The Cyclical Job Ladder

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Abstract
Many theories of labor market turnover generate a job ladder. Due to search frictions, workers earn rents from employment. All workers agree on which jobs are, in this sense, more desirable, and slowly climb the job ladder through job-to-job quits. Occasionally, negative shocks throw them off the ladder and back into unemployment. We review a recent body of theory and empirical evidence on labor market turnover through the lens of the job ladder. We focus on the critical role that the job ladder plays in transmitting aggregate shocks, through the pace and direction of employment reallocation, to economic activity and wages, and in shaping business cycles more generally. The main evidence concerns worker transitions, both through non-employment and job-to-job, between firms of different size, age, productivity, wage premium, and the resulting earnings growth. Poaching by firms up the ladder is the main engine of reallocation, which shuts down in recessions.
1. INTRODUCTION

In a competitive labor market, a worker is paid his marginal product, possibly adjusted for job amenities, and is indifferent as of where he works. Job search and recruiting, however, are not the frictionless process that is required for perfect competition. It takes time, resources and luck for the worker to locate a vacant job, thus for the firm to locate a qualified worker. As a consequence, employment relationships develop rents, typically heterogeneous: some jobs are more desirable than others. Workers keep searching while employed, to improve their working conditions, in terms of pay, hours and amenities. At the aggregate level, this turnover process is a major engine of employment reallocation across firms, industries, occupations, and locations, and thus profoundly affects productivity growth. For the individual worker, this random process is a possible source of idiosyncratic earnings uncertainty.

When workers agree on which jobs are more desirable than others at equilibrium prices, so they share a common ranking of available jobs, this turnover process is described as a job ladder. Workers slowly climb this ladder primarily through job-to-job quits. Occasionally, negative shocks throw workers off the ladder and back into unemployment, from where they have to resume their climb for better rents. In this article, we review a recent body of theory and empirical evidence on labor market turnover through the lens of the job ladder. While the concept of a job ladder has been studied for some time, recent work provides a new perspective on business cycles, so we speak of the cyclical job ladder. Specifically, this work studies the role that the job ladder plays in transmitting aggregate shocks, through the pace and direction of employment reallocation, to economic activity and wages, and in shaping business cycles more generally. Poaching by firms up the ladder is the main engine of aggregate reallocation and individual earnings growth, but shuts down in recessions. This view complements the more common focus on worker flows in and out of employment.

In the job ladder view, an employer-to-employer (EE) transition is the result of a choice made by the worker, who has the option of staying in his current job. Empirical measure-
ment can only capture outcomes. Some workers take a break between jobs, so they appear to experience a short spell of non-employment, whether unemployment (U) or non participation (N), yet they are making an EE transition according to the theoretical definition. Other workers change jobs without any breaks, but they “jump ship” because their current job is at risk of termination, so they appear to make an EE transition but do not have the full option of the old job. Yet other workers do lose their job and are lucky enough to find another one right away, so quickly that standard monthly surveys miss the non employment spell altogether, and what is truly a EUE spell is time-aggregated into an EE transition. Finally, some workers voluntarily quit a job to a lower rung on the ladder to accommodate other members of their household, such as spousal relocation.

With these caveats in mind, the most commonly cited source of empirical evidence on EE transitions are the monthly flows computed from the matched files of the monthly Current Population Survey (CPS) according to the methodology proposed by Fallick and Fleischman (2004) and continuously updated by the authors. This series begins in 1994 when the CPS, as part of its redesign, introduced “dependent coding” to detect changes of employer, industry and occupation. Rather than asking the question about employer identity and tasks anew every month, the interviewer reads out the previous month’s answer and asks whether there was any change. This dramatically reduced false EE transitions due to coding error, misspelling and the like. The data, reported in Figure 1 through May 2017, reveal that the EE transition rate (as a fraction of initial employment) averages about 2% per month, is procyclical and on a declining trend from over 3% in the 1990s to below 2% since the Great Recession. In addition, the cyclical rebound of the EE rate in the 2010-2017 expansion has been anemic. This secular decline appears to fit a more general picture, whereas worker turnover rates to and from E, U and N have been steadily declining in the US since the 1980s, and so have business entry, job creation and job destruction rates, leading Davis and Haltiwanger (2014) to alert to declining business dynamism in the US.

The importance of job-to-job transitions for employment reallocation is easy to gauge. Although the job-to-job monthly transition probability in the US averages below 3% per month, an order of magnitude smaller than the monthly transition probability from non-employment to employment, the stock of employment in the denominator of the 3% is much larger than the stock of unemployment and marginally attached non-participants in the denominator of the latter. As a consequence, the number of new hires who are currently employed elsewhere is comparable in magnitude with those who are not. In addition, over one third of all hires from non-employment, and one half if we exclude (re)entrants into the labor force, are recalls of previous employees (Fujita and Moscarini (2017)), thus do not contribute to reallocation, like job-to-job transitions do. Therefore, the great majority of workers who change employer in the US do so by moving directly from job to job.

In this article we introduce the cyclical job ladder as an accounting framework for labor market turnover data. We show that this framework is the equilibrium outcome common to the few existing business cycle models of the labor market with on the job search, whether random or directed. We then use this framework to interpret a wealth of empirical evidence on employment reallocation and firm dynamics over the business cycle. We draw two main conclusions. The data support the job ladder view, where workers agree by revealed preferences on ranking jobs by the characteristics of the employer: size, average wage paid, productivity. Nonetheless, a significant amount of noise remains in the direction of worker turnover. Over the business cycle, the pace of job ladder climbing is negatively correlated with the rate of unemployment, and thus slows down in recessions. Not only the job-to-job
quit rate declines, but this happens especially from the bottom of the job ladder, and the distribution of employment shifts down there. This phenomenon is a drag on the recovery in economic activity and in earnings growth following recessions.

In Section 2 we illustrate our accounting framework for labor market turnover, which we call the dynamic job ladder. This framework summarizes a set of equilibrium predictions shared by several models of the labor market with on-the-job search and business cycle shocks, as we discuss in Section 3. We then use this accounting framework to interpret empirical evidence that we present in Section 4. Brief conclusions take stock.

2. THE DYNAMIC JOB LADDER AS A TURNOVER ACCOUNTING FRAMEWORK

2.1. Background environment

The defining feature of a job ladder is that workers agree on a ranking of jobs. Each job has a fixed idiosyncratic attribute $z \in [z, z]$ — which, for now, we refer to as the job’s type — such that all workers always prefer a job with higher $z$. For this reason, we also refer to $z$ as a rung on the ladder.

A unit measure of ex-ante homogeneous workers can be either employed or unemployed. The labor market, in which both unemployed and employed workers look for jobs, is affected by search frictions. Job matches face an exogenous per-period probability of destruction.
δ, sending the worker back into unemployment.¹ Unemployed workers face a per-period probability \( \lambda_{ut} \) of meeting a vacant job, while a worker employed in a type-\( z \) job (and whose job has not just been destroyed by a \( \delta \)-shock) meets a vacant job with probability \( \lambda_{et}(z) \).² Only vacant jobs “look for” workers, and likewise face endogenous per-period probabilities of meeting job seekers. When a worker and a vacant job meet, the worker draws the job’s type from a sampling distribution with cdf \( F_t(\cdot) \), at which point a decision has to be made whether to consummate the match or keep searching.

2.2. The dynamic job ladder

Due to the randomness of the search and job destruction processes, our ex-ante homogeneous workers end up distributed across jobs with heterogeneous types. A key object for this analysis is the measure of workers employed in any job type \( z \), which we denote by \( \ell_t(z) \). The dynamics of that measure (as those of the unemployment rate \( u_t \)) are governed by the gradual selection of workers into heterogeneous job types, mediated by the search process — what we call the job ladder. Because the probability of success in job search, from both unemployment and employment, may vary over time, due for example to business cycle shocks, the job ladder is dynamic.

A formal representation of the dynamics of \( \ell_t(z) \) is obtained by subtraction of the outflow from the inflow into the set of workers employed in type-\( z \) jobs:

\[
\ell_{t+1}(z) = (1 - \delta) \left[ 1 - \lambda_{et}(z) \bar{F}_t(z) \right] \ell_t(z) + (1 - \delta) \int \lambda_{et}(x) \ell_t(x) \, dx + \lambda_{ut} f_t(z) u_t
\]

where \( f_t(\cdot) \) is the density of \( F_t(\cdot) \), \( \bar{F}_t(z) = 1 - F_t(z) \), and \( L_t(z) = \int \ell_t(x) \, dx \).³ In (1), a fraction \( \delta \) of the initial \( \ell_t(z) \) workers are displaced exogenously into unemployment. Of the remaining \( 1 - \delta \), a fraction \( \lambda_{et}(z) \) sample a new job, which they only move into if it has higher type than \( z \), in accordance with the job ladder assumption, an event of probability \( \bar{F}_t(z) \). The rest stay. On the inflow side, type-\( z \) jobs hire employed workers initially employed in jobs with type \( x < z \) the \( \ell_t(x) \) workers initially in type-\( x \) jobs contact a type-\( z \) firm with probability \( (1 - \delta) \lambda_{et}(x) f_t(z) \), so that the total inflow into \( \ell_t(z) \) from initially employed workers is \( (1 - \delta) \int \lambda_{et}(x) \ell_t(x) \, dx \). Finally, a measure \( \lambda_{ut} f_t(z) u_t \) of initially unemployed workers are offered a type-\( z \) job, and we assume that they always take it up (a natural assumption since all unemployed workers are identical).

Equation (1) can be expressed in terms of cumulated measure, by integration:

\[
L_{t+1}(z) = (1 - \delta) \left[ 1 - \Lambda_{et}(z) \bar{F}_t(z) \right] L_t(z) + \lambda_{ut} F_t(z) u_t
\]

where

\[
\Lambda_{et}(z) = \frac{1}{L_t(z)} \int \lambda_{et}(x) \ell_t(x) \, dx
\]

¹The assumption that the job destruction probability \( \delta \) is constant and equal across jobs is merely for simplicity and can be relaxed at the cost of added notational complexity. The assumption that it is exogenous is also for simplicity, and is tantamount to assuming that the flow payoff in unemployment is low enough relative to the output of the worst possible job that unemployment is never preferable to employment.

²The assumption here is that workers who are hit by a job destruction shock must wait for one period before they get a chance to search again. The choice of assumption in this regard does not affect the substance of the discussion in this article.

³Throughout this article, we denote the cdf of any distribution by a capital letter, its density by the corresponding lowercase letter, and the survivor function using a bar.
is the average job contact rate of workers employed in jobs of type $z$ or less. Because $L_t(z) = 1 - u_t$, Equation (2) covers the dynamics of unemployment as a special case.

The dynamic job ladder Equation (1) — or its cumulated counterpart (2) — is the cornerstone of the descriptive framework that we use to interpret the evidence presented in Section 4. That equation formally arises as an equilibrium prediction in at least two large and popular classes of frictional labor market models, namely random search models and directed search models. We discuss those theoretical underpinnings, and the more specific predictions of each of those two theoretical paradigms, in Section 3. Readers primarily interested in the evidence may skip that section and go directly to Section 4.

Before we proceed to the details of each model, we note that this section has remained deliberately vague about two related points: the interpretation a job’s type $z$, and the definition of a job itself, or more narrowly the way in which “jobs” are combined into firms. The latter is of particular empirical relevance, as many data sets (particularly matched employer-employee data sets) convey information at the firm or establishment level rather than at the level of a single job. The ways in which firms can be introduced in the analysis differ between models, and will be discussed below.

3. The Dynamic Job Ladder: Theories

3.1. Preferences and production technology

A description of the theory requires specification of a few additional features of the environment. All agents are infinitely-lived, risk neutral and discount the future with factor $\beta \in (0, 1)$. In each period, an unemployed worker produces a fixed flow $b$ of output, while maintaining a vacant job costs an amount of output specified below. When matched to a worker, a job produces $y_t + z$ units of output per period, where $y_t \in \{y, \underline{y}\}$ is the aggregate component of productivity (common to all jobs) which follows some first-order Markov process, and $z \in [\underline{z}, \overline{z}]$ is the time-invariant, job-specific component.

3.2. Random Search

In this subsection we present the shell of a random search model which is shared by most recent applications of models of random on-the-job search to business cycle analysis.

3.2.1. The search technology. In each period, all unemployed workers search for jobs, while employed workers whose jobs have not just been destroyed receive an i.i.d. opportunity to search on the job with probability $s$. Each job seeker samples one vacant job with equal probability $\lambda_t$.

The contact probability $\lambda_t$ is endogenous and determined by the search behaviors of workers and employers. Specifically, on the aggregate level, employers post an endogenous number $A_t$ of job vacancies (or job Adverts) in period $t$, while workers put a total search effort of $S_t = u_t + s(1 - \delta)(1 - u_t)$ (as the unemployed inelastically supply one unit of search effort per period and the employed supply one unit with probability $s$). The total per-period number of contacts between job seekers and job vacancies is then assumed to be a function $m(S_t, A_t)$ of aggregate worker search effort $S_t$ and employer hiring effort $A_t$. The function $m(\cdot)$, called the matching function, is typically assumed to be linearly homogeneous, increasing and concave in both of its arguments. Consistency then requires that the total flow of job-worker contacts be interchangeably given by $\lambda_t S_t = m(S_t, A_t)$,
which, by linear homogeneity of \( m(\cdot) \), implies that the contact probability \( \lambda_t \) is given by:

\[
\lambda_t = \frac{m(S_t, A_t)}{S_t} = m(1, \theta_t) := p(\theta_t)
\]

where \( \theta_t := A_t / S_t \) is the labor market tightness. Note that, by the properties of the matching function, \( \lambda_t \) is an increasing and concave function of market tightness.\(^4\)

The key assumption of random search — what distinguishes it from directed search — is that all workers are compelled to search on the same market, where they sample heterogeneous vacant jobs at random. Thus all workers face the same labor market tightness \( \theta_t \).\(^5\) By contrast, in the directed search paradigm discussed below, workers are allowed to choose between different search markets, and thus face different levels of market tightness.

### 3.2.2. Job acceptance

Upon meeting a vacant job, a worker samples the idiosyncratic productivity \( z \) of the job from an endogenous cdf \( F_t(z) \). At that point, the worker and the employer must decide whether to form the match or return to their respective search markets. An employer will accept any match that yields profits higher than the value of a vacant job (typically zero, see below). A worker will accept any match that gives them higher utility value than their current status (unemployment or, as the case may be, employment in a previous job with a different productivity level \( z' \)).

The specifics of the acceptance decision depend on the contractual details of the economy. For the purposes of this article, we assume that, in equilibrium, workers all agree on ranking jobs based on their idiosyncratic productivity \( z \): a worker employed in a type-\( z \) job will turn down any alternate job with type \( z' \leq z \) and accept any job with \( z' > z \). We thus focus on what Moscarini and Postel-Vinay (2013) call a Rank-Preserving Equilibrium (RPE).\(^6\)

We finally note that, workers being ex-ante homogeneous, an unemployed worker always accepts any job offer. Then, once employed, he only accepts outside offers from employers who are more productive firms than his current one. In that sense, equilibrium turnover in this economy takes the form of a job ladder at all points in time.

### 3.2.3. Job creation

To complete the description of the model, we must discuss the determination of two remaining endogenous objects, namely the aggregate stock of job adverts \( A_t \) and the sampling distribution of job types \( F_t(\cdot) \). Once again, the specifics of this part of the economy depend on the model’s structural details, and several options have been used in the literature. The overarching principle, however, is free entry of vacancies on the search market: employers post vacancies up to the point where the value of doing so equals

\[^4\]Incidentally, the probability of a vacant job contacting a worker (say \( \eta_t \)) is determined as a function of \( \theta_t \) by a similar consistency requirement: \( \eta_t A_t = m(S_t, A_t) \), implying \( \eta_t = m(1/\theta_t, 1) = p(\theta_t) / \theta_t \), a decreasing and convex function of tightness.

\[^5\]In more sophisticated versions of the random search model, contact probabilities \( \lambda_t \) may differ between workers. This will be the case if workers are allowed to endogenously vary their search effort. But even in those richer models, all contact probabilities depend on a common market tightness.

\[^6\]RPE, which we impose as an assumption in this article, has been shown to be the unique type of equilibrium under various popular assumptions about the contractual arrangements available to workers and employers. Those include contract-posting under full employer commitment and equal treatment (Moscarini and Postel-Vinay, 2013), contract-posting without commitment or equal treatment (Coles and Mortensen, 2016), and sequential auctions (Postel-Vinay and Robin, 2002).
the cost of posting the marginal vacancy, thus driving the net value of the marginal vacancy to zero.

While the formal translation of free entry can take many forms, there is an important interpretational distinction between the case where the productivity of the job, \( z \), is a feature of the vacancy, known by the employer at the time of posting, and the case where \( z \) is purely match-specific and is only revealed when contact with a worker is made. In the former case, vacancies with different \( z \)'s will have different values, whereas in the latter case, vacancies are ex-ante homogeneous and all have the same value.

The former case arises naturally when employers are large, ex-ante heterogeneous firms, each characterized by a fixed value of \( z \) (as, for example, in Moscarini and Postel-Vinay, 2013). In that context, we assume for simplicity that the population of firms is fixed and that productivity is distributed across firms following an exogenous distribution \( \Gamma(z) \). A firm of type \( z \) optimally sets \( a \) to equate the cost \( c'(a) \) of its marginal vacancy to its value.

Letting \( a_t(z) \) denote the adverts posted in equilibrium by that firm, the aggregate stock of vacancies is \( A_t = \int_{-\infty}^{\infty} a_t(x) d\Gamma(x) \) and the sampling distribution of firm types is

\[
F_t(z) = \frac{1}{A_t} \int_{-\infty}^{z} a_t(x) d\Gamma(x).
\]

Alternatively, one can assume that productivity \( z \) is match-specific and only revealed upon contact between a job and a worker, at which point it is drawn from some exogenous distribution \( F(\cdot) \). Like in the previous case, free entry dictates that employers post vacancies up to the point where the cost of the marginal vacancy equals its value. Yet, all vacancies now being ex-ante homogeneous, the marginal cost and marginal value of a vacancy are the same for all employers. Therefore, this version of the model has one unique free-entry condition (unlike the previous version, which has one such condition per value of \( z \)), which directly determines \( A_t \). The sampling distribution of job types \( z \) is then the exogenous \( F(\cdot) \).

While the distinction between those two cases may seem something of a technicality, it actually has important empirical content, which we discuss below in Subsection 3.4.

3.2.4. Job ladder dynamics. Taking stock of the model’s properties, it is easy to see that, on the equilibrium path, the density \( \ell_t(z) \) of workers across job types \( z \) evolves following a job-ladder equation similar to (1,2). Expressed in cumulated terms:

\[
\ell_{t+1}(z) = (1 - \delta) \left[ 1 - s \lambda_t F_t(z) \right] \ell_t(z) + \lambda_t F_t(z) u_t
\]

which formally coincides with (2) in the special case where \( \Lambda_{ct}(z) \equiv s \lambda_t \) is independent of \( z \).

3.3. Directed Search

Most recent applications of directed search theory to business cycle dynamics build on the seminal work of Menzio and Shi (2011). This section sketches a slightly simplified version

\[\text{This value equals the probability that the vacancy contacts a worker (} \eta_t \text{) times the probability that that worker accepts the match (} \frac{u_t + (1-\delta) \Lambda_{ct}(z)}{u_t + (1-\delta)(1-u_t)} \text{), the probability that a random job seeker be either unemployed or employed at a firm less productive and therefore less attractive than } z \text{ times the expected profit from that match, conditional on the worker accepting the match (a function of } z \text{ which depends on model details).}\]
of their model, and the exposition borrows from their paper. For brevity and simplicity, we focus on the planner’s problem, the solution to which can be decentralized in a market economy allowing for a sufficiently large contract space, as shown by Menzio and Shi (2011).

3.3.1. The search technology. In each period, and for each existing match, the planner first chooses a destruction probability \( d \in [\delta, 1] \), bounded from below by the exogenous job destruction probability \( \delta \). Then, unemployed workers search for jobs, and employed workers whose job was not just destroyed also receive an opportunity to search with probability \( s \). After the realization of these events, the planner distributes job seekers across different search markets (or “locations”) and decides how many vacant jobs to open in each market.

Following standard results in directed search, the planner sends workers in different employment states (i.e. unemployment or employment in jobs of different productive types) to different markets, and never sends two workers in the same employment state to different markets.

Then, in each separate market, job seekers and vacancies are randomly brought together by a similar technology as the one described in the random search case. Specifically, if a given market has \( A \) vacancies and \( S \) job seekers, the number of meetings occurring in that market is \( m(S,A) \), where \( m(\cdot) \) is a matching function with the same properties as in the random search case. Accordingly, the probability of any job seeker meeting a vacancy is \( m(S,A)/S = p(\theta) \), where \( \theta = A/S \) is the (now market-specific) tightness.

Finally, when a job seeker contacts a vacant job, the idiosyncratic productivity \( z \) of their potential match is drawn from the exogenous distribution \( F(\cdot) \). The planner then decides whether to implement the match or keep the job vacant and send the worker back to his initial employment status.

It may be useful at this juncture to re-emphasize a key distinction between random and directed search. Here, workers first pick one of many heterogeneous markets in which to search. Then, within that chosen market, they sample ex-ante homogeneous jobs at random. Under random search, by contrast, workers all search in the same market where they sample (possibly) ex-ante heterogeneous job at random.

3.3.2. The planner’s problem. At the beginning of each period, the aggregate state of the economy is \( \psi_t = (y_t, u_t, \ell_t(\cdot)) \), which consists of aggregate productivity \( y_t \), the unemployment rate \( u_t \), and the distribution of workers across job types \( \ell_t(\cdot) \). Observing \( \psi_t \), the planner then chooses the destruction probability of each existing job type \( d_t(z) \), the tightness \( \theta_{ut}[\theta_{zt}(z)] \) in the market where unemployed workers (workers employed in a type-\( z \) job) search, and the probability \( c_{ut}(z') \) \( [c_{et}(z, z')] \) with which a meeting between a type-\( z' \) vacant job and an unemployed worker [a worker employed in a type-\( z \) job] is converted into a match. The planner makes those choices to maximize the present discounted sum of output.

Formally, the planner’s problem is to solve:

\[
W(\psi_t) = \max_{[\theta_{ut}, \theta_{zt}(\cdot), d_t(\cdot), c_{ut}(\cdot), c_{et}(\cdot)]} \left\{ Q(\theta_{ut}, \theta_{zt}(\cdot), d_t(\cdot), c_{ut}(\cdot), c_{et}(\cdot); \psi_t) + \beta E_{\psi_{t+1}|\psi_t} W(\psi_{t+1}) \right\} \tag{4}
\]

subject to the laws of motion of the unemployment rate \( u_t \) and the distribution of employment across job types \( \ell_t(\cdot) \), where \( Q(\cdot; \psi_t) \) is period total output from all filled jobs. A key contribution of Menzio and Shi (2011) is to notice that the unique solution to this problem has the separable form \( W(\psi_t) = W_u(y_t) u_t + \int_0^\infty W_e(z, y_t) \ell_t(z) dz \), where \( W_u(y_t) \)
and $W_e(z, y_t)$, called the component value functions, are interpreted, respectively, as the planner’s value of an unemployed worker and that of a worker employed in a type-$z$ job.

As a consequence, solving the planner’s problem (4) amounts to separately maximizing each of the component value functions, i.e. to solving one (much simpler) dynamic programming problem per employment state.\footnote{The main simplification lies in the fact that none of the component value functions depends on the infinite-dimensional state variable $\ell_t(\cdot)$. In other words, the planner’s value function $W(\psi_t)$ is linear in $\ell_t(\cdot)$ and $\psi_t$, so that the relevant state variable from the perspective of solving (4) is just $y_t$, a scalar.} Menzio and Shi (2011) call this property Block Recursiveness. They further show that $W_u(y_t)$ and $W_e(z, y_t)$ solve relatively simple and intuitive Bellman equations, and establish that the value $W_e(z, y_t)$ of working at a job of rank $z$ is increasing in $z$ — a property that is both intuitive and relevant to the job ladder.

### 3.3.3. Job acceptance

When meetings between job seekers and vacancies are realized, the planner must decide which of those meetings to convert into actual matches. The planner will implement any match that increases his value function. First considering employed job seekers, a worker initially employed in a type-$z$ match and meeting a type-$z'$ match contributes a value of $y_t + z + \beta E_{(z', y_t)} W_e(z', y_{t+1})$ if he stays in his initial match and $y_t + z' + \beta E_{(z', y_t)} W_e(z', y_{t+1})$ if he moves into the new match. Because $W_e(z, y_t)$ is increasing in $z$, the planner will choose to implement the new match if and only if $z' \geq z$ (in other words, workers climb a z-ladder). In the notation of the planner’s problem, this implies that 
\[ c_{et}(z, z') = 1 \{ z' > z \} . \]

Following a similar logic, the planner will implement a match between an unemployed worker and a type-$z'$ job if $y_t + z' + \beta E_{(z', y_t)} W_e(z', y_{t+1}) \geq b + \beta E_{y_{t+1}} W_u(y_{t+1})$. This condition defines a cutoff value $z''_u(y_t)$ such that the acceptance rule is $c_{ut}(z') = 1 \{ z' \geq z''_u(y_t) \}$. In general, this acceptance will thus vary with aggregate productivity $y_t$. For simplicity, we assume again that $b$ is low enough that $z''_u(y_t) \leq z$ for all possible $y_t$, so that unemployed workers always match with any job they meet.

### 3.3.4. Job creation

When deciding how many jobs to open in each market, the planner weighs the cost of opening a marginal vacancy, a flow output $k$, against the benefit of doing so. We first consider the market where workers initially employed in a type-$z$ match search. Adding a vacancy to that market increases the number of contacts per job seeker in that market by $\rho' (\theta_{et}(z))$. Because only contacts that draw a productivity $z' > z$ are converted into matches, each contact in that market has expected value $\int_z^{\infty} z' - z + \beta E_{y_{t+1}} W_e(z', y_{t+1}) - W_e(z, y_{t+1}) dF(z')$. As a result, optimal tightness in that market is determined by the condition
\[ k \geq \rho' (\theta_{et}(z)) \int_z^{\infty} z' - z + \beta E_{y_{t+1}} W_e(z', y_{t+1}) - W_e(z, y_{t+1}) dF(z') \]
with complementary slackness, i.e. $\theta_{et}(z) = 0$ if the inequality is strict.\footnote{The specification of the Menzio and Shi (2011) model has the further implication that $W_e(z', y_t) - W_e(z, y_t)$ is independent of $y_t$. Because of that, the job creation condition implies that $\theta_e(z)$ is constant over time. In what follows, we will therefore drop the time subscript on $\theta_e(z)$.

The main simplification lies in the fact that none of the component value functions depends on the infinite-dimensional state variable $\ell_t(\cdot)$. In other words, the planner’s value function $W(\psi_t)$ is linear in $\ell_t(\cdot)$ and $\psi_t$, so that the relevant state variable from the perspective of solving (4) is just $y_t$, a scalar.}

Following a similar logic, and bearing in mind our assumption that unemployed workers always match when they meet a job, the job creation condition on the market for unemployed job seekers is $k = \rho' (\theta_{ut}(z)) \int_z^{\infty} y_t + z' - b + \beta E_{y_{t+1}} W_u(z', y_{t+1}) - W_u(y_{t+1}) dF(z')$.}
3.3.5. Job destruction. Finally, the planner must decide which job types to destroy. He will optimally destroy a type-$z$ job if the value of that job, $W_e(z,y_{t+1})$, falls short of the value of sending the worker into unemployment. It can be shown that, under our simplifying assumption of a low enough $b$ to ensure that unemployed workers always match with any job, the planner will never deliberately destroy a job and always sets $d_t(z)$ at its lowest possible value, i.e. the exogenous job destruction rate $\delta$.

3.3.6. Job ladder dynamics. Putting all of the above pieces together, the dynamics of the distribution of employment across job types implied by the directed search model are again characterized by a job-ladder equation similar to (1,2). Expressed in cumulated terms:

$$L_{t+1}(z) = (1 - \delta) \left[ L_t(z) - sF(z) \int_\theta p(\theta_e(x)) \ell_t(x) dx \right] + p(\theta_{ut}) F(z) ut_t$$

which formally coincides with (2) with $\lambda_{et}(z) \equiv sp(\theta_e(z))$ and $\lambda_{ut} = p(\theta_{ut})$. Both $\lambda_{et}(\cdot)$ and the sampling distribution $F_t(\cdot)$ are time-invariant in this case.

Upon first inspection, Equation (5) looks formally similar to its random-search counterpart (3), the only formal difference being that, under directed search, workers face different labor market tightness ratios depending on the market they search in (which is determined by their current employment status), whereas under random search, all workers search in the same market and face the same market tightness. That similarity of form, however, conceals differences in interpretation that have meaningful empirical consequences, as we now discuss.

3.4. Firms

As briefly mentioned in Subsection 3.2, a natural way to think of firms in the context of our job ladder models is to define firms as clusters of jobs with equal type $z$. The typical assumption is that there is a (usually exogenous) measure $\gamma(z)$ of firms with constant labor productivity $z$, whose average equilibrium size, $n_t(z) = \ell_t(z)/\gamma(z)$, is determined by the firms’ vacancy posting and compensation policies. The size of a type-$z$ firm (the “boundaries” of the firm) is limited by search frictions and convexity of the hiring cost.

Under this interpretation, our simple job ladder has the implication that, if size $n_t(z)$ is increasing in $z$ at some initial date, then it will continue to be increasing in $z$ at all subsequent dates. This is because high-$z$ firms, being more attractive to workers, hire workers at a higher rate and lose workers at a lower rate than low-$z$ firms. This (strong) prediction is particularly useful for measurement purposes: whereas the “true” rung of a firm on the job ladder, i.e. $z$, is unlikely to be observed in the data, firm size is much more easily measured. We return to this fact in our discussion of the evidence.

As further mentioned in Subsection 3.2, this model of the firm is only consistent with the assumption that $z$ is an attribute of the vacancy, known at the time of posting, rather than a purely match-specific shock, only revealed upon contact with a worker, as the latter case rules out ex-ante firm heterogeneity. While random search models can easily accommodate an ex-ante known $z$, unfortunately that assumption has a substantive impact on the predictions of the directed search model. Note that the Menzio and Shi (2011) model works under the interpretation of $z$ as purely match-specific. If, alternatively, $z$ were a feature of the vacancy, the planner could choose the type of a vacancy before he opens it and would use vacancy type to direct employer search. That is, the planner would assign vacancies
of a single type to any single market. Hence the solution to the planner’s problem would dictate that workers currently employed in type-\(z\) jobs, who all search in the same market, could only meet vacancies of a given type (say \(\varphi(z)\)). That model would therefore predict a very rigid job ladder, where workers can only be observed to move from type-\(z\) jobs into type-\(\varphi(z)\) jobs. Such a strong restriction is unlikely to hold in the data.

Schaal (2017) partly gets around this problem by taking a different perspective on the theory of the firm. He extends the Menzio and Shi (2011) model to allow for diminishing marginal returns to labor (keeping the hiring cost linear), interpreting \(z\) as firm-level TFP, which he further allows to change stochastically over time. The “productivity state” of a firm is now defined by a (TFP, size) pair, \((z_t, n_t)\). His model also gives rise to a job ladder, albeit one defined in terms of the pair \((z_t, n_t)\), which makes it analytically much less transparent than the uni-dimensional job ladder considered in this article.\(^{10}\) Yet Schaal (2017) shows, in extensive calibration exercises, that his model’s predictions are consistent with some of the evidence discussed below.

### 3.5. Extensions and limitations

#### 3.5.1. Interpreting idiosyncratic job types.

What we loosely referred to as a job’s idiosyncratic “type” \(z\) in Section 2 was more restrictively defined in this section as job productivity. While viewing productivity as the main source of job heterogeneity is common in the literature, the theories presented above can easily accommodate, subject to minor modifications, more general interpretations of \(z\) as any job attribute over which workers have common preferences (typically, any nonpecuniary job amenity).

#### 3.5.2. Flow parameters.

The assumption of a constant job destruction probability \(\delta\) can easily be relaxed to allow for a time- and job type-dependent job destruction rate \(\delta_t(z)\), following a stochastic process possibly correlated with \(y_t\).\(^{11}\) Moreover, the random search model presented in Subsection 3.2, which assumes that all employed jobseekers face the same contact rate \(\lambda_{et}(z) \equiv s\lambda_t\), can be modified to allow for job type-dependent contact rates.\(^{12}\) Both of those extensions come at the cost of some extra notational clutter, but are relatively straightforward to implement.

#### 3.5.3. Godfather shocks.

The job ladder presented thus far is unidirectional, in that it predicts that no worker will ever be observed moving from a type-\(z\) job into a lower type-\(z' < z\) job. However one chooses to interpret \(z\), such a strong restriction is unlikely to hold in

---

\(^{10}\)It is still the case in Schaal’s model that workers initially employed in type-(\(z, n\)) firms will only be observed to move to firms with a unique type \(\varphi(z, n)\). However, because two firms currently with equal \(z’s\) will have different TFP and size histories, the model features dispersion in size \(n\) conditional on \(z\) (and in \(z\) conditional on \(n\)). Focusing, for example, on the size ladder, workers initially employed in size-\(n\) firms will therefore be observed moving into firms with a range of different sizes.

\(^{11}\)See Moscarini and Postel-Vinay (2016a) for an application to random search. Allowing job destruction to very endogenously with aggregate productivity is also possible, although considerably more complex in the context of random search (Lise and Robin (2017), provides an example). Under directed search, the complete Menzio and Shi (2011) model has endogenous job destruction.

\(^{12}\)The natural way to do this is to let workers choose their own search intensity (see, e.g., Bagger and Lentz (2016)), in which case workers on different rungs of the job ladder face different returns to job search and will consequently choose different search intensities.
the data.\textsuperscript{13} An important extension of the job ladder is to relax this restriction by assuming that employed workers face an additional reallocation shock, commonly referred to as a Godfather shock:\textsuperscript{14} with probability $\rho$, an employed worker loses his job but immediately contacts a substitute job, whose type is drawn at random from the sampling distribution $F(t)$. As the worker receives this contact, his outside option is unemployment, and he will therefore take up the new job, whatever its type. While the shock $\delta$ reflects layoffs or quits that result in a measurable unemployment spell, the reallocation shock $\rho$ captures such events as moves due to spousal relocation, or displacements followed by immediate re-hiring by another employer.

Allowing for a Godfather shock, the job ladder Equation (1) becomes:

$$
\ell_{t+1}(z) = (1 - \delta)(1 - \rho) \left[ 1 - \lambda_{zt}(z) F_t(z) \right] \ell_t(z) + (1 - \delta)(1 - \rho) f_t(z) \int_x^z \lambda_{zt}(x) f_t(x) dx + (1 - \delta) \rho f_t(z) (1 - u_t) + \lambda_{zt} f_t(z) u_t
$$

which integrates as:

$$
L_{t+1}(z) = (1 - \delta)(1 - \rho) \left[ 1 - \Lambda_{zt}(z) F_t(z) \right] L_t(z) + [(1 - \delta) \rho (1 - u_t) + \lambda_{zt} u_t] F_t(z)
$$

Just like $\delta$, the reallocation probability $\rho$ can be made time- and job type-dependent.

3.5.4. Sorting. As should be clear by now, the theoretical linchpin of the job ladder dynamics is the assumption that all workers agree on a common ranking of jobs. While that assumption does not rule out worker heterogeneity, it does fail when said heterogeneity induces sorting between workers and jobs. To take a particularly obvious example, assume that workers are characterized by an individual-specific productive trait $x$ and modify the production technology to assume that a type-$x$ worker, when matched to a type-$z$ job, produces $q(x, z) = 1 - (x - z)^2$. In that case, workers with different traits $x$ will obviously not rank job types $z$ in the same way: workers will prefer jobs with types $z$ “close” to their own $x$ (although the equilibrium assignment will likely not be perfect because of the search frictions).

Sorting arises in many recent contributions to the search literature, from a variety of model specifications that are much more complex than the simplistic example outlined here.\textsuperscript{15} While job ladders can still be found in those models, each worker, with his own type $x$, will now have his own $x$-specific job ladder. Those heterogeneous job ladders typically do not aggregate into a simple, workable accounting framework like the one presented in Section 2.

\textsuperscript{13}For example, given two (large enough) firms $A$ and $B$ in a matched employer-employee data set, one will observe simultaneous movements of workers between $A$ and $B$ in both directions, which is difficult to reconcile with the simple models outlined above.

\textsuperscript{14}In reference to Marlon Brando’s famous line in Francis Ford Coppola’s film The Godfather: “I’ll make him an offer he can’t refuse”. Here, a worker hit by the reallocation shock receives “an offer he can’t refuse”.

\textsuperscript{15}Failure of a common ranking may also arise when production technology is globally increasing, but complementary, in firm and worker types, from opportunity cost equilibrium effects. For example, under capacity constraints, a more productive employer may be ranked higher by a productive worker, but lower by an unproductive one, because the latter would have to accept an abysmal wage to persuade the highly productive firm to commit a job slot where he has a weak comparative advantage (Lopes de Melo (2017)).
4. MEASUREMENT AND EMPIRICAL EVIDENCE

In order to gauge the empirical content of the job ladder model, the first step is to test its defining property: all workers agree on a common ranking of jobs, possibly within a certain labor market delimited in space, occupation, industry, skill requirements. This test has two parts. First, how do we identify the “rungs” $z$ of the job ladder? That is, how do we define empirically a “job” in the ladder? Second, how do we elicit worker preferences? Namely, how do we test whether workers agree in their rankings of these “jobs”? By backward induction, we take these two questions in the reverse order.

4.1. Ranking jobs

In practice, an empirical definition of a job ladder rung takes the form of a set of observable job characteristics $X$ such that two jobs with equal $X$ are on the same rung of the job ladder. Depending on the type of data at hand, the job attributes determining the rung a particular job sits on may include information commonly available in longitudinal worker-level data sets (e.g. wage, hours, industry, employer size . . . ) or information available in some matched employer-employee data sets (employer age, employer identity, employer value added . . . ). We return to the possible choices of those characteristics $X$ below. For now we note that, given any empirical definition of a job ladder rung, we can appeal to workers’ revealed preferences to test whether workers do agree in their ranking, i.e. if there are “universally” good and bad jobs when “jobs” are defined by a certain set of characteristics $X$. Given any two jobs — or two job types — $X_1$ and $X_2$, we rank $X_1$ higher if and only if we observe more workers quitting from $X_2$ to $X_1$ than vice versa, over some period of time (otherwise the ranking is tautological). This ranking should be global, therefore transitive, and exclude cycles.

Existing longitudinal datasets allow to estimate worker flows between different employment states and types of jobs. The gross poaching inflow share is the fraction of new recruits filling a given type of job who are already employed, as opposed to non-employed. Intuitively, this share should be increasing up the ladder. In practice, this measure can be applied to a firm or class of firms, grouped by their observable characteristics (Moscarini and Postel-Vinay, 2009). Matched-employer employee longitudinal datasets, which also contain the identity of the employers, allow to further estimate this share at the firm level (Bagger and Lentz, 2016).

A stronger test of a common ranking of jobs also takes into account retention. Net poaching, first proposed and implemented by Haltiwanger et al. (2017) as a refinement of Moscarini and Postel-Vinay (2009)’s gross poaching inflow share, is the difference between the hiring into and separations from a given job type that only involve job-to-job quits. In practice, this measure can be applied to a firm, as the number of workers hired by that firm who are currently employed at other firms minus the number of own employees who quit directly to other firms, both normalized by that firm’s size. Computing net poaching rates again requires longitudinal surveys of workers with at least some information on their employers, ideally also their identity. Just like the gross inflow share, the net poaching rate should be increasing up the ladder.

In order to use the poaching inflow share and the net poaching rate as job ranking criteria, we need to verify the intuition that they are increasing in job ladder rung $z$. To this purpose, we use our simplest random search job ladder model and focus on its Rank-
Preserving equilibrium dynamics. To simplify notation, we drop the time index and replace \( \lambda_e (1 - \delta) \) by \( \lambda_e \). As a notation reminder, \( f(z) = F'(z) \) is the sampling density of rung \( z \), \( \ell(z) = L'(z) \) is the measure of workers employed on that rung, and \( n(z) = \ell(z)/\gamma(z) \), with \( \gamma(z) \) the measure of firms on rung \( z \), is the average size of a firm on rung \( z \). Finally, \( f(z)/\gamma(z) \) is the sampling weight of a firm on rung \( z \).

Applying the definition given above, the gross poaching inflow share equals \( \lambda_e L(z)/[\lambda_e L(z) + \lambda_u u] \), which is clearly increasing in \( z \) as \( L(\cdot) \) is.

For the net poaching rate, some involved algebra shows that monotonicity in \( z \) needs not hold out of steady state. The main reason is the the poaching inflow depends only on the rank’s sampling weight, while the outflow also depends on its size. Barring mutual restrictions between the two, in principle anything goes. One possible restriction is balanced matching, whereas a rank’s sampling weight is proportional to its current size. But the simplest restriction is steady state; because aggregate shocks are small relative to the dispersion in job ladder rungs, this should provide also an accurate answer over the business cycle.

In steady state, the following identities hold:

\[
L(z) = (1 - u) \frac{\delta F(z)}{\delta + \lambda_e F(z)} \quad \text{and} \quad \ell(z) = L'(z) = (1 - u) \frac{\delta (\delta + \lambda_e) f(z)}{[\delta + \lambda_e F(z)]^2}
\]

The gross poaching outflow \( GPO(z) \) and inflow \( GPI(z) \) of a type-\( z \) firm are

\[
GPO(z) = \lambda_e F(z) n(z) \quad \text{and} \quad GPI(z) = \frac{f(z)}{\gamma(z)} \lambda_e L(z)
\]

Dividing by firm size \( n(z) = \ell(z)/\gamma(z) \) to express them as rates:

\[
GPOR(z) = \lambda_e F(z)
\]

\[
GPIR(z) = \lambda_e L(z) \cdot \frac{[\delta + \lambda_e F(z)]^2}{(1 - u) \delta (\delta + \lambda_e)} = \lambda_e F(z) \cdot \frac{\delta + \lambda_e F(z)}{\delta + \lambda_e}
\]

These gross poaching rates, both in and out, do not depend on sampling weights. Clearly, \( GPOR(z) \) declines with \( z \), while the monotonicity of \( GPIR(z) \) is ambiguous.17

Next, the net poaching rate is net growth rate of a firm’s employment due to job-to-job moves in and out of it, which is clearly increasing in rung \( z \):

\[
NPR(z) = GPIR(z) - GPOR(z) = \frac{\lambda_e \left[ \delta (F(z) - F(z)) - \lambda_e F(z)^2 \right]}{\delta + \lambda_e}
\]

### 4.2. Identifying job(ladder rungs)

To estimate these worker flows and the job preferences they reveal, we need to settle what are the “jobs” that workers move in and out of. In principle, a valid ranking candidate is

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16 Extending the derivations below to richer random search models, e.g. allowing for Godfather shocks, is straightforward and produces similar results. Moreover, as we saw, directed search also gives rise to similar expressions.

17 Note also the difference between the gross poaching inflow rate \( GPIR(z) \) and the gross poaching inflow share at the same rank \( z \), which in steady state is simply \( \lambda_e F(z)/(\delta + \lambda_e) \). Both have in the numerator the number of hires from other employers, but the inflow rate is normalized by total firm size, a stock, the inflow share by the total number of hires, a flow.
any job, or employment relationship. This includes self-employment, as well as different positions within the same firm, an internal job ladder. At this level of disaggregation, however, the task appears daunting. Because each employment “match” might contain an idiosyncratic component, there may be no such thing as the same job vacated by a worker and filled by another one. It is natural to identify a job by occupation and employer, whose characteristics such as industry, location, age, and size may capture demand, technology, or wage policy.

Theory indicates in the expected present discounted value of wages, including future unemployment spells and wages paid by future employers, the defining property of a job ladder rung. It is clear that such a value, being an expectation, can only be measured empirically through the lens of a model. This approach, while valid and legitimate, is based on a specific model, whose empirical rejection may be due to some specific assumptions, and say nothing per se about the existence of a job ladder. Therefore, in the following we focus on indirect measures of a job ladder rung, namely, four characteristics of the employer that correlate with its appeal to the worker in a variety of wage-setting environments: size, average wage paid, productivity, and the poaching shares/rates themselves.

4.2.1. Firm size. The robust empirical correlation between employer size and wage, well documented at least since Brown and Medoff (1989), suggests employer size as a measure of the job ladder rung. Search frictions imply imperfect competition in the labor market, specifically a finite elasticity of the labor supply faced by each firm, which has some control over the wage it can offer. Firms that pay more, either because more productive/profitable or by choice, retain and poach more workers, hence are larger. This is the hypothesis formalized in Burdett and Mortensen (1998). The steady state Equation (6) for rung-level employment reveals that indeed firm size \( n(z) = \ell(z)/\gamma(z) \) is increasing in \( z \) provided that sampling weights \( f(z)/\gamma(z) \) do not decrease too fast in \( z \).

In the literature, firm size (employee count) is the most commonly used measure of a firm’s desirability and recruiting success. The reasons are easily explained. Firm size is a salient feature of the political debate, as reflected by actual policy (such as the mandate of the Small Business Administration), precisely because it is associated to frictions and constraints, especially in the credit market. But the main reason is that firm size is a well-defined and model-free statistical notion. Its measurement, compared to the alternatives discussed below, requires vastly less structure and assumptions, although it is not totally straightforward, because it still requires defining the boundaries of a firm. The emphasis on firm size, as a practical ingredient of empirical investigation of the job ladder, in turn reduces the empirical content of job ladder theories that do not contain a well-defined notion of a firm, thus severely restricts the range of available models that can be tested.

Employer size is not available in the Current Population Survey, the most important dataset of the US labor market. Because studying the job ladder in terms of employer size also requires knowledge of gross worker flows, empirical applications exploit two types of datasets: either longitudinal surveys that do ask about employer size, most notably in the US on the household side the Survey of Income and Program Participation (SIPP), and on the employer side the Job Openings and Labor Turnover Survey (JOLTS) broken down by establishment size, or administrative data on employers from longitudinal matched employer-employee datasets, such as the quarterly Longitudinal Employer Household Dy-

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18Burdett and Mortensen (1998) assume uniform sampling weights, \( f \equiv \gamma \).
anomics (LEHD) in the US, including publicly available tabulations of annual gross worker flows by firm size (Business Dynamics Statistics, BDS), the Integrated Database for Arbejdsmarkedsforskning (Integrated Database for Labor Market Research, IDA) from Denmark, the Bénéfices Réels Normaux (BRN) from France. 19

Moscarini and Postel-Vinay (2009), (2012) exploit these datasets to document the existence and cyclicality (discussed later) of a job ladder by employer size. They show that the gross poaching inflow share is increasing in size. Haltiwanger et al. (2017) challenge these findings based on their stronger net poaching test. They work with administrative data from the LEHD, whose geographical coverage of private sector employers increased over time and recently completed. They confirm Moscarini and Postel-Vinay (2009)’s finding that the gross poaching share is increasing in firm size, and document that large firms hire more from employment than from non-employment, while the opposite is true of small firms, whose hiring and separation rates are in turn higher than at large firms. Net poaching, however, is decreasing in size. Building on the important findings by Haltiwanger, Jarmin and Miranda (2013), they ascribe the failure of the job ladder by size to firm age. Some small but young firms appear to be especially attractive to workers making job-to-job transitions, maybe because of their growth potential. Among mature firms, net poaching is clearly increasing in firm size.

Our caveat concerns time aggregation. Because the LEHD only reports the amount and source of earnings within a quarter, it misses non-employment spells that do not cover the entire quarter. Even Haltiwanger et al. (2017)’s most conservative definition of job-to-job transitions will include many transitions that in reality involve a short non-employment spell, a form of measurement error that arises from time aggregation. Even in their time aggregated data, small firms hire more from non-employment. Therefore, it is likely that the surprisingly high tendency of small, especially young, firms to poach workers is in reality due to job losers who quickly find new jobs by downgrading on the employer size scale, and whose non-employment spell is missed by time aggregation.

To investigate this possibility, we compute net poaching rates for small (less than 25 employees), medium-sized, and large (more than 100 employees) firms in the SIPP covering 1996-2013. The dataset contains a longitudinal employment record for many representative samples of workers, with dates of job accession and separation. We construct job-to-job transitions as in Moscarini and Postel-Vinay (2017), allowing for up to a week of non-employment between jobs, and treat any non-employment spell longer than a week as giving rise to transitions in and out of non-employment. We then compute average job-to-job transition rates from and to each of the three size classes. Finally, to mimic at least some of the time aggregation in the LEHD, we recode all transitions from non-employment to employment following non-employment spells that last up to two months, ENE and ENNE, as job-to-job transitions. Table 1 reports the resulting net poaching rates for both cases. In the first column, our best estimates are small in magnitude and, most importantly, negative for small firms and positive for large firms, as predicted by a job ladder by employer size; medium-sized firms break the ranking and provide the only evidence against it. The

19The longitudinal dimension of these data sets is essential to be able to classify firms based on their size before observing gross worker flows (hires from and separations to other firms and non-employment) and avoid what Moscarini and Postel-Vinay (2012) called the reclassification bias, whereas small firms that grow fast are mechanically reallocated to larger size classes, especially in aggregate expansions. This rules out the Business Economic Dynamics dataset from the Bureau of Labor Statistics.
second column shows that time aggregation inflates net poaching rates a lot, and produces a spectacular, yet spurious failure of the firm size ranking by net poaching in the SIPP. We conclude that the existence of a job ladder by firm size deserves further investigation.

Table 1 Net poaching rates by firm size

<table>
<thead>
<tr>
<th>Firm Size Class</th>
<th>Net Poaching Rate exact</th>
<th>Net Poaching Rate time aggregated</th>
</tr>
</thead>
<tbody>
<tr>
<td>small, 1 to 25 employees</td>
<td>-.019</td>
<td>.568</td>
</tr>
<tr>
<td>medium, 26 to 99 employees</td>
<td>-.052</td>
<td>.397</td>
</tr>
<tr>
<td>large, 100 employees and above</td>
<td>.016</td>
<td>-.252</td>
</tr>
</tbody>
</table>


4.2.2. Firm wage. An intuitive measure of the appeal of a job is the wage it pays to similar workers performing similar tasks. Wage differentials arise in the presence of search frictions as an equilibrium outcome of imperfect competition, whether or not firms differ in their demand or technology. If they do differ, equilibrium wages correlate across jobs/firms with revenue-based TFP under most wage-setting protocols. The predictions of job ladder theory for wages are, however, weaker than commonly thought. In the presence of permanent firm heterogeneity, both sequential auctions (Postel-Vinay and Robin, 2002) and tenure contracts (Burdett and Coles, 2010) imply that wages can fall immediately after a voluntary job-to-job transition, precisely because workers care about present discounted values, not about spot wages alone. In some theories, spot wages are not even uniquely pinned down. Nonetheless, it is natural to consider spot wages, which are much easier to measure than their present values and do correlate with such values in some prominent theories.

Even so, it remains a formidable challenge to extract from a single observation, a wage payment, the separate contributions of (observable or unobservable) worker characteristics, firm characteristics, and complementarity thereof. Workers care only about the last two when making turnover decisions. This identification is the subject of a vast literature on sorting patterns between workers and firms in labor markets. Starting with Becker (1973)’s seminal contribution, based on competitive equilibrium, theoretical investigation in this area eventually moved towards the search frictional paradigm (Shimer and Smith, 2001). On the empirical front, the additive “AKM” decomposition (Abowd, Kramarz and Margolis, 1999) is still the benchmark, even though it is known to provide the wrong decomposition into worker and firm characteristics in a variety of frictional settings.20 Most of the recent research on wage inequality exploits matched employer-employee datasets and operates within this sorting paradigm, which, as mentioned before, does not naturally give rise to a job ladder.

Despite these caveats, Haltiwanger et al. (2017) assign each firm in the US to a rung on a job ladder based on the average quarterly earnings of its “stable” employees, who are neither new nor about to separate, independently of their characteristics and of possible complementarities. They carefully document the magnitude and cyclical behavior of many

---

20Recently, the analysis of labor market sorting incorporates on-the-job search and the job ladder, even in the presence of aggregate uncertainty and business cycles (Lise and Robin, 2017). Bonhomme, Lamadon and Manresa (2016) introduce a new identification strategy which applies also to this richer class of models. Lise and Postel-Vinay (2016) and Postel-Vinay and Lindenlaub (2017) widen the notion of frictional sorting to multi-dimensional types, in a stationary framework.
types of worker flows between non-employment, low- and high-paying firms. They establish the existence of a robust job ladder by wage (earnings) based on net poaching rates. The results are robust to ranking firms by their AKM earnings fixed effects rather than raw earnings. Despite the limitations of this exercise, these gross flows are novel and certainly very interesting. The time aggregation problem still applies, so the true positive relationship between average earnings and net poaching rates across firms is likely to be even steeper.

**4.2.3. Firm productivity.** The identification of firm and worker contributions to the success of an employment relationship is necessary to isolate the firm component that can be used, under appropriate assumptions, to measure the job ladder. The concerns raised above about this identification problem can be, in principle, completely resolved by directly measuring the firm component. This is the idea behind ranking firms by their productivity. From this viewpoint, revenue-based TFP is an appropriate measure; even if this is high due to market power rather than technological superiority, it still measures a firm’s willingness to pay for its inputs, including workers. The traditionally problematic decomposition of revenue-based TFP into physical productivity and mark-ups, which requires strong theoretical assumptions, is relevant only to measure the social value of the job ladder in terms of employment reallocation.

Two major hurdles still stand in the way of measuring firm-level productivity relevant to the job ladder. First, required information on firm-level revenues, value added, or physical output per worker, is seldom available in matched employer-employee datasets. Second, even armed with the appropriate data, extracting marginal (and not just average) productivity requires estimating the production function. The misallocation literature tackles both hurdles head on, but is typically limited to the manufacturing sector, which is special and small in terms of employment.

The data required to estimate firm-level revenue-based TFP have been available for some time in several European countries, but to the best of our knowledge have not been used to test for the existence of a job ladder. Crane, Hyatt and Murray (2017) extract firm-level revenues from the Census Bureau’s Business Register and link this information to employment and wages from the LEHD. They then use revenues per worker, within industry in order to partially control for heterogeneity in technologies and input costs and estimate productivity, as one of four possible criteria to rank firms. They are, however, interested in sorting, and do not entertain the hypothesis of a simple job ladder entirely driven by job heterogeneity. Some of their evidence on the cyclicality of worker flows, however, corroborates stylized facts inspired by the job ladder literature. We discuss it in the next subsection.

**4.2.4. Poaching rates.** Firm size, wage and productivity may be very imperfect measures of that firm’s or job’s position on a job ladder. Job amenities alone complicate the picture. Another approach to ranking jobs circumvents altogether measures of the “rungs” on the labor demand side, and exploits revealed preferences on the labor supply side. In any job ladder model, a higher-ranked firm tends to win more often the competition for employed workers, hence to poach and to retain more employees. Bagger and Lentz (2016) show in Danish matched employer-employee longitudinal data that the ranking of firms by their gross poaching inflow share is stable and persistent over time. In principle, one could also rank firms by their net poaching rate. Closest to the definition of a job ladder, Sorkin (2017) assumes a common ranking, and proposes and implements on LEHD data a recursive
algorithm to rank all firms by pairwise comparisons of job-to-job flows, and to resolve instances of cycles through match-specific shocks, similar to Godfather shocks.

One limitation of this revealed-preference approach is that ranking is true by definition at each point in time, and is truly useful only if highly persistent over time. In this case, one can then study the business cycle dynamics of employment, sales, value added etc. of firms placed at different positions on the ladder. Alternatively, we can study salient characteristics, such as size, industry, occupation, wage and productivity of firms ranked by revealed preferences. Sorkin (2017) shows that firms ranked higher by his pairwise comparison criterion do not necessarily pay more. He interprets this result in terms of unobserved but permanent job amenities, which explain 15% of residual wage inequality.

4.3. Job-to-job transitions and earnings dynamics

As mentioned, the predictions of on-the-job search models for individual wage dynamics are not as robust as those regarding turnover, namely the job ladder. Wages and their changes depend on the nature of the contracts. Firms always have an incentive to use any commitment power to backload wages: given a value promised to the worker, which is all the worker cares about, it is cheaper for the employer to pay a low wage in the short run and commit to future raises, because those raises might be paid by other employers who will poach the worker. Hence, losing a worker to outside competition is less painful the longer the worker has been there, because it will at least spare the firm paying the high wages. Under this backloading scheme, workers who voluntarily quit from job to job might experience a decline in their spot wage, in exchange for future raises. Conversely, if the firm can only commit to a constant wage without backloading, as in Burdett and Mortensen (1998), a worker only quits a job for a higher wage. For this reason, job ladder models rarely address wage dynamics.

One property of wage dynamics that arises naturally in several job ladder models is positive skewness and high kurtosis of individual earnings growth rates, both on the same job and when changing jobs, with or without an intervening jobless spell. Most earnings changes are positive and small, when the worker receives outside offers that are either matched or accepted, and are rarely negative but large when the worker loses his job. Positive skewness and high kurtosis are the hallmark of the distribution of annual earnings changes in the US economy, documented by Guvenen et al. (2016) from administrative Social Security data. Hubmer (2017) calibrates a life-cycle job ladder model with stochastic accumulation of general human capital, including skill loss during unemployment, job search effort, risk aversion and incomplete markets, to match turnover moments and wage inequality. The calibrated model replicates well the (untargeted) cross-sectional skewness and kurtosis of SSA earnings growth, even when conditioning on age and history of realized earnings. Hubmer finds that the majority of lifetime earnings growth is due to human capital accumulation, but most high-frequency variation in earnings, especially its asymmetry and thick tails, is due to job ladder outcomes. In this sense, the job ladder is also an essential ingredient to understand uninsurable labor income risk which is usually assumed as exogenous in canonical macroeconomic models. Hubmer, however, also finds that a signifi-

\footnote{Moscari and Postel-Vinay (2016b) study the quantitative wage implications of contract posting, their (Moscari and Postel-Vinay, 2013) extension of Burdett and Mortensen (1998)’s steady-state pure wage posting to a business cycle environment.}
cant share of the earnings variation that Guvenen et al. (2016) observe in the data is not risk but rather the result of choices, search effort and job acceptance, which in turn depend on the worker’s asset position, hence on his past saving decisions.

In the general spirit of this article, rather than tying ourselves to a specific version of the job ladder model, we present evidence that can be used to inform any model and provides some general overview. We illustrate the covariance structure of earnings changes and turnover in the SIPP longitudinal microdata covering 1996-2013. Table 2 shows results from regressions of individual month-over-month change in nominal earnings on “market-predicted” transition rates and unemployment rates. Those “market-predicted” variables are constructed as in Moscarini and Postel-Vinay (2017): they are counterfactual unemployment and transition rates which measure how likely it is at any time for a worker to experience a job-to-job, job-to-unemployment, unemployment-to job, etc. transition (or to be unemployed), based on what is currently happening to similar workers. These market-predicted rates allow to disentangle the direct association of job change and wage change events for a given worker from market forces that affects wages even in the absence of employer changes. Market fixed effects sweep out any permanent heterogeneity in relative wage growth and turnover across demographic groups, due to differential trends in either labor demand (such as skill-biased technical change) or supply (for example, changes in the demographic composition of the labor force).

The first column of estimates in Table 2 shows results for the sample of all employed workers, job movers and job stayers together, controlling for individual job mover status. The remaining two columns show results from the same regression on separate samples of job movers and job stayers (obviously those last two regressions do not include a job-to-job transition indicator among the regressors).

Table 2 Individual wage growth and reallocation

<table>
<thead>
<tr>
<th>Dependent variable: change in individual log nominal monthly earnings</th>
<th>all employed workers</th>
<th>job movers</th>
<th>job stayers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual EE transition</td>
<td>0.039* (0.001)</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Market-predicted EE transition rate</td>
<td>0.077* (0.012)</td>
<td>0.513* (0.177)</td>
<td>0.040* (0.010)</td>
</tr>
<tr>
<td>Market-predicted unemployment rate</td>
<td>−0.007 (0.006)</td>
<td>−0.132 (0.094)</td>
<td>−0.001 (0.005)</td>
</tr>
<tr>
<td>Market-predicted UE transition rate</td>
<td>−0.001 (0.001)</td>
<td>−0.010 (0.016)</td>
<td>−0.000 (0.001)</td>
</tr>
<tr>
<td>Market-predicted NE transition rate</td>
<td>0.019* (0.003)</td>
<td>0.218* (0.043)</td>
<td>0.011* (0.002)</td>
</tr>
<tr>
<td>Market-predicted EU transition rate</td>
<td>−0.058* (0.015)</td>
<td>−0.340 (0.251)</td>
<td>−0.050* (0.013)</td>
</tr>
<tr>
<td>Market-predicted EN transition rate</td>
<td>−0.098* (0.010)</td>
<td>−0.868* (0.152)</td>
<td>−0.064* (0.008)</td>
</tr>
<tr>
<td>Sample size</td>
<td>5,521,578</td>
<td>186,353</td>
<td>5,335,225</td>
</tr>
</tbody>
</table>

Source: SIPP, 1996-2013. All regressions include a constant, a time trend, and market fixed effects. Standard errors are in parentheses. Asterisks indicate statistical significance at the 1 percent level.

Results in the first column show that job-to-job movers experience on average higher wage growth compared to job stayers.

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22 “Similar” in this case means workers of the same age, race, gender, education, state of residence, and, for employed workers also union status, employer size (3 classes), major industry (12), occupation (5), and a government worker dummy.
(+3.9%) earnings growth than job stayers, confirming that workers tend to move (directly from job to job) into better-paying jobs, even controlling for the turnover and earnings growth experienced by their demographic group. Beyond this direct effect of an actual job-to-job transition, the first column also shows that workers with higher market-predicted job-to-job transition rates — that is, workers who are, given their demographics, “at risk” of switching jobs, even though they don’t actually do it — also tend to have higher earnings growth.

Columns two and three confirm and extend the results in column one: both job movers and job stayers benefit (in the form of faster earnings growth) from higher general job-to-job mobility, but movers more so than stayers. Although this evidence is reduced-form and purely descriptive, we could interpret this last finding as suggesting that when the returns from searching on the job are higher, i.e. when the job ladder is steeper, workers search harder.

As a side note, as we pointed out in Moscarini and Postel-Vinay (2017), we find no evidence of any positive association between the exit rate from unemployment into employment (UE) and wage growth, which we would expect from bargaining models where firms have no commitment power.

4.4. The cyclical job ladder

Moscarini and Postel-Vinay (2009, 2012) uncover a robust implication of a job ladder model when embedded in a business cycle environment. An increase in the job contact rate, as well as a decrease in the separation rate uniformly across jobs, both typical of an aggregate expansion, reallocate more quickly workers up the ladder. As a consequence, in expansions we should expect employment to grow relatively faster at types of jobs that we ranked higher. Moscarini and Postel-Vinay (2012) systematically implement this insight by ranking jobs by firm size. When unemployment is high, at the end of and for years after a recession, employed job applicants are both crowded out by market congestion and less needed to grow the firm. As a consequence, small, low-paying firms can grow and retain workers. As the expansion unfolds but the unemployment pool dries out, large, high-paying firms can keep growing by poaching employees from small firms, which stall as both hiring from unemployment and retention become harder. When a recession hits, large firms, which were less constrained, have more employment to shed. One robust implication is that the growth rate of employment at large firms should comove more strongly (positively) than that at small firms with the average job finding probability of the unemployed.

Following Shimer (2012), most of the business cycle variation in the unemployment rate has been ascribed to movements in the job-finding probability of unemployed workers, rather than the separation rate into unemployment. Assuming a constant separation rate for simplicity, theory indicates in the level of the unemployment rate, highly correlated with that of the job-finding rate, the most relevant aggregate factor comoving with job ladder dynamics. Accordingly, Moscarini and Postel-Vinay (2012) study the correlation between the level of the unemployment rate, HP-filtered with very high smoothing parameter to eliminate very low-frequency demographic trends, and the differential growth rate of employment across types of jobs, mostly defined by employer size. They use annual data from the BDS, covering the entire US private sector in 1979-2009, and study the differential growth rate of employment between firms initially sized more than 1,000 and less than 50 employees. They find that the correlation with unemployment is −0.52, and even stronger.
when regressing the differential growth rate on unemployment at the state level, with state fixed effects. They confirm the general pattern with data from several European countries. Here in Figure 2 we replicate Moscarini and Postel-Vinay (2012)’s Figure 1, and extend it to 2015, which covers the entire Great Recession and its aftermath (shaded areas indicate NBER-dated recessions). The patterns still stand out, but the Great Recession, and especially the subsequent recovery, is an important exception.

Moscarini and Postel-Vinay (2016a) analyze this important recent episode both more extensively and in more detail, and indeed detect an anomaly relative to previous cyclical episodes in the US and in other countries. The job ladder appears to have gotten stuck: the job-to-job quit rate fell sharply starting in 2007, as in any recessions, but then stayed low for years thereafter; nonetheless, and despite the abundance of unemployed recruiting prospects, over that same period employment at small firms suffered disproportionately. It is natural to explain this exception based on the unusual credit crunch, which hit small firms disproportionately, but this explanation does not square with the persistently weak pace of total job-to-job transitions.

Unemployment is a well-known lagging indicator. Recessions are much more closely associated with above-average changes in the unemployment rate. Fort et al. (2013) clarify this distinction and find that indeed the (HP-filtered) level of, rather than the change in, the unemployment rate is a better predictor of the relative performance of large and small firms, while both level of and change in the unemployment rate correlate strongly with the relative growth performance of young and mature firms.
Haltiwanger et al. (2017) rank jobs by size or wage. They find that gross poaching rates, both inflow GPIR and outflow GPOR, are procyclical, when using the level of unemployment as a cyclical indicator, for large and small firms as well as for high and low wage firms. The net poaching rate, however, is not only near zero at large firms, but also acyclical, while it is positive and strongly countercyclical at small firms. Conversely, the net poaching rate is higher on average and procyclical at high wage firms, lower and countercyclical at low wage firms, even when using changes in the unemployment rate as a cyclical indicator. While the relative cyclicity of net poaching rates over the firm ladder, whether by size or wage, is in line with the predictions of Moscarini and Postel-Vinay (2013)’s random search model, we remark that the same time aggregation problem that potentially plagues levels applies to cyclicality, because time aggregation is more severe in expansions, when the very short unemployment spells that the LEHD tends to miss are more common.

Corroborating Moscarini and Postel-Vinay (2013)’s hypothesis, and Moscarini and Postel-Vinay (2012)’s evidence based on firm size, Crane, Hyatt and Murray (2017) find that low productivity firms gain employment share during and after recessions. Just as important is the reason for this “sullying”: the job ladder shuts down.23 Because cyclical patterns on the labor supply side indicate exactly the opposite “cleansing” effect of recessions, with low-productivity workers disproportionately leaving employment, Crane, Hyatt and Murray conclude that assortative matching is procyclical. Finally, they find that these results are robust to ranking firms in terms of either their AKM wage fixed effects or their gross poaching inflow shares.

5. CONCLUSIONS

In this article, we review existing research on labor market turnover with a special emphasis on employer-to-employer transitions, which account for the majority of employment reallocation between different types of firms and naturally provide workers with bargaining power in wage determination. We present a body of empirical evidence that we interpret through the lens of a model of turnover, the Job Ladder, where all workers aspire to climb, through job search, to the same “good” jobs, and are occasionally thrown back into unemployment, from where they have to start climbing again. This process is the equilibrium outcome of a wide range of micro-founded, structural models of the labor market in the presence of search frictions. Our past work and the present article highlight, in particular, the role that the job ladder plays in shaping aggregate employment reallocation and individual earnings changes over the business cycle. The shutdown of the cyclical job ladder in recessions accounts for much of the observed decline in reallocation and earnings growth.

A great deal work remains to be done. On the theory side, we need to better integrate into the job ladder/frictional business cycle framework two important aspects of a firm’s experience, idiosyncratic productivity shocks and diminishing returns, which are central to the competitive view of reallocation and misallocation, based on the Hopenhayn (1992) model. Work in this direction is still in its infancy. And we need to flesh out much more fully the implications of many job ladder models for earnings dynamics.

On the measurement side, we are still far from a fully satisfactory estimate of EE transitions. Moscarini and Postel-Vinay (2016a) find a much less pronounced downward

23This specific finding is consistent with the collapse of the job ladder by wage documented by Haltiwanger et al. (2017) as the main engine of declining reallocation.
trend in the EE rate in the SIPP, where time aggregation can be in principle undone, than in the CPS. In work in progress, Fujita, Moscarini and Postel-Vinay (2017) find that some of the secular decline and of the dramatic and persistent 2008-2009 cyclical drop in the EE rate in the CPS are spurious, the result of decreasing eligibility for and response rates to the dependent interviewing questions due to changes in the interviewing procedure introduced in 2007-2009. Beyond these purely data issues, eventually progress in measurement will have to rely in part on theory.

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LITERATURE CITED


