 and 0.019, respectively. These values are similar to the corresponding Abowd-Zellner adjusted data (0.135 and 0.022). In the remainder of our paper, we will use the average transition flow rates, as well as labor market stocks, adjusted using the Abowd-Zellner estimates of misclassification as our benchmark to assess the performance of our model, though we will refer to both adjustments when we evaluate the cyclical performance of our model.

Next we turn to the cyclical behavior of the gross flows. Table 3 presents summary statistics from the data for the business cycle properties for gross flows using the unadjusted data as well as the Abowd-Zellner adjusted and de*NUN*ified flows data. The series are quarterly, produced by taking the quarterly average of monthly series, and all series are then logged and HP filtered.

We focus our discussion of this table around four basic observations. First, although as noted previously the stock of nonparticipants does not vary much over the business cycle relative to the other two stocks, Table 3 shows that the flows between nonparticipation and the other states exhibit large movements at business cycle frequencies. Specifically, whereas the fluctuations in the participation rate are an order of magnitude smaller than the fluctuations in the unemployment rate, the fluctuations in the transition rates into and out of nonparticipation are of roughly the same order of magnitude as those in the much-studied flows between E and U. For example, looking only at the two flow rates into employment, f_{UE} and f_{NE}, one would not be led to conclude that the participation rate plays only a minor role in accounting for employment fluctuations. The reason that the labor force participation rate does not move more over the cycle is because of the offsetting effect of an increased U-to-N transition rate during good times.

Second, consistently with the earlier work of Blanchard and Diamond (1990), the U and N states are not observationally equivalent. For example, whereas the flow rate from E into U is strongly countercyclical, the flow rate from E into N is weakly procyclical.

Third, some of the cyclical properties revealed in Table 3 might reasonably be viewed as counterintuitive. For example, although the participation rate increases during good times, both of the flow rates out of participation, f_{EN} and f_{UN}, actually increase during good times.

Fourth, the fact that the U-to-N flow rate decreases during recessions is contrary to an apparent piece of conventional wisdom that holds that unemployed workers are more likely to become discouraged during bad times. Note that this is not inconsistent with the fact that the stock of discouraged workers is higher during recessions: even with a constant flow rate between unemployment and discouragement, the fact that the stock of unemployment is higher in recessions will also imply that the stock of discouraged workers is higher.

The cyclicality of flows are very similar for each of the two misclassification adjustments we considered. However, applying the misclassification adjustment following the estimates of Abowd and Zellner increases the volatility of the flow rates involving nonparticipation considerably while the de*NUN*ification process does not result in a notable change for the volatility of these flow rates. This is consistent with the type of adjustment that the two correction procedures involve. The Abowd-Zellner correction is a time-invariant correction method that applies the correction probabilities to any occurrence of the state N while de*NUN*ification applies the correction to the high frequency reversals between N and U. When we compare models to the data, we will report comparisons with the data adjusted using both methods to provide a better assessment of the performance of our models.

For future reference we note a related finding in the recent work by Elsby, Hobijn, and Şahin (2015). They find that the composition of the unemployment pool shifts toward more attached workers during recessions; this factor accounts for around 75 percent of the decline in the U-to-N transition rate during recessions. The most important dimension of attachment turns out to be prior employment status. This feature will be present in the quantitative model that we study. Moreover, our relatively parsimonious model will deliver natural explanations for all of the patterns just documented.

II. Labor Supply and Gross Worker Flows

Our core model is one of individual consumption and labor supply in the presence of imperfectly insurable uncertainty and job-finding frictions. The individual is subject to a variety of shocks. Some of these shocks are shared by other agents (they are aggregate shocks), whereas others are purely idiosyncratic. Through the budgets, prices—notably the wage per efficiency unit of labor and interest rate—appear, and we assume that all agents face the same prices. Moreover, we take these prices as exogenous. Thus, our strategy is to solve for individual behavior given prices and then aggregate across the population, taking into account that some shocks are shared. Our focus is on how labor supply decisions are made across the population and we do not require that prices clear the labor market at all points in time: we solve for a partial equilibrium. However, as we explain in detail below, the prices we do subject the agents to are calibrated so as to clear markets on average.[11]

Our setting blends together the Bewley-Huggett-Aiyagari heterogeneous-agent assumptions to model consumption choice with a search model restricting the individual's ability to choose in the labor market. The latter incorporates search both on and off the job. Overall, our aim is for the modeling as well as the calibration to be standard and in line with the large associated literatures. Thus, we did not design the model to deliver certain outcomes for our focus of analysis: how the gross flows across labor market states change over the business cycle.

Thus, consider an individual with preferences given by

$$E_t \sum_{t=0}^{\infty} \beta^t [\log(c_t) - \alpha e_t - \gamma s_t],$$

where $c_t \geq 0$ is consumption in period t, $e_t \in \{0, 1\}$ is employment status in period t, and $s_t \in \{0, 1\}$ is a discrete variable that reflects whether the individual engages in active job search in period t. The parameters $\alpha > 0, \gamma > 0$ are the disutilities of work and active search, respectively, and $0 < \beta < 1$ is the discount factor. A key element of our model is that an individual's (net) return from work in the market is stochastic. In reality the relevant shocks could influence both the reward to market work and the opportunity cost of market work, but since it is ultimately the relative value of market work that matters, we capture this with a single shock, which we model as an idiosyncratic shock to market productivity, z_t. We assume it follows an AR(1) process in logs:

$$\log z_{t+1} = \rho_z \log z_t + \varepsilon_{t+1},$$

where the innovation ε_{t+1} is a mean zero, normally distributed random variable with standard deviation σ_ε.[12]

The traditional literature on individual labor supply assumes that the relevant market conditions faced by an individual are prices, most notably the wage rate (w) and the interest rate (r). A key innovation of our labor supply model is to expand the set of market conditions to also include four parameters $(\lambda_u, \lambda_n, \lambda_e$, and $\sigma)$ that describe labor market frictions. We will refer to λ_u, λ_n, and λ_e as employment opportunity arrival rates: λ_u is the probability that a non-employed individual who engages in active search receives an employment opportunity, λ_n is the probability that a non-employed individual who does not engage in active search receives an employment opportunity, and λ_e is the probability that an employed individual receives an additional employment opportunity with another employer. The subscripts u and n reflect the fact that active search will determine whether an individual is counted as

[11] In an earlier version of the paper, we also closed the general-equilibrium side of the model, which requires assumptions on how prices and frictions are determined. Under the assumptions we made, it turned out that the results were very similar to those obtained in the corresponding partial equilibrium analysis. See Krusell et al. (2012).

[12] Because z is mean-reverting, some movements in the return to market work will be predictable whereas some will not. A richer model would include more detail, perhaps with part of the predictable component reflecting age effects, and with multiple random components that differ in persistence. We view our approach as a parsimonious first step.

unemployed or not in the labor force. The parameter σ is the employment separation rate and is the probability that an individual employed in period $t-1$ loses his or her job at the beginning of period t. We collect the aggregate variables into a vector, $\Lambda \equiv (w, r, \lambda_u, \lambda_n, \lambda_e, \sigma)$, that follows a law of motion over time. We describe how we calibrate this law of motion in the sections below.

A salient feature of the data on gross worker flows that we presented in the previous section is that even after cleaning the data to remove spurious flows, there remain large movements of non-employed individuals between active and passive search. To capture this in our model we assume that the disutility of active search, γ, is random. In our calibrated model we assume that draws are iid over time and distributed according to a three-point distribution with mean $\overline{\gamma}$ and support $\{\overline{\gamma} - \varepsilon_\gamma, \overline{\gamma}, \overline{\gamma} + \varepsilon_\gamma\}$ with equal probability at each point.

An employed worker's labor earnings are the product of three components: the market wage per efficiency unit of labor services (w), the idiosyncratic worker component z described above, and a match quality component (q). Whenever an individual receives an employment opportunity, it is accompanied by a realization of the match quality q, which is an iid draw from a log normal distribution with mean 0 and standard deviation σ_q. This value is fixed for the duration of the match and is observed at the time the employment opportunity is received.

There is a UI program, specified so as to capture key features of the UI system in the United States while also maintaining tractability. To be eligible for UI, a worker must have previously been employed and experienced an employment separation shock. That is, individuals who leave employment by choice are not eligible. In order to be eligible to receive benefits, we assume that an individual needs to engage in active search. Although we implicitly assume that the UI authority can monitor search activity, we do not assume that the UI authority can observe any received employment opportunities, so the receipt of benefits imposes no restrictions on an individual's decision to accept an employment opportunity. To capture the fact that UI benefits have finite duration while minimizing the state space, we assume that an eligible individual loses eligibility each period with probability μ. We will represent a non-employed individual's eligibility status by the indicator variable I^B, with the convention that a value of one indicates eligibility. Another feature of the UI system in the United States is that benefits are related to past earnings, subject to a cap. To capture this we assume that an individual's UI benefit is a linear function of his or her idiosyncratic shock z, up to a maximum of $\overline{b}$.[13] Formally,

$$b(z) = \begin{cases} b_0 z & \text{if } b_0 z \leq \overline{b} \\ \overline{b} & \text{otherwise} \end{cases}.$$

We assume a market structure that is standard in the incomplete markets literature. The individual cannot borrow and there are no markets for insuring idiosyncratic risk, but can accumulate an asset, whose level we denote by a, and offers a rate of return given by r. To capture the presence of various transfer programs that implicitly provide some insurance, we assume that there is a proportional tax τ on

[13] We index benefits to z rather than past earnings in order to economize on the state space while still allowing for feedback from market opportunities to UI benefits.

labor earnings and a lump sum transfer T. Combining these features, the individual's period budget equation is given by

$$c_t + a_{t+1} = (1+r)\,a_t + (1-\tau)\,w z_t q_t e_t + (1-e_t)\,I_t^B s_t(1-\tau)\,b(z_t) + T,$$

where, as above, $e_t \in \{0,1\}$ is the employment indicator.

Next we describe how events unfold within a period. At the beginning of period t an individual will observe new realizations for z, γ, I^B, and Λ. To detail the subsequent events we need to distinguish individuals according to three scenarios. In the first scenario, the individual was not employed in the previous period and did not receive an employment opportunity while searching. In the second scenario, the individual was not employed in the previous period but did receive an employment opportunity and associated match quality while searching. In the third scenario, the individual was employed in the previous period.

We begin with the individual in the first scenario. Having received new realizations for z, γ, I^B, and Λ, this individual chooses whether to engage in active or passive search and makes a consumption-saving decision. Following these decisions, the outcome of search will be realized. If the individual receives an employment opportunity (and an associated draw of match quality) he or she will enter period $t+1$ as an individual in scenario two.

Next consider an individual who enters the current period in scenario two. This individual begins the period with an employment opportunity in hand. If the individual accepts the employment opportunity they will work this period, receive labor earnings, make a consumption-savings decision, and enter the subsequent period as an individual in scenario three. If the individual chooses to reject the employment opportunity, they are now identical to an individual who entered the period under scenario one, and once again makes choices about search effort, consumption, and saving.

Finally, we consider an individual who enters the period in scenario three. In the process of transiting from the previous period to the beginning of this period we allow for two types of developments. First, we implicitly assume that employed workers engage in passive search and hence may receive additional employment opportunities. Second, as noted earlier, we allow for the possibility that past employment positions are destroyed, causing the worker to be separated. While there are various ways that one could formulate the joint outcomes, we assume that this individual experiences one of four mutually exclusive events as follows. With probability $1-\sigma-\lambda_e$ the individual retains the previous employment opportunity and does not receive an additional opportunity. With probability λ_e the individual retains the previous opportunity but also receives an additional employment opportunity with an iid draw from the match quality distribution. With probability $\sigma\lambda_u$ the individual is separated from the previous employment opportunity but receives a new employment opportunity with a new draw from the match quality distribution.[14] Lastly, with probability $\sigma(1-\lambda_u)$ the individual

[14] We interpret these individuals as the very short-term unemployed, who find a job within the month of separation, which is the main reason we use λ_u for the probability of a new offer. Alternatively, we could have set

is separated from the previous employment position and does not simultaneously receive a new employment opportunity.

In the event that the individual has only one employment opportunity, the situation is identical to scenario two. In the event that the individual has two employment opportunities, it is optimal to take the one with the higher match quality and discard the other, at which point the individual again is in scenario two. Note that the combination of on-the-job search and heterogeneous match quality implies that our model features a job ladder in which employed individuals tend to transition to higher paying jobs over time. Finally, an individual who is separated and has no employment opportunity is identical to an individual in scenario one.

We express the individual's decision problem recursively. We formulate the problem at the point where all new shocks have been realized, so that the individual knows the current value of z, the current value of γ, whether they have an employment opportunity and if so the value of the match quality, the current UI eligibility status, and the assets brought into the period.

An individual without an employment opportunity (i.e., what we called scenario one above) decides both whether to engage in active or passive search and on consumption versus saving. Let $U(a,z,\gamma,I^B,\Lambda)$ and $N(a,z,\gamma,I^B,\Lambda)$ denote the Bellman values for such an individual conditional upon active search (i.e., unemployed) and passive search (i.e., out of the labor force), respectively. An individual in this "jobless" situation will have a value denoted by $J(a,z,\gamma,I^B,\Lambda)$ that is simply the maximum of these two options:

$$J(a,z,\gamma,I^B,\Lambda) \;=\; \max\{U(a,z,\gamma,I^B,\Lambda),N(a,z,\gamma,I^B,\Lambda)\}.$$

An individual with an employment opportunity (i.e., what we called scenario two above) has an additional decision: whether to accept or reject the employment opportunity. An individual who rejects the employment opportunity will become identical to an individual who did not have an employment opportunity, and hence receive the value $J(a,z,\gamma,I^B,\Lambda)$. Let $W(a,z,q,I^B,\Lambda)$ denote the Bellman value for an individual who accepts an employment opportunity. An individual with an employment opportunity will choose the maximum of these two values, which we will denote by $V(a,z,q,\gamma,I^B,\Lambda)$:

$$V(a,z,q,\gamma,I^B,\Lambda) \;=\; \max\{W(a,z,q,I^B,\Lambda),J(a,z,\gamma,I^B,\Lambda)\}.$$

this probability equal to $\sigma\lambda_e$, on the grounds that a separating worker has the same chance of getting an outside offer within the period as does a non-separating worker. As a practical matter this makes little difference, but our choice captures the possibility that a separating worker may be able to generate additional offers through contacts (our calibration will have $\lambda_u > \lambda_e$). More generally we could have introduced another independent parameter to capture this probability.

Having developed the notation for all of these Bellman values we can now write out the individual Bellman equations that define these values. Working backward from the end of the period decisions, the Bellman equation for W is given by

$$\begin{aligned} W(a, z, q, I^B, \Lambda) = \max_{c \geq 0, a' \geq 0} \{ \ln c - \alpha + \beta E_{z', q', \gamma', \Lambda'} [(1 - \sigma - \lambda_e) V(a', z', q, \gamma', 0, \Lambda') \\ + \lambda_e V(a', z', \max\{q, q'\}, \gamma', 0, \Lambda') \\ + \sigma \{ (1 - \lambda_u) J(a', z', \gamma', 1, \Lambda') \\ + \lambda_u V(a', z', q', \gamma', 1, \Lambda') \}] \} \end{aligned}$$

subject to

$$c + a' \, = \, (1 + r) \, a + (1 - \tau) \, wzq + T.$$

The future terms on the right-hand side reflect the four mutually exclusive events discussed previously that can transpire between the end of this period and the beginning of the following period for an individual who works today.

Next consider the Bellman equations for active and passive search. For active search we have

$$\begin{aligned} & U(a, z, \gamma, I^B, \Lambda) \\ & \quad = \max_{c \geq 0, a' \geq 0} \{ \ln c - \gamma + \beta E_{z', q', \gamma', I^{B\prime}, \Lambda'} [\lambda_u V(a', z', q', \gamma', I^{B\prime}, \Lambda') \\ & \qquad + (1 - \lambda_u) J(a', z', \gamma', I^{B\prime}, \Lambda')] \} \end{aligned}$$

subject to

$$c + a' \, = \, (1 + r) \, a + (1 - \tau) \, I^B b(z) \, + T,$$

and for passive search we have

$$\begin{aligned} N(a, z, \gamma, I^B, \Lambda) \, = \, \max_{c \geq 0, a' \geq 0} \{ \ln c + \beta E_{z', q', I^{B\prime}, \Lambda'} [\lambda_n V(a', z', q', \gamma', I^{B\prime}, \Lambda') \\ + (1 - \lambda_n) J(a', z', \gamma', I^{B\prime}, \Lambda')] \} \end{aligned}$$

subject to

$$c + a' \, = \, (1 + r) \, a + T.$$

Our model provides a clear mapping to the data with regard to classifying a worker as either employed, unemployed, or out of the labor force. Specifically, an individual who works in period t is labeled as employed. An individual who is not employed in period t but engages in active search during period t is labeled as unemployed. The residual category, an individual who is not employed in period t and does not engage in active search, is labeled as out of the labor force.

To generate implications for aggregate gross worker flows we assume that there are a large number of workers, each of whom is just like the individual described above, with all of the shock realizations being iid across individuals. Given a set of market conditions (i.e., prices and frictions), we can then look for a stationary distribution of individuals. In this stationary distribution there is an invariant distribution of individuals over the individual state variables, an invariant distribution of individuals over the three labor market states (employment, unemployment, and out of the labor force), and an invariant distribution over gross flows.[15]

A. *Calibrating the Stationary Distribution*

This section describes our procedure for calibrating the parameters of our model so that the stationary distribution with constant market conditions matches the gross worker flows in the data. The numerical solution methods are explained in online Appendix A.2.

The model has a large number of parameters that need to be assigned: preference parameters β, α, $\overline{\gamma}$, and ε_γ, idiosyncratic productivity shock parameters ρ_z and σ_ε, the variance of the match quality shock σ_q, frictional parameters (σ, λ_u, λ_e, and λ_n), the tax rate τ, the transfer T, the parameters of the UI system (b, $\overline{b}$, and μ), and prices (r and w). Because data on labor market transitions are available monthly, we set the length of a period to be one month.

Several parameters are set without solving the model. We calibrate the shock process z to estimates of idiosyncratic wage shocks, and so assume an AR(1) process, with $\rho_z = 0.996$ and $\sigma_\varepsilon = 0.096$. Aggregated to an annual level this would correspond to persistence of 0.955 and a standard deviation of 0.20, which we take as representative values from this literature.[16] Note that the tax rate on labor income is inconsequential, since it effectively amounts to a renormalization of the wage. We introduce it as a way to generate the revenue for the lump-sum transfer and UI system in an internally consistent manner. In line with various studies, we set $\tau = 0.30$.[17] The lump sum transfer T will be set so that the government budget balances in steady state equilibrium.

The parameters of the UI benefit system are chosen as follows. First, the parameter μ is set to $1/6$ so that the average duration of benefits is equal to six months. We set the cap on benefits to be 46.5 percent of the average wage in our steady state equilibrium. In our model, all exogenously separated individuals are eligible for UI

[15] Although we only analyze the labor supply side of the market, we note that our framework is consistent with a general equilibrium model that features two islands, one associated with employment (work island) and the other associated with nonemployment (leisure island). The work island consists of many districts, each with a constant returns to scale production function using capital and labor. In this setup, the productivity z is attached to a worker and follows them as they move across districts. The match quality shock q is worker-district specific. Free mobility of capital implies that the marginal product of capital is equated across districts, which because of constant returns to scale will also imply that the efficiency wage per unit of labor is also equated across districts. See online Appendix A.9 for details.

[16] See, for example, estimates in Card (1994), Floden and Linde (2001), and French (2005).

[17] Following the work of Mendoza, Razin, and Tesar (1994) there are several papers which produce estimates of the average effective tax rate on labor income across countries. Minor variations in methods across these studies produce small differences in the estimates, but 0.30 is representative of their estimates.

and will collect if they are unemployed and search actively. In reality, many exogenously separated individuals may either not be eligible or choose not to apply. We therefore set our replacement rate b so that total UI payments in steady state is in line with the data. Over the 1978:I–2012:III period, total UI payments are 0.75 percent of total compensation. We use a replacement rate of 0.23, which results in total UI payments of 0.74 percent of total earnings.

The remaining parameters are chosen so that the steady state equilibrium matches specific targets. Although this amounts to a large set of nonlinear equations which is solved jointly, we think it is informative to describe the calibration as a few distinct steps.

We begin with the five parameters α, $\overline{\gamma}$, σ, λ_u, and λ_n. We discipline the value of $\overline{\gamma}$ relative to the value of α based on measures of search time relative to working time. In particular, since average time devoted to search for unemployed workers is approximately 3.5 hours per week in the American Time Use Survey (ATUS) according to Mukoyama, Patterson, and Şahin (forthcoming), and average hours of work for employed individuals are approximately 40, we set $\overline{\gamma} = \frac{3.5}{40}\alpha$. Intuitively, holding all else constant, the disutility from working α will directly affect the desire of individuals to work and hence exerts a direct influence on the employment rate. The gap between λ_u and λ_n will influence how the non-employed are split between active and passive search. For a given gap, the level of λ_n will directly impact on the flow from N to E. And the value of σ will intuitively have a direct impact on the flow from E into U. Accordingly, we set the values of α, σ, λ_u, and λ_n so as to match the labor force participation rate (0.66), the unemployment rate (0.068), the E-to-U flow rate (0.014), and the N-to-E flow rate (0.022). All these values are averages from 1978:I to 2012:III.

The two parameters λ_e and σ_q will directly impact the nature of job-to-job transitions in the model. Accordingly, we set these two values so as to match a job-to-job transition rate of 2.2 percent per month (from the Current Population Survey, using the tabulation of Fallick and Fleischman 2004 for 1994:I to 2012:III) and an average wage gain upon experiencing a job-to-job transition of 3.3 percent (from Tjaden and Wellschmied 2014).

The final preference parameter to be determined is ε_γ, which governs the variation in the disutility associated with active search. This parameter plays a very specific role in terms of allowing our model to match the patterns in gross worker flows. As noted previously, a key feature of the gross flow data is that even after correcting for potential spurious flows due to misclassification, there are still large flows between U and N. Taking these flows at face value, they suggest important temporary shocks that influence the decisions of non-employed individuals. We generate these flows by assuming a shock to the disutility of active search. While this could reflect real demands on an individual's time that make search more costly, it could also reflect psychological effects associated with the job search process. We set ε_γ so as to match this aspect of the gross flow data.

While our subsequent analysis is partial equilibrium, we impose that our steady state values for r and w are consistent with factor prices generated from a Cobb-Douglas aggregate production function with capital share parameter equal to 0.30 assuming factor inputs are those implied by our steady state model. We set β so that the return to capital $(1 + r)$ derived from the background general equilibrium

TABLE 4—CALIBRATION

Parameter values											
β	ρ_z	σ_ε	μ	α	$\overline{\gamma}$	λ_u	λ_n	σ	λ_e	σ_q	ε_γ
0.99465	0.996	0.096	1/6	0.485	0.042	0.278	0.182	0.0178	0.121	0.034	0.030

TABLE 5—GROSS WORKER FLOWS IN THE DATA AND THE MODEL

AZ-adjusted data				Model			
From	To			From	To		
	E	U	N		E	U	N
E	0.972	0.014	0.014	E	0.972	0.014	0.014
95% CI	(0.970, 0.974)	(0.013, 0.015)	(0.012, 0.015)				
U	0.228	0.637	0.135	U	0.219	0.652	0.130
95% CI	(0.211, 0.246)	(0.616, 0.657)	(0.119, 0.152)				
N	0.022	0.021	0.957	N	0.022	0.020	0.958
95% CI	(0.019, 0.025)	(0.018, 0.023)	(0.954, 0.960)				

model is 1.00327 (1.04 in annual value). This leads us to $\beta = 0.99465$. This value of r implies $w = 2.48$. The government budget balance condition then implies that $T = 1.36$.

Table 4 summarizes values for the calibrated parameter values and Table 5 displays the implications for steady state gross flows in our calibrated model, as well as the corresponding average values for these flows for the United States over the period 1978:I–2012:III. We report the 95 percent confidence intervals for the flow rates in the data that were calculated using bootstrapping on the microdata. Further details regarding data sources and the construction of labor market flows are provided in online Appendix A.1.

While the nonlinear nature of the model prevents a perfect match to the gross flow data given the number of free parameters and the additional moments being matched, Table 5 indicates that the model does a very good job of matching the gross flows found in the data. All flow rates lie within the 95 percent confidence intervals for the flow rates. To the best of our knowledge, ours is the first structural model to present such a close fit to these data. Previous work has not been able to provide such a close match to the flows between unemployment and nonparticipation, and since flows must sum to one, these earlier studies have necessarily missed on the other flows as well.

Gross Flows by Wealth.—The previous discussion focused on the ability of the calibrated model to match the aggregate gross flows data. The model also has predictions for these flows conditioned on individual state variables. In particular, the model makes predictions for the pattern of gross flows by wealth. The CPS does not contain data on wealth, so here we exploit the Survey of Income and Program Participation (SIPP) to assess the model's predictions regarding the relationship between gross flows and wealth.

The SIPP consists of a collection of multi-year panels. Within a panel, respondents are interviewed three times per year about the previous four months. Panels

Table 6—Flow Rates by Wealth Quintile Relative to the Aggregate

	Data						Model				
	Q1	Q2	Q3	Q4	Q5		Q1	Q2	Q3	Q4	Q5
EU	1.82	1.15	0.87	0.70	0.54	*EU*	1.13	1.05	0.97	0.97	0.96
EN	1.15	0.92	0.91	0.97	1.09	*EN*	4.54	1.24	0.54	0.63	0.72
UE	0.88	1.08	1.04	1.10	1.06	*UE*	1.05	0.92	1.02	1.03	1.02
UN	1.06	0.94	0.99	0.94	1.04	*UN*	1.54	1.04	0.81	0.87	0.80
NE	1.05	1.34	0.99	0.89	0.84	*NE*	1.16	1.33	0.89	0.70	0.73
NU	1.79	1.37	0.86	0.63	0.47	*NU*	0.73	1.87	1.11	0.88	0.83
EE	0.95	0.99	1.01	1.02	1.02	*EE*	0.93	1.00	1.01	1.01	1.01
UU	1.07	0.97	0.97	0.95	0.91	*UU*	0.87	1.02	1.03	1.02	1.03
NN	0.97	0.96	1.01	1.02	1.03	*NN*	1.00	0.97	1.00	1.01	1.01
JJ	1.29	1.12	0.94	0.88	0.79	*JJ*	1.68	1.01	0.92	0.96	0.95

range in duration from two to four years. We use the 1990–2008 SIPP panels, which cover October 1989 through November 2013 with gaps. Between one and four times per panel, households report their assets, including checking and savings accounts, mutual funds, retirement accounts, and real estate. We approximate household wealth in each month using the most recent wealth measure. Similar to the CPS, the SIPP reports labor market status of respondents over a panel, which allows the calculations of individual worker transitions. Although the labor force status definitions in the SIPP differ slightly from those in the CPS, we create a labor force status nearly analogous to the CPS. As is well known and discussed extensively in Fujita, Nekarda, and Ramey (2007), the flow rates computed using the CPS and SIPP differ in levels. Since our model is calibrated to the CPS data, we report the flow rates for each quintile relative to the overall average flow rates in Table 6 to make the comparison of the model with the data easier.

Overall, the model does a reasonably good job of matching the qualitative features found in the SIPP data. In particular, the E to U flow rate decreases with wealth both in the SIPP data and in our model. In the model this is driven by wealth effects: wealthy individuals who suffer a job loss are more likely to leave the labor force. The E to N flow rate is U-shaped with respect to wealth both in the SIPP data and in our model: workers in the upper and lower wealth quintiles are more likely to leave employment for nonparticipation. This pattern reflects two different reasons for leaving the labor force in the model. Workers in the lowest quintiles are typically the ones with low productivity making them leave the labor force, while at the highest wealth quintiles, the wealth effect is important in causing labor force withdrawal. These two forces are more stark in our model than they are in the data. The U to E flow rate, often referred to as the job-finding rate, is approximately flat with respect to wealth both in the model and in the data. The N to E flow rate decreases by wealth both in the data and in our model. Once again, in the model this is driven by wealth effects. Finally, we note that the job-to-job (JJ) flow rate decreases by wealth both in the data and in the model. In the model this is driven by the fact that employed individuals with high wealth are more likely to have higher quality matches, making job-to-job transitions less likely.[18]

[18] Note that in Table 6, *EE* refers to workers who continue to be employed regardless of changing jobs or not, while *JJ* stands for job-to-job transitions.

Although the deviation is quantitatively small, the *UE* rate exhibits a slight departure from the data: Q1 exhibits the lowest *UE* rate in the data, while exhibiting the highest in the model. This results in the reverse pattern in *UU*. Our view is that this departure comes from the parsimony of our model. For example, we assume that λ_u is homogeneous across workers. Once we add some heterogeneity in λ_u, as we observe for characteristics such as age and skills in the data, one could easily imagine that the workers in Q1 would end up having a somewhat lower *UE* rate compared to the current version of the model.

Two other patterns which do not match qualitatively are the *U* to *N* flow rate and the *N* to *U* flow rate. The *U* to *N* flow rate is approximately flat with respect to wealth in the data while it is higher for workers with lower wealth in our model. In our model, unemployed individuals with low wealth are more likely to have entered unemployment from *N* and so are close to the boundary between these two regions, making them more likely to transition to *N*. The *N* to *U* flow rate decreases with wealth in the data, whereas in our model it is non-monotonic: consistent with the data it is decreasing after Q2, but it increases going from Q1 to Q2.

In addition to implications for gross flows by wealth, the model has detailed implications for asset accumulation and decumulation related to labor market status as well as for the distributions of wealth and productivity. We discuss these in some detail in online Appendix A.3 and argue that they are in line with empirical microeconomic studies.

B. *Calibrating the Aggregate Shocks*

Our main goal is to examine the extent to which our labor supply model of gross worker flows can match the properties of fluctuations in Tables 1 and 3 when subjected to empirically reasonable shocks to market conditions. We will assume that the only source of shocks is to frictions, i.e., we will assume that the two prices, *w* and *r*, remain constant. This is a natural starting point for this kind of analysis since many researchers, e.g., Hall (2005), have argued that a model in which wages are perfectly rigid offers a good account of labor demand movements in the sense that it accounts for cyclical movements in the job-finding rate in a model with a fixed labor force. Moreover, the state of the literature on wage cyclicality is still unsettled. We will thus take as given the fluctuations in frictions found in the data and ask whether such a model also provides a good account of labor market flows in a model that explicitly allows for an endogenous participation margin.

Modeling Shocks to Frictions.—There are a few different ways that we could proceed. One strategy would be to estimate the model using some type of simulated moments estimator on time series data. We instead adopt a much simpler and, we think, more transparent approach that offers some important insights into the role that different driving forces play in shaping the cyclical properties of gross worker flows. Specifically, given that our focus is on business cycle fluctuations and that a key feature of business cycles is comovement among series, we effectively focus on perfectly correlated movements in market conditions that reflect business cycle movements. We then ask whether such movements can account for business cycle fluctuations in gross worker flows if the relative variances of the movements in each variable are set to empirically reasonable values. Intuitively, we want to consider shocks to labor demand that manifest themselves in fluctuations in frictions. However, for our purposes, the ultimate source of labor demand shocks is immaterial and, indeed, the shocks we consider are consistent with a variety of such sources.

The simplest implementation of this method would posit a latent aggregate state s that follows a Markov process, with prices and frictions all being functions of this latent aggregate state s.[19] As is common in the business cycle literature with heterogeneous agents, we assume that the shocks to market conditions follow a two-state Markov process. We will refer to one state as the "good" state (denoted by a superscript G) and the other state as the "bad" state (denoted with a superscript B). The good state will have a high value for the employment arrival rates λ_u, λ_e, and λ_n, and a low value for the employment separation rate σ. We denote the two possible realizations for the market conditions shock as $(\lambda_u^G, \lambda_n^G, \lambda_e^G, \sigma^G)$ and $(\lambda_u^B, \lambda_n^B, \lambda_e^B, \sigma^B)$. We parameterize these shocks as $\lambda_u^G = \lambda_u^* + \varepsilon^\lambda$, $\lambda_u^B = \lambda_u^* - \varepsilon^\lambda$, $\sigma^G = \sigma^* - \varepsilon^\sigma$, and $\sigma^B = \sigma^* + \varepsilon^\sigma$, where λ_u^* and σ^* are the values for the model calibrated to match average transition rates. We assume that movements in λ_e and λ_n are such as to maintain constant ratios relative to λ_u. We assume that the transition matrix for the Markov process is symmetric, with diagonal element denoted by ρ.

In our model, both the level and fluctuations in f_{UE} closely mimic the level and fluctuations in λ_u. For this reason we choose the value of ε^λ so that the fluctuations in f_{UE} in the simulated model match the standard deviation of the fluctuations in f_{UE} found in US data. This leads to $\varepsilon^\lambda = 0.0662$. Given values for the λ_is, which influences the impact of time aggregation on measured f_{EU}, the level and fluctuations in f_{EU} closely follow the level and fluctuations in σ, so we choose $\varepsilon^\sigma = 0.00239$ so as to match the fluctuations in f_{EU}. We match the volatility values based on the Abowd-Zellner correction procedure. The value of ρ is set to 0.983, which generates an empirically reasonable amount of persistence.

III. Fluctuations in Gross Worker Flows

This section presents the quantitative implications of our calibrated model for the flows of workers across labor market states over the business cycle.[20] We begin with a discussion of stocks and then turn to flows. As some key mechanisms in our model involve a compositional channel, we also examine data that allows corroboration of these effects. We also conduct a variance decomposition of unemployment changes in the data and the model into the different gross flows.

[19] More generally, one might consider a specification in which the innovations are perfectly correlated but in which the individual components display different degrees of persistence.

[20] A relevant question is whether the business cycle analysis we conduct offers important insights beyond those that would emerge from considering steady state differences in response to permanent changes in frictions. We address this in detail in online Appendix A.11. While this analysis does convey some of the qualitative elements of our analysis, it misses others and is quite different quantitatively. In particular, intertemporal substitution effects are not captured in a steady state exercise, and as a result the participation rate becomes countercyclical.

Table 7—Behavior of Stocks

	Data			Model		
	u	$lfpr$	E	u	$lfpr$	E
std(x)	0.1170	0.0026	0.0099	0.1207	0.0015	0.0096
corr(x, Y)	−0.84	0.21	0.83	−0.99	0.37	0.995
corr(x, x_{-1})	0.93	0.69	0.92	0.87	0.71	0.89

A. *Cyclical Properties of Stocks*

We begin with the less stringent test in which we assess the ability of the model to match the cyclical movements in the three labor market stock variables: employment, the unemployment rate, and the participation rate. Table 7 shows the results for the benchmark model and the data. To compute correlations with output in our partial equilibrium model we generate a series for output by taking our model generated series for capital and efficiency units of labor and using them as inputs into a Cobb-Douglas production function with capital share parameter of 0.30. All the model generated statistics are aggregated to quarterly frequency, logged, and HP-filtered using a smoothing parameter of 1,600, following the exact procedure that we apply to the data.

Table 7 reveals that our model of labor supply with shocks to frictions as the sole driving force does a very good job of accounting for the behavior of the three labor market stocks, not only qualitatively but also quantitatively. The key result here is that the behavior of the participation rate in the model closely matches its behavior in the data. In a two-state model with an exogenously fixed participation rate, shocks to job-finding and job-loss rates that match the movements in the data will necessarily provide a close match to observed movements in E and U precisely because movements in participation are modest in comparison to movements in employment. The key issue then is whether our model featuring an endogenous participation margin will generate empirically reasonable movements in the participation rate. Table 7 shows that our model is able to account for more than half of movements in the participation rate, as well as the modest procyclical nature of these fluctuations.

It is important to emphasize that it is not clear a priori that this model would match even the qualitative features of participation rate fluctuations. The reason for this is that there are several competing forces. In a much simpler model based on steady state analysis, Krusell et al. (2010) show that holding all else constant, decreases in job-finding rates and increases in job separation rates lead to less time spent in employment, thereby lowering income. The negative wealth effect on labor supply associated with this decrease in income leads individuals to seek to increase time spent working in order to compensate for the loss in income. Individuals who desire to work more will be more likely to engage in active search when not employed, and will be less likely to leave a job when employed. These responses tend to generate a countercyclical participation rate.

But another force works in the opposing direction. In this model, participation for a non-employed worker represents an investment decision, in that a worker needs to pay the up-front cost associated with active search in order to generate a potential flow of income associated with successful job search. In good times there are three factors tending to increase the return on this investment. First, the probability of a successful search is greater. Second, the fact that separation rates are lower implies that a job match will last longer. Third, and most importantly, because arrival rates of outside opportunities for employed workers are higher, the prospects for wage increases via job-to-job transitions are greater.[21] Taken together, these three factors make it more likely that the individual will engage in active search in good times, leading one to expect procyclical participation.

There are also effects that interact with the presence of UI benefits. In bad times there is an increase in separations, and these workers are all assumed to be eligible for UI. But collecting UI requires active search. Benefits may induce some individuals to search actively who otherwise would not. On the other hand, lower arrival rates of jobs in bad times can increase the probability that benefits expire for an individual, which may lead to fewer individuals receiving benefits.

Despite the opposing forces at play, Table 7 shows that our model not only matches the key qualitative properties found in the data, but also does a good job quantitatively.

B. *Cyclical Properties of Gross Flows*

We next consider the more stringent test of whether the model is able to account for the key patterns in the gross flows that underlie these patterns for the stocks. Table 8 displays the key business cycle facts about the gross flows in the data and in the model. While we targeted the volatility of f_{EU} and f_{UE} using the Abowd-Zellner adjusted data, we also include the data based on the alternative adjustment.

The model is able to account for the key cyclical patterns: it captures the countercyclicality of unemployment inflows (E-to-U and N-to-U flow rates), the procyclicality of unemployment outflows (U-to-E and U-to-N flow rates), and the procyclicality of flows between E and N. Although the model is very successful in replicating the cyclicality of the flows, there are some discrepancies between the data and the model in terms of the magnitudes of fluctuations for some of the flows. However, it is important to note that the alternative method for correcting for classification error (what we refer to as "de*NUN*ification") implies levels of volatility that are much more in line with those predicted by our model. In view of this we feel that less weight should be attached to the discrepancies in volatility levels in Table 8.

The model is also able to account for the procyclicality of job-to-job flows; Table 9 displays the cyclical properties of the job-to-job transition rate in the data and in the model.[22] In addition to using the CPS, we use two additional data sources to compute the job-to-job transition rate, the Survey of Income and Program Participation (SIPP) and the Longitudinal Employer-Household Dynamics (LEHD), since the CPS measure of the job-to-job transition rate increasingly diverged from other measures, thus casting doubt on its reliability.[23] The model generates cyclical

[21] We document this mechanism in online Appendix A.4.

[22] As in the case of the other flows, we do not make the time-aggregation correction. Mukoyama (2014) develops a method for time-aggregation correction in the case of the job-to-job transition rate and finds that it does not significantly alter the cyclical properties of the data.

[23] The details of the data are presented in online Appendix A.5.

TABLE 8—GROSS WORKER FLOWS

	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
Panel A. AZ-adjusted data						
std(x)	0.089	0.083	0.088	0.106	0.103	0.072
corr(x, Y)	−0.63	0.43	0.76	0.61	0.52	−0.23
corr(x, x_{-1})	0.59	0.29	0.75	0.62	0.38	0.30
Panel B. DeNUNified data						
std(x)	0.069	0.036	0.076	0.066	0.041	0.063
corr(x, Y)	−0.66	0.29	0.81	0.55	0.57	−0.56
corr(x, x_{-1})	0.70	0.22	0.85	0.58	0.48	0.57
Panel C. Model						
std(x)	0.089	0.057	0.088	0.029	0.051	0.076
corr(x, Y)	−0.79	0.21	0.69	0.47	0.57	−0.96
corr(x, x_{-1})	0.76	0.21	0.70	0.34	0.66	0.87

TABLE 9—JOB-TO-JOB TRANSITION RATE

Data source:	CPS	SIPP		LEHD	
Time period:	1994:I–2012:III	1990:III–2012:III	1996:III–2012:III	2000:III–2012:III	Model
std(x)	0.057	0.078	0.080	0.094	0.098
corr(x, Y)	0.69	0.36	0.43	0.94	0.54
corr(x, x_{-1})	0.60	0.68	0.68	0.93	0.72

fluctuations in the job-to-job flows that are similar to those in the data, especially those in the SIPP and the LEHD.

Some of these cyclical patterns in the gross flows are quite intuitive and so do not merit much discussion. For example, the procyclical flow rate from U to E is mechanically driven by the procyclical shocks to λ_u, and the countercyclical flow from E to U is mechanically driven by the countercyclical pattern in the shocks to σ. Procyclical job-to-job flows are also mainly because of procyclical λ_e. However, as noted earlier, we believe that two of the patterns that the model is able to replicate are at least somewhat counterintuitive. Specifically, during good times the transition rates from E to N and U to N are both higher, despite the fact that the stock of workers in N is countercyclical. In what follows we therefore focus on describing the economics behind these patterns.

In thinking about the response of flows to a change in market conditions it is useful to distinguish two broad types of effects. At any point in time, individuals are distributed across the space of individual state variables. For a given set of market conditions, decision rules partition this space into the three labor market states E, U, and N and gross flows result from individuals crossing the boundaries between these regions. Hence a key determinant of these flows will be the mass of individuals who are near the boundary. When market conditions change, the boundaries of these regions change, and some individuals will change labor market states even conditionally on not experiencing any change in their individual state variables. Note, however, that these are essentially one time changes in flows, in the sense that once the boundaries have adjusted and individuals are reclassified, going forward in time the flows will again be dictated by the mass of individuals crossing fixed boundaries. While both one-time and persistent effects will shape the resulting correlation patterns, in the presence of persistent shocks to market conditions the correlations will intuitively be dominated by the persistent responses, which reflect movements of individuals across boundaries, rather than the movements in the boundaries themselves.

We start with the flow from U to N. To understand its behavior, it is essential to consider the changing composition of the unemployed. In particular, the key dynamic is that in good times the composition of this group shifts toward individuals who are less attached to work (i.e., close to the boundary of indifference between U and N), thereby increasing the fraction of unemployed individuals who cross the boundary into nonparticipation.[24] To see why, note that in good times unemployed workers exit to employment more quickly, so the pool of unemployed individuals is relatively more composed of individuals who have just entered unemployment. Since employed workers are less likely to enter unemployment in good times (recall that the job separation probability decreases in good times), new entrants to unemployment are dominated by individuals that transition from N to U. But these individuals are more likely to be close to the boundary, making them more susceptible to a transition that puts them back in the N state. Put differently, workers who flow into unemployment as a result of an exogenous separation shock are more likely to be attached workers than the other workers (who flow in either by a voluntary move from employment or by moving from nonparticipation). The fraction of attached workers defined in this manner in total unemployment is countercyclical (with a correlation of -0.65 with output) in the model. In Section IIIC, we document empirical evidence that shows that the composition of the unemployed pool shifts toward more *attached* workers during recessions using various proxies for attachment.

A related but distinct channel that may play a role in generating composition effects is the receipt of UI benefits. In our model a UI-eligible individual must actively search in order to receive benefits. Intuitively, an individual who is eligible for benefits is less likely to transition to nonparticipation. In our model, the higher separation rate in bad times implies that a higher fraction of the unemployment pool is UI-eligible in bad times, consistent with the evidence presented in Chodorow-Reich and Karabarbounis (2016). Our model does not include UI extensions to the duration of UI benefits, but allowing for them would generate similar effects. To better understand the specific role of UI, we recompute the business cycle statistics in a model without a UI system in online Appendix A.12. We find that the U-to-N flow rate remains procyclical suggesting that the composition effect in our model is not driven by the effects of UI. This finding is consistent with the recent literature on the labor supply and job search effects of UI extensions analyzed in Rothstein (2011) and Farber, Rothstein, and Valletta (2015). These effects are estimated to be

[24] In fact, for a given distribution of workers in the unemployment pool the immediate impact of a decrease in frictions is to expand the participation region (i.e., shrink the region of the state space that maps into N) and decrease the fraction who cross from U into N. But the resulting dynamic effects associated with lower frictions change the composition of the unemployment pool and increase the U to N flow.

small suggesting that UI extensions themselves cannot account for the strong procyclicality of flows from *U* to *N*.[25]

Next we consider the flow from *E* to *N*. In the model this flow is very weakly procyclical. Note also that similarly to the data, this flow exhibits very little serial correlation. These two properties stem from the fact that the persistent response in the *EN* flow turns out to be very close to zero, so that the statistics for this flow are dominated by the immediate one-time changes in flows that are associated with the change in boundaries defined by the decision rules.[26] To understand these effects it is important to note that there is an option value associated with staying employed. In particular, an employed individual understands that after a quit and hence a transition to *N*, it will be costly to return to *E* in the future (due to search costs and the time it takes to receive an employment opportunity). It follows that an employed individual needs to consider this option value when deciding whether to remain employed. As is standard in such a setting, an individual will remain employed even when it is "statically" suboptimal, on account of the option value of staying employed. When an aggregate shock decreases the level of frictions, the implicit costs of finding employment go down, and the option value diminishes. This results in a one time flow from *E* into *N*.

Lastly we consider the *N*-to-*U* and *N*-to-*E* flows. In the model the former flow is countercyclical and the latter is procyclical, as in the data. To see why the model delivers this pattern, note that the primary source of flows from *N* into *U* or *E* is those individuals who are close to the boundary but on the *N* side. A small shock to individual state variables could push such an individual across the boundary and into the *U* or *E* regions. For an individual to flow into *U*, the individual must not receive an acceptable employment opportunity in the meantime, since this will take them from *N* into *E* instead. But during good times the increase in job opportunity arrival rates implies that marginal *N* workers are more likely to receive offers that take them into *E*, thus decreasing the flow of these workers into *U*.

Note that our discussion highlights composition effects for flows involving workers in *U* but not for the other states. The reason for this is that the extent to which composition effects matter is very much influenced by the duration of spells within a state. If most workers in *N* stay in *N* for a long time, then it is hard for changes in the characteristics of workers flowing in to have a large impact on composition. In contrast, if workers do not stay in a state for long, then changes in the characteristics of workers who flow into the state can have a large impact on the composition. In fact, if one looks at the fraction of workers who stay in each of the three states from

[25] There is another channel through which UI extensions could affect the labor market, which is the effect of UI on vacancy creation examined in Hagedorn et al. (2015). They find the macro effect on vacancy creation to be quite large. When a worker and an employer agree to form a match, the extension of UI benefits may require an employer to offer higher wages given that more generous UI benefits improve the bargaining position of workers. This effect would show up as a lower value to an employer of a filled job. To the extent that the effect of UI is through the job creation/labor demand margin, it is already taken into account in our calibration of the cyclicality of the job offer arrival rates. Since we continue to be agnostic on the sources of fluctuations in job offer arrival rates (the λ_is), our model is consistent with UI having a large effect on job creation as estimated by Hagedorn et al. (2015).

[26] The small persistent effect in turn reflects the combined effect of several small effects, including compositional effects (this time including the distribution of match quality) and changes in wealth.

TABLE 10—HETEROGENEITY IN *U*-TO-*N* TRANSITION PROBABILITIES

Subgroup of the unemployed	f_{UN}	Change in unemployment share ω in recessions (percent)
Gender		
Men	17.9	4.5
Women	27.2	−4.5
Age		
16 to 24	28.1	−6.1
25 to 54	18.2	5.3
55 and over	24.9	0.8
Education		
No high-school degree	22.7	−3.1
Only high-school degree	18.9	0.4
Some college	17.9	2.3
College degree	15.8	0.4
Labor force status one year ago		
Employed	14.3	4.2
Unemployed	18.9	2.3
Nonparticipant	37.2	−6.5
Reason for unemployment		
Job leaver	19.8	−4.7
Job loser	14.8	12.5
Entrant	34.2	−7.8

Notes: Calculated using the CPS microdata. Education statistics are for workers for 25 years and older.

one month to the next then it is apparent that composition effects will be most relevant for the pool of unemployed workers.[27]

C. *Composition Effects in the Data*

A key channel through which our model is able to match the cyclical flows into and out of the labor force is through changes in the composition of the unemployment pool over the cycle. Consistent with our model, Elsby, Hobijn, and Şahin (2015) argue that a large part of the cyclicality of *U*-to-*N* flows can be attributed to cyclical shifts in the composition of unemployed workers. As argued above, what is key in our model is the variation in the share of workers who are close to the *UN* boundary. One proxy for closeness to this boundary is the extent of attachment that an individual has to being in the labor force. To examine this, Table 10 summarizes other compositional shifts over the business cycle that might proxy for labor force attachment, such as gender and education. As the table shows, the unemployed pool shifts toward male, prime-age, and more educated workers, as well as toward workers who were employed a year ago and workers who classify themselves as job losers.[28] The table also shows the unemployment to nonparticipation transition

[27] This is also consistent with the empirical findings of Elsby, Hobijn, and Şahin (2015) who only find important compositional effects for flows out of unemployment.

[28] We include temporary layoffs in job losers. Figure A4.1 in online Appendix A.4 plots the cyclical variation in the share of unemployed accounted for by various subgroups: job losers, job leavers, and entrants. Figure A4.2 separates temporary layoffs from job losers. The cyclical properties of the fraction of job losers remains very similar.

Table 11—Variance Decomposition of Changes in the Unemployment Rate

	Total between		
	U and *E*	*U* and *N*	*E* and *N*
Model	74.1	31.1	−3.8
Data-Abowd-Zellner	70.1	30.0	0.6
Data-De*NUN*ified	67.7	28.7	0.3

rates. Most of the groups whose unemployment shares rise during recessions also have lower unemployment to nonparticipation transition rates. In other words, the composition of the unemployed pool shifts toward workers who are more attached to the labor force during recessions.

D. *Participation Flows and Unemployment Rate Fluctuations*

As an additional test of the model's implications for flows, we use the method of Elsby, Hobijn, and Şahin (2015) to assess the importance of various flows in accounting for unemployment rate fluctuations. Table 11 summarizes the results for our model and the data. The key result is that our model does a very good job of matching the variance decomposition results derived from the data that have been adjusted for classification error using either the Abowd-Zellner correction or the de*NUN*ified correction. In particular, in all three cases the flows between *U* and *N* account for roughly 30 percent of unemployment rate fluctuations, with the remaining share driven virtually entirely by flows between *E* and *U*. Table A10.1 in online Appendix A.10 shows the contribution of each flow to the fluctuations in the unemployment rate. This table reveals that although the model does a good job of attributing unemployment fluctuations to fluctuations in flows between *U* and *N*, it underpredicts the role of the *UN* flow and overpredicts the role of the *NU* flow relative to the data. This is an artifact of the model's implications for cyclical properties of flows between *U* and *N*. As Table 8 shows, the model underpredicts the volatility and procyclicality of the *U*-to-*N* flow rate and overpredicts the countercyclicality of the *N*-to-*U* flow rate thereby attributing a more important role to *N*-to-*U* flows in accounting for unemployment fluctuations. In the second robustness experiment in online Appendix A.7, we consider a lower value for the persistence of the idiosyncratic productivity process and set $\rho_z = 0.94$. For that specification, the volatility of the *U*-to-*N* flow rate increases and it becomes more procyclical. Consequently, as we report in Table A10.1, the model does a better job in matching the relative contributions of these two flows.

We take the result of this exercise to imply that our model not only captures the key qualitative patterns in the cyclical correlations of the various flows, but also accounts for the quantitative significance of flows into and out of the labor force over the business cycle.

E. *Sensitivity Analysis*

In this subsection, we examine the robustness of our findings along various dimensions.

Role of Job-Finding and Job-Loss Shocks: Throughout our analysis we assumed that there were aggregate shocks to both the job-finding rates and to the job-loss rates. It is also of some interest to assess the relative importance of these two types of shocks. To evaluate this we simulate the model with the business cycle shock to the job-loss rate shut down but all other parameters kept unchanged. In the interest of space we do not present the detailed results but instead offer a brief summary. For the behavior of the three labor market stocks the main finding is that this specification reduces the volatility of both the unemployment and employment rates by about one third relative to the benchmark, while leaving the volatility of the participation rate almost unchanged.

The behavior of the gross flows are relatively unaffected with two exceptions. The first is the volatility of f_{EU}. Not surprisingly, with shocks to σ shut down the volatility of f_{EU} is reduced dramatically. However, the time aggregation implicit in our model specification does lead to countercyclical movements in f_{EU} even in the absence of shocks to σ, though this effect accounts for only about 30 percent of the movement in f_{EU}. The other notable difference is that the correlation between f_{UN} and output turns negative. This is consistent with the explanations that we have articulated above.[29] Specifically, we argued that the procyclical movement in f_{UN} resulted from a composition effect, due to the fact that in good times the unemployment pool was increasingly composed of individuals who entered U from N. But the decrease in the job-separation rate during good times was one of the factors that influenced the size of this composition effect, since in good times it served to reduce the number of individuals in U who entered from E. It follows that shocks to the job-loss rate are important in shaping the observed behavior of flows between U and N.

Role of Job-to-Job Transitions: In our discussion of the model's implications for the cyclicality of the participation rate we emphasized the role of intertemporal substitution that operates via the implicit effect of on-the-job search on wage cyclicality. To confirm this we have also conducted our analysis in a version of the model that eliminates on-the-job search. Full details are provided in online Appendix A.8, but the key result that we want to emphasize here is that the participation rate becomes strongly countercyclical in this version of the model. Moreover, the volatility of the participation rate is reduced by almost an order of magnitude relative to our benchmark model.

Role of the Idiosyncratic Productivity Process: We also consider how changing the features of the idiosyncratic productivity process affect our findings. In particular, we consider alternative values for the persistence parameter ρ_z (0.94 and 0.97 at annual frequency) with adjustments to σ_ε in order to compensate for the implied change in the cross-sectional variation in z. Complete results are provided in online Appendix A.7; here we present the key findings. For both values of ρ_z there is a very slight worsening in the model's ability to match the steady state flows. For the higher value of ρ_z the implied business properties are virtually unchanged. For the

[29] This helps to explain why the volatilities of the participation rate are relatively unaffected even though the volatility of unemployment and employment declines.

lower value of ρ_z there is one slight change in the business cycle results: instead of the participation rate being mildly procyclical it becomes mildly countercyclical. While this specification does not capture the cyclical behavior of the participation rate, it does a better job in matching the volatility and cyclicality of the flows between *U* and *N*. In addition, as we discussed before, it captures the relative contribution of the flows between *U* and *N* in accounting for unemployment rate fluctuations better.

In the second exercise we lower the value of σ_ε^2 so that the implied annual standard deviation is 0.15 instead of 0.20. Once again, we seek to match the same targets, implying changes to several other parameter values. The same two findings emerge here as well: the overall fit to the average gross flows in the data is slightly worse, and in the business cycle exercise the correlation between the participation rate and output is once again modestly negative (-0.21).

We draw two main conclusions from these two exercises. First, the properties of the idiosyncratic shock process matter for the ability of the model to match the average gross flows data. And second, matching these flows does matter for the model's implications for business cycle fluctuations.

F. *Summary*

The discussion following our main results on flows laid out the key intuition for the qualitative patterns found in Table 8. Several mechanisms we emphasized are intimately connected with changes in the composition of individuals in different labor market states, and we then turned to the data to find that the compositional changes appear to occur in the data as well. Of course, the extent to which the model can reproduce the quantitative features of fluctuations in gross flows depends not only on the qualitative patterns but also the quantitative magnitudes of the various effects. It is reasonable to think that a key factor for the quantitative results is the mass of individuals that are near the participation boundary. In this regard, the discipline in our quantitative work derives from the fact that our steady state model is consistent with the average level of gross flows.

IV. Conclusion

We have developed a model of individual labor supply in the presence of frictions and used it to simulate the effects of aggregate shocks to frictions on labor market outcomes for a large set of households. Our model is calibrated to match the average values of the gross flows between all three labor market states. Our key finding is that fluctuations in job-finding and job-loss rates alone do a good job in accounting for both the qualitative and quantitative business cycle patterns in the gross flows data.

Importantly, despite the fact that our model assumes a constant wage rate per efficiency unit of labor, intertemporal substitution effects play a key role in allowing the model to account for the movements in the participation rate. This channel emerges because of cyclical movements in frictions: a higher job-finding rate in good times implies that workers can climb up the job ladder more quickly, implying faster wage growth. This highlights the important interactions between the two benchmark frameworks that we have merged: the frictionless model of intertemporal substitution, as in Lucas and Rapping (1969), and the frictional model as in Mortensen and Pissarides (1994).

We believe that our model provides a compelling description of labor market flows. At any point in time most individuals are far from indifferent between working and not working. Flows from employment to unemployment do not reflect desired labor supply. But at any point in time there are individuals who are close to indifferent between working and not working and for these individuals desired labor supply, and how it responds to changes in the economic environment, does matter. In particular, intertemporal substitution effects and involuntary separations into unemployment can coexist. All in all, we consider our current model a much more satisfactory account of how labor market participation evolves over the business cycle. It is also interesting to note, in particular, that as a corollary our model with worker heterogeneity can match the fluctuations in the participation rate with a rather standard formulation of household preferences, something which has proved challenging with other setups.

Our model offers a rich yet parsimonious description of individual labor supply in a setting with heterogeneity, search frictions, and an empirically reasonable market structure. It is the first paper to consider the effects of aggregate shocks on individual labor market transitions in this setting. However, it is also simplistic in some dimensions relevant for the microeconomic data. One of these dimensions regards our model of the household as an infinitely-lived unit. Clearly, an extension that distinguishes different members of the households would be relevant, as would an age dimension, along the lines of Low, Meghir, and Pistaferri (2010). We do believe that our framework is a very useful starting point for these and many other extensions. It can also be used to understand how policy influences labor supply responses. For example, we could use our model to analyze how changes in features of the UI system would influence the labor supply side of the labor market.

Related, we also believe that it is useful for assessing a variety of further issues. One involves using the model to study specific historic episodes; in fact, in online Appendix A.6 we indicate how one might begin to conduct an analysis of the participation movements during the Great Recession from the perspective of the model. Another interesting issue involves heterogeneous effects of business cycles on various subgroups of the population. While we have focused on aggregate shocks to frictions, we can also study the effects of other aggregate shocks, including shocks to the wage distribution and the returns to saving. It would also be relevant in this context to consider a general equilibrium model where prices as well as frictions are endogenous. Given our results here, we are rather hopeful that such a model can be constructed.

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15. Robert Axtell. Endogenous Firm Dynamics and Labor Flows via Heterogeneous Agents # #Support from the John D. and Catherine T. MacArthur Foundation, the National Science Foundation (0738606), the Small Business Administration (SBAHQ-05-Q-0018), and the Mercatus Center at George Mason is gratefully acknowledged. I have no relevant or material financial interests that relate to the research described in this paper or the associated model. Earlier versions of this work were presented at research institutions (Aix-en-Provence, Arizona State, Brookings, Carnegie Mellon, Emory, Esalen, Essex, George Mason, Georgia, Georgia Tech, James Madison, Leicester, Leiden, Limerick, Nanyang Technological University, New School for Social Research, Office of Financial Research, Oxford, Queen Mary and Westfield, Sant' Anna (Pisa), Santa Fe Institute, Turino) and conferences (Eastern Economic Association, INFORMS, Society for Computational Economics, Southern Economic Association) where comments from attendees yielded significant improvements. For helpful feedback on the manuscript I am grateful to Zoltan Acs, Luis Amaral, Brian Arthur, David Audretsch, Bob Axelrod, Bob Ayres, Eric Beinhocker, Margaret Blair, Pete Boettke, David Canning, Kathleen Carley, John Chisholm, Alex Coad, Herbert Dawid, Art DeVany, Bill Dickens, Kathy Eisenhardt, Joshua Epstein, Doyne Farmer, Rich Florida, Duncan Foley, Xavier Gabaix, Chris Georges, Herb Gintis, Joe Harrington, John Holland, Stu Kauffman, Steve Kimbrough, Paul

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