Earnings Growth, Job Flows and Churn

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Abstract

How much do workers making job-to-job transitions benefit from moving away from a shrinking and towards a growing firm? Using matched employer-employee data, we show that earnings growth in the transition increases with net employment growth at the destination firm and, to a lesser extent, decreases if the origin firm is shrinking. This contrasts with the muted association between a firms' excess turnover and workers' earnings growth. These results imply that firm dynamics are key to workers' earnings growth during job-to-job transitions and provide guidance to theories of job-ladder mobility.
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1. Introduction

Workers' earnings changes are concentrated around periods in which they change jobs (see e.g. Topel and Ward (1992); Moscarini and Postel-Vinay (2017); Hahn et al. (2017)). From a different perspective, workers' job changes are part of the flow of jobs from firm to firm, reallocating productive factors and, presumably increasing productivity and creating a surplus (e.g. Baily et al. (1992); Hsieh and Klenow (2009)). This paper asks how the two relate, specifically, how much does a worker gain by being part of a job flow. Implicit in this question is a hypothesis that some worker-level transitions are different than others, as some reallocate labor from shrinking firms to growing firms and others are part of the excess churn. Then, is the promise of earnings growth what induces a worker to be part of the job flow, or from the other side, is some of the dividend from job reallocation shared with the worker?

In this paper, we show that labor-force dynamics at both destination and origin firms influence the earnings outcomes of workers. This is to say that, even beyond the firm's fixed characteristics such as age, size, or whether they are high or low average wage firms, the labor-force dynamics at these firms affects workers' earnings growth. These employment dynamics include net employment growth as well as gross flows, i.e. churn or excess hiring. Quantitatively, these labor-force dynamics are important to earnings growth in a job transition: in a regression, the elasticity of earnings growth to the destination firms' employment growth is about half the size of the elasticity with respect to the firms' average wage level. Differences in the growth rates at the destination and origin firm imply a 90-10 differential in earnings growth of \$1,624, which is about 20% of the 90-10 differential implied by the difference in average wages at origin and destination. In other words, workers' earnings increase when they move to a faster-growing firm, and this is quantitatively important even after controlling for other firm characteristics.

Not every worker hired at a growing firm, however, directly accounts for its net growth because these firms are simultaneously separating and replacing workers and, similarly a separation from a shrinking firm may be replaced. In fact, we document that firms with faster net growth have even higher separation rates and thus larger gross flows. Faster shrinking firms also have higher hiring rates and higher gross flows than a more slowly shrinking firm. These patterns are important to our central question because there is an empirical distinction between net employment growth, to which earnings growth has a large elasticity, and gross flows, to which earnings are less sensitive.

To answer how a worker's earnings growth is affected by being part of the cross-firm job flow, we show that earnings growth from a job reallocation is composed of three factors: the positive effect from being hired at a growing firm, the negative effect from leaving a shrinking firm and both are tempered by the less-than-one probability this worker's transition contributed to the net employment change at the origin or destination firm.

Conditional on a bevy of other characteristics, the earnings-growth effect of being part of a job reallocation we find to be 1.7 percentage points. Given that the average earnings gain in our sample is about 7.3%, the premium associated with being part of the job flow is 23% of the expected gains from a job-to-job transition. Because the probability that a job transition is part of a job flow is about 21%, transitions with the job flow account for about 6% of overall earnings growth in job-to-job transitions.

These estimates of the job-flow earnings premium suggest that wages are an important signal for reallocating workers towards growing firms, similar to empirical evidence in Carrillo-Tudela et al. (2020) and along the lines of structural models including Kaas and Kircher (2015); Coles and Mortensen (2016); Bilal et al. (2019). To make these implications more specific, we sketch a simple, random search model in which a large firm hires in response to a productivity shock. To generate the empirical patterns we observe, a earnings *growth* premium for hires at growing firms, we show there must be a decreasing density function of earnings from which the firm hires. The logic is that firms that are eager to hire increase their yield by posting higher earnings, but this only translates into larger growth for the worker if their average prior earnings does not also increase by too much.

The considerable cross current, gross flows mean that non-growing firms are also hiring and optimizing their recruiting process. Our results suggest an important discipline on these two types of hires: firm growth, not hiring itself, has a stronger effect on earnings growth for workers. For one studying firm dynamics, these results inform the costs of reallocating inputs—growing firms pay extra to increase their stock of labor. To understand workers' earnings dynamics, these results highlight one of the reasons that job transitions may have very disparate outcomes: firm dynamics influence the potential gains.

This project links the hiring and separation rates of firms to workers' job-to-job transitions. To do so, we use the Longitudinal Employer-Household Dynamics (LEHD) dataset, administrative data that links nearly every worker to their firm and measures earnings at a quarterly frequency. From this dataset, we pull nearly 2.7 million job-to-job transitions from 1998-2013 and drawn from 17 states. Because this is administrative data and relatively high frequency, this dataset lets us identify job-to-job transitions and gives us a clear measure of workers' earnings growth from the surrounding periods. This relatively long panel also allows us to see multiple job transitions, meaning we can use individual-level fixed effects in our estimates to control for worker composition reflecting, e.g. sorting. More fundamentally, our question inherently requires matched employee-employer data because worker-side survey data does not observe changes at the firm-level.

We are not the first to have looked at earnings growth across job-to-job transitions. Topel and Ward (1992) is an important early example emphasizing the outsized role of job transitions in overall earnings growth. Hahn et al. (2017) further decomposes changes in aggregate earnings due to entrants, exits, transitions, and stayers. Relating job transitions to the characteristics of firms, Haltiwanger et al. (2018) highlight the reallocative role of job-to-job transitions from less productive to more productive firms and Bachmann et al. (2017) and Elsby et al. (2017) are important examples considering the joint-dynamics of gross and net flows of a firm. While the previous three papers focus solely on flows, our paper analyzes the effects of these dynamic characteristics on earnings growth. The role of firm characteristics such as age, size, and average wages on earnings has focused on the static characteristics of the firm and on workers' wage levels. Our paper extends these findings to show that these same static and dynamic firm characteristics affect the growth of workers' earnings.

These facts about earnings growth in job transitions and our focus on employer dynamics serve as evidence to the role of the firm in a frictional labor market and should help to inform a growing literature of labor market search models with large firms. Belzil (2000) establishes a relationship between faster-growing firms and wages above the workers' fixed effect. Davis et al. (2013) find that vacancy-fill rates are related to firm-level characteristics such as employment growth, turnover, and size. Similarly, Kettemann et al. (2018) show that job-filling rates are higher at high-paying firms and that these rates are increasing in firms growth rates even after controlling for the firm's static components of wages. Our results suggest that employer growth and gross worker flows are not just important for job-filling rates, but also for the earnings growth of workers. Earnings growth, instead of levels, is an important distinction between Kettemann et al. (2018) and ourselves: by focusing on the growth rate, we difference out unobservable individual-level characteristics which may not be randomly allocated across destination firms.

A number of structural models of firm recruiting are consistent with our empirical findings. Our finding that growing firms pay a wage premium suggest that in addition to the increased recruitment intensity in Gavazza et al. (2018) or Bilal et al. (2019), firms use higher wages to recruit workers. One example of such a framework that is consistent with our earnings result is convex recruitment costs and directed search found in Kaas and Kircher (2015).

The rest of the draft is organized as follows. In Section 2 we describe the LEHD and the variables we build in it. In Section 3 we present the unconditional relationships between earnings growth, job flows and churn. In Section 4 we describe our findings from an earnings change regression. Then, in Section 5, we construct the probability that a worker flow is part of a job flow, and quantify the associated earnings growth premium. We contextualize this within a model in Section 6. Finally, we conclude in Section 7.

2. The Data

Our data comes from the LEHD, a matched employer-employee panel put together from administrative data collected from state unemployment insurance files. Because states begin participating at different times, we trade off geographic breadth and time-frame. We opt for a 17 state sample, which includes Texas and California and runs from 1998-2014. The observations are quarterly and we observe only earnings, rather than the hourly wage.

2.1. Sample Selection

To construct our sample, we randomly draw 5% of individuals in the labor force in our 17 states.[1] Employment in these states represents 42% of national employment. Because the dataset is created from unemployment accounts, we do not include anyone not covered by unemployment insurance, which includes all federal employees. Also because of this provenance, the earnings measured are those that appear as W2 pre-tax labor income, but we will miss contracting work and other income. For each individual we sample, we extract their age and compute their birth year from the individual characteristics file (U.S. Census Bureau (2016b)). For more details of the sample, see Abowd et al. (2009).

From this sample, we use the job-history file (U.S. Census Bureau (2016a)) which lists earnings at each job spell during a worker's lifetime. For each period in which the worker has earnings, we select a "dominant" employer. This is constructed in the same way as Hyatt et al. (2014). That is to say, we add earnings for the current and previous period from every employer from whom the worker has positive earnings. The dominant job is the employer with the highest two-period earnings. A job-to-job transition is a change in dominant job from one period to the next when the new dominant job had positive earnings in the same period as the old dominant job. This means that we will count job-to-job transitions in the uncommon event that a worker is continually employed at two employers but earnings fluctuations

[1] Specifically, we sample individuals, regardless of how many years they are observed. Our sample includes data from California, Colorado, Hawaii, Idaho, Illinois, Indiana, Kansas, Maine, Maryland, Missouri, Montana, Nevada, North Dakota, Tennessee, Texas, Virginia, and Washington.

change which is the dominant job. The quarterly frequency also poses some challenges for measuring job-to-job transitions. Time aggregation implies that there may be transitions through non-employment that last up to 11 weeks. Because we require overlapping quarters of earnings, we also will miss some true job-to-job transitions that occur across a weekend that forms the seam between two quarters.

For firm-level data, we use the establishment-level quarterly-workforce indicators (U.S. Census Bureau (2016c)).[2] This is again collected at the state-level, so we use employment-weights to aggregate establishments within the state to the State Employer ID Number level. This means that multi-state firms will be counted as separate firms in each state, but transitions across establishment within firm are not counted. For each firm, we compute hires as employer-level "accessions," which includes all new employees regardless of how long the match lasts and does not exclude recalls. We trim firms that start up or shut down in that quarter and also those with more than 200% turnover.[3]

We restrict our sample in two principal ways. On the worker side, we restrict to workers who are between 25-65 years old when their job begins. Especially by cutting out the very young, we reduce labor turn-over and the prevalence of very short job-spells. On the firm side, we remove transitions to or from firms that have less than 10 employees. This again eliminates some very large volatility in terms of the measured percentage change in the firm's labor-force. The result is about 2.7 million job-to-job transitions with earnings change measured at the quarterly frequency and 1.1 million job-to-job transitions with earnings measured at the annual frequency. The reason

[2]The firm-level data uses their entire workforce, not our 5% sample.
[3]This is possible though uncommon, given the timing of how we define turnover.

for the large decline in observations of annual earnings growth is that there are many job-transitions where the origin or destination match does not last 6 quarters, which we require to measure annual earnings. This is consistent with observations in Hyatt and Spletzer (2017) who report that about $\frac{1}{3}$ of all job matches last less than 1 quarter. We deflate earnings in all quarters to 2009 dollars.

2.2. Key Variables

From this dataset, we create several variables that will show up in the rest of our analysis. Our primary variable is earnings change, $\Delta w_{i,t}$. For a worker i who switches from one employer to another in period t we skip over that period's earnings to compute the growth rate

$$\Delta w_{i,t} = \ln \sum_{j=1}^{4} w_{i,t+j} - \ln \sum_{j=1}^{4} w_{i,t-j},$$

where $\sum_{j=1}^{4} w_{i,t+j}$ and $\sum_{j=1}^{4} w_{i,t-j}$ are full-year earnings at the origin and destination firm. Full-year earnings requires that the employer-employee match existed for 6 consecutive quarters (from t to $t+5$, and t to $t-5$), insuring that for each of the interior 4 quarters from which we calculate earnings, the worker was employed for the entire duration of the quarter. Since we do not observe when in period t the transition happened, in period t we observe earnings from two employers but do not know how many weeks of work those earnings represent. Using full-year earnings ensures that the earnings we observe cover a full year of employment. Job transitions without earnings for a full year at each firm are dropped from our sample.[4]

[4]Using full-year earnings restricts our analysis to a subset of job transitions where we observe sufficiently long tenure in both the origin and destination job. We relax this restriction and look at quarterly frequencies in Appendix A.

On the firm side, we measure job flows in several ways. Net job flows at the firm are represented by

$$\Delta L_{j,t} = \frac{H_{j,t} - S_{j,t}}{\frac{1}{2}(L_{j,t} + L_{j,t-4})}$$

where $H_{j,t}$ are the hires and $S_{j,t}$ are the separations of firm j in period t. The denominator uses the normalization of Davis et al. (1998) to bound the value between -2 and 2 while being consistent with log change to a second-order approximation. We create three more variables, used in some specifications to study non-linear effects from net job flows: net job creation, $\Delta L^{+}_{j,t} = \max(\Delta L_{j,t}, 0)$, net job destruction $\Delta L^{-}_{j,t} = -\min(\Delta L_{j,t}, 0)$, and a zero-change indicator, $\Delta L^{0}_{j,t} = \mathbb{I}_{|\Delta L_{j,t}|<0.02}$. We characterize the origin and destination firms' growth rates one quarter away from the transition period so that the growth rate of the firm is not mechanically affected by the transition of the worker we observe. That is, for a worker who transitions in quarter t, the growth rate and excess hiring rate of the origin firm, $\Delta L_{\ell,t}$ and $F_{\ell,t}$, are calculated from $t-5$ to $t-1$, and for the destination firm, $\Delta L_{d,t}$ and $F_{d,t}$ are calculated from $t+1$ to $t+5$.

To represent job "churn," the gross flows above and beyond net employment growth, we will measure excess hires. Our measure $F_{j,t}$ is the number of hires beyond that which is required to achieve the net growth at the firm. This is equivalent to the churn measure in Elsby et al. (2017) and $\frac{1}{2}$ the churn measure used in Davis and Haltiwanger (2014).

$$\begin{aligned} F_{j,t} =& H_{j,t} - \max(\Delta L_{j,t}, 0) = \min(H_{j,t}, S_{j,t}) \\ =& \frac{1}{2}\left(H_{j,t} - \max(\Delta L_{j,t}, 0) + S_{j,t} - \min(\Delta L_{j,t}, 0)\right) \ . \end{aligned}$$

To measure the static characteristics of workers, we use lifetime wage rank. We define $Q(\bar{w}_i|c)$, which is the quantile of total earnings across all employment and in all quarters conditional on birth cohort. [5]

On the firm side, we measure firm age as the age of the firm's oldest establishment and firm size as the firm's total employment as in the Quarterly Workforce Indicators (QWI). We measure wages of the firm as the log of the average real earnings a firm pays its employees over every quarter the firm is operational during the 15 year sample, $\tilde{w}_j$.[6] Without taking a stand on the origin of the firm effect, whether it comes from the firm itself or the workers it collects, this measure incorporates the full effect the worker may gain from the firm at which they are employed. We also control for the origin and destination firm's industry using fixed effects at the 2 digit NAICS level.

In addition to the standard controls we include here, we have tried estimating the effects within industries, interacting the industry dummy with all of our variables of interest, and while there are certainly differences nothing that is qualitatively different from those that pool across industries. To more aggressively control for unobservable firm effects we can also include firm-level fixed effects, akin to Abowd et al. (1999) estimators. From a purely empirical perspective this is reasonable, and our main coefficients of interest are robust to this specification. However, we choose not to include it because the assumptions behind a firm-level fixed effect is at odds with the spirit of our exercise, which focuses on the dynamics of firms, rather than their static characteristics, hence we would rather not devote so many degrees of freedom

[5] By conditioning on birth cohort, we control for the earnings rank of the worker relative to their position in the life-cycle earnings profile. Conditioning on year of birth also accounts for the partial measurement of workers' lifetime earnings due to the limited duration of our sample.

[6] We have also used wage rank, $Q(\tilde{w}_j)$, as the quantile of $\tilde{w}_j$. While using this regressor instead does not change the other coefficients much, its coefficient is less easy to interpret.

to the latter.

2.3. Probabilistically Identifying Net Flows

For our central question, the earnings differences associated with net flows, it is non-trivial to label a particular worker transition as such. This is because hires at a growing firm generically exceed the net growth at the firm and separations at shrinking firms exceed net losses. So an individual generically cannot be perfectly identified as either a gross or net flow. Hence, in this section we describe how we probabilistically distinguish transitions that are part of net or gross flows. The basic idea is that if a firm has much more gross turnover relative to its net flow, the worker is more likely to be part of the churn.

We will consider a worker's transition to be part of the net flow overall under three conditions: (i) part of net growth at the destination and net shrinking at the origin firms, (ii) part of net growth at the destination firm and separated and replaced at the origin or (iii) a replacement hire at the destination firm and part of net shrinking at the origin firm. Generically, that is, we require that at least one side of the worker's transition contribute to the net growth or shrinking of a firm.

For most transitions, however, we cannot deterministically identify them into one category or another so instead we will introduce a probabilistic measure. To understand how we calculate this probability, consider a worker who moves from a stagnant origin firm, $\Delta L_\ell = 0$, to a firm with a net increase of one worker and a total hiring of 2 workers meaning there was 1 separation. This worker had a 50% chance of being a net-growth hire and a 50% chance of being a replacement. We can treat the origin analogously, as a firm separating 2 but also hiring 1, shrunk by 1 and each separation had a 50% chance of being part of the net job flow.

We then calculate the probability of being part of the job flow, $\Pr[JF]$, contributing to the net reallocation of workers between firms, as follows:

$$Pr[JF] = n_d n_\ell + n_d \frac{F_\ell}{S_\ell} + n_\ell \frac{F_d}{H_d} \ . \tag{2.1}$$

The terms are subscripted by d for the destination and ℓ for the origin. n_x is the probability a worker is part of the flow in direction x. At the destination $n_d = \frac{\Delta L_d^+}{H_d}$ is the fraction of hires that go to net growth and zero for shrinking firms and at the origin $n_\ell = \frac{\Delta L_\ell^-}{H_S}$ is the fraction of separations that shrink the firm and zero for separations from growing firms. The gross flow terms $\frac{F_\ell}{S_\ell}$ and $\frac{F_d}{H_d}$ are essentially the reciprocal: at the destination this is the probability a hire is an excess hire and $\frac{F_\ell}{S_\ell}$ is the chance a separation is replaced.

To put this whole probability into words, $n_d n_\ell$ is the chance the transition was both a net growth at the destination and net shrink at the origin, while $n_d \frac{F_\ell}{S_\ell}$ and $n_\ell \frac{F_d}{H_d}$ are the chance of a net growth at the destination and replaced loss at the origin or net loss at origin and replacement hire at the destination. The first and second terms are the probability of being part of job reallocation towards a growing firm and the first and third terms are the probability of job reallocation away from a shrinking firm. This is an inclusive notion of being part of net job reallocation because a worker can contribute by moving into a faster growing firm or by leaving a shrinking firm. Importantly, each term reflects that workers moving between firms with a large amount of turnover are less likely to have been part of net reallocation.

3. Unconditional Relationships Between Earnings Growth, Job Flows and Churn

To quantify the effect of firm-level job reallocation on earnings growth, we first consider the relationship between firms' net employment growth and workers' earnings growth. Here we show that workers leaving shrinking firms, on average have less earnings growth and those going to growing firms have more earnings growth than the average job-to-job flow. Because a transition with the job flow takes a worker leaving a shrinking firm to one growing, the earnings effect will be the difference between the two.

Figure 1 plots the local, unconditional correlation between earnings growth and net employment growth at the origin and destination firm for workers who make a job-to-job transition, and the relationship between net growth and earnings growth for workers who remain with their employer. We find that earnings growth in job transitions is strongly, positively correlated with the net growth of the destination firm. The origin firm's growth rate has a weaker correlation and shows lower earnings growth when workers transition away from a shrinking firm. For comparison, we also include the earnings growth of workers who stay at the same firm in Appendix A. There, stayers have a lower level, meaning less earnings growth overall, but also a correlation with the firms' employment growth that is between the correlations for destination and origin. The rest of the paper will focus on earnings growth of transiters, but the non-zero slope for stayers is a useful check suggesting some passthrough in the spirit of Guiso et al. (2005). In Appendix A, we also show that these patterns hold with quarterly earnings and quarterly job flows, albeit the transiters' effects are slightly steeper but the level is closer to that of the stayers, which highlights the way in which our sample of year-long tenured employees is a selected subset of all job changers.

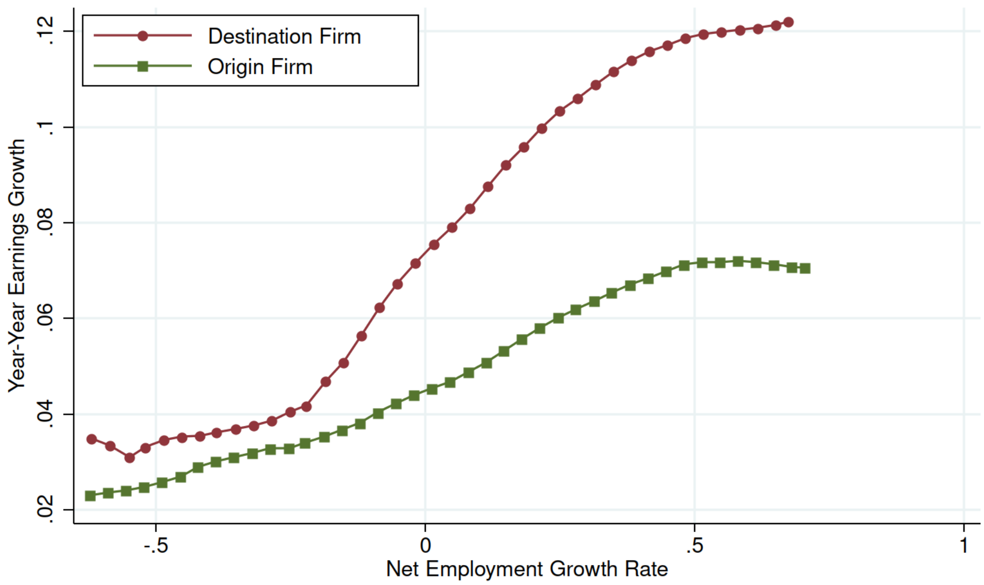

Figure 1: Nonparametric plot for earnings growth associated with net job flows at origin firm (Green) and destination firm (Red).

To set up the rest of the intuition when measuring the contribution of net flows, we need to understand how net and gross flows interrelate. If it were the case that fast growing firms hold on to nearly all their hires, then n_d would be close to one and the gains from reallocation would be almost exactly the gains of going to a growing firm. In fact, churn is strongly correlated to net employment growth. Figure 2 shows that net employment growth and excess hires, our measure of gross "churn," are related in a V-shape. This symmetric relationship also holds at the quarterly frequency, shown in Appendix A, and indicates that as net growth increases, turnover of workers at the firm is also increasing.

The upshot of Figure 2 is that adjusting $Pr[JF]$ for gross flows is quite important. For growing firms, separations are also increasing and thus, we would overstate the role of net reallocation if we assumed every worker hired to a growing firm contributes to the firm's net job growth. Similarly, separating workers at both growing and shrinking firms are often being replaced.

Thinking about Figure 2 in its own right, this suggests that gross flows are not random occurrences. Instead, they have a systematic relationship with firm growth. This was actually implied by the "hockey stick" figure of Davis et al. (2013) and Bachmann et al. (2017) find a similar pattern in Germany, which they explain using unanticipated separation shocks. This explanation is actually very good motivation for our probabilistic treatment of net growth: for Bachmann et al. (2017), excess hires are the result of separations that were either larger or smaller than expected and thus exist to get firms back to their optimal scale. A hire by a firm simply responding to a separation shock is conceptually quite different than a hire that leads to net growth, so we attempt to separate them.

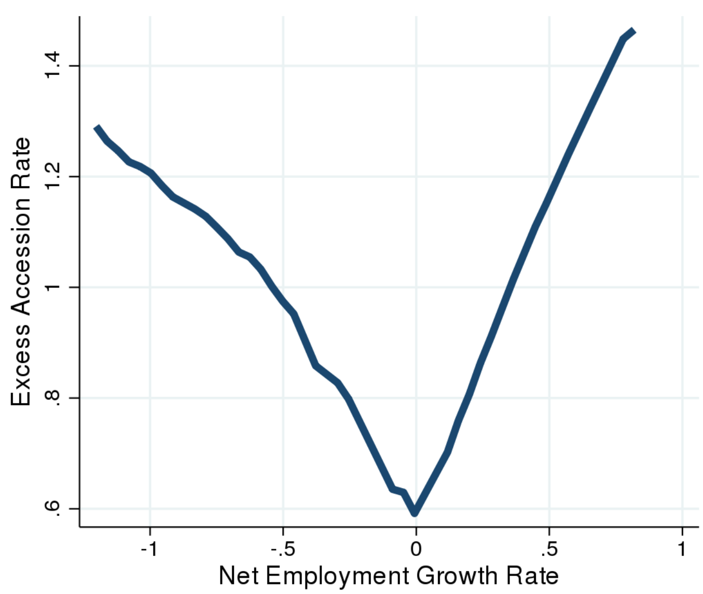

Figure 2: Nonparametric plot showing the V-shape of excess hires, churn, over net employment growth.

4. Firm-level Labor Dynamics and Individual Earnings Growth: Conditional Results

Many firm characteristics play into workers' earnings growth during transitions, and in this section we will check that the patterns in Section 3 remain after conditioning on other, known determinants and compare their magnitudes to that of firm labor dynamics. Here we present our primary reduced form estimates of earnings growth with the origin and destination firms' characteristics. We estimate the following regression specification:

$$
\begin{aligned}
\Delta w_{i,t} = & \beta_{1,d}\Delta L_{d,t} + \beta_{1,\ell}\Delta L_{\ell,t} + \beta_{2,d}F_{d,t} + \beta_{2,\ell}F_{\ell,t} \\
& + \beta_{3,d}\tilde{w}_d + \beta_{3,\ell}\tilde{w}_\ell + \beta_4 Q(\bar{w}_i|c) + x'_{\ell,d}\beta
\end{aligned} \tag{4.1}
$$

where $x'_{\ell,d}$ denotes origin and destination log employer size, employer age, a quadratic in worker age, gender, 2-digit 2012 NAICS industry dummies and time effects for the quarter of the transition. The indices for the origin, ℓ, and destination, d, are functions of i, t but we suppress notation for this. Results for the regression in Equation 4.1 are presented in Table 1. The first column is the baseline specification. The second breaks net employment growth, ΔL_j into job creation and destruction, ΔL_j^+ and ΔL_j^-. Column (3) looks at the same specification but with worker-level fixed effects. Column (4) includes the accession rate, H, in lieu of the excess accession rate F. All of the coefficients except firm age at the destination firm in Column (3) are significant at the 99% level.

The first two coefficients, net employment growth at the origin and destination firm are most interesting to us. Both are consistent with the positive slopes we showed in Figure 1. While both moving from and going to a net growing firm brings a positive earnings gain, the elasticity is much larger at the destination firm. The coefficients in Column(1) mask the asymmetry between net job creation and destruction. Column (2) splits ΔL_j in two, between job creation and job destruction, $\Delta L_j^+, \Delta L_j^-$ at the origin and destination $j \in \{\ell, d\}$. The largest coefficients are on job creation at the destination, ΔL_d^+ and job destruction at the origin, ΔL_ℓ^-. Workers who are hired at a growing firm have greater earnings growth than otherwise expected, with an elasticity of 10.7%. Workers who leave shrinking firms see their wages decline relative to that which is otherwise expected. The elasticity of earnings growth to job destruction at the origin is about -7.3%. Note that job creation at the origin firm has little positive effect on earnings growth.

Column (3) adds individual-level fixed effects. Meaning that we are now looking within an individual's labor market history comparing earnings growth when the same individual transits to e.g. a growing firm or a shrinking firm. While differencing earnings removed individual effects from earnings levels this removes individual trends. Further, this is one way of addressing selection on unobservable characteristics, i.e. some workers may be more likely to switch to growing firms and more likely to have earnings growth in the process. Column (3) shows our results are not driven by this potential composition effect.

Column (4) is particularly important because it clarifies why we focus on net employment growth rather than simply hires. Comparing coefficients, which are comparable elasticities, there is an empirical distinction: employment growth itself is more important than hires or the turnover coefficients F. Essentially the question here is whether what matters for earnings growth is hiring or net growth/creation? The coefficient on the accession rate is positive but much smaller than the net flow rate. To paraphrase much prior work that distinguishes gross hires from net growth (e.g. Elsby et al. (2017), Column (4) helps differentiate whether earnings growth primarily reflects recruitment itself, which would mean the accession rate is quantitatively largest, or if the earnings growth premium is driven by firms trying to increase their labor input, implying employment growth itself is largest. The result motivates our exercise below, which estimates the probability a hire is part of the net employment growth and not part of the excess turnover.

Finally, Table 1 also allows us to quantify the relationship of earnings growth and firm dynamics to other firm static characteristics known to be important such as size, age, and average wage. The coefficient on the wage level of the firm, $\tilde{w}_x$, is large. It is about twice the size of employment growth, ΔL_d, and four times the size of ΔL_ℓ. But, the magnitudes of all the coefficients are very small. We see earnings growth coming from workers climbing a job-ladder, and like many of the other characteristics such as size and F_x, for instance, they are mostly subsumed by the effect of going from lower- to higher-wage firms. ΔL_x, however, still has a large effect on earnings growth, even after conditioning on the workers' movement in the average-wage ladder.

To reinforce these findings, we use a semi-parametric approach, allowing the relationship between ΔL_x and $\Delta w_{i,t}$ to be fully flexible while maintaining linearity in the other regressors. This is shown in Figure 3. It looks remarkably similar to the unconditional relationship between earnings growth and net firm growth at both origin and destination which we displayed in Figure 6 in the Appendix. As emphasized in our regression specification, the effects from ΔL_d are stronger when the firm is growing more quickly. This can be seen from the convexity of the line through the portion with most mass, closer to zero. Towards the tails, these effects tend to flatten out. For the origin firm growth, ΔL_ℓ, Figure 3 shows very clearly the large losses associated with fast shrinking firms, and the relatively flat line right of zero implies relatively minor gains from leaving a fast growing firm.

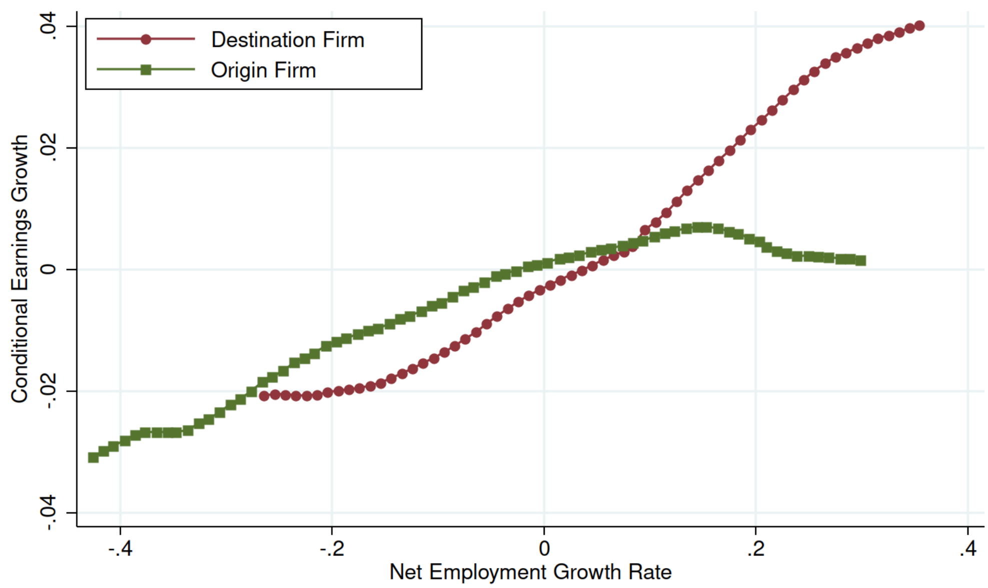

Figure 3: Annual frequency, semi-parametric plot for earnings growth associated with net job flows at origin firm (Green), destination firm (Red), conditional on gross flows and firm worker characteristics from Regression Equation 4.1.

To compare the implied effects of firm dynamics on earnings growth, we put our estimates into 2009 dollar values. We use the point estimates from Table 1 and the transition patterns from the data to estimate the 90th percentile most earnings growth associated with each characteristic and the 10th percentile most earnings loss—that is, the dispersion in earnings growth across job-to-job transitions that can be ascribed to each firm characteristic. The difference in firms' average wages implies a 90-10 differential of $\$7,578$, the difference between firm sizes explains $\$2,250$ and $\Delta L_\ell, \Delta L_d$ implies a 90-10 differential of $\$1,624$. This is to say, whether a worker moves from a low- to a high-wage firm is the largest predictor of the dispersion in earnings growth during a job-to-job transition. But moving up the firm size distribution and moving towards growing firms have effects of approximately the same scale, each accounting for 20-30% of the average wage effect.

While these results suggest a strong relationship between earnings growth of the worker and the net growth of the firm, we can think of mechanisms which could imply causality in either direction. A reasonable interpretation is that this relationship is driven by firms' recruiting behavior. Growing firms may have stronger incentives to fill a vacancy, and therefore attract workers with higher wages. Section 6 introduces a model that provides some guidelines for mechanisms working through the firm's incentive to recruit. However, we cannot rule out mechanisms which would work in the opposite direction. For instance, if sorting of productive workers into firms or teams yields higher productivity, then perhaps this occurs more often at growing firms, and the wage growth premium results from this higher productivity. Such a mechanism is at work in Hagedorn et al. (2017) and Herkenhoff et al. (2018).

5. Quantifying the Contribution of Net Job Flows

In this section, we will present our estimates to answer our initial question: How does moving with the job flow contribute to earnings growth among job-to-job transitions? To revisit the logic of our answer, Section 3 presented the first part: going to a growing firm implies more-than-average earnings growth, leaving a shrinking implies less-than-average and thus going with the job flow subtracts the former from the latter. However, Figure 2 showed that growing and shrinking firms have considerable turnover, so a hire at a growing firm is actually likely to be a replacement hire, rather than net growth. Table 1 showed this distinction matters because net growth measures had significantly larger earnings growth elasticities than excess hires or total hires.

We cannot directly observe whether a particular hire at a growing firm replaced a separation or is part of net employment growth, and similarly, we cannot tell if a separator from a shrinking firm was replaced. However, we can estimate the probability that a worker was part of the job flow across firms based on the origin and destination firms' net and gross flows.

Consider our baseline regression specification from Equation 4.1 and replace other firm dynamics terms, ΔL_x, F_x, H_x, with $\Pr[JF]$.

$$\Delta w_{i,t} = \gamma_1 \Pr[JF] + +\beta_{3,d}\tilde{w}_d + \beta_{3,\ell}\tilde{w}_\ell + \beta_4 Q(\bar{w}_i|c) + x'_{\ell,d}\beta \tag{5.1}$$

These results are in Column (1) of Table 2. We then break apart the effect of going towards a growing firm and leaving a shrinking firm, $n_d n_\ell + n_d \frac{F_\ell}{S_\ell}$ or $n_d n_\ell + n_\ell \frac{F_d}{H_d}$, in Column (2). These confirm the logic from earlier, workers hired for firm growth experience above-average earnings growth, and those leaving as part of firm shrinking experience below-average earnings growth. The former is stronger than the latter, so their net effect is positive. We use several measures which indicate that a job transition is part of the net reallocation of workers, moving with the job flow. Columns (3) and (4) use coarser measures as a baseline check. In Column (3), we replace $\Pr[JF]$ with an indicator $\mathbb{I}_{\Delta L_d - \Delta L_\ell > 4\%}$, another possible notion of job flows but which does not control for the rate of excess hires.[7]

From these estimates, we can conclude that workers moving with the job flow reap a considerable earnings benefit. The coefficient on $\Pr[JF]$ in Column (1) suggests that a transition with a 100% chance of being with the

[7]An alternative construction, $\mathbb{I}_{\Delta L_d > 2\% \cap \Delta L_\ell < -2\%}$ is quantitatively quite similar.

job flow gets 1.7 percentage points more earnings growth than a job transition that is certainly part of the worker churn. This is 23% of the earnings increase of an average transition, 7.3%. Again, the positive effect from transiting with the job flow comes from the effect of growth at the destination firm. Column (2) suggests that a worker who contributes to employment growth at the destination has 9.1 percentage points more earnings growth, more than double the earnings growth of an average transition.

Of course, the missing piece is how frequently workers move with the job flow. About 46% of hires are to firms growing more than 2% in a year while 34% of hires go to firms *shrinking* more than 2%. Separations come from shrinking firms 37% of the time, and from growing firms 43% of the time. Of course, Figure 2 suggests that many of these hires do not contribute to net employment growth. We find 20.7% of hires contribute to net job flows, the sample average of our $\Pr[JF]$ measure. This implies that the average transition gets \$183 from the premium associated with moving with a job flow—the 0.017 coefficient times 0.207 and converted to dollars. This effect is composed of a \$516 premium from workers going to growing firms, but a \$243 loss from leaving a shrinking firm.

These results make clear that the earnings growth premium can be ascribed disproportionately to the flow of jobs from one firm to another, rather than the flow of workers. This distinction between a job flow and worker flows is especially important given that gross worker flows, which do not necessarily contribute to firm growth or job reallocation, are a large proportion of job transitions. These gross flows drive down the average effect of this job reallocation premium, as the probability of a worker being a part of this reallocation is relatively small despite the large wage effects when there is reallocation.

This distinction of job flows and worker flows is also important for distinguishing plausible mechanisms for firm dynamics and wages. Search models which feature large firms can allow for worker flows and job flows to move independently or with an arbitrary joint distribution. In these, the potential earnings gains in a transition is one of the central mechanisms incentivizing workers to move. But, the source and extent of these gains will vary depending on the underlying mechanism: particularly they may arise due to search frictions that leave room for workers to better allocate themselves or to complementarities in the production function of the firm. This implies that the joint dynamics of worker flows, job flows, and their resulting earnings growth are an important identifier of the relevant mechanisms. Models and mechanisms such as those in Kaas and Kircher (2015); Elsby et al. (2017); Bilal et al. (2019) vary greatly in the implied relationship between firm growth, worker flows, and earnings. To properly test these mechanisms requires additional information about the nature of productivity growth. Changes in earnings alone cannot distinguish between productivity growth vs the change in that which is passed through to workers via earnings. We do not observe productivity in our sample and consider this an important avenue for future research.

6. Implications for Equilibria in Job Search Models

We have presented very robust coefficients on ΔL_d and these underly the premium associated with job mobility with the flow. Along with the purely empirical interest, these provide guidance to equilibrium relationships in search models in which growing firms offer premia to attract workers. In a world with either directed or random search, a firm that wishes to recruit more quickly (and thus grow) will post a job promising a higher value to the worker. In random search, this increases the yield on the posting quite mechanically: if the match distribution G is also the reservation value of potential new hires, a higher value posting is higher in G, i.e. acceptable to more workers, and therefore more likely to result in a match.[8] As such, in this section we provide conditions on the key equilibrium object: the distribution G that determines earnings from where firms recruit.

In this simple random search framework, the key element of the equilibrium is the distribution of match values from which the firm hires, $G(W)$, with density $g(W)$. In the simple case we explore, an employed worker with value W_ℓ rejects an offer W^* iff $W^* < W_\ell$ where W_ℓ is their reservation value. If the workers' meeting rate is $p(\theta)$ then the rate at which a worker accepts an offer W^* is $p(\theta)G(W^*)$, i.e. the probability of a match times the probability the value of their last match was less than W^*.

There are two important caveats about simplifications in our model. First, G is both the distribution of workers' match values and the distribution of reservation values. This is an important coincidence, when we discuss G in what follows, we really mean to interpret it as the distribution of reservation values from which a firm will recruit. That it is also the equilibrium distribution of W creates an obvious target in the data, but which our condition—required to to be consistent with our findings from the data—does not always match. Hence, it is important that we emphasize G as the distribution of origin match values of job-to-job transitors, whereas a more sophisticated model would be necessary to decouple the two meanings of G.

Our finding relates the expected percent growth in the worker's value, $E[\log W^* - \log W_\ell]$, to the growth in the firms' size, ΔL. But, of course, in

[8]With directed search, higher posted values have a similar effect, but now the reason is different: on the worker-side, they face a trade-off between the workers' value and job finding rate, which dictates the size of step they take at different levels of the job ladder.

the data we observe earnings and not necessarily match values, but mapping between match value and earnings requires additional assumptions on the earnings determination process and the contract space. Instead, we will treat match value W as the analog to our measured earnings. For a version of our regression using an approximation of total match value, see results in the Online Appendix A, in which the results still hold.

Proposition 6.1. *Earnings growth is increasing in firm growth,* $\frac{\partial E[\log W^* - \log W_\ell]}{\partial \Delta L} \geq 0$*, if* $g'(W^*)] \leq 0$

It is easy to see that any time $\Delta L > 0$, they will post a higher value W^*. Taking the perspective of a firm, they meet workers with probability $q(\theta)$ and an offer of W^* is accepted with probability $q(\theta)G(W^*)$. To simplify the exposition, we will present a static cost minimization problem for a firm that grows by hiring $H = L' - (1-\delta)L > 0$ workers. Obviously, there are also dynamic costs and benefits the firm considers, but they are not essential for our argument once we assert the firm is growing. This firm chooses a posted value W at cost $\omega(W)$, where $\omega > 0, \omega' > 0\ \forall W$, and number of vacancies v at cost $\kappa(v)$, where $\kappa > 0, \kappa' > 0\ \forall v$:

$$\min_{W,v>0} \omega(W)H + \kappa(v) \ :\ H = G(W)q(\theta)v$$

The first order condition on this sets

$$\omega'(W^*) = \kappa'\left(\frac{H}{G(W^*)q(\theta)}\right)\frac{g(W^*)q(\theta)}{(g(W^*)q(\theta))^2} \tag{6.1}$$

in which H has canceled from both sides, but is still embedded in the marginal posting cost. If, however κ' is a constant then W does not depend on H and instead growth occurs by increasing v. Assuming $\kappa'' > 0$, as in the strictly convex posting costs considered in Kaas and Kircher (2015), then differentiating W with respect to H we get

$$\omega'' dW = \frac{k'' gq \frac{1}{Gq}}{(Gq)^2} dH - \frac{k'' gq \frac{Hgq}{(Gq)^2}}{(Gq)^2} dW + \frac{k' g' q}{(Gq)^2} dW - \frac{2k'(gq)^2}{(Gq)^3} dW$$
$$dHk'' gq = dW \left(w''(Gq)^2 + 2k' \frac{(gq)^2}{Gq} - k' g' q + k'' H \frac{(gq)^2}{(Gq)^2} \right)$$

The sufficient condition for $\frac{dW}{dH}$ to be positive is if $\kappa'' \geq 0$ and if $g' \leq 0$. The latter is consistent with a requirement we need later also. This means that as firms that grow will adjust both their vacancies v and the acceptance rate of their offer, by changing $G(W^*)$.

Then the question is, when the posted value W^* increases, what conditions on G are required so that the worker hired has more earnings *growth*? Let W_ℓ be the value from which the worker was hired. The expected growth in percentage terms is then, $E[\log W^* - \log W_\ell] = \log W^* - \int_{\underline{W}}^{W^*} \log W dG(W) \frac{1}{G(W^*)}$. Note that the limit of integration is W^*, because those are the only workers the firm will successfully hire and to make this truncated distribution integrate to 1, we divide by $G(W^*)$.

Then, when W^* increases, the distribution G can not be increasing too much, or the mean below W^* will also increase. Thus, we need the following necessary condition to be satisfied:

$$\frac{\partial}{\partial W^*} \left(\log W^* - \int_{\underline{W}}^{W^*} \log W \frac{g(W)}{G(W^*)} dW \right)$$
$$= \frac{1}{W^*} - \log W^* \frac{g(W^*)}{G(W^*)} + \int_{\underline{W}}^{W^*} \log W \frac{g(W) g(W^*)}{G(W^*)^2} dW \geq 0$$

We can see that this condition is satisfied with equality for a uniform distribution. Substituting in $g(W^*) = 1$ and $G(W^*) = W^*$, assuming a support of $[0, 1]$ to simplify the algebra.[9]

$$
\begin{aligned}
&\frac{1}{W^*} - \log W^* \frac{g(W^*)}{G(W^*)} + \int_0^{W^*} \log W \frac{g(W)g(W^*)}{G(W^*)^2} dW \\
=&\frac{1}{W^*} - \log W^* \frac{1}{W^*} + \int_0^{W^*} \log W dW \frac{1}{W^{*\,2}} \\
=&\frac{1}{W^*} - \log W^* \frac{1}{W^*} + (W^* \log W^* - W^*) \frac{1}{W^{*\,2}} \\
=&\frac{1}{W^*} - \log W^* \frac{1}{W^*} + \log W^* \frac{1}{W^*} - \frac{1}{W^*} = 0
\end{aligned}
$$

Then, to make this inequality strict, it is sufficient for $g(W^*)$ to be decreasing, $g' < 0$ because the density is subtracted.

7. Discussion/Conclusion

In this paper, we show that firms' employment dynamics are related to the earnings growth that workers receive when they switch jobs. Workers' earnings growth is particularly responsive to employment growth at the destination firm and employment declines at the origin firm. Furthermore, net employment growth is considerably more important than gross hires. Combining these findings, we estimate how moving with the cross-firm job flow affects earnings growth for job-to-job transitions.

All of these empirical facts are themselves quantitatively important: there are large differences in earnings growth between otherwise similar-looking job

[9]We could also do this with $g = \frac{1}{\bar{W} - \underline{\mathrm{W}}}$, $G(W) = \frac{W - \underline{\mathrm{W}}}{\bar{W} - \underline{\mathrm{W}}}$, on the support $[\underline{\mathrm{W}}, \bar{W}]$ but it requires more algebra and solving for a few constants when we integrate.

transitions. We highlight an important dimension driving these differences: the labor force flows of the origin and destination firms. The faster the destination firm is growing, the larger the earnings growth, with a $1,624 premium for going to the top decile of firm growth rather than the bottom. Further, being part of the net flow of workers across firms brings with it a 23% wage premium.

We see these findings as informative for the relationship between firm dynamics and wages empirically, but also as testable implications for a range of quantitative and theoretical models of the labor market. Most promisingly, search models of the labor market where firms employ multiple workers are a largely recent development. These models provide an ideal framework for understanding the relationship between wage growth, firm growth and underlying sources of inequality. Our empirical results are ideal targets for calibrating such models because of some sharp predictions about the elasticity of earnings growth of job switchers to growth at origin and destination.

The relatively simple search model we presented provides a skeleton or prototype for such models. In it, the crucial mechanisms are that productivity shocks lead firms to increase their recruiting intensity by posting higher wages. Our findings, however, then can help refine the theory because they make a sharp prediction about the equilibrium that would produce necessary characteristics of the distribution of prior earnings from which this growing firm recruit. They require that the distribution is decreasing.

But our central question requires that we look beyond the observed relationship of earnings growth and net job flows because not all worker transitions are net job flows. We link and distinguish gross and net flows, with the latter accounting for about one in 5 transitions. Excess, gross worker flows, however, are not distributed evenly across firms, and we showed that they are correlated at the firm level with a V-shape. They are important to distinguish, however, because they have dissimilar elasticities for earnings growth, with gross flows much less determinative of earnings growth than net job growth. This gives insight into how firms use the promise of earnings to grow, rather than just to hire. Thinking only empirically, this also points out an important dimension by which job transitions can be distinguished.

Our final result is a composite of these intermediate findings. We saw that net firm growth matters, and even more so than gross worker flows at the firm, so we probabilistically identified the former. This probabilistic identification allows us to estimate our primary result, that workers changing job-to-job with the job flow enjoy a 23% earnings growth premium. However, on aggregate this is a smaller portion of the overall gains from job-to-job transitions because gross worker flows are so much more prevalent than net. We presented a model that was consistent with this relationship, where high growth in employment comes from high returns to filling a (productive) vacancy, and this translates to higher earnings growth for transiting workers. Of course, there are alternatives which may also produce this relationship, but our results provide testable implications for any framework which allows for the interaction of worker and job flows. In addition to being consistent with our headline result, we provide details on the relationship between earnings growth and net flows at the destination firm, origin firm, gross flows, and the asymmetry of growing vs. shrinking firms in the marginal effects on earnings. We also provide details on the aggregate prevalence of net and gross flows and the firm-level relationship between them (i.e., the V-shape.).

In addition to contributing empirically to an emerging literature, we hope this work also highlights two important directions for research. Empirically, the need for good measures of productivity for the full panel of firms is obvious. Much of what we have discussed has in its background that firm growth likely is related to productivity changes. Several important articles have recently begun to introduce such measures, such as Bagger et al. (2020) or Haltiwanger et al. (2018) but we believe there is a great deal of room to explore the rich relationship between size changes and productivity changes at the firm level and earnings growth at the worker level. Further, we have only begun to understand the coexistence of net and gross flows and, in particular how they fit into our models of job ladders. These have generally static notions of firms and imagine turnover to be perfectly correlated with wage or poaching rank, but as we have seen in this work, turnover is neither constant nor given purely by wages nor is it obvious that a single ranking would capture the empirical relationship between poaching and turnover. In exploring this further, we can both understand the role of turnover in firm growth and, in that it informs our notion of job ladders, workers' earnings growth.

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Table 1: Baseline Estimates of Earnings Growth across Job-to-Job Transitions.

	(1)	(2)	(3)	(4)
ΔL_ℓ	0.0280		0.0437	0.0321
	(0.00144)		(0.00290)	(0.00151)
ΔL_d	0.0717		0.0769	0.0651
	(0.0033)		(0.0023)	(0.00145)
ΔL_ℓ^+		-0.00961		
		(0.00221)		
ΔL_d^+		0.107		
		(0.00236)		
ΔL_ℓ^-		-0.0731		
		(0.00246)		
ΔL_d^-		-0.0412		
		(0.00214)		
H_ℓ				-0.00659
				(0.00063)
H_d				0.0141
				(0.00071)
F_ℓ	-0.00386	-0.00210	-0.00214	
	(0.00066)	(0.00066)	(0.00179)	
F_d	0.0117	0.00947	0.0181	
	(0.00075)	(0.00076)	(0.0021)	
$ln(Emp_\ell)$	-0.00429	-0.00458	-0.00404	-0.00429
	(0.00015)	(0.00015)	(0.00036)	(0.00015)
$ln(Emp_d)$	0.00158	0.00186	0.00175	0.00162
	(0.00014)	(0.00015)	(0.00036)	(0.00014)
$Firm\ Age_\ell$	0.00047	0.00041	0.00045	0.00045
	(0.00004)	(0.00004)	(0.00009)	(0.00004)
$Firm\ Age_d$	-0.00021	-0.00016	-0.00008	-0.00018
	(0.00004)	(0.00004)	(0.00008)	(0.00004)
$\tilde{w}_\ell$	-0.143	-0.143	-0.120	-0.145
	(0.00083)	(0.00083)	(0.00216)	(0.00082)
$\tilde{w}_d$	0.157	0.156	0.130	0.158
	(0.00083)	(0.00083)	(0.00229)	(0.00083)
Constant	0.192	0.195	0.615	0.193
	(0.00986)	(0.00985)	(0.0516)	(0.00982)
N	1054000	1054000	476000	1054000
R^2	0.105	0.105	0.0789	0.105

Includes controls for worker age and its quadratic, age gender, lifetime earnings rank conditional on birth cohort, industry and time effects. Standard errors in parentheses. All columns present annual earnings growth. Column 3 contains the individual fixed effects estimation. Column 4 includes the accession rate, H, in lieu of the excess accession rate F.

Table 2: Estimates of Earnings Growth due to Job Flows in Job-to-Job Transitions.

	(1)	(2)	(3)
$\Pr[JF]$	0.017		
	(0.00148)		
$n_d n_\ell + n_d \frac{F_\ell}{S_\ell}$		0.0906	
		(0.00195)	
$n_d n_\ell + n_\ell \frac{F_d}{H_d}$		-0.0418	
		(0.00171)	
$\mathbb{I}_{\Delta L_d - \Delta L_\ell > 4\%}$			0.0123
			(0.0006)
$Q(\bar{w}_i \mid c)$	0.0166	0.0157	0.0166
	(0.00183)	(0.00183)	(0.00183)
$ln(Emp_\ell)$	-0.00436	-0.00447	-0.00436
	(0.00015)	(0.00015)	(0.00015)
$ln(Emp_d)$	0.00148	0.00207	0.00151
	(0.00036)	(0.00014)	(0.00014)
$Firm\ Age_\ell$	-0.011	-0.0109	-0.011
	(0.0002)	(0.0002)	(0.0002)
$Firm\ Age_d$	9E-05	9E-05	9E-05
	(0.000002)	(0.000002)	(0.000002)
$\tilde{w}_\ell$	-0.142	-0.139	-0.141
	(0.00073)	(0.00073)	(0.00072)
$\tilde{w}_d$	0.15	0.146	0.151
	(0.00074)	(0.00074)	(0.00074)
Constant	0.248	0.255	0.233
	(0.00882)	(0.00881	(0.00877)
N	1054000	1054000	1054000
R^2	0.102	0.104	0.102

Includes controls for worker age and its quadratic, age gender, lifetime earnings percentile conditional on birth cohort, industry and time effects. Standard errors in parentheses. All columns present annual earnings growth.

Table 3: Earnings Growth from Reallocation vs. Average Job Transition.

	β	Flow Probability	Job Flow Effect	$\mathbb{E}(\Delta w)$
$\Pr[JF]$	0.017	0.207	\$ 183.6	\$ 2921
$n_d n_\ell + n_d \frac{F_\ell}{S_\ell}$	0.091	0.111	\$ 515.8	\$ 2921
$n_d n_\ell + n_\ell \frac{F_d}{H_d}$	-0.042	0.109	\$ -242.9	\$ 2921

Column (1) shows the estimated average effect of job flows, Column (2) the sample average of $\Pr[JF]$, Column (3) multiplies (1) and (2) and converts that into dollar terms and column (4) lists the average earnings growth in our sample. The second and third rows break JF into flows at the destination and origin.

Online Appendix

A. Additional Figures

A.1. Graphical description of our measurement timing

To better describe the timing and construction of our variables, Figure 4 presents a schematic. We measure this way so that the transition of the individual we are watching is not part of the firm-level transition rate. That is, the shrinking of the origin firm does not include the separation of the worker whose earnings we are following.

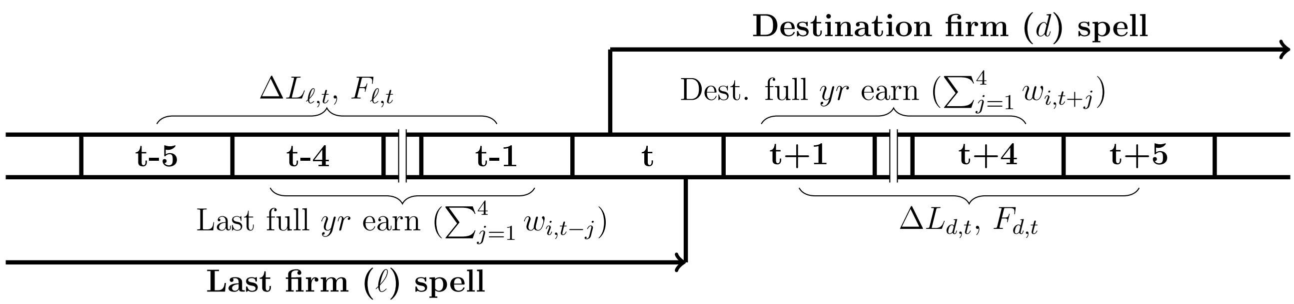

Figure 4: The timing of our employment and earnings growth measures.

A.2. Changes in the Present Discounted Value of Earnings

Here, we mimic our regressions in Section 4 but use the change in discounted present value of earnings as the dependent variable for each employment transition. To construct this measure we compute the discounted sum all earnings after the transition. We take the log difference between that and a hypothetical measure discounted sum had the worker stayed in the same firm.

The approach, using counter-factual wages is similar to that introduced in Jacobson et al. (1993) and used extensively to estimate the long-run earnings losses due to job separation. Our regression takes the form

$$V_{i,t} = \gamma_0+\gamma_1 w_{i,t-1}+\gamma_2 \sum_{j=1}^{4} w_{i,t-j}+\gamma_3 w_{i,t_0}+\Gamma_{a\times\tau}(\,age\times tenure)+\sum D_t \quad \text{(A.1)}$$

That is, we look at the recent history of earnings over the past year, initial earnings from the match, a polynomial of the interaction of age and job tenure and a set of dummies for the year. The inclusion of time fixed effects is necessary due to censoring of the present discounted value of earnings, especially for observations late in the sample. We then use these regression estimates to project $E_{t-1}v_{i,t}$ among the workers who move firms and were not in the original regression. This lets us construct $\Delta\hat{v}_{i,t}$, which forms the empirical analog to our previous $\Delta w_{i,t}$.

We then estimate the same regression as in Equation 4.1, but using $\Delta\hat{v}_{i,t}$ and excluding $Q(\tilde{w}_i|c)$ because much of life-time income is embedded in $E_{t-1}V_{i,t}$ and this is systematically related to how late in the sample we observe the transition.

A.3. Stayers

A.4. Quarterly frequency

In this section we present quarterly frequency estimates for Figures 1 and 2. Earnings growth is slightly lower among the job movers, which reflects both selection and job tenure effects. In the quarterly sample we have many short-tenured workers who do not last a full year at their two matches and these workers tend to gain less in job-to-job transitions.

In Figure 8, we see the same V-shaped relationship between excess hires and the net employment growth as in Figure 2. Note that at the quarterly frequency, the excess hire rate, the churn rate, is much lower than at the

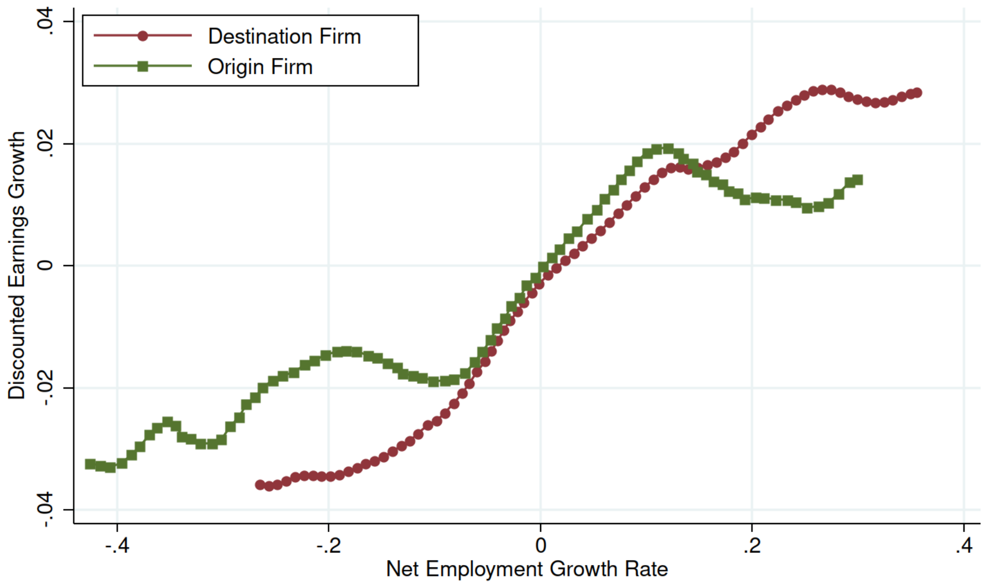

Figure 5: Semi-parametric plot for growth in present discounted value of earnings associated with net job flows at origin (Green) and destination (Red). Other terms from regression 4.1 are linearly conditioned on.

annual frequency. This is almost by construction because the total number of hires accumulates over a longer period.

A.5. Job Flow Probability

In Table 4 we show the probabilities that a given job transition in our sample was a move from a growing, shrinking, or stagnant ($< 4\%$ absolute change in employment) firm to a growing, shrinking or stagnant destination firm. The sum of all cells is 1. While the plurality of transitions are to growing destination firms, there are substantial numbers of job transitions to shrinking and stagnant firms. To identify what worker flows are associated with a job flow, we not only have to consider the movement of workers into growing firms and away from shrinking ones, but also the gross flows and churn of these associated firms.

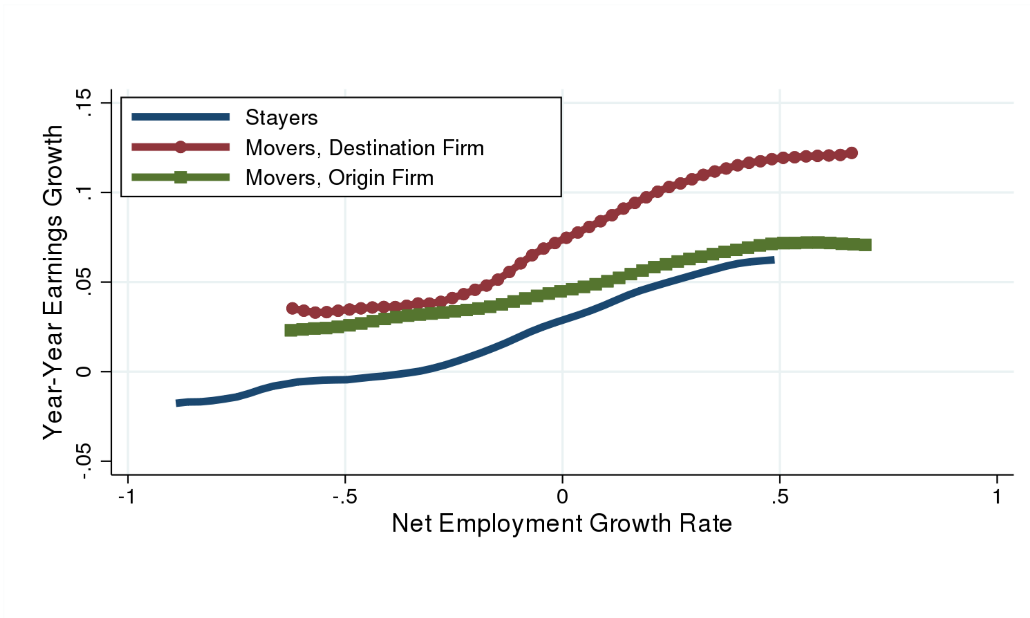

Figure 6: Nonparametric plot for earnings growth associated with net job flows at origin firm (Green), destination firm (Red) and stayers (Blue).

Table 4: Probability matrix of Job Transition Types

	Destination		
Origin	Grow	NoChng	Shrink
Growth	0.22	0.08	0.13
NoChng	0.08	0.05	0.06
Shrink	0.16	0.07	0.15

A.6. Distribution of Earnings Gains

To ilustrate the importance of some firm-level variables in terms of their implied effect on earnings growth, we look at the earnings differentials implied by their regression coefficients at different percentiles. We take the dollar amount implied by the coefficient on the variable in our baseline regression and multiply it by the difference between the following percentiles of that variable: 75-25, 90-50, 50-10, and 90-10. The difference in earnings growth

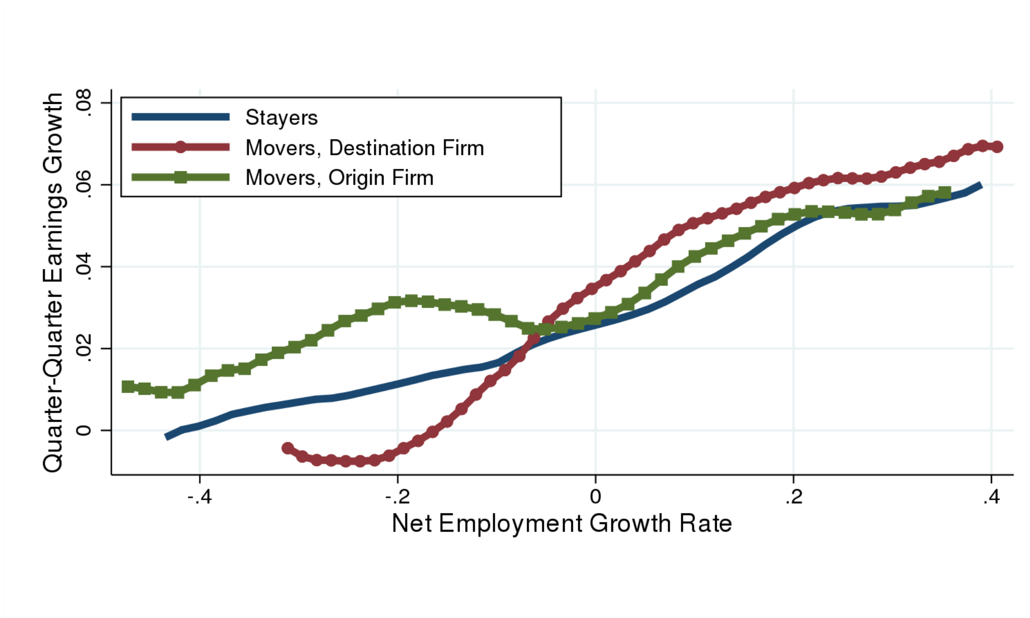

Figure 7: Quarterly frequency, nonparametric plot for earnings growth associated with net job flows at origin firm (Green), destination firm (Red), and stayers (Blue).

across the distribution of these firm characteristics is large.

Table 5: Distribution of Implied Earnings Gains

Variable	p75-p25	p90-p50	p50-p10	p90-p10
ΔL	453.9	853.3	770.7	1624
ΔL_d	398.8	1022.4	332.7	1355.1
ΔL_ℓ	192.7	50.2	564.5	614.7
$\tilde{w}$	3442	5589	1989.4	7578.4
$ln(Emp)$	1037.8	590	1661.6	2251.6

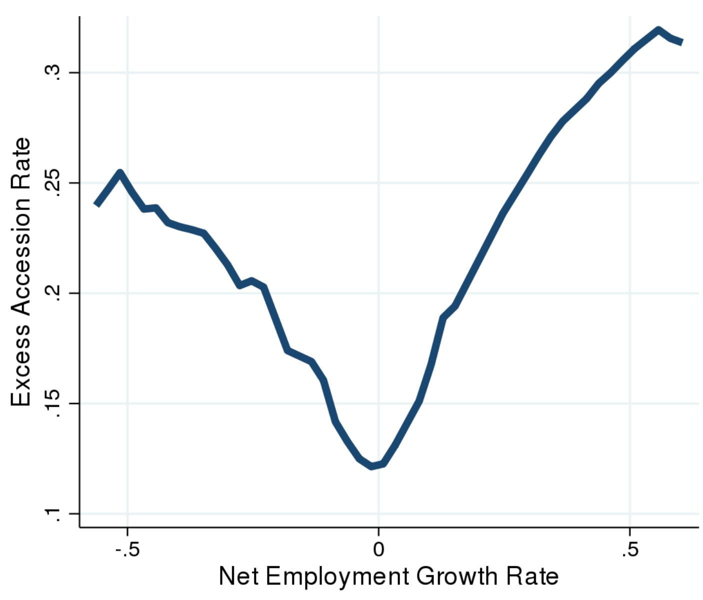

Figure 8: Quarterly frequency, nonparametric plot showing the V-shape of excess hires, churn, over net employment growth.