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# Quantifying the Contribution of Search to Wage Inequality†

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*We empirically establish that one-third of job transitions leads to wage losses. Using a quantitative on-the-job search model, we find that 60 percent of them are movements down the job ladder. Accounting for them, our baseline calibration matches the large residual wage inequality in US data while attributing only 13.7 percent of overall wage inequality to the presence of search frictions in the labor market. We can trace the difference between ours and previous much higher estimates to our explicit modeling of nonvalue improving job-to-job transitions.* (*JEL* J24, J31, J64)

Mincerian wage regressions explain only about a third of the observed inequality in wage data. Search theoretic models of the labor market offer a compelling explanation for this phenomenon. Their central assumption is that sampling job offers in unemployment takes time and is subject to the opportunity cost of foregone wages. Identical workers, therefore, accept a range of heterogeneous job offers.[1] The literature has come to call this *frictional wage dispersion*. Understanding how much of residual inequality results from search frictions opposed to unobserved worker heterogeneity is of first order importance for judging the efficiency of labor markets and designing appropriate social insurance schemes.

Structural models that seek to answer this question conclude that more than 40 percent of wage inequality within worker skill groups can be explained by the search friction (see Postel-Vinay and Robin 2002 and Carrillo-Tudela 2012). Hornstein, Krusell, and Violante (2012) (henceforth referred to by HKV) show that on-the-job search is the key mechanism that generates large frictional wage dispersion. A high offer arrival rate on the job implies that workers are giving up less when moving

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[1] See Mortensen (2003) and the references therein.

out of unemployment. This makes them willing to accept relatively poor job offers. Moreover, they quickly move up the job ladder, which means a larger share of workers with relatively high wages.

In this paper, we provide evidence from the Survey of Income and Program Participation (SIPP) that an important share of job-to-job transitions is not value improving. Accounting for this, we calibrate a structural search model with worker and job heterogeneity that replicates observed overall and residual wage inequality. It attributes less than 14 percent of overall wage inequality, or 16 percent of within education group inequality, to the search friction. This result comes in spite of our inclusion of a number of important channels that enlarge the set of acceptable job offers to the worker: skill accumulation on the job, skill loss in unemployment, and search on the job. The crucial novelty is the introduction of reallocation shocks that we calibrate to the share of wage losses after a job-to-job transition. Without them, in a recalibrated model, the variance of the wage offer distribution more than doubles and the contribution of the search friction jumps to over 38 percent, in line with the findings in the previous literature.

The basic intuition for our quantitative results can be summarized in three steps. First, as we demonstrate using a variation of the on-the-job search model studied by HKV, when all job-to-job transitions are value improving, workers quickly move into the high-ranked jobs from which they are unlikely to accept further offers. Calibrated search efficiency, therefore, has to be high in order to replicate the size of observed job-to-job flows. This, in turn, means that workers are concentrating in the high-ranked jobs even faster. Moreover, because workers give up relatively little search efficiency when accepting employment, they have low reservation wages.

We break this causal chain by introducing what Jolivet, Postel-Vinay, and Robin (2006) label a *reallocation shock*: a fraction of the on-the-job offers leaves the worker only to decide between accepting a random outside offer or moving into unemployment. Workers are more likely to accept the offer in this event than when the alternative is staying with their old job. As a result, they move into high-ranked jobs more slowly. Both the inferred overall offer arrival rate on the job and the arrival rate of voluntary offers needed to replicate empirically observed mobility are lower.

Second, keeping the wage offer distribution fixed, wages are less dispersed in the presence of reallocation shocks. They are more compressed at the top because workers move up the job ladder slower. The effect on the reservation wage is a priori ambiguous because reallocation shocks decrease the expected value of high-ranked jobs, which decreases the reservation wage, while a lower offer arrival rate on the job increases the reservation wage. For realistic calibrations, we find the second effect to dominate, which compresses the wage distribution from the bottom.

Third, reallocation shocks lead us to infer a less dispersed wage offer distribution. We follow Low, Meghir, and Pistaferri (2010) in identifying the distribution from the excess variance of wage growth for job switchers relative to job stayers. In the absence of reallocation shocks, many workers hold high-value jobs and most job transitions imply small wage improvements such that a high excess variance of wage growth for job switchers can only be rationalized by a very dispersed job offer distribution. In the presence of reallocation shocks, negative wage growth observations and a larger share of acceptable voluntary outside offers mean that the same excess variance of wage growth is consistent with a far less dispersed wage offer distribution. The consequence of a more compressed wage offer distribution is that job effects explain far less of total wage variation.

Can we find evidence for reallocation shocks in the data? Fujitai (2011), using data from the UK Labour Force Survey, shows that an important share of workers who search on the job do so to avoid unemployment. We extend his analysis using the SIPP employment data to show that reallocation shocks are an important driving force behind observed flows. About a third of all job-to-job transitions yield lower nominal wages for the worker and neither observable nonwage benefits nor higher expected wage growth can account for workers accepting these lower wages. Instead, workers who initially accept a wage cut are more likely to switch jobs again shortly afterward. Our quantitative model allows us to map the share of losses into the size of reallocation shocks explicitly controlling for measurement error and stochastic innovations to workers' wages. We estimate reallocation shocks to be responsible for 60 percent of observed losses.

The remainder of the paper is structured as follows. Section I gives an overview of related literature. In Section II we lay out the simple analytical model that highlights the importance of reallocation shocks. Section III provides empirical evidence for their presence in the data and highlights stylized facts of residual wage dispersion. We present our full model in Section IV. Section V discusses its parameterization. Section VI presents and analyzes the results, and Section VII concludes. Additional information on the analytical derivations, the empirical part, and the numerical algorithm is relegated to the Appendix.[2]

## I. Further Related Literature

Burdett, Carrillo-Tudela, and Coles (2011) and Ortego-Marti (2012) show that workers' reservation wages fall significantly in a job ladder model augmented by skill accumulation on the job and skill depreciation in unemployment, respectively. These models match the mean to minimum residual wage in the data, potentially rationalizing all residual inequality as frictional.[3] We incorporate these features into our model to give it a fair chance of generating substantial frictional inequality. We show that the inferred job offer distribution provides an upper bound for the share of residual inequality that can be thought of as frictional.

Another strand of related literature tries to decompose residual inequality from reduced-form specifications. Abowd, Kramarz, and Margolis (1999) and Hagedorn and Manovskii (2010) find that search frictions explain between 7–25 percent of the French interindustry differential and 6 percent of US wages, respectively. These models rely on exogenous labor mobility and either a permanent component of worker heterogeneity (Abowd, Kramarz, and Margolis 1999) or a stationary shock process (Hagedorn and Manovskii 2010). Our structural model allows us to

[2] All programs used for data analysis and model solution are available on the authors' web pages.

[3] Other recent papers that study conditions under which frictional wage inequality can explain all residual inequality are Papp (2013) and Michelacci, Pijoan-Mas, and Ruffo (2012). An earlier example is Bontemps, Robin, and Van Den Berg (2000).

explicitly model the selection of workers into matches.[4] Moreover, we confirm findings from previous studies that residual wage inequality increases strongly over a worker's life cycle. This suggests a permanent shock component in individual wage potential. Our model allows for such a nonstationary shock process and our decomposition of workers' wages over the life cycle shows that a substantial part of heterogeneity is the result of different employment histories during working life.[5] Finally, also using the SIPP, Low, Meghir, and Pistaferri (2006) use a selection model to infer the wage offer distribution and the shock process of individual wage potential from US wage data. While we ask a different question and use a different empirical strategy, our estimates yield a comparable magnitude for the relative size of idiosyncratic and employment risk.

## II. Intuition from a Simple Model

HKV show that the job offer arrival rate on the job is a key parameter determining the wage distribution, and thus the amount of frictional wage inequality, in job ladder models. The higher the on-the-job offer arrival rate is compared to in unemployment, the smaller is the option value the worker gives up by remaining unemployed and waiting for better offers. Consequently, the minimum wage accepted by workers decreases. Additionally, a high offer arrival rate on the job implies that workers quickly move up the job ladder. This leads to relatively many workers located at high paying jobs. The fact that 1 in 40 employees in the US labor market switches jobs every month seems to hint at high-offer arrival rates on the job.

Using an extension to the model studied by HKV, we now demonstrate that one can match high job-to-job transitions with substantially lower job offer arrival rates when introducing what Jolivet, Postel-Vinay, and Robin (2006) label a *reallocation shock*: A fraction of all on-the-job offers do not allow the worker to stay with his current job, but only leave him to choose between accepting other employment or becoming unemployed. One may think of these shocks as both transitions within layoff notice period as well as those originating out of nonpecuniary motives, such as moving in with one's spouse or closer to one's parents.[6] We show that these shocks crucially affect the wage distribution, both directly and indirectly by the lower inferred on-the-job offer arrival rate.

Our exposition here is parsimonious and focuses on a few key equations. Appendix A provides a full characterization of the solution. There is a unit mass of homogeneous workers receiving wage offers at Poisson rate $\lambda_u$ when unemployed and with rate $\lambda$ when employed. Wage offers are random draws from a cumulative wage offer distribution $F(w)$ with upper support $w_{\max}$ that the worker can accept or

[4] Abowd, McKinney, and Schmutte (2010) discuss that the exogeneity assumption in Abowd, Kramarz, and Margolis (1999) is violated because workers sort into jobs with higher match quality. A part of the contribution of this paper, therefore, lies in using additional wage information from job-to-job transitions to quantify the amount of endogenous upward mobility. We thank an anonymous referee for suggesting this interpretation.

[5] Hagedorn and Manovskii (2010) assume transitory shocks to the worker component and attribute 6 percent of US wage dispersion to search frictions. Using their identification strategy on our nonstationary shock process, search frictions explain almost none of the variance of log wages in our simulated data.

[6] This is in distinction from a transition where the benefit might have been nonmonetary but related to the new job like a more permanent work contract or employer provided health insurance.

reject. Time is continuous and workers discount the future at rate $r$. It is easy to see that the worker follows a reservation wage strategy where the minimum accepted wage is denoted $w^*$. The asset value of being employed with current wage $w$ is

$$\begin{aligned} rW(w) = w &+ \lambda(1-\lambda_d)\int_{w}^{w_{\max}}[W(z) - W(w)]\,dF(z) \\ &+ \lambda\lambda_d\int_{w^*}^{w_{\max}}[W(z) - W(w)]\,dF(z) \\ &- (\omega + \lambda\lambda_d F(w^*))(W(w) - U). \end{aligned}$$

The worker receives a "normal" on-the-job offer with probability $\lambda(1-\lambda_d)$, where $\lambda_d$ is the probability that an on-the-job offer is a reallocation shock. The second line is the value of accepting an outside offer after a reallocation shock. Note that now workers accept all wage offers above the reservation wage because they do not have the option to stay with their old jobs. The third line states the value of moving into unemployment, which either happens with probability $\omega$ after exogenous job destruction or when the worker refuses an offer after a reallocation shock that occurs with probability $\lambda\lambda_d F(w^*)$. When setting $\lambda_d = 0$, the model reduces to the job ladder model studied by HKV. The asset value of unemployment reads

$$rU = b + \lambda_u\int_{w^*}^{w_{\max}}[W(z) - U]\,dF(z).$$

An unemployed worker receives benefits $b$ and samples job offers at rate $\lambda_u$.

We now establish that a larger share of reallocation shocks decreases the job offer arrival rate inferred from employment transition data and reduces the share of workers with relatively high wages. We then demonstrate that this lowers the amount of wage dispersion implied by the model. The on-the-job offer arrival rate is typically identified by matching a fixed job-to-job transition rate, which we label *JTJ*, and which is given by:

$$JTJ = \lambda(1-\lambda_d)\underbrace{\int_{w^*}^{w_{\max}}[1 - F(z)]\,dG(z)}_{=:\,ANO} + \lambda\lambda_d\underbrace{[1 - F(w^*)]}_{=:\,ARO},$$

where $G(w)$ is the realized distribution of wages. We define *ANO* as the average probability that a normal on the job offer is accepted and *ARO* as the probability that an offer is accepted after a reallocation shock. Solving for the implied on the job offer rate gives

$$\lambda^* = \frac{JTJ}{(1-\lambda_d)ANO + \lambda_d ARO}.$$

Increasing the share of reallocation shocks $\lambda_d$ decreases the inferred on-the-job offer rate $\lambda^*$ for two reasons. First, job offers after a reallocation shock are accepted with probability *ARO,* which is larger than the average probability of a normal on-the-job offer being accepted ($ANO$). Second, it indirectly affects the latter by changing the wage distribution $G(w)$, which we derive in Appendix A:

$$(1) \qquad G(w) = \frac{F(w) - F(w^*)}{1 - F(w^*)} \frac{\overbrace{\omega + \lambda^* \lambda_d}^{=:\, D}}{\underbrace{\omega + \lambda^* \lambda_d}_{=:\, D} + \underbrace{\lambda^*(1 - \lambda_d)}_{=:\, C}[1 - F(w)]}.$$

Reallocation shocks have two effects on the wage distribution. First, like exogenous destruction, they move workers into unemployment from which they subsequently accept any offer above their reservation wage ($D$). In addition, $C$ shows that they decrease the amount of regular job offers, and thus the speed that workers climb up the job ladder. Consequently, $G(w)$ becomes steeper at low values, i.e., more workers have relatively low wages implying that the probability of a normal offer being accepted ($ANO$) rises.

In Section VB, we infer the wage offer distribution $F(w)$ from wage data and show that the mechanisms just outlined have large quantitative implications for the inference. To fix ideas, we study the effects of changes in $\lambda_d$ on wage dispersion for a given $F(w)$. HKV propose the ratio of the mean to the minimum wage (Mm-ratio: $\overline{w}/w^*$) as a summary statistic to compare wage dispersion across different classes of search models.[7] The measure has become a popular statistic in the literature, and, for comparability, we use it as one summary statistic for wage dispersion later in the paper.

In Appendix A, we show that the reservation wage is characterized by

$$(2) \quad w^* = b + (\lambda_u - \lambda^*) \int_{w^*}^{w_{\max}} \frac{1 - F(z)}{r + \omega + \lambda^* \lambda_d F(w^*) + \lambda^* \lambda_d F(z) + \lambda^*[1 - F(z)]} \, dz.$$

It is the sum of the flow benefits in unemployment and the option value to keep searching in unemployment. As in a pure job ladder model ($\lambda_d = 0$), the latter is decreasing in the difference $\lambda_u - \lambda$ because workers are giving up less in terms of search efficiency when moving out of unemployment. Similarly, $r$ and $\omega$ decrease the value of additional search because workers become more impatient and high-wage offers have a lower duration, respectively. Using comparative statics, we demonstrate that changes in $\lambda_d$ affect the minimum wage directly and indirectly via the implied search efficiency on the job:

$$\frac{dw^*}{d\lambda_d} = \underbrace{\frac{\partial w^*}{\partial \lambda_d}}_{<0} + \underbrace{\frac{\partial w^*}{\partial \lambda^*} \frac{\partial \lambda^*}{\partial \lambda_d}}_{>0}.$$

[7] In the models they study, this measure is independent of the wage offer distribution $F(w)$. This does not hold in the environment studies here (see Appendix A for a proof).

Table 1—Parameterization Simple Model

| Parameter | Value |
|---|---|
| $b$ | $0.4\,\overline{w}$ |
| $\lambda_u$ | 0.3 |
| $F(w)$ | $\ln \mathcal{N}(0, 0.04)$ |
| $JTJ$ | 2.5 percent |
| $r$ | 0.33 percent |

*Notes:* Unemployment benefits $b$ are a fraction of the mean wage $\overline{w}$. $JTJ$ designates the job-to-job transition rate.

The direct effect of a reallocation shock can be directly read from (2). With probability $F(w^*)$, like exogenous job destruction, it decreases the expected duration of holding employment. Moreover, the further a worker moves up the job ladder, the more likely he will move into a lower ranked job, which decreases the difference in valuation between higher and lower ranked jobs. Both factors decrease the incentive to wait for better offers when moving out of unemployment.[8] However, the increase in reallocation shocks decreases $\lambda^*$, which increases the reservation wage. Theoretically, the effect $\lambda_d$ has on the minimum wage is, therefore, ambiguous and may change depending on parameter values.

The mean wage, is given by

$$\overline{w} = \int_{w^*}^{w_{\max}} w\, dG(z).$$

Provided our earlier discussion, it should be intuitive that it is a decreasing function of $\lambda_d$. More reallocation shocks imply a steeper $G(w)$, and hence a lower mean wage.

For the remainder of this section, to be able to supply graphical representations to our argument, we impose parametric assumptions on the model. Table 1 lists the parameter values. All of them are relatively common in the literature (HKV use similar parameter values in their exposition).

Figure 1 demonstrates how the wage distribution becomes steeper as $\lambda_d$ increases. Figure 2 shows the drop in the inferred on-the-job offer arrival rate. The model estimate reacts particularly sensitively to changes at small values of $\lambda_d$. Regarding the reservation wage, Appendix A shows that it rises up to $\lambda_d = 0.35$ and starts to decrease again slowly afterward. The resulting Mm-ratio from varying $\lambda_d$ given our parameter values is reported in Figure 3. Especially for low values of $\lambda_d$, the Mm-ratio decreases quite sharply in the share of reallocation shocks.

[8] It is this effect that has Hornstein, Krusell, and Violante (2007) conclude that reallocation shocks should unambiguously increase the Mm-ratio.

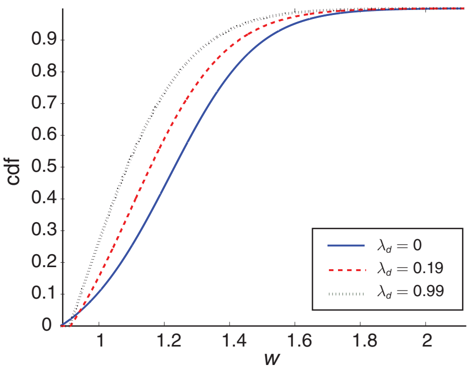


Figure 1. Wage CDF $G(w)$

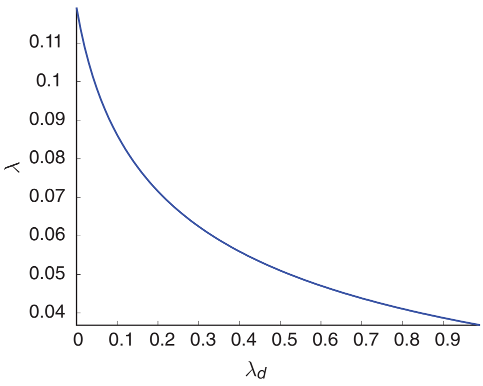


Figure 2. Implied $\lambda$

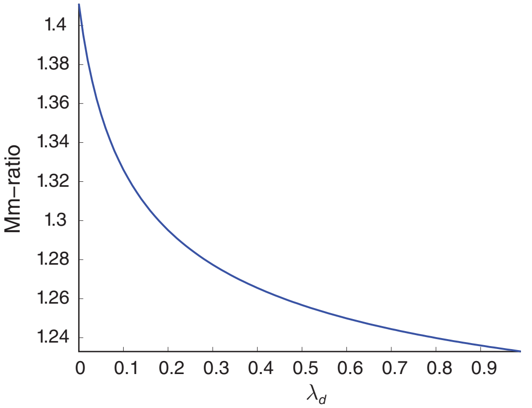


Figure 3. Mm-Ratio

*Notes:* Figure 1 shows the implied distributions of wages paid $G(w)$ for different reallocation shock probabilities $\lambda_d$ using the parameterization reported in Table 1. Figure 2 reports the implied search efficiency $\lambda$ for the same exercise, and Figure 3 reports the resulting Mm-ratio.

## III. Reallocation Shocks and Residual Wage Dispersion in the Data

In this section, we introduce our dataset, the Survey of Income and Program Participation (SIPP), and discuss sample selection. We compile different pieces of evidence to show that reallocation shocks are an important feature of the data and link them to existing evidence in other studies. We also obtain the distribution of residual wages from a Mincerian wage regression. Residual inequality is large and shows a substantial increase with worker age.

### A. *Data Source and Sample Creation*

Our analysis requires detailed longitudinal information on wages, worker, and job characteristics at a very high temporal resolution. The dataset most adequate for these requirements is the SIPP, of which we employ the 1993 and 1996 panels.[9] It is a representative sample of the noninstitutionalized civilian US population maintained by the US Census Bureau.[10] The level of detail it provides in individual records allows us to accurately identify an individual's main job and hourly wages on that job.[11] Our initial sample consists of 5,243,222 person/month observations.

Our data cover the years 1993–1995 (1993 sample) and 1996–1999 (1996 sample) providing us with up to 48 months of observations per individual. We use observations from individuals aged 23–55, for whom we require complete information on the individual's employment status, age, and employer id. We only consider an individual's primary job[12] and drop workers that are recalled by former employers or have missing reporting months during a job spell.[13] Moreover, we drop workers reporting to be school enrolled, the self-employed, family-workers, members of the armed forces, workers at nonprofit companies, and anyone whose wage information was imputed by the SIPP.[14] Finally, we truncate the wage distribution at the top and bottom 1 percent to take care of outliers and top-coding.[15] These restrictions leave us with 2,039,345 person/month observations.

We identify job-to-job transitions as those transitions in which the worker works in two consecutive months without reporting unemployment in between,[16] and either the worker's employer identification number or his two-digit occupational identifier changes.[17] Section B of the online Appendix provides a discussion for alternative measures of job-to-job transitions and compares our estimate to those obtained from CPS data.

### B. *Reallocation Shocks and On-the-Job Search*

This section provides empirical evidence from previous studies and our own data that reallocation shocks are an important feature of employment transitions. While we cannot infer their size directly from the data, Section IV uses a moment from the data together with an extended search model to quantify the share of these shocks.

[9] Our dataset is based on CEPR SIPP extracts available for download at http://www.ceprdata.org/sipp/sipp_data.php. We modify these abstracts to include further information contained in the SIPP files but not in the original abstracts. Online Appendix A provides additional information on the differences between the two datasets and the steps we take to merge them.

[10] The 1996 panel oversamples poor households. We use population weights provided by the SIPP throughout our analysis.

[11] The survey reports at most two jobs for each four-month recording period. In case an individual holds more than two jobs, the two jobs with most hours worked are reported.

[12] As primary job, we consider the position where the largest share of hours worked is spent.

[13] In case of recall, we choose to exclude those observations because recalled workers likely possess a different search technology than what we include in our model specification.

[14] Since our investigation starts from the observation that wage predictions conditional on worker observables explain only a relatively small part of wages, it would seem odd to include wage observations that are mere predictions of these very models.

[15] Earnings are top-coded at $33,333 and $50,000 for a four month period in the 1993 and 1996 sample, respectively.

[16] Theoretically, we could use the weekly employment status and count job-to-job transitions only, when a worker is employed in two consecutive weeks. However, it seems reasonable to assume that a few days in between jobs may be spent on a potential relocation or other prework sensitivities. Hence, we only discard observations where the worker reports to actively seek a job during nonemployment.

[17] We think of job-to-job transitions as a change in the technology operated by the worker; therefore, we include both changes in job ids (as in Fallick and Fleischman 2004) and occupation (as in Moscarini and Thomsson 2007).

The existing literature already highlights several shortcomings of a pure job ladder model. Fallick and Fleischman (2004) find for the CPS that a worker who reports to be actively searching on the job is more likely to be unemployed the next month. Fugita (2011)uses a question in the UK labor force survey that asks employees to state a reason for their engaging in on-the-job search. He finds that of those who report to be actively searching, 12 percent do so for fear of losing their current job and another 27 percent because they are unsatisfied with their current job due to nonpecuniary reasons. Nagypál (2005) shows for a basic job ladder model that the job offer arrival rate on the job has to be higher than during unemployment in order to replicate observed flow rates. Jolivet, Postel-Vinay, and Robin (2006) show that in the PSID 23.3 percent of job-to-job transitions are associated with nominal wage decreases. Including reallocation shocks into a Burdett and Mortensen (1998) model, they find that these shocks account for a third of all job-to-job offers. Using the SIPP, Connolly and Gottschalk (2008) find that 44.1 percent of all job-to-job transitions lead to lower real wages. They stress that a higher future expected wage growth may explain initial wage cuts and estimate that 64 percent of male and 81 percent of female wage cuts are truly transitions to lower valued jobs.[18]

Regarding our own data, the SIPP asks workers who terminate a job for their reason to do so. The answers further corroborate the evidence previously cited: only 55 percent of those responding state that they *quit to take another job*. In contrast, 19 percent of jobs ended because the previous job did not provide the possibility to continue.[19] Adding another 4 percent of cases which pertain to personal or family related issues, this yields up to 23 percent of transitions where, for one reason or another, staying with the old job may not have been an option. There are a number of caveats to the informativeness of this variable. Some of the possible answers are not mutually exclusive, or do not map directly into our interpretation of a reallocation shock. Even more problematic, in less than 30 percent of the cases we identify as job-to-job transitions, the worker provides an answer.[20, 21]

Instead of trying to infer search efficiency from this rather noisy variable, we follow a different strategy in combining employment flow data with accompanying wage dynamics. As we report in Table 2, a pervasive phenomenon in the data are job-to-job transitions resulting in nominal wage losses. In the whole population, roughly one-third of all transitions result in workers earning lower hourly wages in the month after the transition compared to the last month on the previous job.[22] Conditional losses are substantial with workers, on average, receiving about 20 percent lower wages than they received previously.[23]

[18] Vice versa, they find that 1.3 percent of females' and 8.6 percent of males' transitions with wage improvements actually go into lower valued matches.

[19] This includes the answers *on layoff*, *job was temporary and ended*, *discharged/fired*, *employer bankrupt*, *employer sold business*, and *slack work or business conditions*.

[20] For a negligible share the question is not applicable because only the main job changed, but the worker stays with his old employer. See online Appendix B for a detailed discussion on how we identify job-to-job transitions.

[21] Nagypál (2008) discusses the same issue.

[22] As a robustness test, we also constructed three-month averages of wages before and after a movement to mitigate other sources of reporting error in the months surrounding the transition. This did not affect our estimates.

[23] In online Appendix B, we report the same figures for real wage changes. In that case, the share of loss-making transitions increases to roughly one half, with average losses of about 15 percent. In principle, the worker should

Table 2—Wage Cuts after Job-to-Job Transitions

| Sample stratification | Share loss | Mean loss |
|---|---|---|
| *Whole sample* | 0.344 | −0.196 |
| *Job characteristics* | | |
| Nonunion to union | 0.346 | −0.196 |
| Health insurance | 0.352 | −0.196 |
| Education | 0.352 | −0.196 |
| *Old wage* | | |
| Lowest 25 percent | 0.232 | −0.16 |
| 25–75 percent | 0.352 | −0.198 |
| Top 25 percent | 0.457 | −0.215 |

*Notes:* The table shows the share of workers incurring a cut in nominal hourly wages after a job-to-job movement for our sample population as a whole as well as for several subsets. Mean loss reports the mean wage loss in log points conditional on suffering a wage cut upon movement. Under *Job characteristics*, the first line excludes workers from the sample who transit from nonunionized to unionized jobs, the second and third line additionally exclude workers who move from jobs without health insurance to an employer providing an insurance policy and movements where the new employer subsidizes expenses on education. The panel *Old wage* divides workers based on their wages on the old job.

*Source:* Authors' calculations based on SIPP data

More than one-third of loss-making transitions may seem like a fairly large share at first glance. One possible objection is that wages do not accurately capture the full present value of the new job. As a robustness check, in the segment entitled *Job characteristics*, we exclude transitions from nonunionized to unionized jobs since the latter should have higher expected duration and, potentially, higher present value. This does not materially affect our result. Neither does controlling for observable benefit payments such as moving from jobs without health insurance to jobs that provide insurance or into jobs which subsidize education.[24] Moreover, losses from job to job transitions are a frequent phenomenon across all segments of the wage distribution from top to bottom as can be seen in the segment *Old wage*. They are twice as likely to occur in the upper quartile of the distribution than in the bottom one, as might be expected given that higher wage earners also have more to lose. Still, even in the bottom part, more than 23 percent of transitions end up in lower paying jobs.

We perform a whole battery of further data stratifications to check whether a particular subgroup or time period is driving the results. Their results are reported in detail in online Appendix B. Share of losses and conditional changes do not materially change whether we split the sample by year to control for business cycle effects, by gender, age or tenure.[25]

only consider real wages. But in the presence of some wage rigidity, the worker expects a wage loss on his current job as well and compares nominal wages.

[24] Given that e.g., Dey and Flinn (2008) show, also using the SIPP, that wages and nonwage benefits are positively correlated, this should perhaps not be surprising.

[25] One exception occurs when we limit our sample to those individuals who report being paid by the hour. In that case, the share of losses drops to 23 percent and conditional losses to 7.8 percent. Still, this figure appears to understate the phenomenon for the population as a whole because this group is a highly selective subsample of the population with relatively low wages.

In online Appendix B, we also give consideration to an alternative explanation put forward by Postel-Vinay and Robin (2002). They lay out a framework in which workers will accept wage cuts upon job-to-job transitions, if the option value of working at the other firm is sufficiently high. Indeed, Papp (2013) shows that this framework can rationalize a large amount of wage cuts and large frictional wage dispersion. The key operating mechanism in this class of models is that workers who experienced wage losses have, on average, steeper observed wage growth afterwards, i.e., wages are backloaded. As we show, there is no indication of that occurring in our data.[26]

As a further piece of evidence that wage losses are the result of transitions into lower ranked jobs, we estimate a probit model conditioning the event of experiencing another subsequent job-to-job transition on the initial wage change upon movement. Workers who experience a loss-making transition are significantly more likely to subsequently transit again. For example, someone having suffered a loss of 20 percent upon movement is 10.3 percent more likely to transit again then someone who experienced an increase of equivalent size, and 5.6 percent more likely than someone whose wage remained unchanged.

These different tests lead us to conclude that most of the occurrences of loss-making transitions are not the result of some benefit not properly accounted for by reported compensation. However, we also should not conclude that they all result from reallocation shocks. Simple measurement error in wages is surely part of the story. Shocks to workers' idiosyncratic wage potential may be another contributing factor. In Section IV, we explicitly include these factors in our model specification in order to quantify the amount of reallocation shocks.

### C. *Residual Wage Dispersion in the SIPP*

Table 3 summarizes measures of residual wage inequality from a regression of log hourly wages[27] on a constant, time dummies, a dummy for disabled workers, a dummy for gender, a dummy for marital status, dummies for race (white, black, Hispanic, other), dummies for education (less than high school, high school, some college, college), 45 regional dummies, the number of kids, experience, and experience square. The mean $R^2$ of this regression is 0.37 and the variance of log residual wages is 0.21 leaving a significant share of wage variance unexplained.[28]

The left part of Table 3 summarizes the Mm-ratio in the data. Since the lowest wages are likely the result of measurement error, we report a number of low percentiles as candidate points. Independent of the precise measure, the Mm-ratio, the

[26] This appears to contradict the finding of Connolly and Gottschalk (2008) cited earlier. However, the authors classify wages into only two categories (low, high) and subsequent wage growth into three categories (low, medium, high). In online Appendix B, we show, using a continuous wage growth measure, that the data suggest no correlation.

[27] See online Appendix A for details on how hourly wages are computed.

[28] In an earlier version of this paper, we also controlled for unobserved individual worker fixed effect similar to Hornstein, Krusell, and Violante (2007). The short observation period of 48 months means that many workers do not experience any job-to-job transition while they are in the sample. As a result, their individual effect captures the full firm effect in wages and the distribution of residual wages has a large mass point at one. We thank an anonymous referee and Tamás Papp for pointing out this issue to us. Nevertheless, we can compare our model results to this statistic when running the same regression on simulated data. Doing so does not change our conclusions drawn in Section VI.

TABLE 3—RESIDUAL WAGE INEQUALITY IN THE 1993–1996 SIPP

| Mm-ratio | | Mm-ratio by age cohort | | Further measures | |
|---|---|---|---|---|---|
| Percentile | | Age | Fifth percentile | var. log wages | Gini |
| First | 3.02 | 25 | 1.95 | | |
| Fifth | 2.14 | 36 | 2.12 | 0.21 | 0.29 |
| Tenth | 1.83 | 49 | 2.25 | | |

*Notes:* The table reports summary measures of residual wage inequality in our data: the mean to minimum ratio, Gini-coefficient and variance of log wages after controlling for worker observables. Since the lowest wage observation in the data is likely the result of measurement error, we report several low percentiles as candidates for the actual minimum wage. Columns 3 and 4 report the Mm-ratio for different age cohorts using the fifth percentile as minimum wage.

*Source:* Authors' calculations based on SIPP data

variance of log wages, or the Gini coefficient, residual wage dispersion is large and comparable to previous studies.

While regressions like the one above provide a measure for wage inequality among observationally equivalent workers, it is not clear that this should be interpreted as frictional inequality. Such an interpretation would, e.g., falsely assign measurement error and unobserved stochastic innovations to individual wage potential to the search friction. The second column highlights a fact extensively analyzed in the incomplete markets literature, e.g., Storesletten, Telmer, and Yaron (2004), but not often addressed in the existing search literature on wage inequality; cross-sectional residual inequality increases substantially over the life cycle. Models with a fixed worker wage potential and no on-the-job search would imply that inequality does not change with age. Models with on-the-job search would even predict a decrease in inequality because workers over time cluster at the higher paying jobs. Therefore, in our model specification, we follow the incomplete markets literature and allow for persistent stochastic innovations to workers' wage potential.

## IV. A Quantitative Model of Wage Dispersion

In this section, we extend our simple model studied in Section II by adding worker heterogeneity. We enrich the worker's decision problem by a number of empirically relevant channels that imply larger frictional inequality.[29] We also add stochastic innovations to individual wage potential and measurement error in wages which allows us to disentangle wage losses resulting from reallocation shocks from those resulting from other sources.

The model is set in discrete time. Workers differ in their idiosyncratic log wage potential $A_t$ and draw job offers from heterogeneous jobs with log wage contribution

[29] Our focus, which is on the decision problem of a worker, faces an exogenous job offer distribution. In an earlier version of this paper, Tjaden and Wellschmied (2012), we used a general equilibrium approach with search and matching in the labor market and a Nash-Bargaining game played by workers and firms. We show that the resulting nonlinear log wage schedule can be almost perfectly approximated by a linear one. For ease of presentation, we opt here for the partial equilibrium representation.

$\Gamma$.[30] When a worker of type $A_t$ and a job of type $\Gamma$ meet, the wage is given by $w_t = \exp(A_t + \Gamma)$.[31] We assume that search is random, and unemployed workers contact job offers at rate $\lambda_u$ in which case $\Gamma$ is drawn from a distribution with cumulative distribution function $F(\Gamma)$ on support $[\Gamma_m, \Gamma_M]$. Employed workers continue to sample job offers from the same distribution. Following our discussion in Section II, we model some job-to-job transitions as the result of reallocation shocks. An employed worker receives a job offer with probability $\lambda$ and can, in general, decide to stay with his old match or form a new one. However, in $\lambda_d$ of those cases, the outside option becomes unemployment.

Unemployed workers receive unemployment benefits $b_t$ and a value of leisure $Z_t$ that both depend on the worker's idiosyncratic state:

$$b(A_t) = \min\{b_{\max}, rr_b \cdot \mathbb{E}[w_t(A_t, \Gamma) \,|\, A_t]\}$$

$$Z(A_t) = rr_Z \cdot \mathbb{E}[w_t(A_t, \Gamma) \,|\, A_t],$$

where $b_{\max}$ are statutory maximum UI payments. Averages are taken over the range of acceptable job offers, which themselves depend on $A_t$. In the case of unemployment insurance, the dependence on the worker's state capture the fact that benefits are a function of prior contributions and workers with higher wage potential contributed more before becoming unemployed. In the case of the value of leisure, we choose this as the closest analogy to the homogeneous agent world.[32]

Workers die with probability $\phi$ and are replaced by an unemployed labor market entrant whose idiosyncratic log wage potential is drawn from the distribution $N \sim N(\mu_N, \sigma_N^2)$. Burdett, Carrillo-Tudela, and Coles (2011) show that introducing experience gains into an on-the-job search model increases the amount of frictional wage dispersion significantly. To allow for this feature, we let the evolution of workers' wage potential depend on the agent's employment status:

$$A_{t+1} = \begin{cases} A_t + \nu + \epsilon_t & \text{if } \textit{employed} \\ A_t - \delta + \epsilon_t & \text{if } \textit{unemployed} \end{cases}.$$

$\delta$ represents skill depreciation while being unemployed and $\nu$ represents learning on the job. $\epsilon$ is a stochastic shock with $\epsilon \sim N(0, \sigma_\epsilon^2)$. We think of shocks to wage potential as demand shocks for specific skills or health shocks. The assumption of a uni-root process in wage potential is in line with most of the labor literature.[33] A

[30] $\Gamma$ is the only source of job effects in our model. These can arise from different job-specific productivities, match specific effects and, as Winfried Koeniger pointed out to us, differences arising from bargaining over quasi-rents from capital.

[31] Following the existing literature, we assume that wages monotonically increase in the job component conditional on the worker component. Eeckhout and Kircher (2011) and Bagger and Lentz (2012) show that when job effects are independent of match specific effects and the production function has a nonzero cross-partial derivative, bargaining models imply a nonmonotone wage schedule, and a specific sorting of workers over firms is an equilibrium outcome. If this was an important aspect of the data, our model would not control for it.

[32] Furthermore, one can think of this as an, admittedly very stylized, reduced form for capturing wealth heterogeneity. High-wage workers tend to have higher asset levels and unemployed workers deplete their assets over time.

[33] See Abowd and Card (1989); Topel (1991); Topel and Ward (1992); Meghir and Pistaferri (2004); and Low, Meghir, and Pistaferri (2010).

nonstationary stochastic specification for wages has also become a standard feature of the incomplete markets literature.[34] It has so far been less common in quantitative search models.

We summarize the worker problem by the value of employment $W$ and the value of unemployment $U$. The value of employment depends on a worker's wage potential and a firm's wage contribution, the value of unemployment on the workers' wage potential alone. The value of employment reads

$$W(A_t, \Gamma) = w_t(A_t, \Gamma) + \beta(1-\phi)$$
$$\mathbb{E}_t\{(1-\omega)[(1-\lambda)H + \lambda[(1-\lambda_d)\Omega_E + \lambda_d\Lambda]] + \omega U(A_{t+1})\}.$$

$\mathbb{E}_t$ is the expectation operator given all information in period $t$ and $\omega$ is an exogenous match destruction shock. For clarity of presentation, we defined the outcome of the choice of whether to quit after a bad shock to wage potential as $H$, the upper envelopes for receiving a regular job offer on the job $\Omega_E$, and the upper envelope for receiving a reallocation shock $\Lambda$. Let $\Gamma'$ be the job component at an outside job offer:

$$H = \max\{W(A_{t+1}, \Gamma), U(A_{t+1})\}$$

$$\Omega_E = \int_{\Gamma_m}^{\Gamma_M} \max\{W(A_{t+1}, \Gamma), U(A_{t+1}), W(A_{t+1}, \Gamma')\}dF(\Gamma')$$

$$\Lambda = \int_{\Gamma_m}^{\Gamma_M} \max\{W(A_{t+1}, \Gamma'), U(A_{t+1})\}dF(\Gamma').$$

The value of unemployment solves

$$U(A_t) = b(A_t) + Z(A_t) + \beta(1-\phi)$$
$$\mathbb{E}_t\{(1-\lambda_u)U(A_{t+1}) + \lambda_u \int_{\Gamma_m}^{\Gamma_M} \max\{W(A_{t+1}, \Gamma), U(A_{t+1})\}dF(\Gamma)\}.$$

## V. Parameterization

This section proceeds as follows. We first discuss our calibration regarding nondistributional parameters (preferences, institutions, flow rates) in Section VA. In Section VB, we discuss our calibration of distributional parameters. Table 4 summarizes our calibration.

### A. *Nondistributional Parameters*

The model period is one month. When comparing monthly wages in the model to hourly wages in the data, we assume an average of 160 work hours per month. The length of a period is of importance, because it puts an upper bound on the job offer

[34] See, for example, Krueger et al. (2010).

TABLE 4—CALIBRATION

| Variable | Target |
|---|---|
| $\beta = 0.997$ | 4 percent annual interest rate |
| $rr_b = 0.25$ | $\frac{b_{mean}}{w_{mean}} = 0.25$ |
| $rr_Z = 0.15$ | $\frac{Z_{mean}}{w_{mean}} = 0.15$ |
| $b_{\max}$ | \$1,168 |
| $\omega = 6.5 \times 10^{-3}$ | EU flow rate of 0.0065 |
| $\lambda_u = 0.124$ | UE flow rate of 0.123 |
| $\lambda = 0.043$ | JTJ flow rate of 0.0147 |
| $\lambda_d = 0.096$ | 34 percent of wage cuts upon JTJ movements |
| $\nu = 2.5 \times 10^{-3}$ | 3 percent yearly experience coefficient |
| $\delta = 2.3 \times 10^{-3}$ | 0.39 percent monthly depreciation coefficient |
| $\phi = 0.04$ | 33 years of working life |
| $\sigma_F = 0.163, \Gamma \sim N(0, \sigma_F^2)$ | Equation (4) = 0.0397 |
| $\sigma_\epsilon = 0.016, \epsilon \sim N(0, \sigma_\epsilon^2)$ | Life-cycle wage profile |
| $\sigma_N = 0.293, N \sim N(\mu_N, \sigma_N^2)$ | Life-cycle wage profile |
| $\sigma_\iota = 0.119, \iota \sim N(0, \sigma_\iota^2)$ | Estimation |
| $\mu_N = 5.618$ | Mean monthly wage \$2,139 |

*Notes:* The left column states the calibrated variable with its value and the second states the relevant moment. EU stands for employment to unemployment, UE for unemployment to employment, and JTJ for job to job.

probability $\lambda_u$ and the minimum duration of an unemployment spell. A maximum of one offer per month is well supported by the data,[35] but the second constraint is likely to be binding.[36]

We calculate the employment to unemployment and unemployment to employment flow rates in our SIPP sample. The exogenous job destruction rate $\omega$ is set such that the total job destruction rate, the sum of endogenous and exogenous movements from employment to unemployment, is 0.65 percent per month. We attach to $\lambda_u$ a value that implies a monthly job finding rate of 12.3 percent.

Information on job-to-job movements and accompanying wage changes identify $\lambda$ and $\lambda_d$. We adjust $\lambda$ to imply that 1.43 percent of workers switch employers every period. Our identifying assumption for separating voluntary and involuntary movements is that voluntary movements always result in expected wage increases. Together with the losses due to stochastic idiosyncratic shocks to wage potential and measurement error, both of which are calibrated below, setting $\lambda_d$ to 0.1 allows us to replicate that 34 percent of job-to-job movements result in nominal wage losses.[37]

[35] Holzer (1988) reports based on NLSY data that 34 percent of the unemployed received at least one job offer and 12 percent received more than one offer per month.

[36] See Clark and Summers (1979). Our model cannot by construction match the high observed outflow rates within the first month. However, time disaggregation below one month is rather costly because our numerical algorithm uses value function iteration, which converges at a rate of $\beta$.

[37] The share of realized job-to-job transitions that result from a reallocation shock is 28 percent, which compares nicely with our survey evidence presented in Section IIIB. In total, 60 percent of loss making transitions result from reallocation shocks. Our explicit modeling of measurement error and shocks to individual wage potential decrease the estimate of reallocation shocks considerably compared to the studies of Jolivet, Postel-Vinay, and Robin (2006) and Connolly and Gottschalk (2008).

The flow rates estimated from our sample are considerably lower than comparable estimates commonly found in the CPS. In online Appendix A, we discuss that this is largely explained by the fact that our sample selection criteria lead us to focus on individuals with relatively stable employment histories. Estimated flow rates from our raw sample are considerably larger and comparable to those found in the CPS.[38]

Consistent with findings from Siegel (2002) for average bond and stock returns, we set $\beta$ to imply a yearly interest rate of 4 percent. Next, we consider the flow value of unemployment. We set the replacement rate $rr_b$ to 25 percent. As argued in Hall and Milgrom (2008) this provides a parsimonious description of the system. The maximum UI benefit payment is set to \$1,168, which is the average across US states. The parameter determining the value of leisure $rr_z$ is set to 15 percent, which yields a total replacement rate of 40 percent when entering into unemployment as in Shimer (2005).[39]

We choose an indirect inference approach in calibrating experience and depreciation.[40] In the data, we regress log hourly wages at zero tenure on individual fixed effects, time fixed effects and a quadratic polynomial in experience. The regression yields an average increase in annual wages of 3 percent per year of experience over a working life of 25 years.[41] We then use our model solution to simulate 30,000 worker histories and draw a panel of the same length as the SIPP. We perform a similar regression[42] in our simulated data to control for selection and adjust $\nu$ to match this statistic. For skill depreciation $\delta$ we run a regression of log hourly wages after an unemployment-to-employment transition on the duration of the previous unemployment spell and worker observables. The results imply that an extra month of unemployment reduces wages by 0.39 percent. We then again replicate this regression in our data and adjust $\delta$ to match the regression statistic.

## B. *Distributional Parameters*

We now describe the way we calibrate the variance of the wage offer distribution $\sigma_F^2$, idiosyncratic shocks to wage potential $\sigma_\epsilon^2$, initial worker dispersion $\sigma_N^2$, and the measurement error process. None of the statistics is directly observable in the data because observed wages at all stages of the life cycle are a function of all three factors. Moreover, workers endogenously select themselves into and out of employment and into employment with jobs of specific wage offers in response to idiosyncratic productivity developments. Instead, we identify them from within our model by jointly calibrating them together with all other model parameters.

[38] Moreover, equation (2) highlights that for a worker's decision problem only the difference between the on- and off-the-job offer arrival rates matters. Both are significantly lower in our study compared to the ones reported by, e.g., Fallick and Fleischman (2004) based on CPS data, but the difference has a comparable size.

[39] The value of leisure is a much discussed object in the literature and Hall and Milgrom (2008) suggest a total replacement rate of 0.71. In online Appendix D we show that using this higher rate leaves our results virtually unaffected.

[40] We thank an anonymous referee for suggesting this approach to us.

[41] Altonji and Williams (1998) report very similar results.

[42] Experience is imperfectly measured in the SIPP. Workers are asked how many years they worked at least six full months since first entering the labor market. We construct the same measure for yearly experience in our simulated data.

*Measuring Job Heterogeneity.*—Similar to Low, Meghir, and Pistaferri (2010), our identification of the job offer distribution rests on the excess variance of job switchers and job stayers in the data. Other than specifying an additive specification for log wages and assuming the firm contribution to be log normally distributed, this identification only relies on the assumption that measurement error for job switchers is the same as for job stayers. Online Appendix C provides evidence for this assumption.

In our SIPP data, we assume that wages are generated by

$$\ln(w_{i,t}) = \alpha_0 + \alpha_1 d_t + \alpha_2 \mathbf{Z}_i + \beta_2 \Gamma_i + e_{i,t}, \tag{3}$$

where $d_t$ captures aggregate states, such as TFP, and $\mathbf{Z}_i$ is a vector of idiosyncratic components. We split the unobservable $e_{i,t}$ into two parts:

$$e_{i,t} = r_{i,t} + A_{i,t}.$$

Like in the model, $A_{i,t}$ is assumed to follow a random walk with drift and innovations $\epsilon_{i,t}$, and $r_{i,t}$ captures measurement error. For our present purpose, we have to make no further assumptions regarding the distributional properties of measurement error.

First-differencing eliminates the idiosyncratic wage components. As mentioned above, we only observe a self-selected subset of the realizations of $\Gamma$ and $\epsilon$ as agents can quit into unemployment after negative idiosyncratic shocks and refuse wage offers. The subsets of observed realizations $\Gamma^{obs}$ and $\epsilon^{obs}$ are themselves random variables that follow distributions of unknown functional forms. However, we can use the workers' decision rules, which determine for each $(A_t, \Gamma)$ combination whether to form or continue a match, to map these moments back into the structural parameters.

Define observed wage growth when a job-to-job transition takes place:

$$\Delta\ln(w_{i,t}^{b}) = \nu + \kappa_t + [\Gamma_i^{obs} - \Gamma_{i-1}^{obs}] + \epsilon_{i,t}^{obs} + \Delta r_{i,t},$$

and when no such transition takes place:

$$\Delta\ln(w_{i,t}^{w}) = \nu + \kappa_t + \epsilon_{i,t}^{obs} + \Delta r_{i,t},$$

where $\kappa_t = \alpha_1(d_t - d_{t-1})$. After regressing out a constant and time dummies, we obtain the residual excess variance of job movers relative to job stayers:[43]

$$\begin{aligned} \text{Var}\left[\Delta\ln(\hat{w}_{i,t}^{b})\right] &- \text{Var}\left[\Delta\ln(\hat{w}_{i,t}^{w})\right] \\ &= \text{Var}\left[\Gamma_i^{obs} - \Gamma_{i,-1}^{obs}\right] + \text{Cov}\left[\epsilon_{i,t}^{obs}(\Gamma_i^{obs} - \Gamma_{i,-1}^{obs})\right], \end{aligned} \tag{4}$$

[43] We delete the top and bottom 0.5 percent of the wage growth observations to get rid of reporting error.

where we have invoked the assumption that measurement error is uncorrelated with the event of job switching.

Equation (4) also holds in our model and we use it as a calibration target for $\sigma_F^2$. The endogenous sorting that causes the observed distribution in the data to differ from the true one is also present in our model.

*Calibrating Idiosyncratic Wage Potential.*—Similar to Storesletten, Telmer, and Yaron (2004), we calibrate the variance of idiosyncratic wage shocks to the life-cycle profile of cross-sectional residual wage dispersion.[44] While we explicitly model initial worker heterogeneity and experience gains, the data possesses well-known idiosyncratic wage components absent from our model that we regress out (gender, race, marriage, number of children, disability, and time dummies).[45] We then choose $\sigma_N^2$ to match the initial variance of residual log wage inequality not explained by job effects and $\sigma_\epsilon^2$ to match its increase over the life cycle.

Lastly, wage fluctuations may result from measurement error. To accurately identify the share of reallocation shocks and to properly calibrate the innovations to individual wage potential, we require an explicit treatment for this source of wage fluctuations. At this point, we need to make further assumptions regarding its statistical properties. Online Appendix C shows that the autocovariance function of within-job wage growth goes to zero at longer lags. Therefore, we follow Meghir and Pistaferri (2004) and postulate an $MA(q)$ process (i.e., $r_{i,t} = \Theta(q)\iota_{i,t} = \iota_{i,t} - \sum_{j=1}^{q} \theta_j \, \iota_{i,t-j}$). The autocovariance function is close to zero after 12 lags, such that we fix $q$ at 12. Assuming $\mathbb{E}(\epsilon_{i,t}^{obs} \, \epsilon_{i,t-j}^{obs}) = 0 \ \forall j \neq 0$, we obtain the parameters $\Theta(12)$ and $\sigma_\iota$ using Maximum Likelihood estimation and Kalman filtering.[46] Online Appendix C supplies further detail on the procedure and shows that $\theta_{12}$ is indeed estimated close to zero.

## VI. Results

We now present the main results of our paper. In Section VIA we demonstrate that our model generates residual wage dispersion of the size estimated in the data and that it matches its life-cycle profile. Moreover, the model provides a close fit to the shape of the overall wage distribution. Section VIB discusses the structurally inferred parameters of the wage offer distribution and of idiosyncratic wage uncertainty. We then go on to determine the relative contributions of job dispersion, development in workers' wage potential, and the distribution of workers over jobs to overall wage dispersion. Our results attribute 13.7 percent of wage inequality to

[44] In principle, we could derive a moment condition similar to the one above to identify idiosyncratic wage uncertainty (see Meghir and Pistaferri 2004 for more details). Whereas the identification of the job component only required two consecutive wage observations, the maximum spell length of 48 months in the SIPP now becomes more of an issue, which is why we opt for a different approach.

[45] We purify our data of these effects, which are well-known drivers of wages, because we think them inadequately represented by our model setup. Gender and race biases are likely the result of discrimination. Marriage stands in for a joint labor supply decision absent from our model. Disability and the number of children likely do represent productivity, but not in a way adequately captured by our model.

[46] We thank Johannes Pfeifer for providing the Kalman filtering routine to us.

TABLE 5—RESIDUAL WAGE DISPERSION

| Mean-min ratio | | | Gini | | $\mathrm{Var}(\log(\tilde{w}_{it}))$ | |
|---|---|---|---|---|---|---|
| Percentile | Model | Data | Model | Data | Model | Data |
| First | 3.01 | 3.02 | | | | |
| Fifth | 2.21 | 2.14 | 0.24 | 0.29 | 0.18 | 0.21 |
| Tenth | 1.89 | 1.83 | | | | |

*Notes:* The table compares the size of the residual wage dispersion generated by our baseline specification to the one found in the 1993–1996 SIPP. The first two columns report the Mm-ratio in the model and the data using the first, fifth, and tenth percentile as possible minimum wages. As further summary statistics, we compare the Gini coefficient and the variance of log wages.

*Source:* Authors' calculations based on model simulation and SIPP data

the presence of the search friction. Using an alternative model without reallocation shocks, the estimate jumps up to the size previously estimated in the data.

### A. *Empirical Fit*

We simulate a cohort of 30,000 workers over their life cycle. From the resulting individual paths we sample 48 month observation spells to generate a dataset of the same length as the SIPP. We then run a regression of log wages on a constant and experience to calculate the model counterpart to our measure of residual wages in the data. Table 5 summarizes our results.

The mean residual wage paid is 3.01 times the smallest observation evaluated at the first percentile. When looking at higher percentiles, model and data line up closely as well. Other summary statistics of inequality also indicate a good fit: the Gini coefficient and the variance of residual log wages are slightly smaller, but close to those found in our dataset.

In Section IIIC, we discussed that a characteristic feature of residual inequality is its increase over the life cycle and used the fact to motivate our stochastic wage potential process. Figure 4 compares the model to the data along that dimension. We closely match the magnitude of the increase over the life cycle, while missing the concave shape at the end.

In our subsequent analysis, we use our model to compute the contribution of search-induced wage inequality to overall wage inequality in the population cross-section. Therefore, we need to verify that our model fits the data along that dimension. As discussed previously, there are a few well-known wage determinants in the data that our model is not designed to include. In what follows, we first regress log wages in our data on a constant and dummies for disability, gender, marriage status, the number of kids, time, and race. These factors account for 13.3 percent of log wage variation. We compare the wage distribution from our model to the resulting distribution. Figure 5 plots the kernel estimator of the density function of wages after transforming the data back to levels against its model counterpart. The two graphs match up almost perfectly well. There is substantial inequality and the distribution features the characteristic right skew.

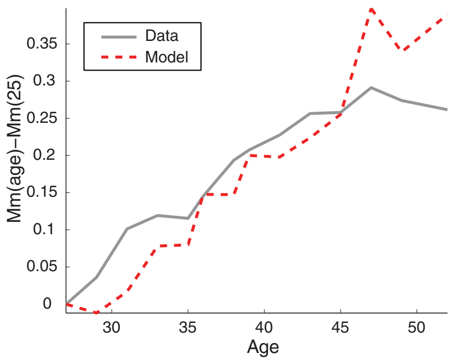


Figure 4. Mm-Ratio over the Life Cycle

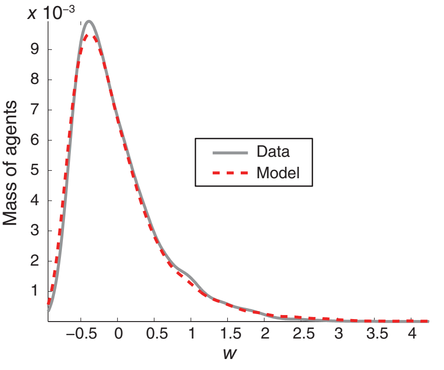


Figure 5. Wage Distributions

*Notes:* Figure 4 plots the Mm-ratio by age in the model against the data. Figure 5 compares demeaned density functions of wages after applying a kernel smoother.

*Source:* Authors' calculations based on model simulation and SIPP data

Table 6—Wage Offer Distribution and Idiosyncratic Risk

| Specification | $\sigma_F$ | $\sigma_\epsilon$ | $\sigma_N$ | $\lambda$ |
|---|---|---|---|---|
| *Baseline* | 0.163 | 0.016 | 0.293 | 0.043 |
| *Job ladder model* ($\lambda_d = 0$) | 0.296 | 0.017 | 0.117 | 0.1 |

*Notes:* The table displays the standard deviations of the wage offer distribution and of the idiosyncratic wage shock. The first line refers to the baseline specification and the second one to a calibration of a "pure" job ladder model.

## B. *Underlying Sources of Inequality*

Confident that our model features the main determinants of wage inequality, we use it to infer the relative importance of differing initial abilities ($\sigma_N$, in our model), uncertainty of idiosyncratic wage potential ($\sigma_\epsilon$), the search friction ($\sigma_F$), and a sorting term to be introduced below in explaining overall wage inequality. Our calibrated parameters are displayed in the first line of Table 6.

Our model implies a direct link between observed wage outcomes and these deep parameters. In order to map it out, we use our simulated data and consider the following variance decomposition, which we separately estimate for each age group in our simulated data:

$$\mathrm{Var}(\ln(w_i)) = \mathrm{Var}(A_i) + \mathrm{Var}(\Gamma_i) + 2\,\mathrm{Cov}(A_i, \Gamma_i) + \mathrm{Var}(r_i).$$

The left panel of Figure 6 illustrates the results. For young workers, job heterogeneity explains about 24 percent of overall log wage variance, but that number drops as workers' employment histories become more diverse. Our model identifies worker heterogeneity as the dominant factor in explaining variations in wages and this effect is increasing in age. Measurement error is responsible for about 2.4 percent of variation. Sorting of workers over job types has a mild positive effect. In a population-weighted average, frictional wage dispersion accounts for 15.5 percent

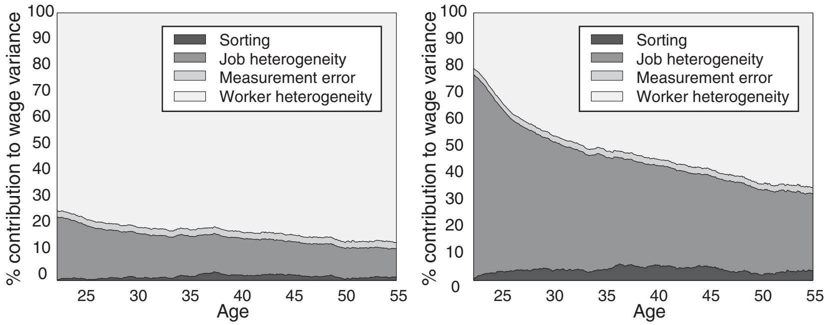


Figure 6. Contribution of Search Frictions to Overall Wage Dispersion Baseline versus Job Ladder Model

*Notes:* The graphs display the cumulative contribution of sorting (black area), firm effects (dark grey area) measurement error (medium grey area) and worker heterogeneity (light area) to the variance of log wages, conditional on age. The left panel is from our baseline specification, and the right panel results from a job ladder model with idiosyncratic productivity risk.

of wage inequality within our model. Given that we eliminated 13.3 percent of wage variation through our fixed effect regression, this implies frictional inequality to account for 13.7 percent of overall wage inequality present in our data.

## C. *On-the-Job Search and Structural Inference*

Previous estimates from structural search models that match overall wage inequality imply a much larger role for frictional inequality than we do. After controlling for observable worker skills, Postel-Vinay and Robin (2002) suggest numbers up to 50 percent and Carillo-Tudela (2012) reports estimates around 40 percent. Even when controlling for education, which explains about 15 percent of wage variation in our data, our model attributes only 16 percent of the within group inequality to the search friction. In this section, we investigate whether the introduction of the reallocation shock alone can explain the large quantitative discrepancy. We also highlight how the mechanisms outlined in Section II interact when we identify the variance of the job offer distribution.

We recalibrate our baseline model to a more common job ladder model setting, $\lambda_d = 0$, and neglect wage losses upon transition as calibration target. With a Mm-ratio of 3.45 at the first percentile, the model yields a residual inequality of similar size as our baseline specification. To demonstrate that measurement error and stochastic wages alone cannot account for the stylized facts outlined in Section IIIB, we compare moments of wage dynamics upon job-to-job movement in the data to our baseline specification and the job ladder-model. Table 7 displays the results.

In the data, job-to-job movements, on average, result in wage gains of 3.3 percent. Conditional on suffering a wage loss upon movement, workers lose 19.6 percent of their previous wages. Our baseline specification fares quite well in reproducing these statistics. Wage gains are too high, but the order of magnitude is comparable. The model does well in reproducing the large conditional wage losses. In online Appendix D, we show that our baseline specification is also in line with the large

Table 7—Wage Changes from Job-to-Job Movements

| Specification | Average gain | Average loss |
|---|---|---|
| *Data* | 0.033 | −0.196 |
| *Baseline* | 0.071 | −0.186 |
| *Job ladder model* ($\lambda_d = 0$) | 0.227 | −0.09 |

*Notes:* The table compares the model baseline specification with a pure on the job search version in their implications for job-to-job transitions. Statistics are the resulting average wage gain upon job movement and the average wage loss, conditional on observing a loss. *Data* refers to computation from the SIPP for nominal wages.

*Source:* Authors' calculations based on model simulation and SIPP data

initial wage gains at job-to-job transitions reported by Topel and Ward (1992) and the convex decrease of these gains over experience. In the pure job ladder model, average wage gains at job-to-job transitions of 23 percent are much too large compared to the data. Since workers in this model only transit to higher ranked jobs, the wage losses are only observed as result of a negative shock to individual wage potential or due to measurement error. A conditional 9 percent average wage loss clearly fails in this respect. We come back to this fact below.

We now investigate what these differences imply for the inferred importance of difference sources of wage inequality. The right panel of Figure 6 shows that this model paints a much changed picture of the different sources of wage inequality, when compared to our baseline specification. The cross-sectional average for the contribution of frictional wage dispersion more than doubles to about 44 percent (38.8 percent of wage variation in the data) with values as high as 78 percent for the youngest workers. Closely related is an almost doubling in the inferred standard deviation of the wage offer distribution as can be seen in the second row of Table 6.

The reason for these results can be traced back to the role of reallocation shocks. Section II demonstrated that in the absence of reallocation shocks, the inferred job offer arrival rate on the job is higher and more workers are in the right tail of the job offer distribution. Table 6 shows that our recalibrated model implies an on-the-job offer arrival rate more than twice as large as our baseline calibration. Consequently, workers quickly move into very high-ranked matches, accept further outside offers only infrequently and wage improvements are relatively small. Since they also do not experience large losses when moving, the implied wage offer distribution has to spread out substantially to reproduce the observed excess variance for job switchers.[47] On the flip side, most initial dispersion is explained by job effects and the inferred initial worker heterogeneity drops by half in terms of its standard deviation. The two model versions tell rather different stories about the sources of lifetime wage inequality. As a robustness analysis, we decrease the share of reallocation shocks exogenously by a half. Results of this exercise are reported in

[47] As rightfully noted by a referee, a higher offer arrival rate on the job lowers the reservation wage. This in turn may lead to a larger excess variance of wage growth of job switchers. However, we find across different calibrations that this effect is never dominant.

online Appendix D. The variance decomposition yields results close to our baseline case, showing that already some reallocation shocks overturn the strong implications from the pure job ladder model.

## VII. Conclusion

We solve a rich structural model of job and worker heterogeneity to quantify the importance of the search friction in generating wage inequality. Our model features several major channels that expand the range of acceptable offers to the workers creating larger *frictional* inequality: skill accumulation on the job, skill loss in unemployment, and search on the job. The baseline calibration reproduces both overall and residual wage inequality. Nonetheless, the search friction accounts for only 13.7 percent of total inequality.

The large quantitative difference to previous estimates stems from our introduction of reallocation shocks upon job-to-job transitions. These shocks allow our model to match a large job-to-job transition rate in the data with a relatively low on-the-job offer arrival rate. As a consequence, the endogenous wage distribution features few workers at high-ranked jobs. The calibrated variance of the job offer distribution is relatively small and only a small share of wage variation can be explained by job differences.

Empirically, we provide various pieces of evidence to show that reallocation shocks provide a fitting description for about a quarter of observed job-to-job transitions. Most importantly, about one-third of all job-to-job transitions end up with lower nominal wages than on the previous job. This finding is robust to both controlling for observed benefit payments as well as all kinds of data stratification.

## Appendix A: Solving the Model of Section II

This section derives implicit solutions for the minimum wage, the mean wage, the wage distribution, and the relationship between job-to-job transitions and the job offer rate for the model presented in Section II.

Recall the worker problem:

$$\begin{aligned} rW(w) \;=\; & w \;+\; \lambda(1-\lambda_d)\int_{w}^{w_{\max}} [W(z) - W(w)]\,dF(z) \\ & +\; \lambda\lambda_d \int_{w^*}^{w_{\max}} [W(z) - W(w)]\,dF(z) \\ & -\; (\omega \;+\; \lambda\lambda_d\, F(w^*))(W(w) - U) \end{aligned}$$

$$rU \;=\; b \;+\; \lambda_u \int_{w^*}^{w_{\max}} [W(z) - U]\,dF(z),$$

where $F(w)$ is the cdf of the wage offer distribution with upper support $w_{\max}$, $\lambda$ is the job offer arrival rate on the job, $\lambda_d$ is the share of reallocation shocks, $\omega$ is the job destruction rate, and $\lambda_u$ is the job offer arrival rate during unemployment. Evaluating

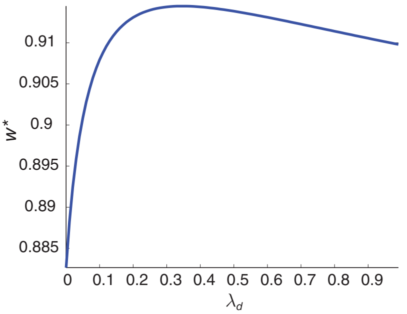


Figure A1. Reservation Wage

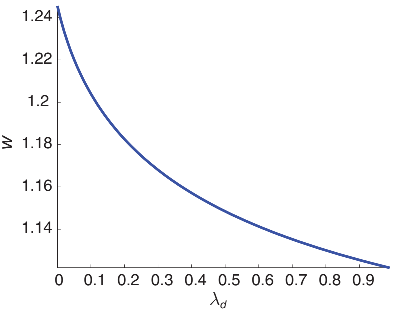


Figure A2. Mean Wage

*Note:* The figure displays the relationship between the share of reallocation shocks, $\lambda_d$, the minimum wage, and the mean wage for the calibration performed in Section II.

the asset value of employment at $w^*$ and setting it equal to the asset value of unemployment yields

$$w^* = b + (\lambda_u - \lambda) \int_{w^*}^{w_{\max}} W'(z)[1 - F(z)]\, dz.$$

Differentiating the asset value of employment with respect to $w$ yields

$$W'(w) = \frac{1}{\omega + \lambda\lambda_d F(w^*) + r + \lambda\lambda_d + \lambda(1 - \lambda_d)[1 - F(w)]}.$$

Therefore, we obtain an implicit solution for the reservation wage reported in Section II:

$$\text{(A1)} \quad w^* = b + (\lambda_u - \lambda) \int_{w^*}^{w_{\max}} \frac{1 - F(z)}{r + \omega + \lambda\lambda_d F(w^*) + \lambda\lambda_d F(z) + \lambda[1 - F(z)]}\, dz.$$

Figure A1 highlights the nonmonotone relationship between $\lambda_d$ and $w^*$ discussed in Section II.

We now derive an implicit solution for the wage distribution $G(w)$. A stationary distribution of employment over wages implies

$$\text{(A2)} \quad (1 - u)G(w)[\omega + \lambda\lambda_d F(w^*) + \lambda[1 - F(w)]]$$
$$= u\lambda_u[F(w) - F(w^*)] + (1 - u)\lambda\lambda_d[1 - G(w)][F(w) - F(w^*)].$$

Rearranging yields

$$G(w) = \frac{u\lambda_u + (1 - u)\lambda\lambda_d}{1 - u} \frac{F(w) - F(w^*)}{\omega + \lambda[1 - F(w)] + \lambda\lambda_d F(w)}.$$

Evaluating (A2) at $w^{\max}$ yields

$$\frac{u}{1-u} = \frac{\omega + \lambda\lambda_d F(w^*)}{\lambda_u[1 - F(w^*)]}.$$

Substituting into (A2) gives the solution for $G(w)$:

$$G(w) = \frac{F(w) - F(w^*)}{1 - F(w^*)} \frac{\omega + \lambda\lambda_d}{\omega + \lambda\lambda_d F(w) + \lambda[1 - F(w)]}. \tag{A3}$$

We now derive an implicit solution for the relationship between $\lambda$ and the job-to-job transition rate that we omit in the main paper for parsimony. Total job-to-job flows are given by

$$JTJ = \lambda\lambda_d[1 - F(w^*)] + \lambda(1 - \lambda_d)\int_{w^*}^{w_{\max}} [1 - F(z)]\, dG(z).$$

Integrating the equation by parts yields

$$JTJ = \lambda\lambda_d[1 - F(w^*)] + \lambda(1 - \lambda_d)\int_{w^*}^{w_{\max}} G(z)\, dF(z).$$

Substituting in $G(w)$ gives

$$\begin{aligned} JTJ = {} & \lambda\lambda_d[1 - F(w^*)] \\ & + \lambda(1 - \lambda_d)\frac{\omega + \lambda\lambda_d}{1 - F(w^*)} \int_{w^*}^{w_{\max}} \frac{F(z) - F(w^*)}{\omega + \lambda\lambda_d + \lambda(1 - \lambda_d)[1 - F(z)]}\, dF(z). \end{aligned}$$

Replace $z = F(z)$ to obtain

$$\begin{aligned} JTJ = {} & \lambda\lambda_d[1 - F(w^*)] \\ & + \lambda(1 - \lambda_d)\frac{\omega + \lambda\lambda_d}{1 - F(w^*)} \int_{F(w^*)}^{1} \frac{z - F(w^*)}{\omega + \lambda\lambda_d + \lambda(1 - \lambda_d)[1 - z]}\, dz. \end{aligned} \tag{A4}$$

Solving the integral yields

$$\begin{aligned} & \int_{F(w^*)}^{1} \frac{z - F(w^*)}{\omega + \lambda\lambda_d + \lambda(1 - \lambda_d)[1 - z]}\, dz \\ & = \Bigg| -\frac{\lambda(1 - \lambda_d)z + [\omega + \lambda]\log(\omega + \lambda\lambda_d + \lambda(1 - \lambda_d)[1 - z])}{[\lambda(1 - \lambda_d)]^2} \\ & \quad + \frac{F(w^*)\log(\omega + \lambda\lambda_d + \lambda(1 - \lambda_d)[1 - z])}{\lambda(1 - \lambda_d)} \Bigg|_{F(w^*)}^{1}. \end{aligned}$$

Finally, we can derive a solution for the mean wage:

$$\overline{w} = \int_{w^*}^{w_{\max}} w dG(z).$$

Integration by parts yields

$$\begin{aligned}\overline{w} &= w^{\max} - \int_{w^*}^{w_{\max}} w\, dG(z) \\ &= [w^{\max} - w^*] + w^* - \int_{w^*}^{w_{\max}} G(z)\, dz \\ &= w^* + \int_{w^*}^{w_{\max}} [1 - G(z)]\, dz \\ &= w^* + \frac{\omega + \lambda - \lambda(1-\lambda_d) F(w^*)}{1 - F(w^*)} \int_{w^*}^{w_{\max}} \frac{1 - F(z)}{\omega + \lambda\lambda_d + \lambda(1-\lambda_d)[1 - F(z)]}\, dz,\end{aligned}$$

which is an implicit solution for $\overline{w}$. Figure A2 shows the resulting downward sloping relationship between $\lambda_d$ and $\lambda$. Upon inspection to the mean and minimum wage, it becomes apparent that their ratio is not a moment independent of $F(w)$ in our model with reallocation shocks.

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